

THESIS ON INFORMATICS AND SYSTEM ENGINEERING C124

**Radio Spectrum and Power
Optimization Cognitive Techniques for
Wireless Body Area Networks**

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Declaration:

Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for any academic degree.

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Raadiospektri ja võimsuse optimeerimise kognitiivsed tehnikad traadita kehavõrkudele

TAUSEEF AHMED

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ABSTRACT

The recent growth in wireless technologies has opened new horizons and research challenges; in particular, the radio spectrum has become a scarce resource. Radio spectrum is the main ingredient required for wireless communication to exist, and with so many licensed wireless technologies already existing, this key resource has already been used up. Scientists and researchers have gathered to solve the spectrum scarcity problem. It has been observed that spectrum scarcity is in fact a spectrum under-utilization issue. With careful planning and advanced spectrum management techniques, this issue can be resolved. Conventional wireless technologies where dynamic network operations and maintenance is not possible, such spectrum management features are not possible. The concept of environment-aware intelligent radio, named cognitive radio, was introduced in the beginning of the 21st century to meet the requirements of future wireless technologies and services. There has been a lot of research going on various aspects of cognitive radio networks since their introduction. Yet, as of today, realizing many of the cognitive features of such networks still poses research challenges, including spectrum management, power assignments, quality of service, interference management, etc.

In this PhD thesis, tasks related to the radio environment and heterogeneity have been investigated for cognitive radio networks. The thesis presents the unsupervised spectrum access and sharing technique based on machine learning sub-domain called reinforcement learning. The approach presented in this thesis takes into account the current conditions of the spectrum band (e.g. signal to noise ratio, primary network existence, secondary inter-cell interference, etc.) and it decides the fate of the spectrum. Since cognitive radios operate in the primary network environment, they must operate under the precautions and not produce any hindrance toward the primary network operations. To cope with such restrictions, a convex optimization approach to assign transmission powers to the cognitive radios has been presented in this PhD thesis. The approach reduces the required transmission power required, it avoids any interference generated towards the primary network and it minimizes the inter-cell interference, this is reflected by e.g. up to $\times 10$ SINR gains and a 10% gain in user satisfaction in high traffic loads conditions.

Furthermore, this thesis describes the synergy between the cognitive radio's concept and the emerging technology of wireless body area networks by presenting cognitive approaches in their operations. The concept of cognitive body area network (C-BAN) is presented in this PhD thesis. Similar to a cognitive radio network, a cognitive body area network can be context aware and reconfigurable in its transmission features. Wireless body area networks for health care and monitoring applications mostly exist in the spectrum band which is used by many other wireless technologies. For patient monitoring in hospitals and nursing homes can also pose many challenges in spectrum management due to the co-existence of multiple networks of the same types. There is a need for careful spectrum management features and cognition in body area networks. A

reinforcement learning based algorithm for spectrum management is presented in this PhD thesis. The algorithm focuses on the channel conditions before making a decision whether to use it or not. This approach makes sure that best channel among available is selected in order to meet QoS requirements of the network. Furthermore, a transmission power assignment scheme is presented for cognitive body area networks. The proposed scheme is based on illumination problem from the convex optimization field. The proposed algorithm can minimize the inter-body area network interference by reducing the transmission power by 4.5 dBm.

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LIST OF PUBLICATIONS

The work of this thesis is based on the following publications; copies of these publications can be found in Appendices (A-E).

- I. **Tauseef Ahmed**, Yannick Le Moullec
“Power Optimization in a Non-Coordinated Secondary Infrastructure in a Heterogeneous Cognitive Radio Network”, *Elektronika ir Elektrotechnika*, Vol. 21, No. 6, pp. 79 – 83, June 2015. (ETIS 1.1)
- II. **Tauseef Ahmed**, Yannick Le Moullec
“Power-Efficient Frequency Allocation Algorithms for Self-Organized Networks”, 2015 *Advances in Wireless and Optical Communications (RTUWO)*, Riga, 2015, pp. 142-145. (ETIS 3.1)
- III. **Tauseef Ahmed**, Yannick Le Moullec
“Frequency and Power Allocation Schemes for Heterogeneous Networks including Femto Cells”, 2015 *23rd Telecommunications Forum Telfor (TELFOR)*, Belgrade, 2015, pp. 277-280. (ETIS 3.1)
- IV. **Tauseef Ahmed**, Faisal Ahmed, Yannick Le Moullec
“Optimization of Channel Allocation in Wireless Body Area Networks by Means of Reinforcement Learning”, 2016 *IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob)*, Bandung, 2016, pp. 120-123. (ETIS 3.1)
- V. **Tauseef Ahmed**, Yannick Le Moullec
“A QoS Optimization Approach in Cognitive Body Area Networks for Healthcare Applications”, *Sensors*, Vol. 17, No. 4, 2017. (ETIS 1.1)

OTHER RELATED PUBLICATIONS

- I. Faisal Ahmed, **Tauseef Ahmed**, Yar Muhammad, Yannick Le Moullec, Paul Annus
“Operating Wireless Sensor Nodes without Energy Storage: Experimental Results with Transient Computing”, *Electronics*, Vol. 5, No. 4, December 2016. (ETIS 1.1)

AUTHOR'S CONTRIBUTION TO THE PUBLICATIONS

The author's main contributions to the papers listed on page 8 are mentioned briefly in the following section:

- I. The author has proposed the approach that combines dynamic spectrum allocation and transmission power optimization for the secondary network users in a heterogeneous cognitive radio network. The author has suggested the use of reinforcement learning and convex optimization procedures, as well as accounting for inter-cell interference, path loss, and fading. The author has designed the experiments with the help of his supervisor. The author has developed the Matlab simulation code and performed the experiments. The author has written a significant part of the paper using feedback and guidance from his supervisor.
- II. The author of this thesis is the main contributor of this paper. The author has proposed the combination of the reinforcement learning based spectrum allocation technique with power optimization procedures based on convex optimization theory. The author has used these techniques for the radio resource management for the self-organizing networks. The author has performed the simulations, in light of his supervisor's guidance, on the Matlab-based simulation tool developed in Paper I. The author has written a significant part of the paper using feedback and guidance from his supervisor.
- III. The author of this thesis has proposed the reinforcement learning and convex optimization radio resource allocation schemes to combat the interference generated in a micro-femto based heterogeneous network. The author has studied the effects on cognitive radio system capacity and QoS when an intruding network (i.e. a femto cell network) is 'feasting' on cognitive radio network radio resources. The author has developed the Matlab code and performed the experiments. The author has written significant part of the paper using his supervisor's advice and suggestions.
- IV. The author of this thesis is the main contributor of this publication. The author has proposed an algorithm for frequency channel assignment in wireless body area networks which is based on the reinforcement learning. The author has proposed an off-body propagation channel model for CM4. The author has developed a simulation tool for the body area networks based on the IEEE 802.15.6 specifications. The author has performed the simulation experiments using guidance of his supervisor. The significant part of the paper is written by the author of this thesis in light of his supervisor's mentorship.
- V. The author has proposed emerging concept of cognitive body area network by combining the cognitive features from cognitive radios and wireless sensor networks. The author has proposed a context aware channel allocation algorithm for the cognitive body area networks. The

author has proposed an optimized transmission power scheme that exploits the illumination problem from convex optimization theory. The author has suggested the use of unsupervised learning approach from reinforcement learning and power optimization from illumination problem to exploit the network knowledge (i.e. SNR, interference, fading, etc.) to improve system performance. Channel and power allocation methods have been proposed based on reinforcement learning mechanism and convex optimization, respectively. Based on IEEE 802.15.6 standard, the author has proposed a revised channel model for off-body communication link incorporating body postures and shadowing. With the help of his supervisor, the author has designed and performed the experiment on IEEE 802.15.6 based Matlab simulation tool. The author has written significant part of this paper under the supervision and guidance of his supervisor.

Abbreviations

Explanations of abbreviations used in the thesis.

5G	5 th Generation Wireless Systems
BLU	Bernoulli Logistic Unit
C-BAN	Cognitive Body Area Network
CM	Channel Model
CR	Cognitive Radio
CRC	Cognitive Radio Controller
CRN	Cognitive Radio Network
CRSN	Cognitive Radio Sensor Networks
CR-WBAN	Cognitive Radio Wireless Body Area Network
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance
DSA	Dynamic Spectrum Access
FCC	Federal Communications Commission
HBC	Human Body Communication
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
ISM	Industrial, Scientific and Medical Radio Bands
ITU	International Telecommunications Unit
LR-WPAN	Low-Rate Wireless Personal Area Network
MAC	Medium Access Control layer
MICS	Medical Implant Communication Service
NB	Narrow Band
PBS	Primary Base Station
PHY	Physical layer
PU	Primary User

QoS	Quality of Service
RL	Reinforcement Learning
RL-CAA	Reinforcement Learning Channel Allocation Algorithm
SBS	Secondary Base Station
SINR	Signal to Noise and Interference Ratio
SNR	Signal to Noise Ratio
SU	Secondary User
TDMA	Time Division Multiple Access
UWB	Ultra-Wide Band
WBAN	Wireless Body Area Network
WLAN	Wireless Lan
WMTS	Wireless Medical Telemetry Service
WPAN	Wireless Personal Area Network
WSN	Wireless Sensor Network

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INTRODUCTION AND MOTIVATION

Over the last few decades, wireless communication technology has emerged exponentially. The intensive everyday usage of wireless technology, such as mobile phones, smartphones, tablets and laptops, etc. has made it impossible to cope with such huge volume of users and amount of data with classical networks [1]. This exponential growth in the wireless communication domain has resulted in an overly crowded radio spectrum. The radio spectrum is the natural resource on which all these network technologies feed on. It is managed and regulated by national or international governmental organizations such as Federal Communications Commission (FCC) and International Telecommunication Union (ITU). These governing bodies assign this key resource to license holders based on some spectrum assignment policy. The current state of the spectrum allocation indicates that almost all usable frequencies have been already allocated. Typically, these current wireless networks are assigned the spectrum, of which they are the licensed proprietor, statically by the governing agencies. These large bands of spectrum are licensed exclusively for their services users [2]. A notable exception is the so-called ISM/MICS bands which remains unlicensed by FCC and ITU.

However, quite often is the case that large portions of these assigned spectrum bands are not used continuously in the time and/or frequency domains. Hence, and as of today, the actual problem is not so much spectrum scarcity but rather spectrum under-utilization [3]–[5]. Solving, or at least alleviating, this apparent spectrum scarcity problem, can be addressed by utilizing the spectrum in manners that are more efficient, i.e. exploiting time and frequency resources when they are not used by their primary licensed users. Doing so will give the huge advantage that more services and users can be satisfied rather than only limiting the services to the licensed users. These limitations related to the so-called air interface have gathered the researchers to devise plans to confront these problems.

With the fifth generation wireless systems (5G) appearing soon, there is a significant need for supporting heterogeneous networks with the same available air interface. To integrate the new systems, current access schemes must evolve to a level where they can meet the 5G requirements. 5G will be based on software driven technologies, where the software algorithms will perform most of the network functionalities. The 5G networks will have cognitive features and advanced automation of the network operations will be performed through algorithms in a much more optimized way as compared to the classical networks. The 5G networks will provide improvements in the system performance, which will lead to higher system capacity, lower latency, and more services and enhanced spectral efficiency [6]–[8].

Internet of things (IoT) is another step ahead in having a real heterogeneity in the 5G system. When the internet and the modern network technologies are merged together, the resultant technology is IoT. IoT is the combination of electronics,

sensors, actuators, software and their connectivity. IoT is enabling the true sense of heterogeneity of interconnected devices and the exchange of data among themselves. Hence, in IoT, any device can connect with anything, i.e. human or any other device, anywhere through a world-wide network [9]–[12].

In relation to the above, it should be noted that recent advancements in the electronics industry has helped to realize miniature sized computational units to perform certain tasks. As mentioned above, wireless communication technology is growing at an exceptionally high acceleration rate. Scientists and researchers felt the need of combining these state of the art technologies to help and facilitate humankind in a variety of applications. This accelerated research helped creating tiny devices which have the capabilities of sensing some physical phenomena, perform data processing and communicate. Such devices are named sensors or sensor nodes. These devices, when deployed to gather certain data from the physical world or to perform certain action based on that sensed data, form a new type of communication network called wireless sensor network (WSN). Sensor nodes in a WSN work in cooperation to perform a certain predefined action. They gather data from the environment in which they are deployed and report to the manager of the network via sink or gateway nodes [13]–[16].

Wireless body area network (WBAN) is a subset of the WSN paradigm and is a special purpose sensor network used for human body monitoring. It can be used for various applications ranging from remote health monitoring to military operations. Among other things, researchers are focusing on the healthcare aspects of the WBAN applications to facilitate human life [17], [18]. There is a great need for enhancing the health sector with the inclusion of WBANs due to the rapid increase of the population of the world and the ageing of the population in many regions. The current health facilities, e.g. hospitals and clinics, have the same capacity as before and this capacity is not going to increase as quickly as the demand for them. The increase in population and current life standards also have increased the life span during the last few decades. In the United Kingdom, it has been predicted that the population over 85 will be three times the current population in 2035 [19]. In the USA, the life longevity has increased to an average of 13.5% [20] and the population ranging from 60 – 80 years will be twice the current population in 2050 [21]. It is expected that this huge increase of population, in particular its older part, will overload the health care systems and the quality of life will degrade. The elderly population require more frequent visitation to doctors or to health care facilities for routine checkup and monitoring their health status. All these factors are alarming for the healthcare systems; thus, researchers are constantly trying to develop systems which can aid remote and automated health monitoring to augment existing healthcare systems.

With the advent of WBANs, remote health monitoring and diagnosis is possible. which can better distribute the load on the existing medical facilities [22], [23]. It is crucial for the patients who have undergone through a serious medical procedure (e.g. surgery or a rehabilitation procedure) as they need constant monitoring by their doctors or healthcare givers. It is often not possible for such

patients to stay in hospitals or under intensive care for longer time periods due to economic or work constraints. WBANs have huge perspectives in such scenarios to aid both the patients and their doctors [24]. WBANs can allow continuous health monitoring of any individual who needs such monitoring. The real-time data, collected by the sensors on the body, is sent to the concerned user, i.e. healthcare giver. There are two main categories of sensors that can be used in WBANs; invasive and non-invasive. These sensors, whether invasive or non-invasive, transmit their data to monitoring station for diagnosis purposes via other communication technologies. Hence, the existence of a WBAN as medical aid player cannot be fully utilized for human betterment unless it is connected to backbone networks (e.g. internet, LAN/WAN, mobile networks, etc.).

There has been a few other health monitoring systems proposed by researchers previously, but these systems were either too bulky to monitor a mobile patient or they had quite high transmission powers [25], [26]. Higher transmission power gives high-energy electromagnetic radiations and exposing the human body to such radiation levels for longer time periods may cause adverse effects on the patient's health. Hence, such systems cannot be used widely and frequently. With the birth of WBANs, the sensors have become ultra-low powered and miniaturization in size have resulted in wearable sensors.

Mostly, WBANs for healthcare applications are working in the 2.4 GHz ISM band. Though this band is unlicensed, it is already populated with many other wireless communication technologies like Wi-Fi, Bluetooth, ZigBee, etc. [27]. WBANs require to access the spectrum while not disturbing other networks, they need to have cognitive capabilities to access and share that spectrum band efficiently. A state of the art augmented healthcare system cognitive body area network incorporating the cognition from cognitive radio (CR) [28] technology and sensor technology from WBANs would be a future demand for the world, especially in Europe. With the 5G and H2020 projects, these ideas are no longer a dream; rather they are in high research demand. Thus, the proposed research in this PhD work is in line with European research [29]–[31].

PROBLEM STATEMENT AND RESEARCH QUESTIONS

Although CR has been an active research field for more than a decade, there are still many open unsolved issues, in particular if it should be used in WBANs. One of the major challenges for realizing the potential benefits of cognitive radio lies in the spectrum management between secondary users aiming to share the primary spectrum. This, in turn, brings another challenge, i.e. interference management. Therefore, interference avoidance is a crucial task in CR spectrum management [32]–[35].

In order to address those issues, one possible approach can be found in the unsupervised learning domain, namely reinforcement learning. In particular, it has been shown in [36], [37] that reinforcement learning can be used as an optimal decision making tool for spectrum management to deal with unknown network conditions.

This PhD work focuses on answering the following research questions:

- 1 What are the best (or at least most suitable) mechanisms to efficiently utilize the spectrum (or spectrum holes) for CR networks?
- 2 Which mechanisms can be used to avoid the interference between the primary networks and the secondary networks?
- 3 How machine learning and in particular reinforcement learning can possibly be used to deal with the spectrum management issue?
- 4 In case of multiple secondary networks that are coexisting in the same location, how to avoid co-channel interferences?
- 5 Can the interference be avoided using power optimizations?
- 6 Can combining the CR concepts of cognitive and opportunistic use of radio spectrum in WBAN give birth to a new networking paradigm, cognitive body area network (C-BAN)?
- 7 How to embed CR concepts and algorithms into resource-constrained processing elements in C-BAN sensor nodes and gateways?
- 8 To what extent will C-BANs be (more) spectrum efficient than their non-CR counterparts?

CONTRIBUTIONS OF THIS PhD THESIS

The spectrum management techniques presented in this PhD thesis exploit self-learning and adaptive methods to improve their capability to track potential changes and react accordingly. The resulting (fully) aware cognitive networks can substantially increase operational efficiency, which would marginalize spectrum under-utilization and therefore offer more room for handling the increasing demand for new wireless services and the growing number of sensor nodes in our environment, including WBANs. The main contributions of this PhD thesis are:

- A. An unsupervised learning approach based on reinforcement learning is presented for dynamic frequency allocations in cognitive radio networks. The proposed algorithm deals with the uncoordinated and opportunistic spectrum access and sharing in secondary networks. The algorithm takes into account the current channel conditions (e.g. signal to noise ratio, interference, etc.). Therefore, it is satisfying the QoS requirement, reducing inter-cell interference and aims at maximizing the overall system performance. The proposed algorithm yields a gain of 4% in terms of spectral efficiency in the system.
- B. A power optimization approach is introduced where the primary criterion for the transmission power assignment is based on interference avoidance towards the primary network and minimizing the co-channel interference among secondary networks. Power optimization improves the system QoS in terms of spectral efficiency and signal-to-noise-and-interference (SINR) ratio; e.g. up to x10 gain in the system's SINR.
- C. The unsupervised reinforcement algorithm for dynamic spectrum access and sharing from contribution A is coupled with the power optimization algorithm from contribution B, enabling both frequency and power optimization in secondary networks. Although the algorithm is a suboptimal approach due to its limitation in the optimization process, it still proves better in term of providing secondary network performance and proves better in transmission power assignments. The proposed scheme provides a 5 dB gain in the system's SINR and a 10% gain in user satisfaction in high traffic loads conditions.
- D. A context aware channel allocation algorithm based on an unsupervised learning technique is presented for resource constrained computational platforms (i.e. sensor networks). The algorithm is based on the contribution presented in A. However, it has been modified in view of using it in computationally low-end platforms by reducing the computational complexity of the algorithm. The algorithm senses and shares the channel if it bears the conditions/criteria defined by the system designer.
- E. The IEEE 802.15.6 standard has not formulated an off-body mathematical channel model. However, the standard document provides experimentally measured values for the channel. These presented values are used as the basis to formulate an off-body mathematical model for the so-called CM4. The proposed model presented in this PhD work takes into account the body postures and shadowing effects.
- F. A power optimization approach is presented for WBANs. The algorithm is based on the illumination problem from convex optimization theory. The algorithm is suitable for the base stations (i.e. gateways) in the WBANs. The algorithm helps in decreasing the transmission power by 4.5 dBm, thereby reducing the co-channel interference in wireless body area networks.

The above-mentioned contributions and their relations to the research papers are illustrated in Table 1.

Table 1: Contribution matrix for this PhD work.

Contributions	Paper I	Paper II	Paper III	Paper IV	Paper V
A	√	√	√		
B	√	√	√		
C		√	√		
D				√	√
E				√	√
F					√

ORGANIZATION OF THE THESIS

This PhD thesis is organized in 5 chapters.

The current chapter introduced and motivated the research work. An overview of the latest research trends related to cognitive radios and body area networks have been presented. The proposed algorithms and research methods have been described in research publications which are included in Appendices A – B of this PhD thesis.

Chapter 1 gives a brief overview of the cognitive radios and basic theory of operation of cognitive radio networks. This chapter's core focus is on the state of the art in radio spectrum management in cognitive radio networks. The main contributions related to this chapter can be found in the appended papers.

Chapter 2 gives a brief review of wireless sensor networks. The detailed discussion and state of the art in wireless body area networks are the focus of this chapter. The proposed concepts of cognitive body area network which can make traditional wireless body area network more aware of their operational radio environments are presented. The main contributions related to this chapter are presented in the appended papers.

Chapter 3 describes the research methods used in the research publications. This chapter is included in order to give a clear understanding of the proposed research approaches as some of the mathematical details are not included in the published papers. Please note that the core of the contributions are to be found in the appended papers.

The last chapter is dedicated to the conclusion of this PhD thesis; moreover, future research perspectives are presented.

1 COGNITIVE RADIO

This chapter describes the basics and the background of the cognitive radio (CR) technology. This chapter also gives an overview of various contributions in the CR domain that are relevant for this PhD work. CR has been actively researched since the year 2000, when it was first presented [38]. It has been explored quite thoroughly since its inception, but many aspects, for example machine learning techniques and algorithms to bring cognition to CRs, are still considered as open research challenges which are yet to be addressed. This chapter mostly focuses on the spectrum assignment related aspects of the CR and only these concepts are introduced and their state of the art presented. This chapter also gives an overview of the machine learning techniques that have been proposed and/or applied by researchers in the CR domain to address various aspects such as spectrum sensing and routing. Note that the main contributions related to this chapter can be found in the papers appended to this thesis.

CR is a key technology that is enabling the vision of intelligent wireless communication networks. The term cognitive radio was coined by J. Mitola who presented the conceptual model of CR [38]. CR technology has the capabilities to address the issues mentioned in the introductory chapter, namely spectrum scarcity or underutilization as well as spectrum sharing among various heterogeneous networks by exploiting the software defined technologies [38]–[41]. The software modules drive a CR as its internal architecture. This algorithmic architecture gives an advantage over the classical hardware components based radios because a CR system is able to configure and reconfigure several of its transmission parameters such as operating frequency, modulation scheme, channel coding, and transmission power and communication technology. Such a CR and its corresponding network, i.e. CR network (CRN), have to deal with challenges due to the fluctuation in the availability of the spectrum and the quality of service (QoS) requirements of various applications. The term cognitive radio can then formally be defined as [38];

“A radio that can change its transmission parameters based on its interactions with the radio environment in which it operates”.

This definition gives two important insights about the main characteristics of CR [38], [39], [42], namely cognitive capability and reconfigurability.

1.1. Cognitive Capability

Cognitive capability refers to the ability of the CR to interact with the radio environment to sense the critical information as a feedback. The task is typically termed spectrum sensing. Spectrum sensing is not simply to monitor certain frequency bands of interest; there are more sophisticated algorithms and procedures working at this stage to capture the spectral information and variations in the radio environment, while avoiding interferences to other users [40]–[46]. Spectrum sensing provides the information about the portion of the unused spectrum band at any specific time. Consequently, the best available spectrum

band and appropriate operating parameters can be selected. This task is typically named spectrum decision. These two first tasks and other key tasks of the cognition cycle are shown in Figure 1 [38], [39], [43]. In the cognition cycle, the radio interacts with its environment and based on the stimuli received from the outside world, the CR will take action accordingly, i.e. by sharing the spectrum from the external environment and it will start transmission and reception. The key steps of the concepts of the cognition cycle are explained later in Sections 1.3.1 – 1.3.4.

1.2. Reconfigurability

The cognition cycle gives the CR an intellectual approach towards spectrum awareness. The CR is a software driven technology, i.e. except the RF interface the algorithms and software modules performs the major radio operations [38], [39]. This capability enables CRs to dynamically program according the external radio environment making the robust radios. The CRs interact with radio environment and search for the spectrum availability for opportunistic use (i.e. spectrum sensing as shown in Figure 1). The spectrum policy algorithms make a decision whether to use the particular spectrum band. The spectrum is used by the CRs (i.e. spectrum sharing from the primary/license user) until the primary network conditions change and the CRs have to move to another spectrum band (i.e. spectrum mobility). The CRs' reconfigurability feature enables them to adjust communication parameters to operate in new environment.

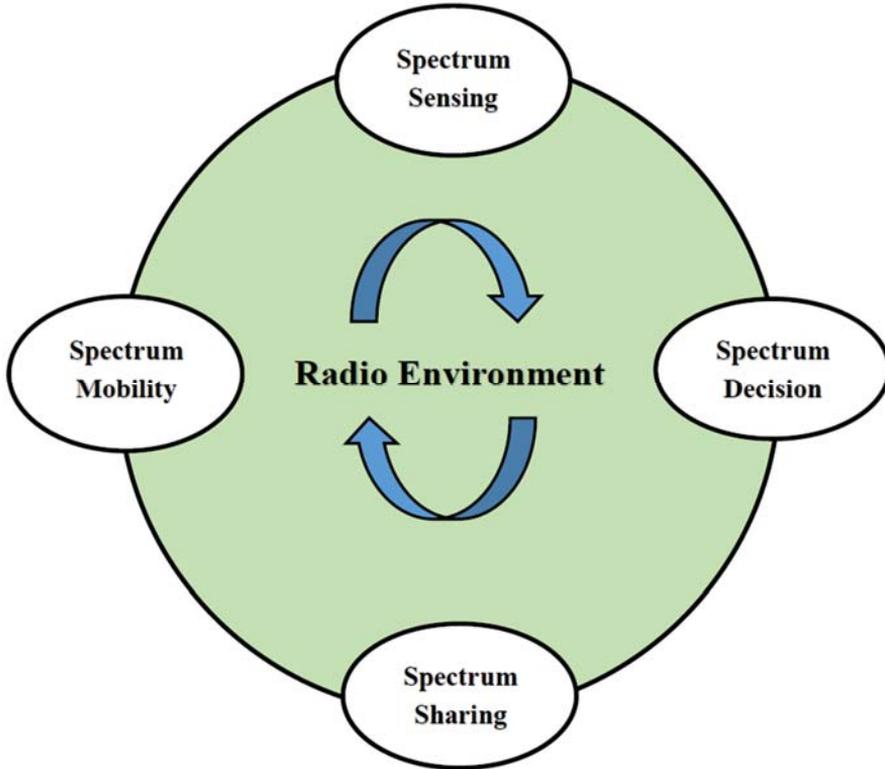


Figure 1: Cognitive radio: concept of operations.

Their operation and interaction with radio environment is a continuous process as shown in Figure 1 and as long as CRs continue to operate, the cyclic process continues.

1.3. Cognitive Radio Network: General Architecture and Features

The main goal of the CRN is to enable flexible access to the spectrum by dynamic spectrum access techniques. The CRNs adapt their operations in an opportunistic manner to avoid any conflict with the users which are licensed for a particular spectrum band. The network users, which have the license to use a band, are called licensed/primary users (PUs) and other opportunistic users are called unlicensed/secondary users (SUs). The crucial task for a CRN is to select the best frequency channel for their users (SUs) and release that channel when the PUs are detected on that same channel. Since most of the available frequency bands have already been assigned, it is a very critical task to share from the licensed spectrum when it is not being used. The key criterion for CRN is always to avoid any interference to the PUs. These licensed frequency bands which are not being used shortly by the PUs are called white spaces or spectrum holes [34], [42], as shown in Figure 2. These spectrum holes or white spaces are not fixed but can appear at a particular instant of time and specific geographical location. If any

spectrum hole is again starting to be used by the PUs, then the CR move to another spectrum hole or it can stay in the same band by altering its transmission parameters like power or modulation scheme to avoid interference to the PUs [47], [48]. The spectrum holes are the basic resource on which the CRNs rely, therefore there is a need for their knowledge for seamless operations of CRNs. These spectrum holes can be created randomly but they can be mitigated for a frequency band in a certain region in a specific time [49].

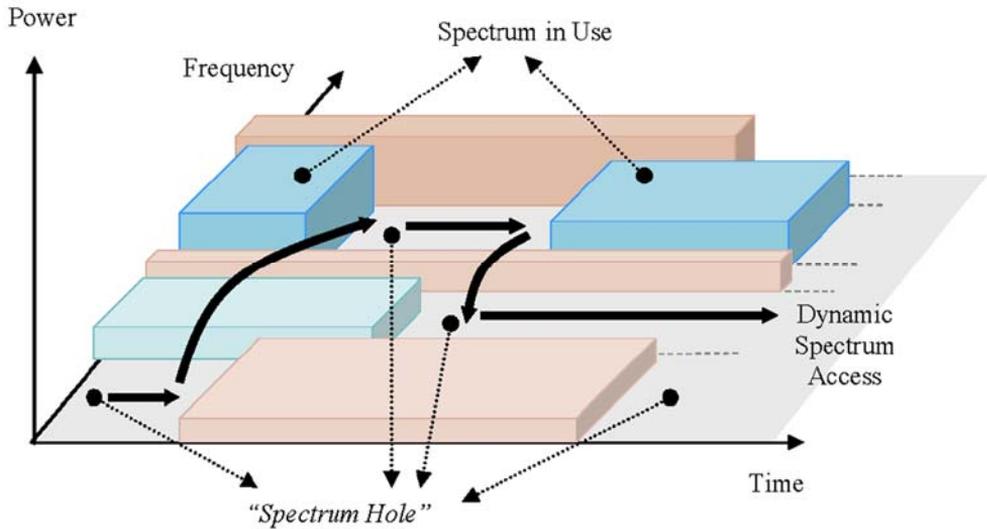


Figure 2: Conceptual view of the spectrum holes in radio spectrum as a function of time, frequency, and power [42].

The authors in [49] have proposed an intelligent algorithm for predicting the spectrum holes; it is based on artificial neural network (ANN). The ANN approach gives far better spectrum holes predictions as compared to traditional means (such as traditional blind linear and blind stochastic search). However, the ANN requires training to achieve those better results; whereas it is quite easy to train in simulation, in a real radio environment where there are many variables, the training can be very complex. In [49], the proposed algorithm only has been investigated in simulation environment and real environmental behavior is yet to

be determined. A typical illustration of the communication environment where the licensed and the unlicensed users can coexist is shown in Figure 3 [42].

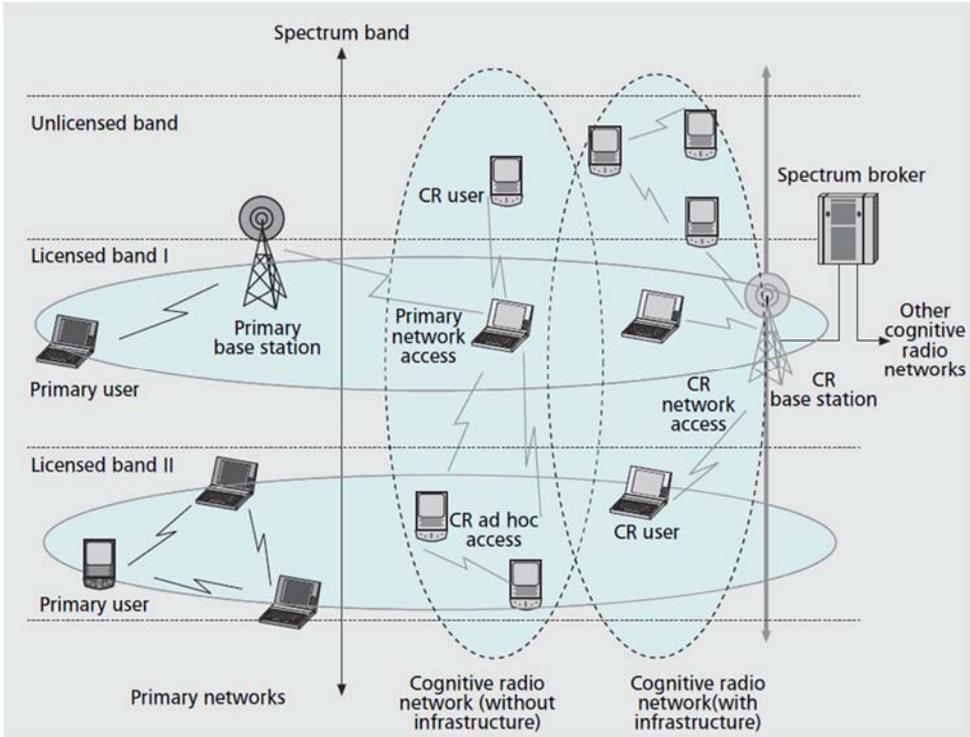


Figure 3: CRN: conceptual working and architecture with licensed/unlicensed bands and SUs opportunistic access to both bands [42].

The license holder network, i.e. primary network, is usually an existing infrastructure having an exclusive license for accessing a particular spectrum band. For instance, an existing mobile network or a television network are considered as primary network. The primary network is composed of PUs and the primary base station (PBS). The PUs are authorized to use the particular band owned by the primary network. The PBS manages all the spectrum control operations for the PUs. The PBS or PUs do not require any modifications or additional functionalities for allowing the coexistence of the secondary networks (CRNs). Thus, at any time, the CRNs and its users must not affect the operations of the PUs. A CRN or secondary network can be composed of a fixed infrastructure or it can be based on ad-hoc network technologies (Figure 3). Since CRNs can operate without a license in a particular licensed spectrum band, spectrum management must be done opportunistically. A secondary network (CRN) can consist of SUs (i.e. CR users) and the secondary (i.e. CR) base station (SBS), in the situation where a CRN has a fixed infrastructure. When the CRN is operating without infrastructure, the CR users can directly communicate with other SUs with ad hoc network topology. Often is the case in ad hoc CRNs that a central CR user may act as main spectrum manager and act as a SBS and

regularizes the spectrum management with co-existing SUs (see Figure 3, where the primary spectrum is accessed by a central CR user and then it is shared with other SUs). In the fixed infrastructure CRNs (Figure 3), there is a central controller referred to as CR base station or secondary base station (SBS) for the spectrum management responsibilities among SUs. There can be another component in the CRN which is involved in the spectrum related tasks; it is called spectrum broker. A spectrum broker is a central network entity that controls the spectrum access and sharing among various CRNs, i.e. centralized CRNs (explained in Section 1.4.1). The spectrum broker is not an essential component of the CRNs, especially when the secondary networks are non – coordinated or distributed (Section 1.4.2).

The secondary networks (CRNs) are quite unique as compared to the traditional radio networks due to their nature of coexistence with the primary networks. This coexistence imposes a challenge on the CRNs and their operations. It is much more difficult for the CRN to manage the typically diverse QoS requirements of their SUs while avoiding any conflict with the primary networks. Thus, to address these challenges, advance spectrum management functionalities must be incorporated into the CRNs.

The major concern of the CRNs and the primary networks coexistence is interference avoidance. Since the PUs have the propriety rights to use the spectrum, interference towards the PUs must be avoided by the SUs or CRNs. While operating under this strict condition, the CRNs have to take into consideration their own users requirements. The QoS of the SUs must also be satisfied while keeping a ‘low profile’ in the licensed band. The authors in [47] address the problem of coexistence of multiple secondary networks, i.e. CRNs, in TV white spaces. They have proposed a coexistence strategy that aims at maximizing the secondary networks’ throughput, i.e. SUs’ throughput. The authors in [50] have proposed a coexistence framework for the CRNs in the TV white spaces. They have proposed two coexistence schemes; centralized or coordinated access and distributed or plug-and-play access.

The coordinated coexistence access framework for accessing TV white spaces is a complicated approach as it relies on a central coordinator or coexistence facilitator that can manage spectrum holes sharing. Both [47] and [50] have considered the coexistence framework for the CRNs, but the impact of these CRNs on the existing primary network space has not been investigated. The PUs also impose another challenge on the CRNs in that while using any spectrum hole or white space, if the PUs’ activity is monitored then the CRN should provide its user a seamless communication while making a shift from one spectrum hole to another one. Based on these requirements (challenges), the main spectrum functionalities required by a CRN in order to access the license bands without causing harmful interference to the license users, emerges [38], [39], [48] (see Figure 1).

1.3.1. Spectrum Sensing

This task determines which portion of the spectrum, i.e. white spaces, are available for opportunistic use. Spectrum sensing is the key functionality of the CRNs; the whole network throughput is based on how the spectrum sensing is done. Spectrum sensing algorithms, based on the continuous interactions with the external environment, detect the presence of the PUs, and if any PUs activity is sensed, the CRN will look for another spectrum holes or white spaces [42]. For this reason, the CRNs have to continuously monitor the licensed users' activity to avoid any interference to them.

Many researchers have concentrated their efforts on cognitive spectrum sensing. The authors of [44] have presented a detailed overview of the various spectrum sensing techniques proposed in the scientific literature. They also have presented various spectrum sharing and allocation schemes to increase spectrum efficiency in CR technology. Yet, the authors have not considered any spectrum policy issue and they have not discussed any implementation considerations. The authors in [48] have discussed a cooperative spectrum sensing and decision strategy for the CRNs. However, the authors have not investigated the spectrum sensing techniques for distributed CRNs. The authors in [51] have proposed a role-based spectrum sensing approach. Their proposed method supports both cooperative and non-cooperative CR spectrum sensing in a simulation environment. Real-life design and implementation considerations have not been presented, which would be a future research challenge. The authors in [52] have given a comprehensive overview of the spectrum sensing techniques. They also have presented a comparison of the traditional or conventional spectrum sensing techniques with state of the art sensing techniques. Furthermore, the authors have proposed a cooperative spectrum sensing approach and they have presented its design and implementation considerations. Complexity, power consumption, sensing interval and system performance are the main aspects for the practical implementation of the system.

1.3.2. Spectrum Decision

Spectrum decision is the ability of a CR to select the best available spectrum bands, i.e. white spaces, to satisfy SUs' requirements. The spectrum sensing capabilities gather the pool of white spaces and then spectrum decision selects the channel best suited for SUs' QoS requirements. The spectrum decision can also be referred to as spectrum assignment as its task is to assigns the spectrum to the CRNs. Spectrum decision can be composed of three sub-functionalities, namely, i) spectrum characterization, ii) spectrum selection, and iii) reconfiguration of the CR. Once the spectrum bands are identified, spectrum decision performs its job.

The authors of [53] have proposed a framework for spectrum decision. Spectrum decision or assignment is always based on certain criteria (e.g. SUs' QoS requirements, interference, etc.). In [53] spectrum decision is based on the criteria of maximizing the network capacity. Furthermore, they have proposed a dynamic

resource management plan to take spectrum decision adaptively. Simulation results show the efficiency of their approach; however, design considerations for real-life implementation lack in the presented work. The authors in [54] have presented a survey of spectrum decision methodologies in CRNs. They have reviewed implementations of spectrum decision in several CR platforms. The authors give a broad picture of the spectrum decision of the CR functionality; however, this is only one aspect and other important spectrum management tasks like sharing and mobility have not been discussed. The authors in [55] have proposed a spectrum sensing and decision approach based on an online learning method. They have considered both the primary and secondary networks and users in their simulation model; however, the research lacks in scope and more generic approach towards realistic models would be a future research challenge.

1.3.3. Spectrum Sharing

This task of the CRN aims at providing a fair spectrum access to the coexisting secondary networks that are competing for the same spectrum holes or white spaces. Careful spectrum management is very important to avoid collisions and interference among competing different network users. There are two types of spectrum sharing schemes, namely, overlay and underlay spectrum sharing. In the underlay mode, which is sometimes also referred to as licensed spectrum sharing technique, the SUs can share the spectrum with PUs but the SUs must operate under the strict constraint of interference avoidance towards PUs. The overlay spectrum sharing mode, also referred to as open spectrum sharing, is when different SUs share the spectrum [44].

The authors in [56] have proposed several approaches to facilitate the underlay spectrum sharing through transmission power control in SUs. They have proposed three power allocation algorithms in light of interference alignment. These three algorithms aim at maximizing one of these aspects of the CRN, i.e. sum rate, energy efficiency or satisfaction of the SUs. They have only compared them among themselves; however, a more rational comparison of their approach is required with the previously known works. The authors in [57] have proposed an approach toward cooperative spectrum sharing in multiple PUs and multiple SUs based on matching theory. Their proposed method is based on two algorithms, namely, distributed matching algorithm and distributed matching algorithm with utility increasing. The authors have compared performance of their both algorithms with each other, however, a detail performance analysis with previous known techniques of spectrum sharing can greatly benefit the future research in this domain. There are many open research questions in spectrum sharing matching problems (e.g. many-to-one or one-to-many) which are yet to be addressed. The authors in [58] have proposed a dynamic power allocation algorithm for spectrum sharing underlay technique in interference alignment based CRNs. The authors have proposed a minimal transmission power for the PU to guarantee the QoS of CRNs. The criterion for the power allocation to SUs is interference management, i.e. interference avoidance, towards PUs. Simulation results have been presented but the proposed algorithm

needs further investigation in terms of interference avoidance toward primary network and to improve the QoS requirements of SUs.

1.3.4. Spectrum Mobility

The CR users, i.e. SUs, can be regarded as visitors to the licensed spectrum bands. Therefore, the CRNs have to monitor the spectrum continuously. When SUs are operating in a spectrum hole and if the network conditions change, i.e. the PUs' activity is observed, then CRNs have to move away from that particular spectrum band. Thus, an important functionality of a CRN is to switch to another frequency band when the channel becomes unavailable. This is referred to as spectrum mobility or spectrum handover. Spectrum mobility must be transparent to SUs, therefore, while switching from one channel to another, the QoS requirements of SUs must be satisfied [34].

The physical realization and implementation of the CRNs demand proper and efficient spectrum handover techniques and approaches in order to avoid any conflict with PUs and satisfy SUs. The authors in [28] have proposed an intelligent algorithm for spectrum decision based on fuzzy logic. Their proposed approach provides an effective frequency channel selection, i.e. spectrum decision, and keeps a backup channel for spectrum mobility. They have compared their algorithm in the Wi-Fi band with a conventional analytical spectrum decision algorithm. Their simulation results show the positive aspects of the proposed algorithm; however, the Wi-Fi band is an unlicensed spectrum band and the authors have not clearly indicated the PUs activity. The authors of [59] have presented an analytical analysis of spectrum mobility in CRNs. However, the research presented in their paper lacks the simulation and implementation considerations.

1.4. Network Topologies in CRN

A CRN is a dynamic wireless network providing services to its end nodes, i.e. CRs (SUs). Similar to a traditional wireless network, a CRN network topology can be classified as either centralized (infrastructure-based) or distributed (decentralized or infrastructure-less or ad-hoc).

1.4.1. Centralized CRN Topology

In the centralized network deployment, a central entity such as a base station (i.e. SBS) or access point is deployed with several SUs associated with it. A generalized scheme of centralized or infrastructure based network topology is shown in Figure 4.

A typical example of a centralized CRN can be IEEE 802.22 wireless regional area network (WRAN) or a cellular network. In a centralized network, the SBS controls all the associated SUs (within the cell or transmission range of the SBS). The CRN uses the dynamic spectrum access (DSA) techniques (e.g. cognitive spectrum management algorithms) for opportunistic access and sharing of the primary spectrum on cooperative manner without causing adverse effects to the primary network, i.e. interference [42].

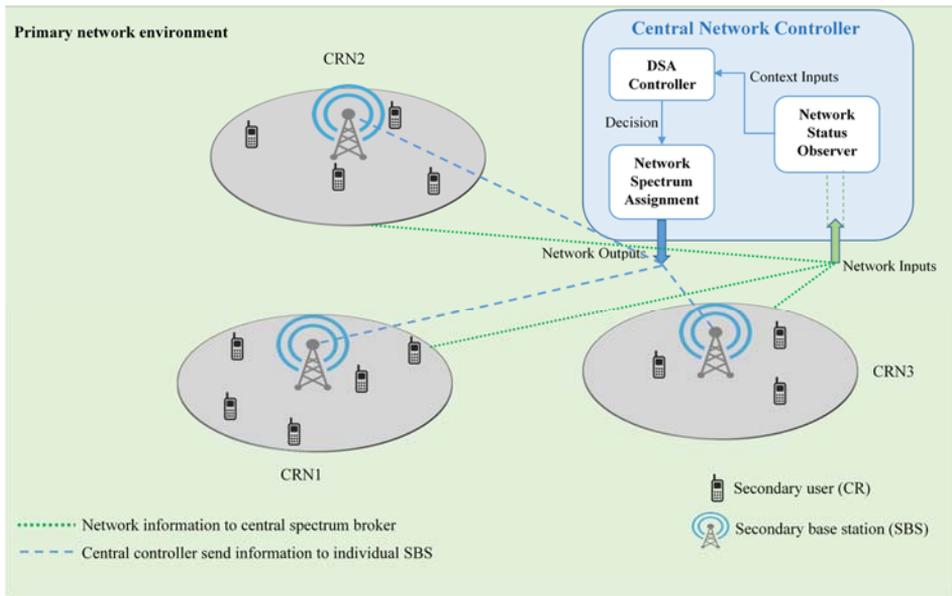


Figure 4: Centralized cognitive radio networks with centralized network controller (spectrum broker) interacting with individual CRNs to gather global spectral information.

Since CRs nodes (SUs) are cognitive, they sense the spectrum and send spectrum observations to their SBS. The SBS also performs spectrum sensing, i.e. observations alongside the reports received from the CR nodes. Once the list of available channels has been gathered, the SBSs decide the best channel to be accessed and the corresponding transmission power. Often, such operations of DSA can be performed by a central network controller or spectrum broker. The SBSs can report these channels and other network information to the network status observer in central controller in order to share the spectrum among other CRNs present in the same physical location and controlled by the same central controller. The DSA controller in the central controller then takes spectrum decision for the governed CRNs send information to each SBS for spectrum assignment. The central controller can be connected to all SBS via the internet or a backbone network. The centralized spectrum assignment schemes concentrate on the spectrum allocation decisions based on the global knowledge of the primary network environment (Figure 4).

1.4.2. Distributed CRN Topology

In the distributed (decentralized) or ad-hoc CR topology, the CRs communicate directly with each other without any central network controller. SUs share their local spectrum observation among themselves when they are within the transmission range of each other. Often a single node can be chosen as a local SBS that is performing the DSA tasks based on its own observations and those gathered from other SUs [42].

The centralized scheme for deploying the network is not always an easy task because it requires high back-end processing of control information. So, to cope with this dilemma, decentralized/distributed networks are considered as the options for future CRNs. The distributed schemes provide flexibility because they can adapt to a vast variety of scenarios. In addition, they provide scalability; with the increase of the number of cells, computational requirements remain constant. In the case of any network entity failure, it would be a single point failure in decentralized schemes as compared to the centralized one where any entity failure can result in the failure of the whole or of a large portion of the network. A generalized framework for a distributed CRN topology is shown in Figure 5. A network controller called decentralized or distributed network controller is hosted by the individual SBS (i.e. the SU node chosen to act as base station) manages the spectrum management. Individual SUs share spectrum reports with the SBS which then uses the DSA techniques to opportunistically share the primary spectrum to its users. The context information (i.e. network status reports) subjected to the DSA controller is based on only the local network knowledge (i.e. local coverage region).

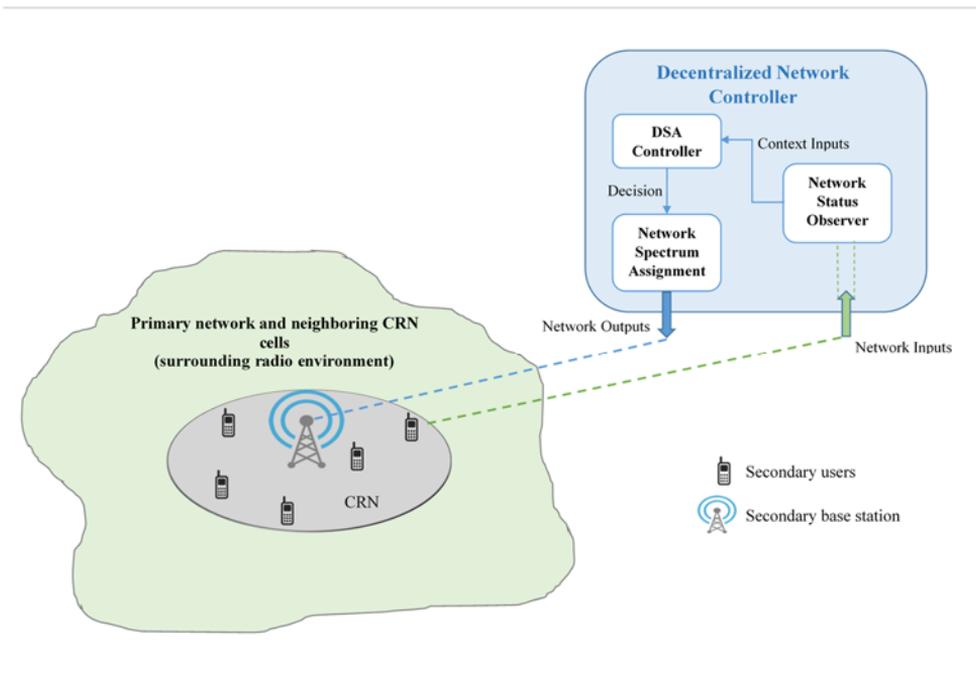


Figure 5: Decentralized (distributed) cognitive radio network with controller located at SBS.

The current mobile cellular networks are difficult to manage and require a lot of human interaction, for example, such as assigning spectrum resources, i.e. assigning frequency channels and transmission powers to the cells. These assignments remain unaltered until the infrastructure is upgraded or modified and a tedious frequency planning is repeated. These networks require lot of human interactions for maintenance and updating. The motivation toward moving to the CRN is that CR technology is based on state of the art algorithms for carrying out network operations like spectrum management, interference management, etc. Since CRNs propose a mostly automated approach, less human interactions are required, so the networks become much more self-organized, which also provides more fault tolerance to the networks.

Many researchers have proposed to exploit state of the art techniques and algorithms from the machine learning domain in order to make CRs automated, more intelligent and environment aware [60]. The next section gives an overview of the machine learning techniques proposed to address various algorithms to make the CR brain empowered.

1.5. Machine Learning

Machine learning is a field in computer sciences which aims towards the design and development of algorithms and techniques to improve a target system based on experience [60]. In other words, as generally defined, machine learning algorithms and techniques require existing knowledge or experience to either respond to or predict the future. Machine learning techniques can be generally classified into two types; supervised learning and unsupervised learning. In supervised machine learning approaches, the algorithm (often referred to as agent) needs training data to train according to the application scenario. On the other hand, unsupervised learning does not require training data sets. The advantage of the unsupervised learning approach is that the agent(s) can interact with the application's environment to get trained and based on that experience it/they can provide a solution or set of solutions to the problem for which they have been specifically formulated.

Machine learning can be applied to a variety of applications, including CRs. As discussed earlier, CRs refer to devices that are capable of learning and adapting to their operating environment. Machine learning techniques are promising for bringing cognition and adaptability to CR devices. The authors of [36] have presented a comprehensive overview of the machine learning techniques that have been proposed for the CRs or that have been envisaged for the future development of CRs. The authors have discussed how the learning techniques (i.e. supervised or unsupervised) can be applied to two main dimensions of CRs, namely, decision making and feature classification. The authors have presented the choice of various machine learning algorithms according to the specific conditions and application scenario.

Machine learning algorithms have been used in original, revised, or combined forms in order to address various challenges in CRs. The authors in [61] have

proposed cooperative spectrum sensing algorithms based on machine learning techniques. The vector energy levels of the radio channels is considered as a feature vector at the CR device and a classifier decides whether the channel is available for use or not. The performance of each classification technique is evaluated in terms of training time and classification delay. Based on the simulation results, the approach proposed in [61] outperforms existing cooperative sensing schemes in term of training time (50 μ s for 1000 samples), average classification delay (0.2 μ s for 1000 samples), and higher PU detection.

The authors of [62] have proposed a reinforcement learning based cooperative sensing algorithm to address the issue of cooperation overheads. Reinforcement learning (RL) is an unsupervised learning technique (explained in Section 3.1) used for adaptive decision making. The authors in [62] have used three RL-based algorithms, namely, Q-learning, Sarsa and Actor-Critic. The Q-learning algorithm shows better performance in cumulative reward, exploration and exploitation behavior as compared to the other two algorithms. Moreover, the Q-learning algorithm provides flexibility in learning time, i.e. longer learning provides stable detection performance and shorter learning provides larger throughput. The results also show that Q-learning provides a PU detection probability of 0.9, which proves its effectiveness in combating correlating shadowing.

The authors in [63], [64] have proposed RL-based spectrum management techniques for ad-hoc CRNs. They have compared their approach with greedy selection/assignment. Simulation results show that RL-based spectrum management algorithms provide better performance in terms of packet delivery ratio (i.e. 97.5% for small topology and 78.5% for large topology) as compared to greedy approach. The proposed algorithms performs much better in terms of exploration and convergence in the dynamic environment.

The authors in [65] have proposed an RL-based model for spectrum handoff to maximize users' satisfaction in multimedia applications. Simulations results show that proposed scheme improves the users' satisfaction in terms of both time delivery and video peak signal-to-noise ratio when compared with delay driven spectrum scheme.

The authors in [66] have proposed an RL-based data transmission scheme to achieve good performance in terms of time delay, energy efficiency and interference avoidance towards PUs. Various routing algorithms have been compared with the proposed algorithm. Simulation results show that the presented algorithm deals effectively with time delay, energy efficiency, and interference avoidance towards the PUs, in particular when the network condition is not known. However, the proposed algorithm needs further research to deal with higher traffic loads, possibly using a multi-agent RL algorithm.

Very recently, the authors in [67] have proposed a distributed RL-based scheme for managing routing in CRNs. The proposed algorithm is compared with a fictitious play learning algorithm and a shortest path algorithm. Simulation results

show that the proposed scheme performs significantly better in changing radio environments; for example, the proposed algorithm has a packet delivery ratio over 90% while its counterparts achieve 70% and 20%. The proposed scheme also performs better in terms of routing delay (i.e. less than 1s) while its counterparts have delays over 1.5 s.

As illustrated above, machine learning has been used successfully as a basis for the cognitive techniques in CRs. Reinforcement learning algorithms are considered in this PhD work for spectrum management in CR because it has been shown that they can be used to obtain optimal solutions in the decision process [36]. The detailed description of the reinforcement learning is given later in Chapter 3.

1.6. Chapter Summary

In this chapter, the state of the art technologies regarding the cognitive radios and cognitive radio networks have been discussed based on the scientific literature in order to understand the future needs of the wireless communication systems. Due to the increase in the wireless communication users and services, there is a shortage of radio spectrum resources. Recently carried-out studies indicate that most of the assigned spectrum remain under-utilized. The lack of radio spectrum resources has thus been recognized as the inefficient usage of said spectrum. To fill out these gaps in the existing wireless technologies, cognitive radio is generating a significant interest for researchers and engineers to opportunistically access and share the spectrum. Since the birth of cognitive radios in 1999-2000, it has been explored in many dimensions by researchers and industry specialists but there is yet much to be done. Therefore, there has been an increasing need for new spectrum management models and policies. The cognitive radio networks operators devise plans to utilize the already assigned spectrum resources, owned by the primary networks like TV or mobile networks, and use the spectrum holes to incorporate more users and services.

Works on CRNs have presented methodologies to utilize the already assigned spectrum to the secondary users while avoiding the degradation of quality of service (QoS) to the licensed users and provide sufficient QoS to the secondary users. The aim is to achieve a dynamic management of the radio spectrum, in which different networks may use a frequency band by the reconfiguration capabilities of cognitive radio mechanisms that allow terminals to interact, learn and take decisions that are more appropriate. In this sense, this provides the ability to perform a secondary usage of radio spectrum, as to ensure that no interference occurs towards primary users, who are licensed for the particular band.

As will be covered later on, the CR concepts presented in this chapter are also increasingly desirable for the operation of WSNs and WBANs. WSNs and WBANs are operating on the unlicensed spectrum bands; however, excessive deployment of such technologies have already crowded these unlicensed spectrum bands. New research challenges require the use of cognitive spectrum management to be incorporated in the WBANs, bringing the CR and WBAN technology to a new paradigm.

2 WIRELESS BODY AREA NETWORK

This chapter describes the background and the state of the art in the wireless body area networks (WBANs). This chapter also describes other researchers' contributions to WBANs and the applications of WBANs. The main contributions related to this chapter can be found in actual papers.

In recent years, researchers have developed miniature radios and electromechanical devices that are increasingly implemented in the physical world for gathering data. These inexpensive low powered devices can be used in a variety of application areas. These miniature devices are providing mean of sensing of some physical phenomena, like temperature, humidity, etc. and then processing and communicating the collected data. Combing such capabilities with the software based smart technologies and providing connectivity with the internet, makes it possible to instrument the world with increasing fidelity. These individual devices are generally referred to as sensors (or sensor nodes) and the wireless network based on such sensor nodes are termed wireless sensor network [13], [14], [68], [69]. A typical WSN setup is shown in Figure 6 where certain physical phenomena measured by sensors is routed via a sink or gateway device to a monitoring station. Individual sensors can connect with sink directly or they relay information via peer sensor nodes. The manager is concerned user who is interested or monitoring the concerned area of sensor fields.

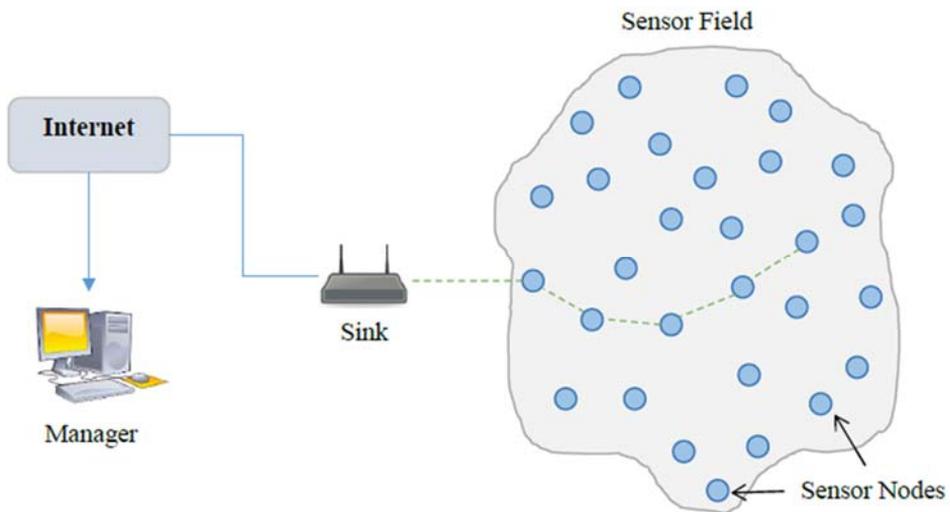


Figure 6: A typical Wireless Sensor Network in which data is collected from sensor field and sent for further process to the manager

An individual sensor node is often engineered based on a resource constrained architecture, i.e. it has limited processing capability, storage capacity and communication bandwidth [16]. A whole set of sensors may perform coordinated actions in a WSN and send their collected information to a backbone network via an intermediate device which is referred to as a sink or a gateway (Figure 6).

Individually these devices (sensor nodes) may do not have enough capabilities to perform certain tasks. However, when these nodes are aggregated in a network (e.g. like a grid of sensors in smart grid), they can have substantial capabilities to perform data processing [70].

WSNs are such diverse networks that they can have a huge variety of application domains; for example, they can be used for environmental data gathering, structural integrity, and monitoring applications [16], [70]–[73]. Due to this diversity in applications' contexts, WSNs may have to operate for long periods of time and nodes may be often quite remote. Therefore, the energy resources, i.e. batteries, super capacitors, or energy harvesting or a combination thereof, limit their overall operations. To increase the available energy required for sensors' operations and to limit their energy consumption, most of the devices' components, including the radio, will most likely to be dormant most of the time [74], [75]. Normally, the sensors are deployed densely in a spatial region to perform certain actions (Figure 6); the number of sensors in a WSN can be up to thousands; this high-density gives rise to a high degree of interactions between the sensor nodes both positively and negatively. This creates an additional challenge for the researchers along with the energy conservation issue.

Despite these operational difficulties, maintenance of the WSNs must remain inexpensive. Manual configuration of such large networks of small devices is often impractical. Therefore, sensor nodes must organize themselves and must be coordinated as a unit to perform the designated tasks (self-organizing networks). The WSNs may provide a mean of programming and managing the whole network as an ensemble, rather than administering devices individually.

As discussed above, the WSNs are composed of low powered sensor nodes for performing tasks in variety of applications. When sensors are used for facilitating the human life, normally ultra-low powered sensor devices are used to comply with human health. Such WSNs, which are specifically targeting the applications around the human body, e.g. health monitoring, sports, and entertainment are called wireless body area networks [76].

2.1 Wireless Body Area Network (WBAN)

WBANs are a key-enabling technology for the healthcare services, in particular for remote patient monitoring. As discussed in the introductory chapter, increasing elderly population in the world is over burdening the existing healthcare systems. Therefore, there is a need for an infrastructure where the patients can be monitored in their comfort zones, i.e. home, and their body vital signs are sent remotely to their health care providers, e.g. doctor or nurses, so that they can observe them continuously via remote terminals. The innovation in healthcare systems or augmenting the existing healthcare facilities is one of the major motivations behind the WBANs' invention. However, WBANs are not limited to only healthcare facilities. Nowadays, international sports are being very competitive and sportsmen need very hard training and their fitness is monitored with modern technologies of WBAN. Such health and fitness monitoring systems

require a combination of WBAN technology and other network technologies like the internet, etc. A typical setting of health monitoring WBAN is shown in Figure 7 [77], where the person/patient is equipped with a variety of sensor nodes (can be either implant or sensors or both) and physiological data from the body is sensed and transmitted to sink node on the body which then forward the data to monitoring stations via other communication networks [78]. WBAN gateways can be connected to other networks through wired or wireless means (Figure 7).

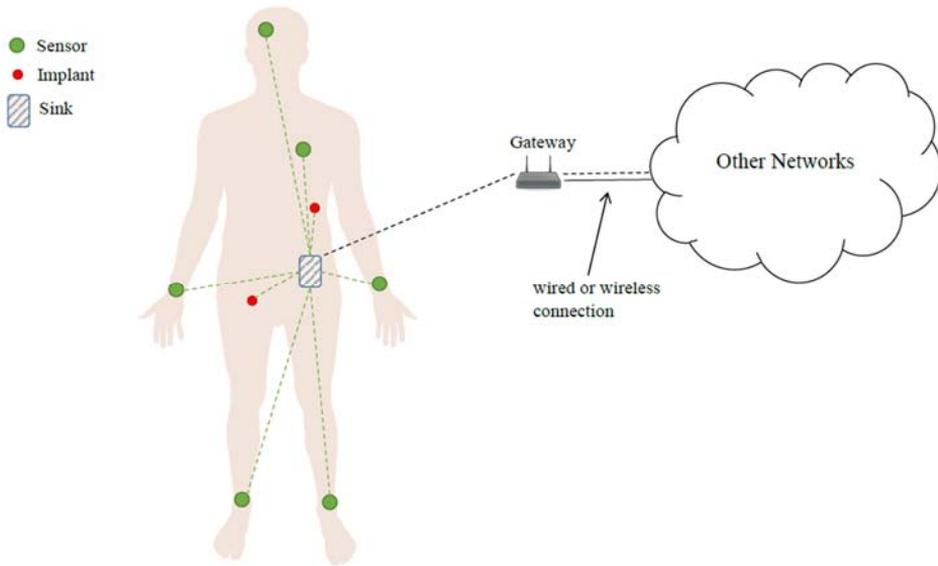


Figure 7: Health Monitoring with WBAN where sink node collects individual data from sensors and send to gateway (based on [77]).

2.2 WBAN: General Architecture

Although WBANs can build upon various wireless technologies and standards, it is worth noting the IEEE 802.15.6 standard which was specifically designed for WBAN applications. This standard is introduced in what follows; the PhD work published in Contributions D - F is based on that standard.

2.2.1 The IEEE 802.15.6 Standard

IEEE 802.15.6 [79] defines the standards for the short-range wireless communication in and/or around the human body. The standard defines two layers of the OSI protocol stack for WBANs, namely the physical (PHY) layer and the medium access (MAC) layer (Figure 8). Due to the wide range of applications in the WBAN domain, three PHY layer options have been defined by the standard [79], i.e.,

1. Narrowband (NB) PHY;
2. Ultra-wide band (UWB) PHY;
3. Human body communication (HBC) PHY.

The corresponding frequency bands of the PHY layer are shown in the Figure 9 [80]. Each PHY standard supports different application and data rates. All three PHY layers standards with their corresponding frequency bands and channel bandwidths are presented in Table 2 [80]–[82]. In the NB the WBANs support various licensed and unlicensed spectrum bands. Wireless Medical Telemetry System (WMTS) band is licensed medical band restricted only for medical professionals. Medical Implant Communication System (MICS) is an unlicensed band with limited bandwidth and data rates is restricted for implants communication. Unlicensed Industrial, Scientific, and Medical (ISM) and Ultra-wideband (UWB) are the suitable choices when higher bandwidth and data rates are required. In IEEE standard a new mode of communication from implant to coordinator (i.e. sink) is introduced and is referred as Human Body Communication (HBC). These various frequency bands are shown in Figure 9 and their corresponding bandwidth and available data rates are presented in Table 2 [80]–[82].

Even there are different solutions bandwidth and data rates, which have been proposed for the PHY layers in WBAN standards by the IEEE, only one MAC layer has been defined for the WBANs. Irrespective of the type of application and the PHY layer used, this is transparent for the MAC layer since it supports all the three PHY layers (Figure 8). However, the MAC layer can be used in either beacon mode or non-beacon mode. MAC layer protocols and communication are explained later in this chapter in the Subsection 2.2.3.

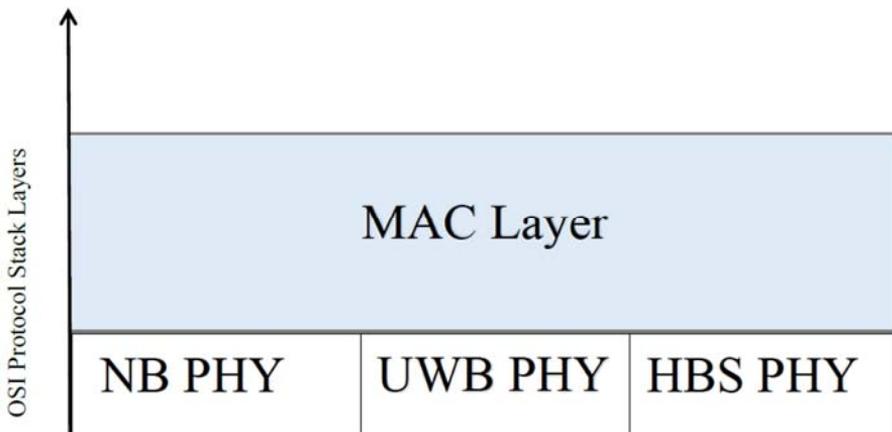


Figure 8: IEEE 802.15.6 Layers defined in standard (based on [79]).

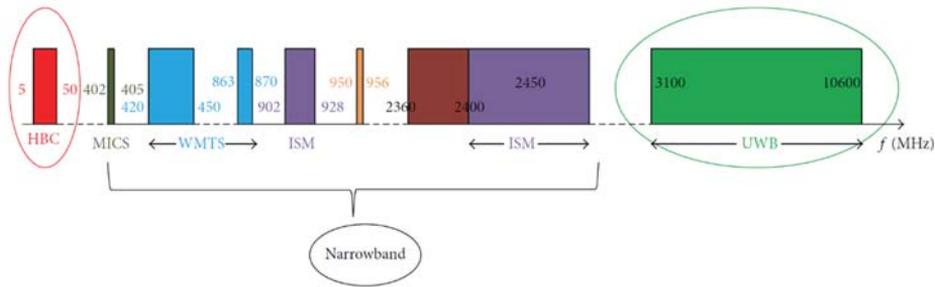


Figure 9: IEEE 802.15.6 frequency bands (with 3 PHYs)(simplified from [83]).

2.2.2 Classification of the Sensor Nodes in a WBAN

A WBAN can consist of in-body and on-body nodes that monitor the body functioning and transmit that information for further processing. There are various types of devices, i.e. nodes that are used in WBAN depending upon the nature of the application.

2.2.2.1 Sensor Node

Sensors in WBANs measure certain type of feature of a human body such as heart-rate, breathing, blood pressure, sudation, and temperature. These sensor nodes sense the data and then transmit it to the central hub or another node depending upon the protocol used for the communication. The IEEE standard 802.15.6 further classifies the sensor depending on its location on and in the human body in a WBAN [79].

2.2.2.2 Implant Node

This type of the sensor node is implanted into the patient's body. The depth of the implant sensor node can depend upon the nature of the physiology of the feature that need to be monitor for any patient. In general, the implant node can be implanted in the skin or it can be deep inside the tissue.

2.2.2.3 Body Surface Node

As the name indicates, this type of sensor nodes is placed on the surface of the human body.

2.2.2.4 External Node

This type of node is not in contact with the human body; instead, it is placed near a human body to monitor aspects like movement or postures of the person being monitored. These nodes can be placed from a few centimeters to a maximum of 5 meters from the body [82].

Table 2: IEEE 802.15.6 frequency bands with respective data rates (based on [80]–[82])

PHY	Frequency Band (MHz)	Channel Bandwidth	Bit rate 0 (kbps)	Bit rate 1 (kbps)	Bit rate 2 (kbps)	Bit rate 3 (kbps)	Bit rate 4 (kbps)	Bit rate 5 (kbps)	Bit rate 6 (kbps)	Bit rate 7 (kbps)
NB	402 – 405	300 kHz	75.9	151.8	303.6	455.4	-	-	-	-
	420 – 450	300 kHz	75.9	151.8	187.5	-	-	-	-	-
	863 – 870	400 kHz	101.2	202.4	404.8	607.2	-	-	-	-
	902 – 928	500 kHz	101.2	202.4	404.8	607.1	-	-	-	-
	950 – 958	500 kHz	101.2	202.4	404.8	607.1	-	-	-	-
	2360 – 2400	1 MHz	121.4	242.9	485.7	971.4	-	-	-	-
UWB	2400 – 2483.5	1 MHz	121.4	242.9	485.7	971.4	-	-	-	-
	3200 – 4700	499 MHz	394.8	789.7	1579	3159	6318	12636	-	-
HBC	6200 – 10300	499 MHz	487	975	1950	3900	7800	15600	557	1114
	5 – 50	4 MHz	164	328	656	1312.5	-	-	-	-

2.2.2.5 Coordinator

The coordinator node is also often referred to as a sink or a gateway between WBANs and the outside networks. This device is basically a central hub among the sensor nodes of various kinds. Its job is to collect all the data from the body sensors, whether implant or on-body sensor, and then transmit this data to a concerned user (e.g. a healthcare facilitator) for further processing so that a proper action can be taken on that data (Figure 7). The coordinator node may often can be referred as a personal server, personal device, and gateway.

2.2.2.6 Relay Node

The nodes which are routing other nodes data toward the coordinator are called relay nodes. They are simply sensors nodes but on occasion, they are used as a hub by the sensor nodes that are far from the sink node. The nodes that are far from the coordinator use these intermediate nodes as hub for routing their data towards the coordinator [15], [81].

2.2.3 Network Topology

The IEEE 802.15.6 standards has envisioned the WBANs to operate in either one-hop or two-hop star network topology with the central node to be placed in the middle of the body [79]. Two possible communication links exist in one-hop star topology; transmission between the sensor nodes to the sink nodes, and transmission link between sink nodes to the sensor devices. In the two-hop star topology, sensor device sends its data to the sink or gateway via peer (relay) nodes [84].

There are two modes of communication in the star topology; beacon mode and non-beacon mode. In the beacon mode, the sink node controls the communication like a base station. It acts as master node and sends the beacon (control) message to define the start and end of the communication. The beacon message is used for the network control and synchronization [84]. In this mode, sink manages the medium access by defining a superframe with data slots for each sensor node. All other nodes are assigned their slot (for data) in the superframe based on time. Each node is assigned at least one time slot and if the data volume exceeds what one time slot can handle, then more slots are assigned in the superframe to that node. This mechanism of accessing the medium is called time division multiple access (TDMA). The medium is accessed periodically and in synchronized way. Time slots are assigned to the nodes based on their data transfer requirements [78], [81].

In the non-beacon mode, any node can send data to the sink without any requirement of synchronization. In this mode, the node has to power up the sink node to make it accept the data. A sink node cannot communicate directly with any sensor node at any time. The nodes have to use carrier sense multiple access with collision Avoidance (CSMA/CA) to access the medium [85], [86].

A comparison of performance of the MAC layers protocols (TDMA and CSMA/CA) are given in Table 3 [78].

Table 3: Performance Comparison of CSMA/CA vs TDMA protocols [78].

Performance metric	CSMA/CA	TDMA
Power consumption	High	Low
Traffic level	Low	High
Bandwidth utilization	Low	Maximum
Scalability	Good	Poor
Effect of packet failure	Low	Latency
Synchronization	Not applicable	Required

In WBANs, conserving the energy of the sensor nodes is highly required as the sensors are mostly battery-powered and it is impractical to change the batteries very often. For example, in case of an implant sensor node, the requirement for the battery life is several years. Therefore, the available energy has to be used very wisely. In WBANs, both one-hop and two-hop star topologies can be used; however, one-hop is a recommended choice as it saves available energy and consumes less power for its operation. A detailed comparison of the one-hop star topology and multi-hop star topology is given in Table 4 [81], [87].

TDMA gives better performance as can be seen from Table 3 and Table 4; it also gives better energy savings and delay response [88]. The authors in [89] have presented a new MAC protocol for emergency handling in health care WBANs. The authors have considered the synchronous (beacon mode) and redefined the IEEE 802.15.4 superframe. The authors in [90] have presented a cognitive asynchronous MAC protocol called cognitive-receiver initiated cycled receiver (C-RICER). The proposed scheme adopts the transmission power and channel frequency to reduce interference thereby saving energy consumption. The performance of the proposed cognitive algorithm is compared in simulation with traditional receiver initiated cycled receiver approach. The algorithm can be useful when the scale of the network is large. However, the algorithm has not been compared with a synchronous access technique neither any physical implementation recommendations have been provided.

Table 4: Comparison of the one-hop star topology and multi-hop network [87].

Criteria	One-hop star topology	Multi-Hop network
Energy consumption	For nodes in close proximity to the sink, the power used to transmit to the sink is low. The nodes further away, however, will consistently require more power to be able to transit information	The nodes that are closest to the sink node, consume more energy as they will have to forward not only their own information but also information from other nodes
Transmission delay	The star topology network presents the least possible delay present in transmission from any sensor to the sink, as there is only a single hop.	Depending upon how the network is configured. The nodes that are closest to the sink node can get their data transfer without any delays. Nevertheless, the nodes, which use relay nodes, their transmission is delayed depending upon how many hops they use.
Interference	Sensor nodes which are farther away from the sink node require transmission with higher power, increasing the amount of interference	Since each node is only transmitting to its neighbor nodes, the energy transmission is kept low, hence it reduces the effects of interference
Node failure and mobility	Only the failed node is affected and rest of the network can perform without any problem.	The part of the network that involves the failed node has to be reconfigured. Overheads are involved.

2.2.4 Communication Architecture

The data sensed by the sensors in the WBANs in any application would be not very useful if it cannot be monitored or analyzed remotely. Therefore, the WBANs must communicate with other communication technologies. Researchers have identified three different tiers in communication architecture of the WBANs as follows [80];

1. Tier 1: Intra-WBAN communication
2. Tier 2: Inter-WBAN communication
3. Tier 3: Beyond-WBAN communication

The communication architecture and the three tiers are illustrated in Figure 10.

2.2.4.1 Tier 1: Intra-WBAN communication

This tier depicts the communication between sensor nodes and the personal server located within Tier 1. Tier 1 is working in and on the body with communication ranges not more than approximately 2 meters. The personal server can be considered as master node or sink node located at the center of the body (Figure 10).

2.2.4.2 Tier 2: Inter-WBAN Communication

This tier covers the communication from the personal server (sink) to the access point (often referred to as the gateway). The gateways are often carefully planned and installed to cover all the communication. Tier 2 is responsible for connecting the WBANs to other communication networks. The communication paradigm in Tier 2 are further subdivided as infrastructure-based architecture and ad-hoc based architecture. Infrastructure based architecture Tier 2 is used where the WBANs are located in a confined or limited physical space, e.g. hospitals, nursing homes, etc. This architecture is better as compared to ad-hoc because its central management provides more control and security. Ad-hoc based Tier 2 architecture is used in much larger areas with multiple access points, which provides multi-hopping of the WBANs data; moreover, mobility is handle more easily. Such a Tier 2 can grow up to 100 meters, so it is much suitable for WBANs larger coverage area [15], [81].

2.2.4.3 Tier 3: Beyond-WBAN Communication

This communication tier can consist of e.g. metropolitan area networks providing the connectivity of the various services (e.g. hospitals, emergency services, health facilities, etc.) to WBANs. The connection between Tier 3 and Tier 2 is provided via a gateway. The shape and the design of Tier 3 in WBANs is very application dependent.

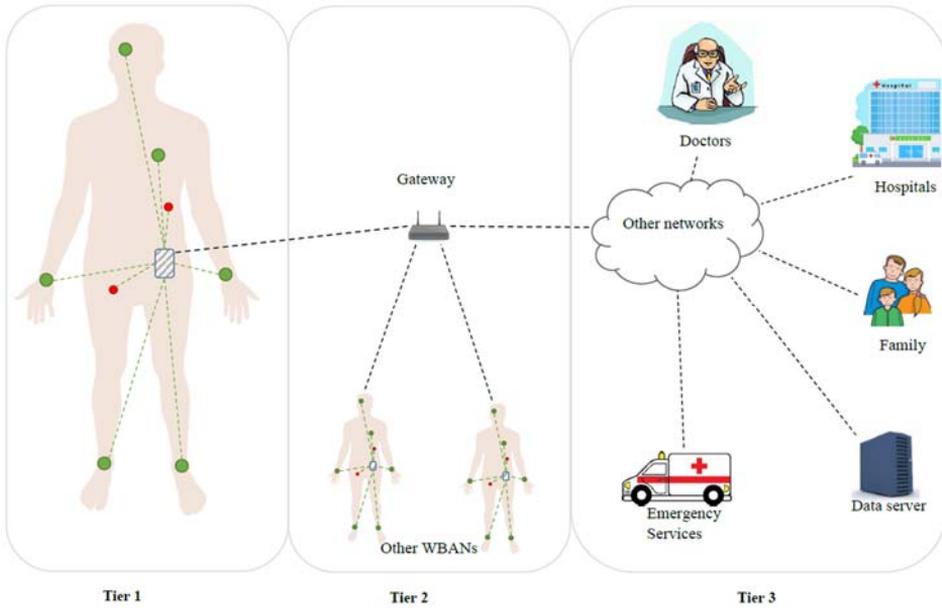


Figure 10: Communication Architecture of WBANs and tiers. [22]

2.2.5 Channel Models

The sensor nodes in a WBAN are placed in and/or around the human body as seen in Figure 7. This creates multiple communication channels based on the position of the sensor in/on the human body. The IEEE 802.15.6 channel model document presents these various channels and describes different scenarios based on the location of the sensor. These channel and corresponding scenarios are presented in Table 5. These scenarios are grouped in such way that the same channel models (CM) can represent them [82].

The maximum distance between the human body node and any external device, e.g. sink or gateway, can be 5 meters maximum. These channel models and the corresponding communication links are elaborated in Figure 11.

The human body is a very complex medium for the electromagnetic waves to travel through or around it. For this reason, different scenarios have been presented in the standard and the different frequency bands, described in Table 2, have different characteristics when interacting with the human body. Due to the complexity of the human body and conditions surroundings it, e.g. shadowing, fading, etc. [82], a generic model of the path loss cannot be presented. Many researchers are exploring the channel and path loss models for WBANs, but such models are yet to reach the level of standardization.

Table 5: IEEE 802.15.6 scenarios, frequency bands and channel models [82].

Scenario	Description	Frequency band	Channel model
S1	Implant to implant	402 – 405 MHz	CM1
S2	Implant to body surface	402 – 405 MHz	CM2
S3	Implant to external	402 – 405 MHz	CM2
S4	Body surface to body surface (LOS)	13.5, 50, 400, 600, 900 MHz 2.4 GHz, 3.1 – 10.6 GHz	CM3
S5	Body surface to body surface (NLOS)	13.5, 50, 400, 600, 900 MHz 2.4 GHz, 3.1 – 10.6 GHz	CM3
S6	Body surface to external (LOS)	900 MHz 2.4 GHz, 3.1 – 10.6 GHz	CM4
S7	Body surface to external (NLOS)	900 MHz 2.4 GHz, 3.1 – 10.6 GHz	CM4

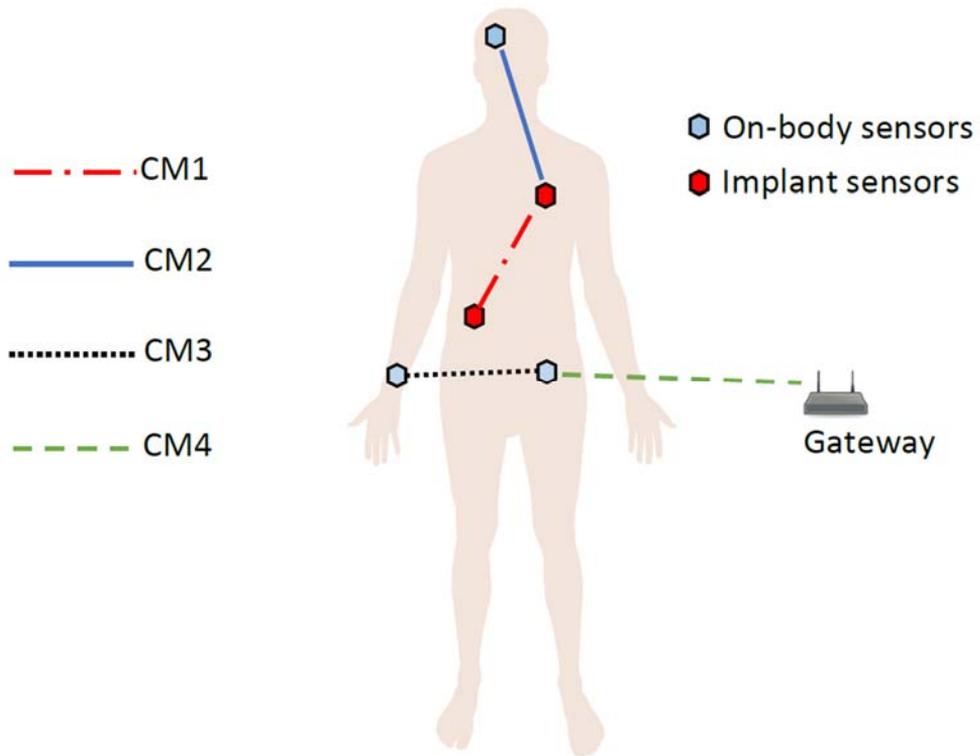


Figure 11: Channel models described in IEEE 802.15.6 standard (based on [82]).

The authors in [91] have presented a survey related to the propagation and channel models for WBANs. For narrow band communication, the authors have discussed the path loss models and fading statistics for on-body channel models presented by various researchers. The authors also have presented an overview of the ultra-wideband channel models for on-body communication. Furthermore, the authors also discussed the inter-body (i.e. body-to-body) communication and off-body channel models. The authors gave a comprehensive overview of the design and evaluation of WBANs; however, the inter-body and off-body channel models have not been formulated mathematically. The authors in [92]–[94] have presented their channel models. These proposed channel models lack the generic behavior and the researchers have targeted only a specific application and environment.

2.2.5.1 Antenna

The signal propagation and corresponding influences on the signal are not only affected by the human body structure, posture; the design and location of the WBAN antennas also play an important role. The authors in [95] have proposed a design for an e-textile antenna for WBAN applications. The antenna can be

easily used in wearable WBAN application with the only downside being that it is operating in the Bluetooth band which is not according to the IEEE WBAN standard. The authors in [96] have presented a WBAN antenna operating at 2.45 GHz for body area network. The proposed antenna presented is textile-based and can be easily used in wearable WBANs. The antenna design presented in [95] and [96] are both very application and frequency band specific and these designs cannot be used without design alteration in another WBAN application with different frequency bands. There is a better solution proposed in terms of spectrum band range diversity which is presented in [97]. The proposed antenna design can work on a broad frequency range (UWB PHY) from 4.01 GHz to 12 GHz. The downside to this design is that it cannot operate in the NB and HBC PHYs.

2.2.5.2 Interference

A human being who is being monitored is an example of a unit WBAN. Most likely, there would be a number of such WBANs that would be located in a relatively small geographical area such as a home for the elderly or a hospital.

When WBANs are co-existing in same proximity, use of the same channel gives a high likelihood of interference among them, which is the most common type of interference among WBANs and which is referred to as inter-WBAN (homogeneous) interference (see Figure 12). The IEEE standard document sets a requirement that systems shall work properly within a transmission range of up to 3 meters when maximum 10 WBANs are co-existing [79].

However, if they are active at the same time and sharing same channel, this will give a severe performance degradation for one or many WBANs. WBANs are sharing the spectrum bands with other wireless communication technologies so there may exist other types of interference as well (which are referred to as heterogeneous interference). The possible interferences that a WBAN can experience are shown in Figure 12 [81]. Table 6 gives the comparison of the various IEEE communication standards, which are coexisting with the 2.4 GHz WBANs.

The authors in [27], [98], [99] have discussed interference mitigation and avoidance techniques to avoid inter-WBAN or homogeneous interference. However, the heterogeneous interference due to the coexistence of WBANs and other networks (Table 6) is still an open research challenge for the WBAN researchers.

Due to these complexities and challenges involved in the WBAN channel models, a generic path loss model satisfying the needs of all channel models (scenarios) (Table 5) are yet to be proposed by the scientific community.

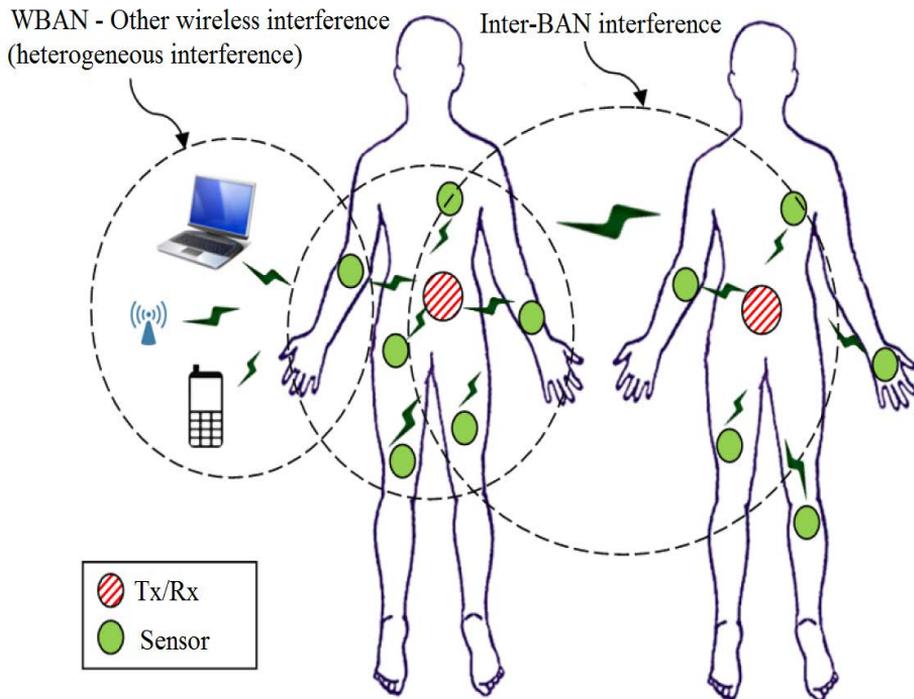


Figure 12: Interferences in WBANs (based on [81])

2.2.5.3 Power requirement of WBAN channel

A major constraint in WBANs is their limited energy supply as most devices in are generally battery-powered. The sensor nodes in WBANs are capable of transmitting the data at a wide range from 1 Kbps to 10 Mbps. Therefore, the WBAN standard requires a high power-efficiency. Currently, most of the WBAN devices are meeting the data transmission requirement but meeting the power requirement of the WBAN (from -10 dBm to 0 dBm) are yet to be met [81]. The authors in [100] have presented a node with measured power ranging from -13 dBm to 3 dBm. The authors in [98] and [101] have presented a game theory based transmission power control in WBANs. The algorithms presented are considering a multi-hop and asynchronous medium access. As discusses previously, multi-hop communication itself is a threat to power, as it requires more power to operate as compared to synchronous medium access. The authors in [102] have presented an adaptive channel gain predictor algorithm which in turn is used to control transmission power through adaptive transmission power control algorithm. The proposed scheme provide energy efficiency by monitoring the highly variable on-body channel and providing the adaptive power control. Presented simulation results show that adaptive transmission power algorithm save up to 25%

Table 6: Brief comparison of various features of IEEE Standards (based on [27], [81]).

IEEE Standard	Frequency band	No. of channels	Transmission range	Individual channel bandwidth	Transmission power	Application
802.11b/g/n	2.4 GHz	13	100 meters	22 MHz	≥ 15 dBm	WLAN
802.15.1	2.4 GHz	79	20 meters	1 MHz	10 dBm	WPAN/Bluetooth
802.15.4	2.4 GHz	16	10 meters	2 MHz	0 dBm	LR-WPAN/WSN
802.15.6	2.4 GHz	79	1 – 5 meters	1 MHz	≥ 0 dBm ≤ -10 dBm	WBAN

energy as compared to traditional power assignment. Though the algorithms proposed are based on experimental data, but the presented results are only analytical or simulation based. The authors have not presented their considerations for actual implementation. The proposed approach has been evaluated for the synchronous mode (beacon-mode) while the asynchronous MAC assess has not been studied. The proposed scheme is only focusing on the on-body communication and algorithms proposed are yet to be studied for the off-body communication. The authors of [103] have proposed an adaptive transmission power control algorithm for an ambient assisted living scenario where battery replacement is often undesirable. Their proposed algorithm saves up to 60% energy when compared to fixed and reactive power assignment schemes. The authors have focused on the on-body channel; however, the performance of the algorithm for the off-body channel has not been studied.

2.3 Synergy of CR and WBAN (C-BAN)

Similar to the conventional wireless networks, WSNs (including WBANs) also use fixed spectrum allocations. WSNs are inherently limited in their performance due to their limited onboard processing capabilities and communication power. With the rapid increase in WSN applications operating in the unlicensed spectrum bands, efficient utilization of the spectrum is a challenge. This challenge can be addressed by exploiting the CR technology (presented in Chapter 1) in the WSNs. The CR technology enables the opportunistic and efficient use of spectrum through cognitive spectrum sensing and dynamic spectrum access schemes. The synergy between the two technologies forms a new networking paradigm called cognitive radio sensor network (CRSN) [16], [104], [105]. A CRSN is a distributed network of wireless sensors with cognitive capabilities for sensing the environment and transmitting their data intelligently over dynamically accessed spectrum. Therefore, porting the CR technology concepts to resource-constrained WSNs can improve the spectrum utilization and it can enable the dense deployment of the WSNs [106], [107].

The remote health monitoring is a potential candidate to take advantage of the promising CRSN technology. Healthcare WSNs, i.e. WBANs, enable efficient remote patient monitoring. The WBANs can provide health assistance in hospitals as an additional patient monitoring system. Since WBANs operate in unlicensed spectrum, their massive introduction will create new challenges like spectrum scarcity, interference, QoS, etc. The CR technology is the philosophy of opportunistic usage of primary users', i.e. licensed spectrum. In the unlicensed band, there is no primary user but there exist many unlicensed other applications; the CR paradigm of primary/secondary user concept be applied to really exploit the unlicensed band to its full extent. The multiple WBANs can coexist in a hospital or other application scenario and they are sharing the same spectrum

space with many other communication technologies, e.g. Bluetooth, ZigBee, etc. (Table 5), and biomedical appliances (incubators, infusion pumps, anesthesia machines, etc.). Such biomedical appliances assist in many critical procedures (e.g. surgery) and interference generated towards those devices can potentially be very dangerous. Such devices in hospitals typically use the 2.4 GHz ISM band. WBANs are also operating in this band and their coexistence can be very dangerous if they are not managed properly.

The CR technology can help the WBANs to opportunistically share this spectrum band. The biomedical devices and other such services that are critical to life and their communication must not be affected due to the existence and activity of other networks in the ISM band. These devices and services can be considered as primary users and WBANs can be thought of as secondary users. Given this, cognitive algorithms can be used for intelligent spectrum sensing and then dynamic access to available vacant channels. This can avoid the interferences (both common WBAN related interferences, i.e. inter-WBAN and heterogeneous interferences) and selecting the best channel among the available ones can also give benefits to the QoS of the WBANs [108]–[111].

Since sensor nodes in WBANs are ultra-low powered, very limited computational capabilities are available on board (resource-constrained microcontrollers or processors are used on sensor nodes). Hence, computationally complex cognitive algorithms cannot be executed on them. These sensor nodes are generally battery-operated and it is highly recommended or desirable to prolong their battery life, as frequent battery replacement is impractical in most cases. Therefore, these devices are not suitable candidates to perform cognitive functionalities, which means that cognitive capabilities are, as of today, not available in Tier 1 (see Figure 10).

The information collected by the sensor nodes in a WBAN is transmitted to the personal data server, i.e. sink (ideally this can be any device which can be programmed like a smartphone or netbook). Typically, this device has sufficient computational and data processing power. Therefore, this device at Tier 2 (see Figure 10) can implement the CR functionalities and turn a WBAN into a Cognitive-WBAN (C-BAN). This device acts as a base station and it can control the sensors' operations via control or ordinary communication channels. This model of the C-BAN can have a centralized or a distributed network approach. A centralized CR controller (CRC), i.e. a CR based sink or gateway, can give more benefits in confined environments (like hospitals, nursing homes, etc.) for an infrastructure based inter-WBAN communication architecture. On the other hand, a decentralized approach can be more suitable for ad-hoc based inter-WBAN communication [108], [110].

The authors in [108] and [109] present a CR-WBAN paradigm with UWB PHY. They referred to the gateway as cognitive gateway since this CRC is an UWB based Tier 2 device with cognitive capabilities. The corresponding hardware architecture is also proposed and presented. Typically, UWB sensor nodes consume lower power as compared to their counterparts in NB based CRC. In that research, the authors have not considered the impact of NB devices' power, which could have really got benefits from CR capabilities to improve their interference issues. The authors in [111] have proposed and presented a centralized infrastructure CR system based on CR gateway controller, i.e. CRC (cognitive radio controller). The CRC acts as master and a central player at Tier 2 level communication and allocates transmission authorities to its clients, which are sensor nodes. The authors aim at addressing the interference towards biomedical devices and improvement of QoS. The authors have also presented a cognitive channel access algorithm for the healthcare application, which exploits the interference tolerance for the biomedical appliances. Since these devices have higher priority so they are treated as PUs while other technologies are considered as SUs.

The MAC layer plays an important role in the cognitive functionalities of the CR technologies such as channel sensing, resource allocation, spectrum sharing and mobility. As discussed previously, the IEEE WBAN standard describes only one MAC layer. Many researcher have proposed different MAC layer protocols to improve the WBANs. The authors in [112] analyze different MAC protocols for CR-WBAN proposed by various researchers. The authors have presented a comprehensive review of all the MAC layer cognitive protocols in Table 1 of [112] which provides a good overview of CR-WBANs. The authors in [113] have presented a spectrum mobility procedure by means of a cognitive spectrum sensing algorithm which is also a MAC layer protocol. The proposed algorithm can ensure the operation of CR-WBANs to operate in a wide range of frequencies and the interference can be avoided by careful spectrum selection. However, such an algorithm comes at the cost of computational complexity and a large context knowledge (radio environment).

Scientists and researchers have started to explore the paradigm of CR-WBANs and a few applications have been proposed and presented in the literature [114] and [115], but there is much to be explored yet and the C-BAN has still to evolve much to reach maturity and wide market adoption.

2.4 Chapter Summary

In this chapter, the background and the state of the art technologies related to sensor networks have been presented. Recent developments in the field of microelectronics and system on chip enable creating miniature sized, cost effective devices for measuring various physical phenomena. These recent advancements, combined with the concepts of CR helped building new types of intelligent wireless communication systems. These ultra-small devices are low powered miniaturized radio communication units with some physical quantity measurement capabilities. These mini radios are termed sensors and their network is referred to as a wireless sensor network. In this chapter, we focused on the WBANs, which are a special kind of WSNs which are designed specifically for sensing features (like heart rate, oxygen level in blood, position of intending personal, etc.) in, on and around human body. The sensors used in WBANs are ultra-low powered as compared to their counterpart in WSNs to avoid any adverse effect on human health. A detailed background and architectural details of the WBANs were discussed in this chapter. Recent trends and research activities in the WBAN domain have been presented in detail. This chapter also described ongoing research efforts to address these primary design challenges toward the successful introduction of WBANs into human life.

Research and development on smart technologies have opened new horizons for their application domains. The CR technology and its intelligent concepts are no longer limited only to mobile communication networks. The CR philosophy can be utilized in the sensor networks and their corresponding subset technologies like body area networks. In the last section of the chapter, the state of the art of CR-WBAN is presented. Though CR-WBAN is a very new research paradigm, many researchers and scientists have taken a step and they have started to explore it. They are devising new methods to make the merger of the two technologies, i.e. CR and WBAN, smoother and more beneficial for human beings.

In the next chapter, the author of this thesis summarize his own contributions to cognitive spectrum management and power optimization in CRNs and WBANs. In the first part of research, the author has proposed algorithms which have been applied to the CRNs and in the second part of the research, he has proposed the C-BANs by incorporating cognitive channel and power assignment algorithms in traditional WBANs.

3 RESEARCH METHODOLOGIES

This chapter describes some of the essential techniques and methods used in the research work published in the papers that form the basis of this PhD thesis. As such, this chapter provides details that could not be included in the papers due to typical scope and space limitations.

In order to make the radios more intelligent, context aware, and reconfigurable for the future networks, they must have cognitive algorithm embedded in their core. In this research, reinforcement learning methods have been used for the frequency allocations in radio networks. For the transmission power allocations, convex optimization techniques have been used. They are discussed in Subsections 3.1 and 3.2, respectively.

3.1 Reinforcement Learning

Reinforcement learning (RL) comes from the field of artificial intelligence and machine learning. Its fundamental concept is to learn a suitable sets of actions among various choices in order to maximize a given reward function while continuously interacting with the given environment [116]. The RL algorithms [117] consider an RL agent, as represented in Figure 13, that interacts with the environment in a succession of time steps. The RL agent receives a context or state (e.g. spectrum holes, or channel conditions) from the current environment and based on that it takes an action (by selecting a channel). The action is then applied and its effects on the radio environment are taken in the form a feedback reward signal to optimize the action until it matches the criteria set by the user.

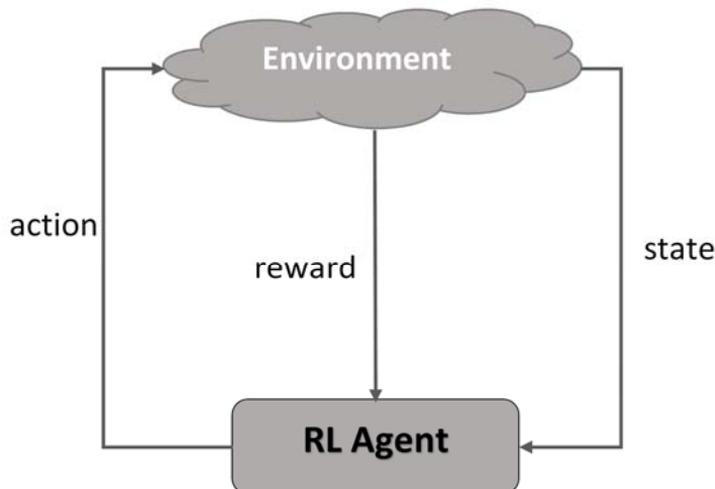


Figure 13: Interaction of the RL with the environment [117]

The agent interacts with the environment (in the context of this work, the environment refers to the radio environment) in discrete time steps t , $t = 0, 1, 2, 3 \dots$. After each time step t , the agent receives some insight of the environment that is characterized as a state $s_t \in S$ (where S denotes the set of all possible states). Then the agent takes the decision on the action that will be made next, i.e. it selects action $a_t \in A(s_t)$, where $A(s_t)$ is the set of all available actions in the state s_t . The result of an action is a reward r_t that the agent receives at each time step t . This reward is a numerical value that represents the immediate return on the success of the previous action selected by the agent (i.e. r_t is the reward associated to the selection of action a_{t-1} in state s_{t-1}). The mathematical flow chart of an RL agent is shown in Figure 14.

The RL agent's interaction with the environment is based on the reward signal r and the M inputs signals. The context input x_i is biased by the weighting value w_i , where i is the number of the input value. \mathbf{x} and \mathbf{w} are real vectors containing the set of inputs and corresponding weights; one can combine the input with their corresponding weights into a single scalar parameter z , given in Equation (1).

$$z = \sum_{i=1}^M w_i x_i \quad (1)$$

Next, the RL agent propagates this input to the output y that is a binary number representing two possible outcomes of the RL procedure. This RL agent is called Bernoulli-logistic unit (BLU) [117]. The outcome of the BLU is a Bernoulli random variable which is based on the logistic function presented in Equation (2).

$$p = f(z) = \frac{1}{1 + e^{-z}} \quad (2)$$

The probability mass function is defined in Equation (3),

$$g(y, p) = \begin{cases} 1 - p, & \text{if } y = 0 \\ p, & \text{if } y = 1 \end{cases} \quad (3)$$

where p represents the probability of the output y and it depends upon \mathbf{x} and \mathbf{w} . To simplify, y can be seen as a two action learning outcome of the process. The learning of the agent can be condensed in the weighting vector so that at each time step t , the agent learns by updating its weighting vector using Equation (4) and any instantaneous change in the individual weight is calculated by Equation (5),

$$\mathbf{w}(t) = \mathbf{w}(t - 1) + \Delta \mathbf{w}(t) \quad (4)$$

$$\Delta w_i(t) = \alpha(t) \cdot [r(t) - \bar{r}(t - 1)] \cdot [y(t - 1) - p(t - 1)] \cdot \mathbf{x}_i(t - 1) \quad (5)$$

where $\alpha(t) > 0$ is called the learning rate and the $r(t)$ is the reward returned by the environment at any instant (step) of time t , and $\bar{r}(t)$ is the average reward which is obtained from the reward signal as shown in Equation (6). The reward signal is a context-dependent entity (in this work, the possible options for the reward signal can be SNR, SINR, Spectral efficiency, etc.),

$$\bar{r}(t) = \beta r(t) + (1 - \beta) \cdot \bar{r}(t - 1) \quad (6)$$

where $0 < \beta \leq 1$. Low values of β assures enough memory of the past rewards. Decreasing the learning rate α with the RL steps improves the convergences speed of the algorithm [117], [116]. Thus, the learning rate is linearly decreased as given in Equation (7),

$$\alpha(t) = \alpha(t - 1) - \Delta \quad (7)$$

where Δ should be small enough to assure a smooth transition between steps and negative values for α should be avoided.

3.2 Power Assignment

Once the frequency of transmission has been selected, the next task is then to assign the transmission powers. Three approaches have been used in this research work for transmission power assignment.

To formulate the problem to secondary networks (i.e. CRNs), the primary criterion for the CRNs is to avoid any interference toward the primary network. To formulate the problem mathematically, let us consider a situation where there are multiple cells of distributed CRNs operating in the primary network area (Figure 14). The main CR operations are performed by the each cell controller, i.e. SBS. Suppose a cell l , and let's define $C(l)$ as the set of frequency units (frequency chunk or channels) which are currently allocated to cell l . Then the objective function to be maximized is given in Equation (8),

$$f = \max_{P_{n,l}} \sum_{n \in C(l)} E \left\{ \log_2 \left(1 + \frac{\gamma_{n,l} P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \right\} \quad (8)$$

where $\sigma_{n,l}^2$ is the average noise plus interference given in Equation (9) and is reported or measured by a generic user at frequency chunk n coming from each one of the interfering cells $c \in A(n)$. $A(n)$ is the set of cells with frequency chunk n is allocated and Γ is the average fading.

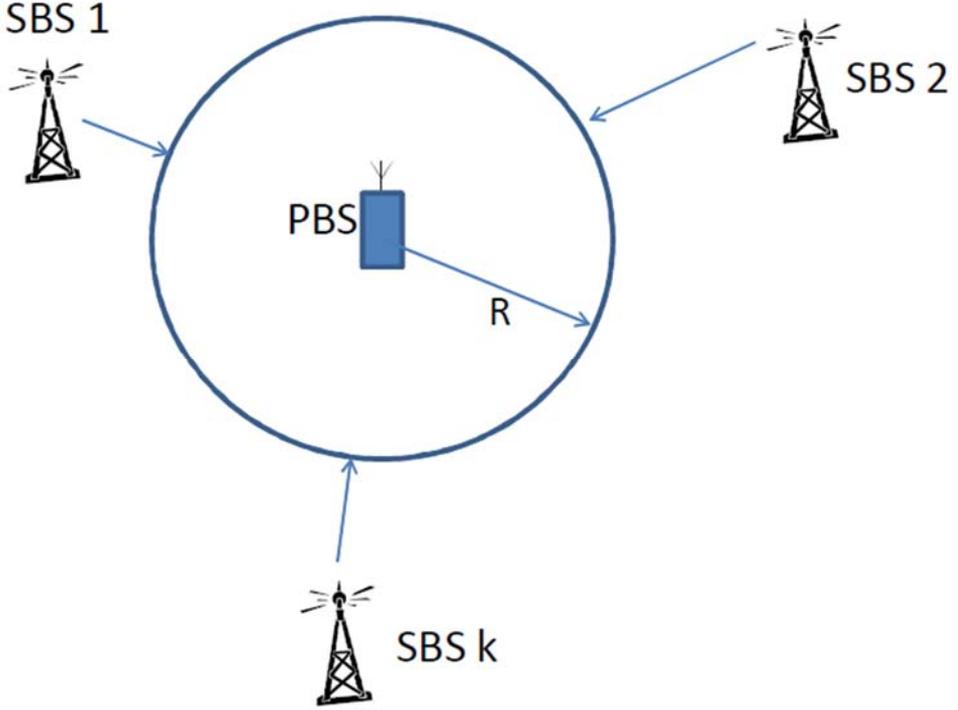


Figure 14: CRNs working in primary network's radio environment with interference boundary at distance R from the primary base station (PBS)

$$\sigma_{n,l}^2 = P_{noise} \sum_{\substack{c \in A(n) \\ c \neq l}} I_n^c \quad (9)$$

In turn, $\gamma_{n,l}$ is the channel gain (in accordance with the propagation model including slow fading) associated to chunk n in cell l . Considering that we are interested by long term variations, it can be assumed that the average channel gain is the same for all frequency chunks defined in Equation 10).

$$E[\gamma_{n,l}] = \bar{\gamma}_l \quad (10)$$

Then, a bound of the objective function is obtained from Jensen's inequality as per Equation (11),

$$E_{\gamma} \log_2 \left(1 + \frac{\gamma_{n,l} P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \geq \log_2 \left(1 + \bar{\gamma}_l \frac{P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \quad (11)$$

This resulting in a convex optimization problem with an objective function given in Equation (12) [118],

$$f = \max_{P_{n,l}} \sum_{n \in \mathcal{C}(l)} \log_2 \left(1 + \bar{\gamma}_l \frac{P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \quad (12)$$

subject to the following constraints:

Constraint 1:

The maximum available power at cell l is given in Equation (13),

$$\sum_{n \in \mathcal{C}(l)} P_{n,l} \leq P_{max,l} = \min \left(P_{max,l}, \sum_{n \in \mathcal{C}(l)} P_{Th,n,l} \right) \quad (13)$$

where $P_{max,l}$ is the total maximum power available at cell l and $P_{Th,n,l}$ is the maximum power allowed at frequency chunk n in order not to interfere the primary which leads to the second constraint on the power.

Constraint 2:

To avoid the interference towards the primary using frequency chunk n , limits are defined in Equation (14),

$$P_{Th,n,l} \geq P_{n,l} \geq 0 \quad (14)$$

where $P_{Th,n,l}$ is the power that cannot be exceeded in order not to interfere the primary receivers. The transmission power assignment approach has to account for the interference generated to the area where the primary users are operating so that it can be ensured that the generated interference is below some pre-defined threshold.

To elaborate further the power assignment approach and constraints, let us take the same example shown in Figure 14. In that respect, the following information about the primary network is assumed to be known:

- Position of the PBS (x_p, y_p) , for simplicity it can be considered as $(0,0)$.
- Radius R around the PBS where the generated interference should be below the threshold I_{Th} (i.e. PBS interference zone). Let us consider that the perimeter of the interference zone consists of a set of points $F(X, Y)$. Specifically, assuming a circle of radius R around the position (x_p, y_p) , the points $F(X, Y)$ are those fulfilling Equation (15).

$$(X - x_p)^2 + (Y - y_p)^2 = R^2 \quad (15)$$

- Transmitted power by the PBS: P_{PBS}
- Frequency band occupied by the PBS (e.g. a band covering a certain number of frequency chunks)

Consider that the frequency chunk n is used in a total of K CRN cells (i.e. K SBSs), then the condition in Equation 16) must be fulfilled,

$$p_{n,1} + p_{n,2} + \dots + p_{n,K} \leq I_{Th} \quad (16)$$

where $p_{n,k}$ stands for the downlink received power coming from each of the SBS where $k = (1, 2, \dots, K)$ which are operating within the PBS interference zone. Equation (16) is another form of Constraint 2 defined in Equation (14). It must be fulfilled for any arbitrary point (x, y) of the perimeter of the interference zone of PBS for any chunk n which is being used by PBS. Equation (16) can be further expanded as presented in Equation (17),

$$\sum_{k \in A(n)} p_{n,k} = \sum_{k \in A(n)} \frac{P_{n,k}}{L_o ((X - x_k)^2 + (Y - y_k)^2)^{\frac{\alpha}{2}}} \leq I_{Th}, \quad \forall (X, Y) \in F(X, Y) \quad (17)$$

where $P_{n,k}$ is the power transmitted by cell k at frequency chunk n , (x_k, y_k) are the coordinates of the k -th SBS, and the propagation model is given by the constant L_o and the propagation factor α .

If the interference condition expressed in Equation (17) is satisfied for the nearest and the farthest PUs from the k -th SBS, it will satisfy Constraint 2 and the primary spectrum is used efficiently (see Figure 15). For cell k , the nearest PU is at $(X_{k,min}, Y_{k,min})$, on the primary interference zone with the shortest distance $d_{k,min}$, and the farthest PU is at $d_{k,max}$ with coordinates $(X_{k,max}, Y_{k,max})$, as shown in Figure 15. The transmission power for frequency chunk n can be computed using Equation (17). The upper bound for the transmission power $P_{n,k}$ is obtained from Equation (18),

$$\sum_{k \in A(n)} \frac{P_{n,k}}{L_o \left((X_{k,\min} - x_k)^2 + (Y_{k,\min} - y_k)^2 \right)^{\frac{\alpha}{2}}} \leq I_{Th} \quad (18)$$

while the lower bound is obtained from Equation (19),

$$\sum_{k \in A(n)} \frac{P_{n,k}}{L_o \left((X_{k,\max} - x_k)^2 + (Y_{k,\max} - y_k)^2 \right)^{\frac{\alpha}{2}}} \leq I_{Th} \quad (19)$$

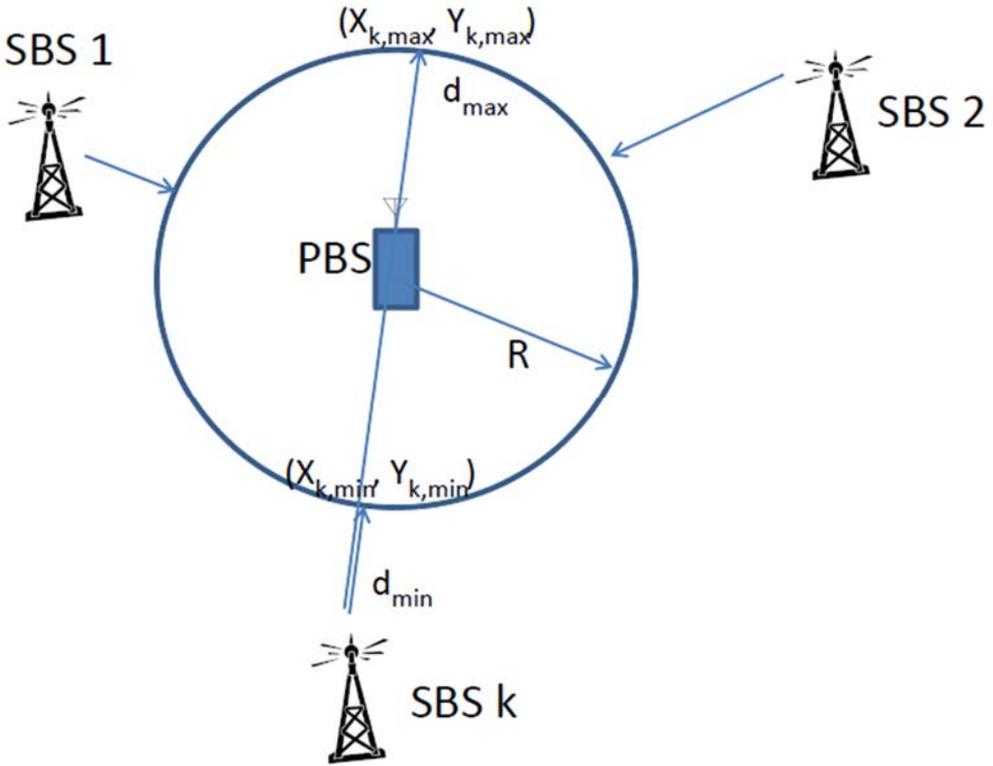


Figure 15: Interference bounds for k -th SBS for the nearest and farthest PU.

When the frequency chunk n is not used by the primary network at any moment (i.e. spectrum hole), then $P_{Th,n,l} = \infty$ hence, Constraint 2 has no effect. In the particular case when there is no primary user, the solution to the optimization problem described in Equation (12) is offered by the classical water-filling approach [118].

For transmission power optimization in WBANs, the algorithm used is from convex optimization theory and is called illumination problem which is described below.

The Illumination Problem

The problem is formulated as a set of lamps illuminating a surface (can be uneven surface) and it is required to achieve a desired level of illumination on the surface. Fixed lamps are used to illuminate a surface which is divided into small patches. The objective of this approach is that each linear patch receives a constant illumination. The concept of the illumination problem is shown in Figure 16, where an uneven surface is to be illuminated by a certain number of lamps. To solve the problem first the uneven surface is linearized by dividing it into small linear portions. The received intensity of the lamp is calculated at the center of the patch which is being illuminated m different lamps [118].

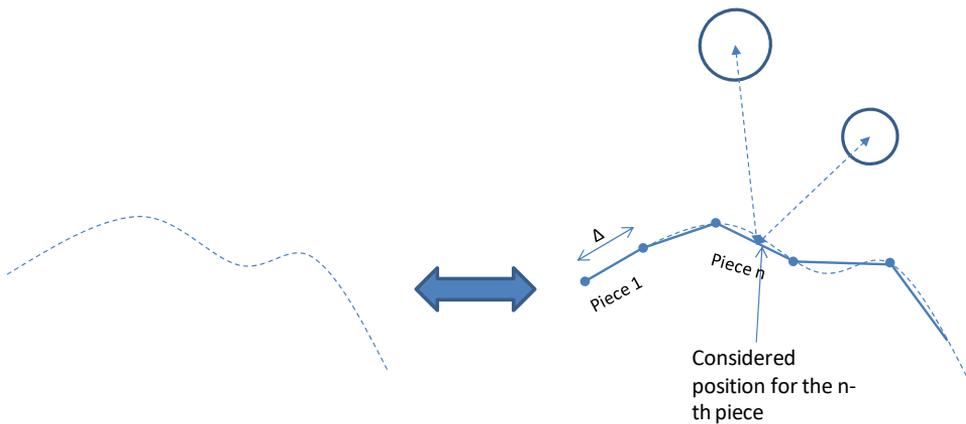


Figure 16: The Illumination Problem concept where uneven surface is to be illuminated by multiple lamps.

To formulate the approach, consider that there are m lamps illuminating n (very small, flat) patches as shown in Figure 17. The j th lamp with power p_j is illuminating the k th patch and the intensity which is being received by the patch is I_k . The intensity I_k at upon linearly on the lamp power p_j . The received intensity at the patch is given by Equation (20);

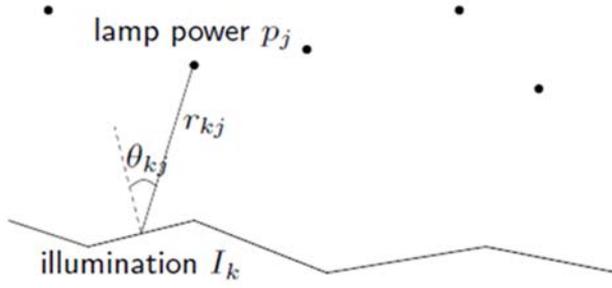


Figure 17: The Illumination Problem formulation [118].

$$I_k = \sum_{j=1}^m a_{kj} p_j \quad (20)$$

where a_{kj} is the propagation losses given in Equation (21), r_{kj} is the distance between the j th power lamp and the center of the k th patch, θ_{kj} is the angle between the angle of ray from j th lamp and the perpendicular at the center of the k th patch.

$$a_{kj} = r_{kj}^{-2} \max\{\cos\theta_{kj}, 0\} \quad (21)$$

From this, a convex optimization objective function can be formulated as per Equation (22);

Minimize:

$$\max_{k=1, \dots, n} |\log I_k - \log I_{des}| \quad (22)$$

Subject to:

$$0 \leq p_j \leq p_{max} \quad (23)$$

while

$$j = 1, \dots, m$$

where I_{des} is the target or desired intensity level (received power). To apply the problem to a wireless network, the following analogies are made:

- Patches: contours of the coverage or interference zone;
- Lamps: radio transmitters;

- a_{kj} : Propagation losses between a transmitter j and the central point of the patch k ;
- I_k : Received power from the transmitter in patch k .

The solution to the Equation (22) are offered by heuristic methods [118] and presented in the paper (Appendix E).

Next chapter summarizes the contribution and presents the discussion and conclusion based on publications.

4 DISCUSSION AND CONCLUSIONS

This PhD thesis concentrated on the cognitive spectrum allocation techniques and power optimization for the wireless networks (i.e. applying cognitive radio concepts to wireless body area networks). The real benefits of the cognitive technology can be utilized if careful spectrum management approaches are introduced. The unsupervised learning approach, namely reinforcement learning, has been used as the primary decision making tool for spectrum management with unknown network conditions.

The first part of the thesis discussed the dynamic spectrum allocation techniques and power optimization for the cognitive radio networks. The second part of the thesis focused on bringing the cognitive features from the CRN concepts to the wireless body area networks. That part of the thesis presents the cognitive spectrum allocation and power optimization in wireless body area networks. In the introductory chapter of this PhD thesis, the following research questions were formulated:

1. What are the best (or at least most suitable) mechanisms to efficiently utilize the spectrum (or spectrum holes) for CR networks?
2. Which mechanisms can be used to avoid the interference between the primary networks and the secondary networks?
3. How machine learning and in particular reinforcement learning can possibly be used to deal with the spectrum management issue?
4. In case of multiple secondary networks that are coexisting in the same location, how to avoid co-channel interferences?
5. Can the interference be avoided using power optimizations?
6. Can combing the CR concepts of cognitive and opportunistic use of radio spectrum in WBAN give birth to a new networking paradigm, cognitive body area network (C-BAN)?
7. How to embed CR concepts and algorithms into resource-constrained processing elements in C-BAN sensor nodes and gateways?
8. To what extent will C-BANs be (more) spectrum efficient than their non-CR counterparts?

This section of the thesis discusses the contributions of the thesis and how they help answering the above questions.

Paper I

The paper presents a novel approach for frequency and power optimization in CRNs. For dynamic frequency allocations, the unsupervised learning technique based on reinforcement learning (described in Section 3.1) is used. This proposed approach is called RL-DSA (RL-Dynamic Spectrum Allocations) and it monitors the radio environment. Based on the feedback signal, i.e. SINR (signal to noise and interference ratio), the algorithm decides whether the observed frequency

subcarrier should be assigned to the CRN. To optimize the transmission powers, a convex optimization approach (described in Section 3.2) is used to assign power levels. The power optimization approach takes into account the interference towards the primary network, inter-cell interference (i.e. among multiple secondary networks), path loss and fading while assigning transmission powers. The performance of the RL-DSA+power optimization is compared with that of RL-DSA+constant power (i.e. non-optimized) in a cellular based CRN by means of simulations. The simulation results show that the RL-DSA+power optimized approach provides better QoS for the overall system up to 10 dB in terms of SINR and 4% improvement in spectral efficiency. Detailed descriptions of the algorithm, simulation setup, and results are presented in Paper I (Appendix A).

Thus, on the basis of the proposed approach and results, Paper I provides answers (or elements thereof) to Questions 1 to 5.

Paper II

The paper presents three schemes for dynamic spectrum and power allocations in non-coordinated secondary networks, namely RL+constant power, RL+power, RI+power coupled. The RL-DSA based approach revised from Paper I is used to access the spectrum and opportunistically share them. The CRNs are distributed so they do not share any spectrum information. Each cell, in a greedy approach, tries to get best possible spectrum resources in order to maximize its QoS (i.e. SINR, throughput, spectral efficiency). The performance of the three above-mentioned schemes is evaluated in a traffic-changing scenario. The three schemes rely on the same RL-DSA algorithm for frequency allocations; however, these schemes differ in their power assignment approach. Simulation results show that RL+power coupled achieves up to 5 dB gain in SINR and 10% more user satisfaction, especially in high traffic load situations. Detailed descriptions of these schemes, simulations setup, and results are presented in the paper (Appendix B).

Thus, on the basis of the proposed approach and results, Paper II provides answers (or elements thereof) to Questions 1, 4 and 5.

Paper III

The paper presents a comparison of performance of a modified version of the proposed spectrum and power management schemes presented in Paper II in a micro-femto based heterogeneous cellular networks. Operating in a heterogeneous radio environment is the true essence of the CRs. The purpose of this paper is to evaluate the behavior of these cognitive algorithms in such heterogeneous environment when their radio resources are consumed by an intruding femto cell based network. These presented frequency and power

allocation schemes are compared with the so-called frequency reuse factor (FRF = 1) scheme. Simulation results show that the proposed cognitive algorithms have significant advantages in terms of SINR and spectral efficiency as compared to a fixed frequency assignment. These schemes yield up to 14% increase in system capacity and they perform better in interference management. Further details are presented in Paper III in Appendix C.

Thus, on the basis of the proposed approach and results, Paper III provides answers (or elements thereof) to Questions 4 and 5.

Paper IV

The paper presents a channel allocation algorithm for wireless body area networks. The proposed algorithm is based on unsupervised learning from the domain of reinforcement learning. The algorithm senses the available channels and based on the context information, it selects the optimal channel from the available channels. The algorithm presented takes into account the traffic load requirements for each WBAN and then assign the appropriate number of channels based on the requirements. Furthermore, to model a realistic WBAN plan, a mathematical model for the IEEE 802.15.6 CM4 has been proposed. Simulation results show that the presented algorithm performs better in error rate and throughput in a fading environment as compared to its counterpart, i.e. static channel assignment. Further details about the algorithm and simulation can be found in Paper IV in Appendix D.

Thus, on the basis of the proposed approach and results, Paper IV provides answers (or elements thereof) to Questions 6 and 7.

Paper V

This paper presents a proposal for embedding cognition into wireless body area networks, i.e. making them cognitive body area networks (C-BANs). The work deals with two important issues of the wireless body area networks, i.e. spectrum sharing and interference. A reinforcement learning based context aware channel allocation algorithm, i.e. RL-CAA, has been proposed and presented. The underlying algorithm is based on that presented in Paper IV; however, it has been modified to include cognitive features, i.e. channel conditions (SNR), interference, QoS requirements, handover management, etc. The algorithm presented is more robust and dynamic. The paper also presents a more detailed mathematical model for the CM4 based on that of Paper IV. Furthermore, to avoid the interference from one gateway to another, i.e. inter-gateway or Tier 2 level interference, a power optimization algorithm based on the illumination problem from convex optimization theory is presented (see Section 3.2). The presented algorithm has been compared with static channel assignment scheme for a health

care application, i.e. nursing home. Simulation results show that the presented algorithm performs much better in terms of throughput and QoS satisfaction in a highly demanding environment as compared to its counterpart. Simulation results also show that the proposed power optimization approach reduces the transmission power by 4.5 dBm, thereby minimizing the interference.

Thus, on the basis of the proposed approach and results, Paper V provides answers (or elements thereof) to Questions 6 to 8.

With the growing needs of wireless connectivity and emerging technology, it has become challenging to design and develop wireless networks using conventional approaches. There are more and more devices competing for the same air interface; thus, there is a need for careful and cognitive spectrum management. Whether the technology is targeting a cellular network or a miniature network (e.g. sensor based), efficient frequency and power assignment are the core tasks of wireless communication networks.

Perspectives

With the development in modern technologies, it is expected that the size of the sensors will further reduced. Hence, it will be possible in the future to carry or wear many more sensor nodes on and/or in the body. Such dense deployments of sensor nodes in many individual WBANs will create new challenges in terms of spectrum management, e.g. interference, QoS, etc. Traditional approaches will no longer be very effective to encounter such challenges. The cognitive capabilities in the proposed C-BANs will be suitable candidate to deal with these challenges. Since most of the WBANs are proposed or designed for the ISM band and with growing diverse services in this unlicensed band, more cognitive functionalities will be required at various layers in the C-BANs.

Interference is a major hindrance for the QoS of the WBANs. With the introduction of C-BANs, efficient and opportunistic spectrum management algorithms can be proposed. In this work, inter-gateway interference avoidance has been proposed through power control. In the future, inter-WBAN and beyond-WBAN interferences could be avoided with the cognitive capabilities of future C-BANs.

Channel modeling has been a tough subject for WBANs' researchers. Off-body and body-to-body channel modeling has been very little investigated in the literature. In this work, an off-body channel model has been proposed based on the body postures and shadowing resulting from various factors. A more comprehensive model of the off-body channel link based on the antenna design and position could be a future investigation task.

Finally, the algorithms presented in this work (i.e. the RL-CAA) has been proposed for channel allocation and simulation results show it as a promising

candidate for future C-BANs. While resource constraints have been considered when designing such algorithms, their detailed hardware implementations and design considerations for resource constrained platforms (in particular their computational power and energy conservation issues) remain to be investigated; for this, further modifications and optimizations to the proposed approach would be needed to improve the matching between the algorithms and architecture.

The research has been envisaged to open new horizons in the research industry working in the healthcare system based on cognitive body area networks. Such futuristic healthcare system may augment the modern health system to benefit the civilization in broad perspective by saving resources.

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KOKKUVÕTE

Raadiotehnoloogiate areng on avanud uusi võimalusi traadita side valdkonnas. Paljud traadita (mh litsentseeritud tehnoloogiatel põhinevad) võrgud üritavad korraga kasutada sama spektrit, mis on seega muutumas napiks ressursiks maailmas. Teadlased ja uurijad lahendavad spektri ülekoormatuse probleeme. On täheldatud, et spektri vähesuse taga on tegelikult spektri alakasutus. Hoolika planeerimisega ja spektri haldamise ennetava tehnikaga on seda probleemi võimalik lahendada. Keskkonnast teadliku intelligentse raadio mõiste nimega kognitiivne raadio võeti kasutusele 21. sajandi alguses, tulevaste traadita tehnoloogiate ja teenuste nõuetele vastamiseks. Kuigi kognitiivsete raadiovõrkude osas on olnud palju uuringuid erinevate aspektide osas, on siiski paljud kognitiivsed funktsioonid sellistes võrkudes endiselt avatud teadusväljakutsed. Paljude teiste probleemide seas on spektri haldamine, võimsuse määramine, häired jne.

Selles doktoritöös on ülesanded seotud raadio keskkonna ja heterogeensuse uurimisega kognitiivsetes raadiovõrkudes. Töös esitatakse mittejuhendatud õppega spektrile juurdepääsu ja jagamise meetodit, mis kasutab masinõppe alamvarianti – kinnitusega õppimist. Esitatud lähenemisviis arvestab jooksvaid tingimusi sagedusalas (nt signaal-müra suhet, esmase võrgu olemasolu, sekundaarseid omavahelisi häireid jne) ja see määrab side toimimise spektriosas. Kuna kognitiivsed raadiod tegutsevad esmase võrgu keskkonnas, siis nad peavad tegutsema ettevaatusabinõudega ja ei tohi tekitada mingeid takistusi esmasele võrgule. Et tulla toime selliste piirangutega, on esitatud kumera optimeerimisega lähenemine saatevõimsuste määramisel kognitiivses raadios. Selline lähenemine vähendab nõutavat saatevõimsust, et vältida häireid esmase võrgu allikate suunas ja see minimeerib kärje sees häireid, mis kajastub nt kuni 10x signaal-müra suhte paranemises ning 10% juurdekasvu kasutajate rahulolus kõrge võrgu liikluskoormuse tingimustes.

Lisaks sellele kirjeldab doktoritöö sünergiat kognitiivse raadio kontseptsiooni ja areneva traadita kehapiirkonna võrgu tehnoloogia vahel. Mõiste kognitiivsed kehavõrgud (C-BAN) kontseptsioon on esitatud käesolevas doktoriväitekirjas. Sarnaselt kognitiivse raadiovõrguga, kognitiivne kehavõrk võib olla kontekstist teadlik ja ümberkonfigureeritav oma edastamise funktsioonides. Traadita kehapiirkonna võrgud tervishoius ja jälgimiseks toimivad enamasti sagedusalas, mis on kasutusel ka paljudes muudes traadita tehnoloogiates. Patsiendi jälgimine haiglates ja hooldekodudes võib põhjustada ka mitmeid tehnoloogilisi väljakutseid spektri haldamise osas mitme sama liiki võrgu kooseksisteerimise tõttu. On vaja hoolikaid spektri haldamise ja tunnetusega funktsioone kehapiirkonnas võrkudes. Kinnitamisega õppimise algoritmi spektrihalduseeskirjad on esitatud käesolevas doktoriväitekirjas. Algoritm keskendub sidekanali tingimustele enne otsuse tegemist, kas seda kasutada või mitte. Selline lähenemine tagab, et parim saadaval kanal on valitud, et täita võrgu kvaliteedi nõudeid. Lisaks on esitatud saatevõimsuse omistamise kava

kognitiivse kehapiirkonna võrgu jaoks. Esitatud kava põhineb valgustuse probleemile kumera optimeerimise valdkonnast. Väljapakutud algoritm saab minimeerida kehavõrgu häireid, vähendades saatevõimsust 4,5 dBm.

Appendix A

Tauseef Ahmed, Yannick Le Moullec

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Power Optimization in a Non-Coordinated Secondary Infrastructure in a Heterogeneous Cognitive Radio Network

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Abstract—In this paper we describe a novel approach that combines dynamic spectrum allocation and transmission power optimization for the secondary network users in an heterogeneous cognitive radio network. The proposed approach builds upon reinforcement learning and convex optimization procedures. Furthermore, the several key components, i.e. inter-cell interference, path loss, and fading have been considered when designing the power optimization algorithm. Simulation results show that the proposed approach improves the QoS of the system by up to 10 dB in terms of SINR and by up to 4% in terms of spectral efficiency while maintaining the average dissatisfaction probability close to that of the non-optimized approach.

Index Terms—Cognitive radio, dynamic spectrum allocation, heterogeneous network, power optimization, radio spectrum management.

I. INTRODUCTION

Cognitive Radio has been attracting a significant interest during the last decade. It was triggered by DARPA's approach on Dynamic Spectrum Access network, with the so-called NeXt Generation (xG) program to solve the current spectrum inefficiency, claimed to be a real bottleneck for the progress of wireless telecommunication. Since then, the problem has been recognized to be not so much spectrum scarcity per se, but more its efficient exploitation. At this point, the term *opportunistic network* has been coined, which devises a plan to effectively and efficiently use the available radio resources. The opportunistic use of the radio spectrum is one of the key benefits of cognitive radio. Thus, many contributions dealing with the sensing of primary users spectrum and its related link layer issues (e.g. power control, modulation schemes, etc.) have been published.

However, a major challenge to realizing the potential benefits of cognitive radio lies in the interference management between non coordinated secondary users and primary users, with the aim of sharing the available spectrum.

In this paper, we consider uncoordinated secondary networks that are asking to opportunistically share, in an

optimum way, the spectrum owned by primary networks without damaging the QoS of the licensed users beyond certain agreed limits. In this work the secondary networks consist of a unique base station which is providing services to the secondary users. We also consider the static load traffic for which each secondary network has to allocate spectrum in an adaptive way. Novel procedures relying on reinforcement learning (RL) [1]–[4] based algorithms are presented (see II.B) to deal with the uncoordinated and opportunistic spectrum sharing problems. We present the study of a decentralized approach for the dynamic spectrum and power allocations in multi-cell orthogonal frequency division multiple access (OFDMA) networks. Each cell independently decides i) the frequency allocation using the RL algorithms and ii) the power allocation based on convex optimization algorithms. In OFDMA, the broad frequency spectrum is divided into smaller bandwidth frequency resources called chunks. While assigning the frequency units, i.e., chunks, the aim is to reduce the inter-cell interference i.e., the interference caused to each other by two or more neighboring cells that use the same frequency resources. The assignment of the power levels is based on convex optimization algorithms [4], where the key factor in deciding the power allocation is inter-cell interference and other degradations.

II. SYSTEM MODEL

A. Decentralized Network Architecture

We consider a decentralized network architecture composed of a hybrid environment of primary and secondary networks. Each secondary entity, i.e. cell, comprises an independent RL agent which performs the spectrum allocation task keeping in mind the objective function of maximizing the signal to noise and interference ratio (SINR) while keeping in consideration the cell users QoS requirement (i.e. spectral efficiency). Considering that a cell has U users at any moment, the secondary base station (SBS), before every assignment, checks the generated inter-cell interference by the U users, and the interference to the primary base station. Note that in this particular example, for simplicity's sake, we are assuming that primary users are not present; more advanced cases will be presented in a future publication. A generalized OFDMA radio interface is

considered for the downlink for users' data transmission. The total system bandwidth W is divided into N chunks, the smallest unit that can be allocated. A chunk is a group of contiguous OFDMA subcarriers with bandwidth $B = W/N$ Hz. Frames are divided into time slots. The minimum radio resource block which is available to users is one chunk per frame. There is an uplink control channel where users send frame-by-frame measurement reports.

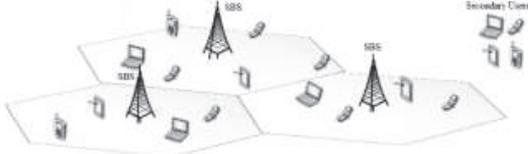


Fig. 1. A typical contiguous 3 Cells' deployment for Secondary Network used in these simulations.

A typical macro cell (MC) based cellular scenario on a geographical location, as shown in Fig. 1, consists of 3 cognitive radio SBSs which are serving secondary users in their vicinity. For simplicity, we consider only secondary users that are using various services and sharing the primary spectrum among themselves. These SBSs allocate both spectrum and power to their users in a non-coordinated or decentralized way. There could also be overlapping areas covered by several SBSs because they are not coordinated and could be run by different operators/vendors. However, in this work we assume no overlap between the cells.

B. Cell Operation

In the short term the cell handles users' traffic and performs the OFDMA fast link adaptation following the channel aware strategy proportional fair (PF) [5]. On the other hand, the spectrum assignment is done on a medium term basis. Specifically, each cell tries to learn the best resources assignment scheme, i.e., frequency and power, by executing the reinforcement learning dynamic spectrum assignment (RL-DSA) algorithm [1], [6] and convex optimization algorithm [3], in an execution period of L frames. On the first execution, a cell randomly selects the initial time to start the proposed combined algorithm; the algorithm first assigns the initial frequencies and then receives the reward signal (SINR) from the environment. The RL-DSA is internally based on random variables and Bernoulli logic.

The key steps of RL-DSA algorithm (described in appendix A) tries various assignments and the one which gives the highest reward (once the the algorithm has converged) is selected, i.e. its frequencies are assigned to the cell. The next execution occurs after L frames. Hence, large values of L are expected for a medium range execution of RL-DSA and water-filling algorithm. The probability that adjacent cells select the same initial time becomes negligible. The individual steps of the algorithm are further detailed in [1], [6].

The objective is to perform both an optimal frequency allocation and power allocation to each SBS so that a maximum throughput (or efficiency) per SBS can be attained, while at the same time the following constraints are satisfied:

- Each SBS should provide service to $U = 15$ users, ensuring a minimum bit rate to each of them in accordance with the considered service. There could be several service types;
- Generated interference should be minimum, i.e., interference to the primary users should remain below the primary threshold value; since we are considering that no primary user exists in the area, the condition of the interference is for the inter-cell interference.

In order to perform a reliable spectrum allocation, the requirement is the user satisfaction. In order to fulfill the users' QoS, we should estimate the spectrum usage in the adjacent cells to calculate the potential inter-cell interference. Previously, frequency allocation optimization with constant chunk powers [1] has been used; in this paper we propose a new spectrum assignment method in which both frequency and power are optimized. The assignment procedure is a two-step process, in which deciding i) the frequency allocation (chunks) is performed as summarized in Appendix A (for details see [1], [6]) and ii) the transmitted power for each frequency chunk is performed as described in the next section. The RL-DSA in our spectrum management has been revised in order to take inter-cell interference into consideration.

C. Power Allocation

Power allocation is based on a convex optimization problem with the objective function given in (1)

$$f = \max_{P_{n,l}} \sum_{n \in C(l)} \log_2 \left(1 + \frac{\bar{\gamma} P_{n,l}}{\Gamma \sigma_{n,l}^2} \right), \quad (1)$$

where $C(l)$ is the set of chunks currently allocated to cell l , $P_{n,l}$ is the power assigned to chunk n in the l th cell. Γ is the average fading. $\sigma_{n,l}^2$ is the average noise plus interference defined in (2) and is reported or measured by a generic user at chunk n coming from each one of the interfering cells $c \in A(n)$ (where $A(n)$ is the set of cells with chunk n allocated) at the time when the resource allocation is updated. $\gamma_{n,l}$ is the channel gain (in accordance with the propagation model including slow fading) associated to chunk n in cell l

$$\sigma_{n,l}^2 = P_{noise} + \sum_{\substack{c \in A(n) \\ c \neq l}} I_n^c, \quad (2)$$

where P_{noise} is the noise power and I_n^c is the received interference for that particular frequency chunk from the other cells which are also using that chunk. There are two main constraints for the power algorithm. The first constraint, which is described in (3), is the maximum power at cell l

$$\sum_{n \in C(l)} P_{n,l} \leq P_{max,l} = \min(P_{max,l}, \sum_{n \in C(l)} P_{TH,n,l}), \quad (3)$$

where $P_{max,l}$ is the total maximum power available at cell l and $P_{TH,n,l}$ is the maximum power allowed in chunk n in order not to interfere.

The latter is the second constraint described in (4)

$$P_{TH,n,l} \geq P_{n,l} \geq 0. \quad (4)$$

If chunk n is not used then $P_{TH,n,l} = \infty$, and thus the second constraint has no effect. The solution to the power optimization problem is given by the classical water-filling approach [3], [7]. The detailed formulation of the power optimization is beyond the scope of this paper and will be presented in subsequent work.

III. SIMULATIONS

We consider a downlink OFDMA-based 3 MC scenario; we focus our study on two case studies. First, we use RL-DSA with constant power assignments where all assigned chunks are assigned equal powers (*Case A*). In the second situation, we use the power optimization algorithm in which all the chunks use different powers based on the surrounding situation (*Case B*). Users are homogeneously scattered in the cellular zone and they are not moving, i.e., for simulation purposes the users do not change their geographical positions and handovers are not considered. Also during the entire course of action, the cell load is static, i.e., the numbers of users do not change. Users always have data ready to send, which means every user will try to occupy as much bandwidth as they can, (full buffer traffic model [8-10]). The performance of the system is measured on the basis of spectral efficiency, SINR and the users' dissatisfaction probability, over one simulated hour. The spectral efficiency is the QoS parameter defined as a performance metric that measures the amount of successfully delivered bits per unit of time and spectrum. The dissatisfaction probability is defined as the percentage of seconds in which the user throughput is below a target throughput called the satisfaction throughput. In the simulations, the user satisfaction throughput is set to 256 Kbps. Other simulation parameters are presented in Table I.

TABLE I. SIMULATION PARAMETERS.

General	
Frame time	2 ms
Chunk Bandwidth [B]	375 kHz
Number of Chunks [N]	6
UE Thermal Noise	-174 dBm/Hz
UE Noise Factor	9 dB
Short Term Scheduling (STS) Method	Proportional Fair (PF)
PF Averaging Window	50 Frames
Spectral Efficiency (theoretical maximum)	5 (bits/s)/Hz [11]
Secondary BS Cell	
Cell Radius	500 m
Maximum BS Power	43 dBm
Minimum Distance to BS	35 m
Antenna Pattern	Omnidirectional
Path Loss at d Km in dB	$128.1 + 37.6 \log_{10}(d)$
Shadowing Standard deviation	8 dB
Showing decorrelation distance	5 m
Small Scale Fading Model	ITU Ped. A
RL-Spectrum Algorithm	
Measurement Averaging Period [I]	2500 Frames
RL-DSA Execution Period [L]	60000 Frames
RL-DSA parameters [$\alpha, \beta, \sigma, \Delta$]	$[100, 0.00001, 0.05, 10^6]$
RL-DSA Exploratory Probability [p_{explore}]	0.1 %
RL-DSA Steps [MAX STEPS]	1000000

We are simulating for the two above scenarios (Case A

and Case B), i.e., with and without power optimization algorithms, and then the results are compared. All simulations have been performed with Matlab.

A. Case A: Frequency Allocation with Constant Chunk Power

There are 15 users in each cell and 6 chunks to be allocated. Each cell requires 3 chunks to satisfy the users' communications. The users are satisfied most of the time, and they do not suffer from resource scarcity. Usually when one cell's users obtain higher spectral efficiency, the other cells experience reduced spectral efficiency due to the inter-cell interference. Since there are only 6 chunks available to be assigned for each cell, some of the chunks are reused, giving birth to the inter-cell interference. When one cell uses the chunk, which is being used in other neighboring cell or cells, inter-cell interference is generated.

B. Case B: Frequency Allocation with Power Optimization

In this part of the simulations we have evaluated the proposed allocation scheme. The combined frequency and power allocation based on RL-DSA and Convex Optimization algorithm is a sub-optimal approach because we do not optimize the frequency and power while performing the resource allocation algorithms. The procedure is as follows:

1. The frequency allocation is carried out assuming a feasible constant power setting as done in the first part of the simulations so that the conditions on the power can be satisfied.
2. The set of allocated frequencies, $C(l)$, to cell l is retained and then the convex optimization is used to obtain the power setting $P_{n,l}$, from (1), per chunk in each cell l .
3. Steps 1 and 2 are repeated for the cell l with the new power settings to obtain the new frequency and power allocations.

The concept behind the whole procedures is that the first time the frequency allocation is performed by the RL algorithms using constant powers, exactly as described in the previous section, and then once the frequency allocation is known, the power allocation algorithm computes the powers for the individual chunks based on how much it received inter-cell interference and fading. When this power allocation is done for all chunks in the cell, then the RL algorithm is executed for these optimized powers to obtain the new frequency allocations. This process is continued until we reach the convergence in the power optimization algorithm. This procedure is done by all the SBS cells after the L frames. Now the chunks are assigned powers individually and the total power which the SBS can allocate is assigned to the chunks depending upon the parameters from the environment taken into account by the power allocation algorithms. Two of the most important parameters which the algorithm considers are the inter-cell interferences and fading.

C. Results

The simulation results from Cases A and B are presented in Fig. 2–Fig. 4. When comparing the results, it can be seen that better performance is achieved when using the power optimization. Firstly, as shown in Fig. 2, the spectral

efficiency of the power-optimized system (Case *B*) is higher than that of the non-optimized case throughout the simulation by up to 4 %. Secondly, as shown in Fig. 3, the average SINR of the system increases by up to 10 % thanks to the power optimization. Although the average SINR somehow decreases and fluctuates in the middle of the experiment for the power-optimized case, it still has better results than Case *A* (*constant power*); in the worst case, the gain is 0 dB. Finally, as shown in Fig. 4, the average user dissatisfaction probability is somewhat similar to that of Case *A*. Thus it can be concluded that in general the system offers better performance in terms of throughput (spectral efficiency) and SINR while providing the same level of user satisfaction.

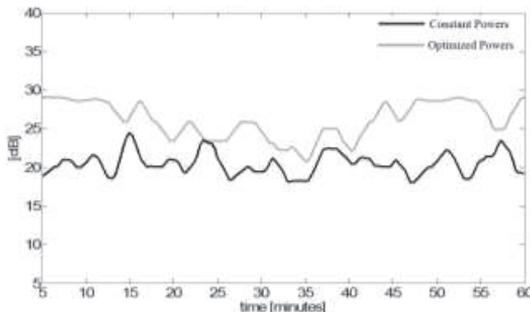


Fig. 3. Average SINR.

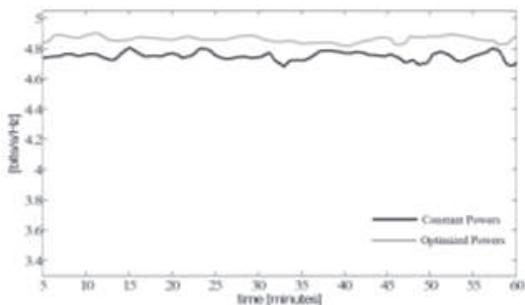


Fig. 2. Average Spectral Efficiency.

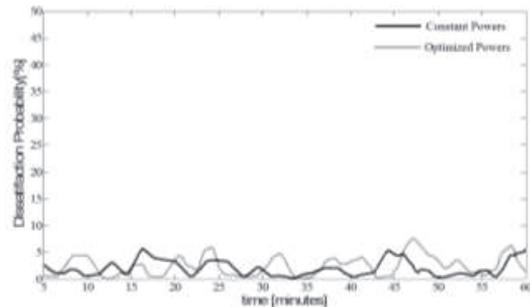


Fig. 4. Average Dissatisfaction Probability.

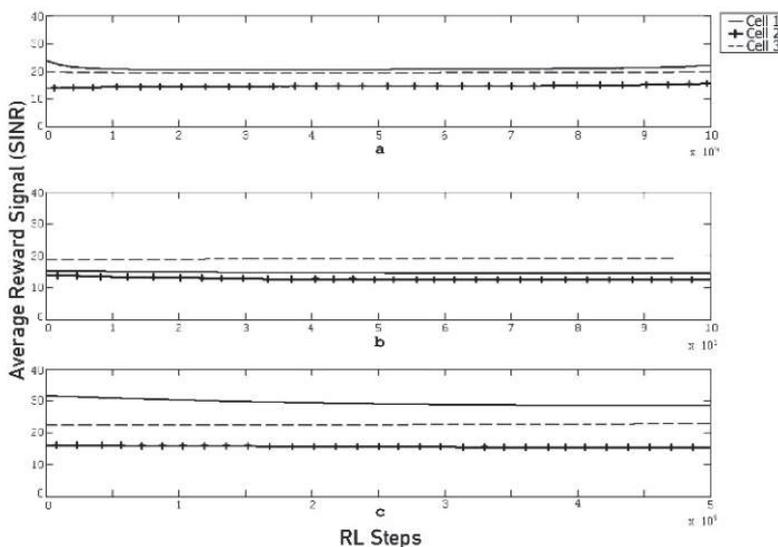


Fig. 5. RL Convergence Behaviour.

D. Convergence Study

The convergence behavior of the RL-DSA coupled with power optimization algorithm is given in Fig. 5. The convergence behavior is studied over three different maximum steps of (RL_MAX_STEP), i.e., a = 1000000, b = 100000, and c = 50000, where RL convergence steps are set to 5000 (which is experimentally chosen over multiple iterations). The convergence condition is set to 0.01. The convergence behavior is studied for three cells; from Fig. 5 it is quite evident that with the inclusion of the power

algorithm with RL-DSA, the convergence behavior is quite in accordance with [6] and convergence is achieved for a, b and c (typically, for RL-based method, this value should be ca. 3000).

IV. CONCLUSIONS

Despite the sub-optimality of the RL-DSA, its combination with power optimization offers better performance than the techniques proposed in [1] and [6], while converging reasonably well for all 3 cells. Future

work will address more complex scenarios with dynamic system and higher numbers of cells and users for the power management algorithm. Furthermore, we will evaluate the applicability of such approaches when adding cognitive capabilities to wireless sensor networks. Indeed, adding cognitive capabilities to wireless sensor networks is highly desirable since the resulting cognitive wireless sensor networks (CWSN) could then feature, among other things, dynamic spectrum allocation and energy optimization, thereby enabling them to better cope with spectrum scarcity and limited battery life-times. In particular, we will address the question of designing such dynamic algorithms so that their implementation on computationally and energy limited resources do not outweigh the expected benefits. Another key aspect that should be investigated is the design and implementation of power management and optimization techniques to deal with fluctuating energy sources in CWSN powered by energy harvesters.

APPENDIX A

RL-DSA is based on the Bernoulli logi unit. The internal architecture of the RL works on the weighted probabilities which are updated on every iterations including the interaction with the environment. The key steps involved in the frequency allocations are listed here and the details of every step is available in [1], [6].

```

1. REPEAT
2.   Received reward signal from the
   environment.
3.   Update the average reward.
4.   FOR all cells AND chunks
5.     Update the internal probabilities of
   the RL - agent.
6.   END FOR
7.   FOR all cells AND chunks
8.     IF internal probabilities for the
   cell status is greater than the
   threshold value (criteria set by user)

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9.     Assign that frequency chunk to the
   cell
10.   ELSE
11.     Do not assign the chunk.
12.   END IF
13. END FOR

```

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Appendix B

Tauseef Ahmed, Yannick Le Moullec

“Power-Efficient Frequency Allocation Algorithms for Self-Organized Networks”, was published in the IEEE conference of Advances in Wireless and Optical Communications (RTUWO), Riga, 2015.

Power-Efficient Frequency Allocation Algorithms for Self-Organized Networks

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Abstract—In this paper we compare three novel schemes for dynamic frequency allocation and transmission power assignment for cognitive radio networks. These spectrum allocation schemes are based on reinforcement learning and power optimization procedures. We propose the so-called RL+Power and RL+Power Coupled schemes and compare them with an existing constant power scheme. Simulation results show that the RL+Power Coupled scheme improves the QoS of the system by up to 5 dB in terms of SINR and by up to 10% in terms of user satisfaction when compared against the two other schemes in a high cell load environment.

Keywords—Cognitive radio, reinforcement learning, dynamic spectrum allocation, power optimization, self organizing network;

I. INTRODUCTION

Modern day communication networks are bringing new trends in existing wireless system scenarios. The focus in wireless communication is shifting from supervised networks towards self-organizing networks. In the future, less and less human interaction will be required to run and administer a network. The future wireless networks will be more autonomous entities which will be governed by environmental factors. Another aspect is that the requirements of the modern communication networks are growing exponentially. Generally speaking, existing communication networks are unable to cope with the future requirements of the wireless networks with higher data rates and capabilities in terms of self-learning, self-organization, and self-optimization. Moreover, there is not much space left in the useable spectrum to deploy these future wireless networks. However, a significant amount of the spectrum is under-utilized due to a large portion of the assigned spectrum being used sporadically.

Hence a new communication paradigm has to be in place which should have the capability of efficiently utilizing those under-utilized spectrum areas in a dynamic way. The key technology to tackle these issues is referred to as cognitive radio (CR), proposed by J. Mitola [1]. CR technology enables the

exploitation of the free spaces available in the spectrum owned by the licensed user and opportunistically share it with the users often referred to as unlicensed users or secondary users (SU).

However, a major challenge to realize the potential benefits of CR networks lies in sharing the spectrum among the SUs in such a way that spectrum conflicts with the licensed user are avoided.

The work presented in this paper is an extension of our previous work [2] where we proposed novel procedures for frequency allocation and power optimization based on reinforcement learning (RL) and convex optimization, respectively. We consider non coordinated secondary networks that opportunistically share the spectrum (owned by the licensed network) among themselves. For simplicity, we consider the scenario where the secondary network consists of a unique base station which governs users in its vicinity. Moreover, we consider that the traffic load is static during small periods of time, i.e., one hour, for which the base station has to allocate resources, i.e., frequency and transmission power, in an opportunistic manner. After every hour, the traffic load in the cell is gradually increasing. Novel procedures based on RL and convex optimization (building upon [3-6]) are used to address the uncoordinated and opportunistic spectrum sharing problems. We present the study of a decentralized approach for the dynamic frequency and power allocation in an orthogonal frequency division multiple access (OFDMA) network.

In OFDMA, the available frequency spectrum is divided into smaller contiguous frequency blocks called subcarriers or chunks. Each cell independently decides the frequency allocations based on the RL algorithm. For the power allocations, three different schemes (an existing one and two novel ones) have been studied and their results compared. In the first scheme, the frequencies are assigned based on the RL based spectrum allocation and then constant transmission powers are assigned. In the second scheme, the optimized powers based on convex optimization algorithm are calculated and assigned to the frequency chunks provided by the RL algorithm. The third scheme is an extension to the second one; the difference is that the RL-based dynamic spectrum allocation is followed by the power optimization and then these power optimized subcarriers

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are again subjected to the frequency and power optimization using the RL and power optimization algorithms. The key criteria in the RL algorithm for assigning the frequency unit (chunk) to any cell is the inter-cell interference, i.e., the interference caused to each other by two or more neighboring cells that use the same frequency chunk. The inter-cell interference along with other power degradations such as path losses is also a key factor while deciding the transmission powers by the convex optimization algorithm [5].

II. SYSTEM MODEL

A. Self-Organizing Networks (SON)

A self-organizing network (SON) is a communication network, which has the inherent capabilities of learning about its operating environment. Such networks can feature mechanisms to learn about their surrounding and change their communication parameters to adjust in changing environments. Self-organizing capabilities enable the automation in the communication networks, hence minimizing human interventions. Cognitive radio is the key technology that enables SONs. Self-configuration and self-optimization are central aspects of the SON learning cycle, as shown in Fig. 1. A SON monitors the network parameters and then adjusts itself according to that particular environment; the new parameters are then assigned so that the users can operate. The SON learning process is a cyclic process; as long as the parameters of the network are not changed, a SON can go along with its last configuration. As soon as some of the network parameters are modified due to changing traffic load or other reasons, the SON cyclic process starts again and new configurations are assigned. Our system in this paper consists of several SONs, which are the cognitive radio secondary networks, using the resources of a primary network and sharing them among themselves opportunistically.

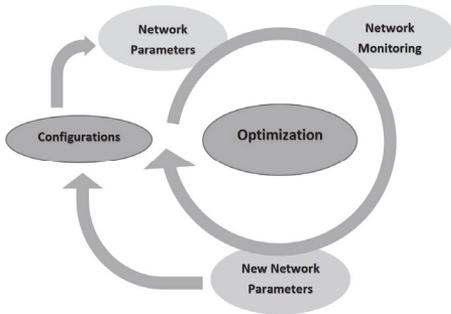


Fig. 1 Self-Organizing Network (SON) Cycle

B. Decentralized Network Based on OFDMA

We consider a decentralized OFDMA based secondary network. They are secondary networks and operate in the primary network area. For simplicity, we assume that the resources taken from the primary network are not be regained by the primary network during the course of simulation. In other words, the secondary networks are SONs and they are not causing any interferences to the primary network.

Each secondary network consists of a cell with a base station, referred to as secondary base station (SBS), at its center. Each SBS has its own resource allocation (RA) mechanism responsible for the spectrum related tasks. The RA mechanism consists of two components: i) the RL agent, which is responsible for the frequency allocation task, and ii) the power allocation algorithm responsible for the transmission power assignment to the frequency chunks or subcarriers. The objective of the RL agent is to maximize the cell quality of service (QoS) by maximizing the signal to noise and interference ratio (SINR), while keeping in consideration the cell users' QoS requirement, i.e., throughput and spectral efficiency.

At any given moment, a SBS has U users (we consider that during a one-hour period of time, the traffic load, i.e., number of users in that cell, does not change). The RL agent starts from a random frequency allocation, i.e., chunk assignment, for any given cell and then iteratively computes various combinations and calculates the resulting SINR for all candidate assignments. The chunk corresponding to the candidate assignment, which gives the highest SINR value (after the RL algorithm has converged), is then assigned to the cell by the SBS.

In this work, a generalized OFDMA radio interface is considered for the downlink for the users' transmissions. In OFDMA, the available bandwidth W is divided into N chunks, so the bandwidth of the single chunk is $B = W/N$ Hz. Time slots are divided into frames. There is an uplink control channel where users' measurement reports are sent. For this example, we use a typical 3 cognitive radio macro cells on a geographical location as shown in Fig. 2. The CR users are using various types of services. The SBS assigns both the frequency and powers in a decentralized approach. Since these cells are non-coordinated, they can belong to different CR network vendors or operators. To simplify the problem, we assume that there is no overlapping between the cells and also handovers from one cell to another are not considered.

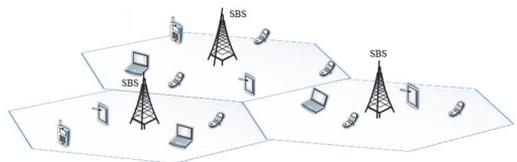


Fig. 2 Cell deployment for secondary CRN used in the simulations

C. Cell Operation

The cells work in a greedy approach, where each cell tries to achieve the best resource assignment scheme, i.e., frequency and power, by using the RL dynamic spectrum access algorithm (RL-DSA) and power allocation algorithm. Assuming that there are no abrupt and short term change in the cell load, any spectrum allocation is valid for the period of time L (where one frame lasts 2 ms), see Table I. Normally L is selected in such a way that the resource assignment procedure is done on a medium term basis (i.e., 120 s). There is a very low probability that the adjacent cells will execute the spectrum allocation procedures at the same time.

The objective of each cell (i.e., corresponding SBS) is to assign both the optimal frequencies and transmission powers so that the maximum QoS (SINR, throughput, efficiency) per cell is achieved. Each cell should provide services to its users to ensure their minimum QoS requirement, which in turn results in the users' satisfaction. The RL-DSA in the SBS should perceive the potential inter-cell interference from the neighboring cells while deciding about the frequency allocations. Previously, in [3] constant transmission powers have been used, i.e., equal distribution of the available power among all. We refer to this assignment technique as constant power in the next sections.

The power optimization is based on the objective function given in (1)

$$f = \max_{P_{n,l}} \sum_{n \in C(l)} \log_2 \left(1 + \frac{\bar{\gamma} P_{n,l}}{\Gamma \sigma_{n,l}^2} \right), \quad (1)$$

where $C(l)$ is the set of chunks currently allocated to cell l , $P_{n,l}$ is the power assigned to the chunk n in the l th cell. Γ is the average fading. $\sigma_{n,l}^2$ is the average noise plus the interference measured or reported by the generic user at chunk n coming from each one of the interfering cells.

In this paper, we propose two other schemes based on RL algorithm and the power optimization algorithm; i) the RL algorithm used with power optimization, referred to as RL+Power, where after the frequency assignment with RL-DSA, powers are calculated by the power optimization algorithm and then assigned to the cell; and ii) the RL algorithm and power optimization algorithms which are executed twice back to back in order to further optimize the RL+Power approach. We refer to the later as RL+Power Coupled. These three resource assignment schemes only differ in the assignment of powers and use the same revised RL-DSA to calculate the chunk assignment. In the next sections we compare their outcomes based on the various QoS parameters by means of simulations.

III. SIMULATIONS

A. Simulation setup

We consider the downlink OFDMA based macro cell scenario of secondary type network, as shown in Fig. 1, which has three cells. The simulations are carried out for various numbers of users per cell and the performance is studied after one-hour communication time has been simulated in Matlab. The simulation parameters are those listed in Table I.

The three performance metrics used for the evaluation are the users' dissatisfaction probability, the SINR, and the spectral efficiency. The users' dissatisfaction probability is defined as the percentage of seconds in which the users' throughput is below a target throughput; this target throughput is called the satisfaction throughput. In our case, the user satisfaction throughput is chosen to be 256 kbps. Other simulation parameters are presented in Table I. The spectral efficiency is the QoS parameter defined as a performance metric that measures the amount of successfully delivered bits per unit of time and spectrum.

It is defined by (2) such that

$$\eta = \frac{1}{K} \sum_{k=1}^K \eta_k \quad (2)$$

$$\eta_k = \frac{TH_k}{W_k} \quad (3)$$

where η is in bits/s/Hz and where (3) is the spectral efficiency per cell, TH_k is the aggregate throughput of all users in the cell k , and W_k is the total bandwidth available for the allocation. All the cells complete the allocation in one specific period of time denoted by L .

The simulations are carried out under the same simulation conditions for different sets of users and the average performance metrics are then compared. In our simulations, users always try to capture the maximum bandwidth (full buffer traffic model [7-9]). The work presented in this paper builds upon the algorithms that are presented in our previous work [2], and we use the same algorithms to study the effects of various assignments schemes (as described in II.C).

TABLE I. SIMULATION PARAMETERS

General	
Frame time	2 ms
Chunk Bandwidth [B]	375 kHz
Number of Chunks [N]	6
Number of Users [U]	{10, 13, 16, 19, 22, 25}
UE Thermal Noise	-174 dBm/Hz
UE Noise Factor	9 dB
Short Term Scheduling (STS) Method	Proportional Fair (PF)
PF Averaging Window	50 Frames
Spectral Efficiency (theoretical maximum)	5 (bits/s)/Hz [10]
SBS Cell	
Cell Radius	500 m
Maximum BS Power	43 dBm
Minimum Distance to BS	35 m
Antenna Pattern	Omnidirectional
Path Loss at d Km in dB	128.1 + 37.6log ₁₀ (d)
Shadowing Standard deviation	8 dB
Showing decorrelation distance	5 m
Small Scale Fading Model	ITU Ped. A
RL-DSA	
Measurement Averaging Period [I]	2500 Frames
RL-DSA Execution Period [L]	60000 Frames
RL-DSA parameters [$\alpha, \beta, \sigma, \Delta$]	[100, 0.00001, 0.05, 10 ⁻⁶]
RL-DSA Exploratory Probability [p _{explore}]	0.1%
RL-DSA Steps [MAX_STEPS]	1000000

B. Simulation Results

The simulation results are shown in Figs. 3 – 6. When comparing the results of the three assignment techniques, it is observed that the RL+Power Coupled scheme provided a better QoS than the other two schemes. The proposed RL+Power Coupled scheme achieves up to 5dB gain in the overall system SINR when there is a high load in the cell (Fig. 3) and subsequently gives a lower average spectral efficiency (Fig. 4). But there is a tradeoff; the RL+Power Coupled technique brings additional cost in the RA, i.e., computational complexity due to

a larger number of operations and thus additional computation time. Fig. 5 shows the average dissatisfaction probability in a high traffic environment; the RL+Power Coupled is giving better performance in terms of user satisfaction. The results also show that the RL+Power Coupled can accommodate higher system throughput, i.e., more than 110 kbps on average in high load situation; in turn this increases the system capacity, i.e., more users can be accommodated with the same amount of available radio resources. Since the main focus of this paper is the power optimization, it can be seen from Fig. 6 that by using RL+Power Coupled, savings of up to 2 dBm per subcarrier when the load is high can be achieved.

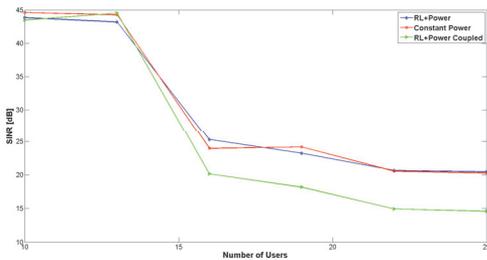


Fig. 3 Average SINR for different numbers of users

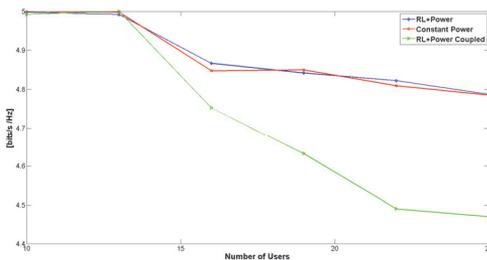


Fig. 4 Average spectral efficiency for different numbers of users

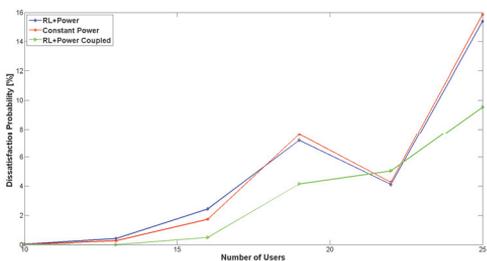


Fig. 5 Average dissatisfaction probability for different numbers of users

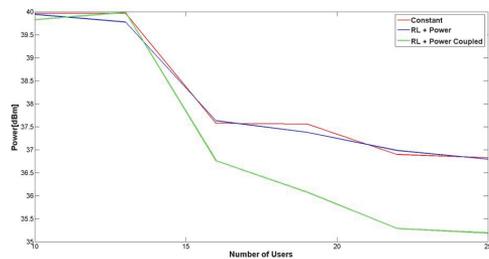


Fig. 6 Average allocated powers/subcarrier for different numbers of users

IV. DISCUSSION AND CONCLUSION

The spectrum allocation techniques based on RL-DSA and the power algorithm are sub-optimal, but they still provide better performance in terms of QoS as compared to existing methods [3]. Our proposed assignment scheme brings added complexity, so there is a tradeoff that system designers must consider. At the same time, the proposed RL+Power Coupled scheme results in better system performance and higher capacity and more importantly, it provides better power performance. Future work will consider how to adapt and apply such techniques to cognitive wireless sensors networks, including their modeling, simulation, and implementation on resource constrained embedded platforms.

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Appendix C

Tauseef Ahmed, Yannick Le Moullec

“Frequency and Power Allocation Schemes for Heterogeneous Networks including Femto Cells”, was published in the 23rd IEEE conference Telecommunications Forum Telfor (TELFOR), Belgrade, 2015.

Frequency and Power Allocation Schemes for Heterogeneous Networks including Femto Cells

Tauseef Ahmed, Yannick Le Moullec

Abstract — In this paper we propose three novel schemes for spectrum management and compare their performance with that of the frequency reuse assignment technique. These schemes are based on reinforcement learning and power optimization algorithms. Simulation results show that our RL-based schemes yield up to 14% increase in capacity and provide better user satisfaction and capacity. Moreover, the RL-based schemes provide better performance in high cell loads and can accommodate femto cells with the same radio resources.

Keywords — Cognitive radio, reinforcement learning, power optimization, femto cell.

I. INTRODUCTION

Cognitive radio (CR) and the concept of dynamic spectrum access (DSA) networks have been proposed to solve the current spectrum usage inefficiency. The idea is to exploit the instantaneous spectrum availability by opening the license spectrum to the secondary users; for example, IEEE 802.22 has been the first standard to exploit spectrum inefficiencies in broadcast TV. The aim of this paper is to present advanced dynamic spectrum allocation techniques based on the fields of machine learning and convex optimization and to compare their performance against that of the existing frequency reuse factor of 1.

Another advantage of CR is that it involves less human interactions for operations and maintenance; in this paper, we consider a decentralized approach for the dynamic spectrum and power allocation in a multicell orthogonal frequency division multiple access (OFDMA). In addition to the secondary macro cell (MC) networks, the co-existence of a femto cell (FC) and the MC is also studied. Novel procedures relying on reinforcement learning (RL) based algorithms are used to face the uncoordinated and opportunistic spectrum sharing issues [1-2]. Each cell independently decides the frequency allocations using the RL algorithms [3] and power allocation based on the convex optimization algorithms [4]. In OFDMA, the frequency spectrum is divided into smaller units called chunks. While assigning the frequency unit, i.e. chunk, the aim is to assign the optimum transmission power levels to

reduce the inter-cell interferences.

This paper presents an extension to our previous work [1]. The performance of the proposed RL-based schemes are compared with the frequency reuse assignment technique. Simulation results show that our schemes improve performance in terms of system capacity and overall quality of service (QoS).

II. SYSTEM MODEL

A. Decentralized Network Architecture

We have considered a decentralized network architecture with a hybrid environment consisting of secondary macro cells and femto cells. They are operating in the primary network coverage area, but for simplicity, we have assumed that the resources borrowed from the primary network will not be regained during the simulation time. Each cell consists of a secondary base station (SBS) that hosts the necessary algorithms for the dynamic spectrum allocation. Fig.1 shows the resource manager (i.e., the RL – DSA controller) hosted by each SBS; it is responsible for assigning the radio resources to cell users. The RL – DSA controller comprises of an RL agent which performs the frequency allocation task while accounting for the objective of maximizing the system overall throughput, i.e., signal to noise and interference ratio (SINR).

We consider that a cell has U users at any given time. The SBS executes the RL-DSA controller as shown in Fig.1 in order to find the optimal frequency and corresponding transmission power. A typical cellular scenario is shown in Fig. 2 where there are 7 cognitive radio cells and the SBSs are located at the center of the cell. There is also one femto cell (FC) operating in the coverage area of Cell 1. The SBSs assign both the frequency and power allocation to users in their respective coverage area in a decentralized manner. Handovers are not considered.

The traffic load conditions are non-static, i.e., the users inside the cell coverage area are homogeneously distributed and are moving at a speed of 10 km/h following a random walk model [5]. In order to perform a reliable spectrum allocation, the requirement is the user satisfaction (QoS). But in order to fulfill the users' QoS, we should estimate the spectrum usage in the adjacent cells to calculate the potential intercell interference. Precisely, each cell tries to learn the best spectrum assignment and power allocation by executing the RL-DSA algorithm and the convex optimization algorithm, respectively.

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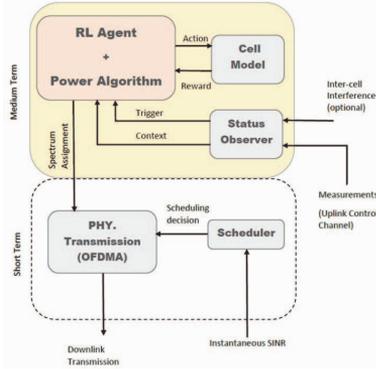


Fig. 1 RL-DSA controller block diagram

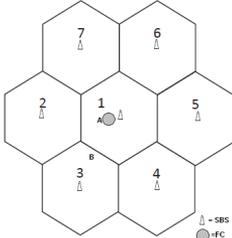


Fig. 2 Secondary network deployment

B. Cell Operation

The resource allocation procedure is a two-step process that decides first the frequency allocation (chunks) and then the transmitted power for each chunk. In this work, a generalized OFDMA radio interface is considered for the downlink for the users' transmissions. In OFDMA, the available bandwidth W is divided into N chunks, so the bandwidth of the single chunk is $B = W/N$ Hz. Time slots are divided into frames. There is an uplink control channel where users' measurement reports are sent. The cells work in a greedy approach, where each cell tries to achieve the best resource assignment scheme, i.e. frequency and power, by using the RL algorithm and power allocation algorithm. Assuming that there are no abrupt and short term change in the cell load (the cell load, i.e., number of users, changes gradually), any spectrum allocation is valid for the time period of L frames, see Table I. Normally L is selected in such a way that the resource assignment procedure is performed on a medium term basis. The objective of each cell (i.e., SBS) is to assign both the optimal frequencies and transmission powers so that the maximum QoS (SINR, throughput, efficiency) is achieved ensuring users' satisfaction. The RL-DSA controller in the SBS should perceive the potential inter-cell interference from the neighboring cells while deciding the spectrum allocations.

To assign the optimized powers, we use the convex optimization. To formulate the power optimization algorithm, let's consider Cell l and let's define $C(l)$ as the set of chunks currently assigned to Cell l ; then the objective function to be maximized is given in (1);

$$f = \max_{P_{n,l}} \sum_{n \in C(l)} E \left\{ \log_2 \left(1 + \frac{\bar{\gamma} P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \right\} \quad (1)$$

where $P_{n,l}$ is the power assigned to the user at Chunk n in

Cell l , Γ is the average fading, $\sigma_{n,l}^2$ is the average noise plus the interference given in (2) measured or reported by the generic user at Chunk n coming from each interfering cells $c \in A(n)$, given in (2);

$$\sigma_{n,l}^2 = P_{noise} + \sum_{c \in A(n)} I_n^c \quad (2)$$

where $A(n)$ is the set of cells with Chunk n allocated. In turn, $\gamma_{n,l}$ is the channel gain (in accordance with the propagation model including slow fading) associated to Chunk n in Cell l . Considering that we are interested in long term variations, it is assumed that the average channel gain is the same for all chunks given in (3);

$$E[\gamma_{n,l}] = \bar{\gamma}_l \quad (3)$$

Then, a bound for the objective function is obtained from Jensen's inequality given in (4);

$$E_Y \left\{ \log_2 \left(1 + \frac{\gamma_{n,l} P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \right\} \geq \log_2 \left(1 + \bar{\gamma}_l \frac{P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \quad (4)$$

resulting in a convex optimization problem with the objective function given in (5);

$$f = \max_{P_{n,l}} \sum_{n \in C(l)} \log_2 \left(1 + \frac{\bar{\gamma} P_{n,l}}{\Gamma \sigma_{n,l}^2} \right) \quad (5)$$

The solution to this problem is given by the classical water-filling strategy.

In this paper, we propose three schemes based on RL algorithm and the power optimization algorithm; i) a constant power algorithm; ii) an RL algorithm used with power optimization, referred to as the RL+Power, where after the frequency assignment with the RL algorithm, powers are calculated by the power optimization algorithm and then assigned to the cell; and iii) an RL algorithm and power optimization algorithms which are executed twice back to back in order to further optimize the RL+Power approach. We refer to it as the RL+Power Coupled. These three resource assignment schemes only differ in the assignment of powers and use the same RL-DSA [2] mechanism to calculate the chunk assignment. In the next section, these novel schemes based on RL and power optimization are compared with the frequency reuse factor of 1 (FRF = 1) and their outcomes are analyzed based on the various QoS parameters by means of simulations.

III. SIMULATIONS

A. Simulation Setup

The downlink OFDMA-based MC and FC scenario of the secondary type network is considered for our simulations as shown in Fig. 2. Each cell consists of a unique base station which is responsible for the radio resource management. The number of users gradually increase from 8 to 32 users per cell in all MC cells. Users generate traffic according to a full buffer traffic model, i.e., all the users try to occupy maximum bandwidth and always have data ready for transmission. They are moving inside the cell but they cannot cross the cell boundary, i.e., handovers are not considered. Additionally, in one of the analyzed scenarios, a femto cell will be added in a given position to one of the cells. All simulations are performed in Matlab, with the parameters presented in Table 1.

The operation of each cell during the simulation is as follows. On the short term, the cell manages the users' data according to conventional proportional fair (PF) scheduling

method [6] and also performs the OFDMA fast link adaptation. Link adaptation is performed using the modulation and coding rate SINR thresholds given in [7, Table 8.1]. The channel state information is assumed to be known at the transmitter side following the channel-aware strategy of PF. On the medium term basis, the proposed dynamical spectrum allocation is performed on a cell per cell basis so as to track possible load traffic variations that may occur along the operation time. To this end, the RL-DSA and convex power optimization algorithms are executed off-line in order to get the spectrum allocations. Execution is done by each cell periodically every L frames.

TABLE 1: SIMULATION PARAMETER

General Parameters	
Frame time	1 ms
Chunk Bandwidth [B]	180 kHz
Number of Chunks [N]	15
UE Thermal Noise	-174 dBm/Hz
UE Noise Factor	9 dB
Short Term Scheduling (STS) Method	PF
PF Averaging Window	50 Frames
Secondary BS Cell Parameters	
Cell Radius	500 m
Maximum BS Power	43 dBm
Minimum Distance to BS	35 m
Antenna Pattern	Omnidirectional
Path Loss at d Km in dB	$128.1 + 37.6\log_{10}(d)$
Shadowing Standard deviation	8 dB
Shadowing decorrelation distance	5 m
Small Scale Fading Model	ITU Ped. A
Target throughput	256 Kbps
Number of Users (U) per cell	{8, 16, 24, 32}
Femto Cell Parameters	
Cell Radius	20 m
Minimum Distance to BS	1 m
Antenna Pattern	Omnidirectional
Power per chunk	10 dBm
Path Loss at d m in dB	$37+30\log_{10}(d)$
Wall Penetration Loss	15 dB
RL-Spectrum Allocation Parameters	
Measurement Averaging Period [L]	5000 Frames
RL-DSA Execution Period [L]	120000 Frames
RL-DSA parameters [$\alpha, \beta, \sigma, \Delta$]	[100, 0.01, 0.05, 10^{-6}]
RL-DSA Exploratory Probability	0.1%
RL-DSA Steps [MAX_STEPS]	1000000
RL-DSA Convergence Steps	5000

The first execution of the RL algorithm in the simulation is chosen randomly between 0 and L for each cell, avoiding that multiple cells execute the resource allocation algorithms simultaneously (i.e., asynchronous operation of the different cells is assumed). Three kinds of spectrum assignment techniques obtained through the RL-DSA scheme are compared with the FRF = 1 scheme in which all

the chunks are allocated to all the cells. In order to compare the system performance between different allocation schemes, the following three metrics are used [8]; i) user dissatisfaction probability, defined as the percentage of seconds in which user throughput is below the target throughput th_{target} (called satisfaction throughput). In our case the $th_{target} = 256$ kbps (MC cells) and $th_{target} = 512$ kbps (FC cell); ii) spectral efficiency per cell denoting the throughput per unit of spectrum; and iii) SINR.

B. Simulation Results

First we only consider the MC scenario. Fig. 3 shows the simulation results of the system in terms of average users' dissatisfaction probability (Fig.3 (a)), average SINR (Fig.3 (b)) and average spectral efficiency (Fig. 3. (c)). The RL Power Coupled scheme and FRF=1 have lower user dissatisfaction than the RL Power and the Constant Power case (fig 3. (a)). Note that, by setting a maximum acceptable dissatisfaction probability of 5%, the maximum number of users in each cell would be around 14 for the RL Power and Constant Power, and around 16 and 18 users per cell for the RL Power Coupled and FRF=1, respectively. This indicates that the RL Power Coupled and FRF =1 can achieve a capacity increase of around 14% and 28% for the same QoS threshold values, respectively. However, the user satisfaction for FRF=1 comes at the cost of extra required bandwidth, which can be seen from Fig. 3 (b & c) because it is using all the chunks in all the cells (low spectral efficiency, and correspondingly the SINR is also worst). On the contrary, the RL Power Coupled scheme is able to achieve increased capacity with a much better SINR (Fig. 3 (b)) and spectral efficiency (Fig. (c)). This concludes in favor of the RL Power Coupled scheme since it provides better capacity at marginal cost in terms of QoS. It can be concluded that, while all three RL DSA schemes are able to perform a more efficient assignment of the available chunks to the cells in accordance with the actual load needs, the RL Power Coupled scheme is able to provide a better performance in terms of dissatisfaction probability and provides extra capacity.

The overall advantage of the three RL-DSA-based schemes in comparison to FRF=1 is quite visible in terms of spectrum efficiency. This fact can be exploited in a heterogeneous environment. To verify this, a femto cell (FC) is deployed inside the coverage area of Cell 1 (see Fig. 2). It is assumed that the FC needs just one chunk to fulfill its traffic requirements. Then, the FC is assigned the chunk based on the criteria which gives the highest SINR to the FC users. To evaluate the performance in this case, we consider two parameters. First, the SINR sensed by the FC user, located at a distance $d = 20$ m (at the edge of the FC) from the FC base station and, secondly, the SINR seen by a reference macro cell (MC) user as a result of the interference coming from the FC and/or other cells. There are two reference MC user locations marked with A and B . The primary frequency allocation criterion for the FC is that it should avoid using the frequency chunk which is being used by Cell 1 in order to avoid serious QoS degradation. The reference MC user A belongs to Cell 1 and it is at the edge of FC. The other MC reference user (labelled B) is

from Cell 3 and is located at the edge of Cell 1 and Cell 3. The FC user has gained up to 22 dB in SINR in the RL-based allocation schemes as compared to FRF=1 since the FC user can be allocated to a frequency not being allocated to the MC closest to the FC. The inclusion of FC in the area also gives rise to some additional interference to the neighboring cells that are using the same frequency chunks at any given time. Fig. 4 shows the percentage of time during which the FC is causing interference to the two reference MC users located at *A* and *B*. *A* receives interference from the FC for about half of the time when the cells have highest loads in case of RL Power and RL Constant Power schemes. On the other hand, with the RL Power Coupled scheme, *A* receives interference from the FC about 70% of the simulation time during high load periods. The constant power and RL power still provide the FC user with better SINR even in the high load situations. When the load increases, the RL Power Coupled behaves in a similar fashion as the FRF=1 scheme.

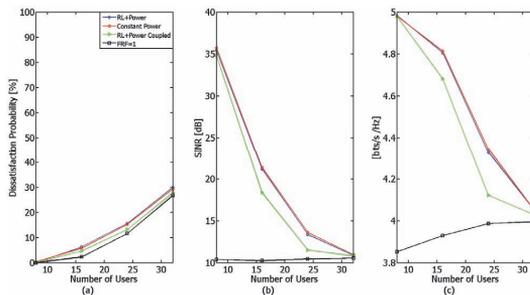


Fig. 3 User dissatisfaction probability, SINR, and spectral efficiency as a function of the number of users for the case without FC

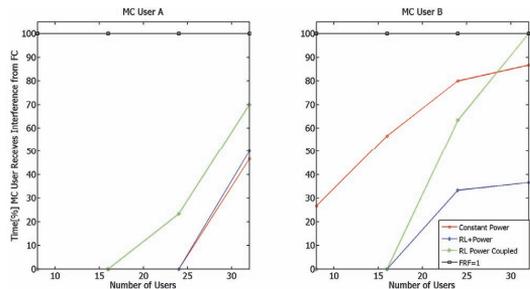


Fig. 4 Interference received by the MC users due to FC, as a function of the number of users

Fig. 5 shows the delta which is defined as the difference between the SINR sensed by the MC user with and without the presence of the FC. The user at Location *A* is not receiving interference from FC until the number of users per cell becomes 24 or higher for the RL based schemes. The average degradation is about 21 dB for the RL based schemes ($U = \{24, 32\}$), which is the same degradation observed in the case of FRF =1. In Location *B*, the MC user receives degradation in the case of RL constant power; on the other hand, when the number of users are higher and more frequency chunks are being used in neighboring cell, the impact of the FC on the MC user at *B* is negligible. As

the load increases, the chunk reuse rate is higher in neighboring cells and the reference MC user starts getting more interference from the neighboring cell rather than negligible interference from the FC, which degrades the overall SINR.

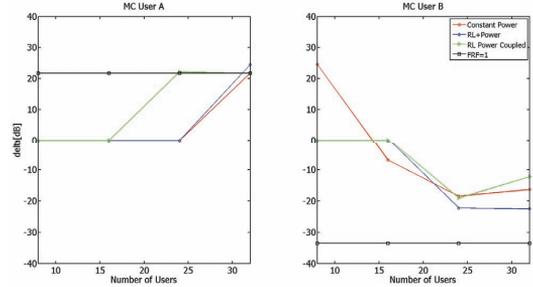


Fig. 5 Delta SINR sensed by the MC users with and without FC, as a function of the number of users

IV. CONCLUSION

The RL-DSA schemes have significant advantages in terms of SINR and spectral efficiency as compared to the fixed frequency assignment (FRF =1). This gain in SINR can be sufficient to accommodate the other network entities like FCs within the same frequency bands. In the case of hosting FCs, and particularly in highly loaded systems, the RL Constant Power and the RL Power schemes provide better performance over the RL Power Coupled and the FRF =1 schemes. The RL-DSA allocation techniques are also advantageous as compared to FRF = 1 in MC-FC scenarios, as long as the FCs are not using the same frequency chunks which are being used by the host cells. In high load cases, the MC users are insignificantly affected by the presence of the FC. This is due to the fact that when the load increases, the frequency consumption becomes higher and more chunks are being reused in neighboring cells, resulting in the MC user getting more interference from the neighboring cell and the interference from the FC is negligible.

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Appendix D

Tauseef Ahmed, Faisal Ahmed, Yannick Le Moullec

“Optimization of Channel Allocation in Wireless Body Area Networks by Means of Reinforcement Learning”, was publish in the IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob), Bandung, 2016.

Optimization of Channel Allocation in Wireless Body Area Networks by Means of Reinforcement Learning

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Abstract—we propose a novel algorithm for channel assignment in wireless body area networks. The proposed approach is based on the machine learning sub-domain known as reinforcement learning, and is named reinforcement learning – channel assignment algorithm (RL – CAA). RL – CAA interacts with the environment in an unsupervised way and selects the optimal frequency channel for the wireless sensor nodes. RL-CAA also takes into consideration the traffic load conditions and assigns the optimal number of channels to fulfill the minimum throughput requirement of the system. The algorithm is evaluated by means of a MATLAB simulator tool based on IEEE 802.15.6 specifications. It allows comparing our algorithm with classical static channel assignment algorithm. The proposed algorithm gives better error rate performance which is on average 30% better than static channel assignment. Since the error rate is reduced, the algorithm also proves better in terms of throughput by giving an average of 77.3 kbps over static channel assignment. Our proposed algorithm proves better in the terms of traffic load considerations and is more robust to the change in the load.

Keywords—*wireless body area network; e-health, reinforcement learning; channel assignment*

I. INTRODUCTION

Wireless body area networks (WBAN) have become the primary choice for the development of health monitoring applications and other biological data collection applications [1]. Since WBANs are attached to, or use in the close vicinity of the human body, special attention must be paid in order to avoid adverse effects on human tissues. For this, the transmission power in WBAN is normally kept very low (ca. 1 mW), and as a result, the transmission range in WBANs is typically 1 to 3 meters from the human body [2].

WBANs normally consist of multiple sensory devices taking the vitals of patients and then propagating the sensed data to the monitoring stations for further analysis. These devices mostly take all the data which can be collected and send all the raw data for further processing to a gateway or central node. In

this way, signal processing is avoided at the child nodes and hence power is saved. The gateway nodes further process the data and send them to a monitoring station, e.g. to be evaluated by a medical practitioner. As the number of sensors grow in the network, the amount of data that need to be transported grows tremendously. So traditional ways of transmitting all data on a single channel are no longer suitable in practice.

II. RELATED WORK

WBANs or wearable technology have become a very popular research area among the scientific community, as briefly outlined in what follows. In [3], the authors present a wireless device for vital sign monitoring on the basis of numerous sensors and wireless connectivity. In [4], the authors present the design of a wearable device for biomedical telemetry. In [5], a wearable sensor is connected to a specific smartphone healthcare application. In [6], the authors discuss the interfacing of a mobile phone with a wearable consumer product. In [7], a wearable ring platform has been presented to identify the user's gestures. In [8], the authors proposed an ultra-low power energy-efficient wearable device equipped with camera, microphone, temperature and accelerometer sensors. In addition the device has indoor solar panel and a thermoelectric generator modules for extending the device's lifespan. Finally, in [9], the authors review the start-of-the-art, problems in the future of health care and its significance.

In our study, we are modeling a dense environment of spatially distributed sensors, i.e. a hospital environment where patients are carrying a sensor (child node) which is transmitting their vital health information to a gateway node. We propose that WBANs can be partitioned into smaller clusters. In the remainder of this paper, we refer to these small clusters of the WBAN as "zones". Each zone can then act as a small network, within a given WBAN, and can be individually assigned channels that are different from its neighboring zones to avoid traffic congestions and interferences. In this work, we have developed a reinforcement learning – channel assignment

algorithm (RL – CAA) suitable for WBANs. The work builds upon our previously developed cognitive radio frequency allocation algorithm named RL – DSA [10]. The new RL-CAA has been evaluated on a WBAN in a simulated environment. We compare RL – CAA with traditional static channel assignment scheme even selection [11] and show that our proposed algorithm performs better in erroneous and dynamic environments.

III. SYSTEM MODEL

A hospital hall environment is considered as our simulation environment. The hall has been logically divided into 4 zones, where each zone has one gateway (parent node) and various numbers of nodes (here 5 for illustration purposes) that are spatially distributed, as shown in Fig. 1. Each zone has an area of 5x5 m² (motivation for this is given in Section IV) and for simplicity we consider that the patients, i.e. child nodes, do not cross from one zone to another (this issue will be addressed in future work). So, in this paper, the number of nodes remain constant in any zone throughout the simulation time. However, all nodes are walking at a speed of 1 meter per second in random directions. Upon reaching the boundary of their zone, nodes change their directions and continue their random walk. At the start of the simulation, as the gateways and the nodes are deployed, each gateway monitors for the ISM 2.4 GHz channels (10 channels are considered). Based on the algorithm selected for channel assignment, each gateway assigns the channels to its governed child nodes and then start receiving the sensors' data.

The gateway acts as the master node which undertakes the tasks related to spectrum allocation and data processing, whereas the child nodes only sense and transmit data. Since in typical scenarios the

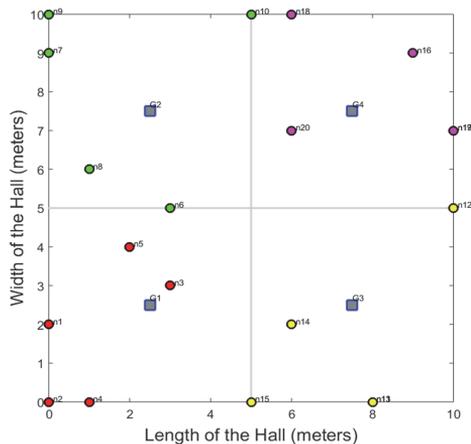


Fig. 1. Simulation environment and spatial distribution of the sensors in 4 zones. G1 to G4: gateways, n1 to n5: nodes associated to G1, n6 to n10: nodes associated to G2, n11 to n15: those associated to G3, n16 to n20: nodes associated to G4, whereas n11 and n13 and n17 and n19 are overlapping nodes.

gateway can have a fixed source of power, the channel assignment algorithm is hosted on the gateway node. In this way, the battery in the child nodes is saved as they do not run any complex algorithm.

A. Static Channel Assignment

In order to compare the performance of the proposed RL-CAA, we have first implemented a modified version of the static channel assignment even selection algorithm [11] according to our application domain. The gateway monitors the available channels on the ISM 2.4 GHz band and the channels which are currently not being used are taken into consideration for the assignment. The gateways are assigned the channel based on their unique id in an increasing order.

For example, if Channel 1 is currently being used, then the gateway will be assigned Channel 2 if it is free and Gateway 2 will be assigned Channel 3 and so on.

B. Proposed RL – Channel Allocation Algorithm (RL – CAA)

Our RL – CAA builds upon our previous work [10], which has been adapted to the WBAN environment. At the start, each gateway runs the RL – CAA in order to find the most suitable channel for the data transmission. The RL – CAA senses all the available channels and the channel with highest SNR response is assigned to the corresponding gateway. The RL – CAA has the capability to dynamically switch to other channels if the channel conditions get worse. When the signal to noise ratio (SNR) of the channel goes below a certain threshold, the RL – CAA can start searching for other channels. It also has the capability to dynamically allocate more channels if there is a change in the load condition of the zone.

The RL – CAA is based on the Bernoulli logic where the internal architecture of the RL – CAA works on the weighted probabilities which are updated on every iterations of the algorithm. The key steps of the RL – CAA are listed in Table I.

TABLE I: RL – CAA ALGORITHM

1. REPEAT 1 to 14 UNTIL
2. Check the available channels' condition, i.e. SNR.
3. Calculate the reward signal based on the channels' SNR.
4. Update the average reward.
5. FOR All Channels
6. Update the internal probabilities of the RL.
7. END FOR
8. FOR All Channels
9. IF Internal probabilities for a channel is greater than the threshold value (criteria set by user)
10. Assign that channel to the gateway node.
11. ELSE
12. Do not assign the channel.
13. END IF
14. END FOR
15. IF Assigned channels throughput is greater than required throughput
16. Assign only that number of channels which are necessary to provide the required throughput, return the other channels acquired by the RL for allocation to the channels' pool.
17. END IF

TABLE II: SIMULATION PARAMETERS

General Parameters	
Frame size	127 Bytes
Transmission Power	1 mW
Throughput (Node)	250 kb/s
Bandwidth	1 MHz
Channel Model	CM4[4]
Zone Area	25 m ²
Maximum distance of a Node & Gateway	3.54m
Averaging Period	1 second
RL – CAA Parameters	
RL Evaluation Steps	1000
RL Convergence Steps	50
α (learning rate of RL)	100
β (reward memory factor)	0.01
σ (probability bias)	0.05

The RL – CAA has the capability to take into consideration traffic load conditions dynamically, which means that if the system throughput goes below a given threshold value, the RL – CAA can assign a gateway with the appropriate number of channels in order to cope with the current traffic load demands. Table II shows some key simulation parameters of the RL – CAA for an 802.15.6- WBAN scenario.

The reward function is calculated based on (1),

$$\bar{r}(t) = \beta r_i(t) + (1 - \beta)\bar{r}(t - 1) \quad (1)$$

where, \bar{r} is the average reward at time t and r_i is the instantaneous reward. β is the reward memory factor. The instantaneous SNR value is chosen to be the reward value.

IV. RESULTS

To evaluate the performance of our RL – CAA, and also to possibly compare it with other channel assignment algorithms, a MATLAB-based WBAN simulator has been implemented. In this simulator, the user can specify the number of gateways and the number of child nodes per gateway. Then the user has to select the channel assignment algorithm and the total simulation time in seconds. The simulation environment is shown in Fig. 1 and the input graphical user interface of the simulator is shown in Fig. 2 with default input values. For simplicity, the simulations performed in this paper correspond to the results for the first two zones with gateways G1 and G2, and 5 nodes per gateway, as shown in Fig. 1.

The models used for the physical, data link, network and application layers of the WBAN follow the IEEE 802.15.6 TG standard and have been implemented in the simulator. The channel models for the WBAN are termed as CM1~CM4, as shown in Fig. 3 [12]. CM4 is related to the off-body communication in the WBAN and is implemented based on [12] using the MATLAB curve fitting tool. CM4 reflects the fact that the human body causes shadowing while transmitting the signal to the gateways.

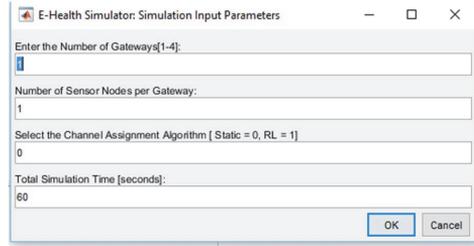


Fig. 2. E – Health simulator input graphical interface.

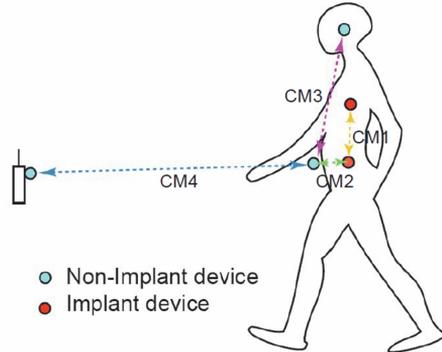


Fig. 3. WBAN channel models [12].

CM4 is implemented in such a way that it takes into considerations the human body shadows and also the body orientation. Since the maximum range for CM4 is distinctively 5 m, the whole simulation area is logically partitioned into 5x5 m² zones. This technique has been adopted from the cellular networks. The zones are made so that child nodes, i.e. carried by the patient moving at a speed of 1 m/s, should not go beyond 5 meters from the gateway node at any time. If any node arrives at the border of its zone, then it changes its direction and continue its random walk.

To evaluate the performance of our proposed algorithm, we have selected the average symbol error rate and the average system throughput. Since WBAN data is critical due to its importance for the patients' health, the erroneous data is discarded and the average error-free data gives the overall system throughput. The average system throughput is defined as the error-free data received at the gateway per second. In order to evaluate the performance and to mimic a hospital environment with lots of reflections/diffractions, we have chosen a highly erroneous and fast fading Rayleigh channel with 2 paths and 4 Hz of Doppler shift frequency. The results are plotted in Fig. 4 and Fig. 5 for the average error rate and the average system throughput, respectively. Fig. 4 shows the average symbol error rate, where the RL – CAA is compared with the static channel assignment approach. As can be observed, our RL – CAA performs better than static channel assignment (their average symbol error rates being 0.1349 and 0.4417, respectively) and RL – CAA giving 30% less error rate. Fig. 5 shows the average system throughput. From Fig. 5, it is quite evident that

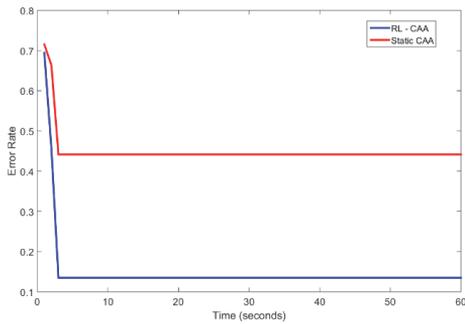


Fig. 4. Average system error rate

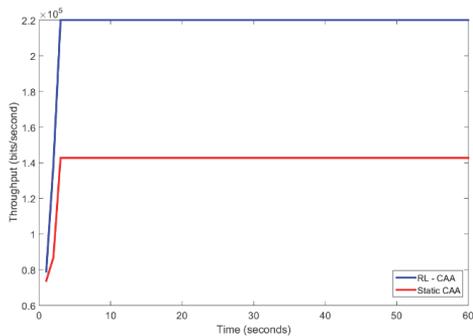


Fig. 5. Average system throughput

in highly erroneous environment, our proposed RL – CAA gives much better performance in terms of throughput. The RL – CA gives 77.3 kbps over the static approach. These results are averaged over time, so they converge after a short duration.

Based on the simulation, the RL – CAA is giving better performance in terms of error rate and throughput. The RL – CAA is a cognitive algorithm so it is more robust to the traffic change as compared to the static channel assignment (which, once the channels are assigned, does not take any load variations into considerations). If we force the change of the load at Time = 30 seconds, the algorithm detects that the throughput requirements are not satisfied with the current channel allocation. Fig. 6 shows the RL – CAA is executed in order to satisfy the change in the traffic load conditions.

V. CONCLUSION AND DISCUSSION

In this paper, a novel algorithm for dynamic channel allocation in WBANs has been presented. The RL – CAA is a cognitive algorithm which undertakes the traffic load conditions as an additional benefit to the channel assignment. It can find the optimal channel for the transmission of data among the available channels. The algorithm is implemented in a MATLAB based WBAN simulator which demonstrates the benefits of the algorithm as compared to traditional approaches.

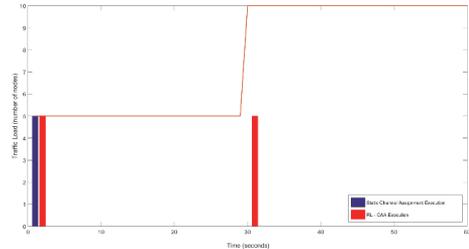


Fig. 6. Dynamic execution of RL - CAA depending up traffic load conditions.

In principle, the RL – CAA is not limited to WBAN; it could also be used in any other wireless sensor network to optimize the frequency channel allocations.

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Appendix E

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Article

A QoS Optimization Approach in Cognitive Body Area Networks for Healthcare Applications

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Abstract: Wireless body area networks are increasingly featuring cognitive capabilities. This work deals with the emerging concept of cognitive body area networks. In particular, the paper addresses two important issues, namely spectrum sharing and interferences. We propose methods for channel and power allocation. The former builds upon a reinforcement learning mechanism, whereas the latter is based on convex optimization. Furthermore, we also propose a mathematical channel model for off-body communication links in line with the IEEE 802.15.6 standard. Simulation results for a nursing home scenario show that the proposed approach yields the best performance in terms of throughput and QoS for dynamic environments. For example, in a highly demanding scenario our approach can provide throughput up to 7 Mbps, while giving an average of 97.2% of time QoS satisfaction in terms of throughput. Simulation results also show that the power optimization algorithm enables reducing transmission power by approximately 4.5 dBm, thereby sensibly and significantly reducing interference.

Keywords: cognitive body area network; reinforcement learning; channel allocation; power allocation; channel model; wireless body area network

1. Introduction

Recent advances in electronics and system on chip design have given birth to a new era of wireless communication systems. Intelligent and low powered devices enable building small and miniaturized wireless networks to help and improve human life, including among other things, wireless body area networks (WBANs). A WBAN is a combination of ultra-low powered, programmable miniaturized sensor nodes combined with wireless radio communication capabilities used to monitor the human body and its physiological features, e.g., heart rate, blood pressure, temperature, etc., using either invasive, or preferably, non-invasive sensors [1–3].

WBANs are touted as one of the key technologies foreseen to help dealing with the challenges found in many healthcare systems around the world. Indeed, current healthcare facilities are facing huge challenges from the growing elderly population and limited human and financial resources. In the USA alone, from 1960 to 2010, life expectancy increased on average by 13.5% [4]. The population aged 60–80 years will have doubled by 2050 (from 33 million to 81 million people) [5]. It is expected that this huge increase will overload the healthcare system and overall quality of life will be affected. Let us consider a patient who has to visit a doctor for a routine blood pressure and temperature check; for this, he/she has to travel to the health facilities. This is costly in terms of time and money and overloads the healthcare system; there are more urgent health issues and cases that must be taken care of by health practitioners. To avoid such situations, a remote system can enable the persons to send information about their health status to health care givers from their homes and thus they do not need

to get out from their comfort zone just to do routine monitoring. This will both greatly benefit the overall health care system and quality of life in general.

A WBAN allows the integration of intelligent small sensor nodes in, on, or around the human body to monitor the human vital signs. The miniature devices are basically small radios that can collect data through their sensors and transmit them to a central node or a master node. This central node can be linked to a backend network where, upon reception, the patients' data can be analyzed for diagnosis and prescriptions. Generally, a WBAN can consist of in-body and/or on-body area networks. An in-body area network allows communication between invasive or implanted sensor nodes to a base station. An on-body area network, on the other hand, allows communication between a non-invasive or wearable sensory device to a base station. Since human tissues are being monitored, the devices used in WBAN have to build upon ultra-low power radio transmitters so as to avoid any adverse effects on the human health.

In this paper, we focus solely on on-body area networks where single or multiple sensors are attached or fitted to a person. A key idea is that instead of having all the on-body sensors transmitting to the base station individually, a central on-body node is used as an intermediate hub and receives all the sensors' data and transmit them to the base station. From here onwards, we will refer to such a sensing device as the node which is routing all the sensors' data to the base station. The base station itself will be referred to as gateway from here onwards.

Although wireless sensor networks in general are not new per se, their design and capabilities are continuously evolving, including the adoption (and adaptation) of certain cognitive elements previously developed for cognitive radios [6,7] either for resource allocation (frequency, power, etc.) and/or signal processing and data analytics. Cognitive capabilities can be exploited in smart routing and provide the ability to foresee any changes in the routing path [8]. Such a trend is also being applied to WBANs and result in what we term cognitive body area network (C-BAN). In this work, we address one of the major issues in such a setup, i.e., the tradeoff between throughput and quality of service (QoS) by means of a cognitive and dynamic approach for frequency allocation. This approach, based on re-enforcement learning, is named RL-CAA (for Reinforcement Learning—Channel Assignment Algorithm). The specific contributions presented in this paper are:

- A context aware channel allocation RL-CAA approach in which the radio environment is first sensed, and based on the feedback received in the form of signal to noise ratio (SNR), the approach decides the fate of the channel. If the channel has a better SNR than other available channels, and if there is no co-channel interference, the channel is assigned to that particular gateway. Based on the throughput requirement, one or more channels can be assigned. The algorithm is robust to traffic changes; QoS satisfaction is its main objective.
- The IEEE 802.15.6 standard has not formulated an off-body mathematical channel model. However, the IEEE standard document provides experimented values that can be used as the basis for such a model. Based on those experimental results, we have formulated a mathematical model for the off-body Channel Model 4 (CM4) using MATLAB that takes on-body posture and shadowing effects into account.
- We propose a novel power allocation algorithm that aims at achieving the desired interference level at the boundary of the gateway's coverage area. Its primary convergence criterion is interference minimization towards other gateways.

The rest of this paper is organized as follows: the current state of the art related to WBANs is described in Section 2. In Section 3, the detailed system model is presented and our simulation scenario is described. The simulation results are presented and discussed in Section 4. Finally, the last section concludes the paper.

2. Related Works

WBANs have become a popular research topic in the last few years. Despite WBANs' potential uses in many fields of human life, they are not yet widely adopted and further research and development are still needed. There are many open research questions and challenges that remain to be addressed. The authors of [9] have presented a comprehensive overview of WBANs. They discussed the network architecture, sensor hardware, 802.15.6 IEEE standard layers [10] and emerging radio technologies available for WBAN applications. They also presented a taxonomy of proposed WBAN projects. They highlighted various open research challenges related to the bandwidth and energy efficient protocols, issues arising from the co-existence of WBANs with other wireless technologies and WBANs' successful integration into society. The authors in [11] have presented an overview of WBAN applications related to healthcare. They recommended various wireless technologies for WBAN medical applications; however, the non-medical aspects of WBANs were not considered and no specific details for designing a WBAN application were presented. In [12], the authors described the prospective usage of WBANs in the future health care system. In [2,12,13], the authors have provided extensive overviews of generic WBANs and their applications, but they fall short in addressing specific research challenges. Like with any other wireless network, interference is a major hindrance in WBANs. Interference occurs commonly if multiple WBANs are deployed next to each other in a given physical location. Inter-network interference can seriously diminish the performance of WBANs if proper interference avoidance methods are not considered. In [14], the authors presented an approach towards inter-network interference mitigation while considering the energy efficiency of WBANs. A power control algorithm was presented for interference mitigation and avoidance. The authors presented simulation results to prove their hypothesis. WBANs are like cognitive radios in the sense that they share the spectrum with other existing technologies such as Bluetooth, ZigBee, Wi-Fi, etc., [12]. In [14], the authors did not mention any interactions, either positive or negative, with other technologies which share the spectrum bands with WBANs. In [15], the authors described the convergence of cognitive radios (CR) and internet of things (IoT), i.e., an overview of how CR technology can be beneficial for various sensor network fields. There may be possibilities for WBANs to also interact with the internet directly at some tier of the communication stack. However, that paper did not present any specific system design or implementation suggestions. In addition to the internet, WBANs may also interact with other existing wireless communication technologies and standards. In [16,17], the authors described the integration of health care system WBANs with other communication technology standards and protocols and they reviewed their aspects. The authors in [16] proposed a unified networking model for hospital scenarios combining various networking technologies. They have analyzed the basic requirements for such systems. Each networking system relies on a wired backbone network and a detailed analysis highlights how combining wired and wireless network would really give the future hospital network designers a clear picture. The authors in [17] proposed a hybrid model of WBAN data transmission and sharing. Their proposed architecture combines WBAN communication tiers with the cloud for data sharing and delivery in healthcare applications. However, including the cloud may pose some data security challenges that are now being acknowledged by this research community as a critical issue.

Since WBANs operate in a traffic changing and interfering environment, many distributed WBANs can be located in the same vicinity and there could be other communication technologies (e.g., Bluetooth, ZigBee, etc.) communicating in the same spectrum bands. This could give rise to a competition for the available spectrum, i.e., channels. Hence, there must be mechanisms for channel allocation and sharing in such a way to satisfy the traffic and throughput requirements. Another constraint for operating in such a heterogeneous environment is interference. To avoid interference, some power control mechanism must be incorporated in the WBANs. In [18], the authors have presented a channel sharing protocol for WBANs, but only for medical applications. Therefore, such an approach lacks information about spectrum sharing among networks to facilitate their co-existence in the available spectrum. In [19], the authors investigated channel allocation schemes in general

for a wireless sensor network (WSN) based on game theory. The authors considered a general WSN for investigating the behavior of their algorithm, showing that it exploits the network knowledge to reduce interference and improve overall WSN performance. Such an approach could lead to additional studies for WBANs. The authors in [20] proposed a multichannel MAC coordination framework called decentralized time synchronized channel swapping. The proposed protocol combines the benefits of decentralized time division multiple access and spontaneous alignment of nodes' time slots across channels and flexible time synchronization by instantaneous adoption of available slots. The authors compared their proposed MAC protocol for channel swapping with time synchronous channel hopping and efficient multichannel MAC protocols. Simulation and experimental results show that the proposed approach leads to a significant reduction in convergence time and provides higher network throughput with and without the presence of interference. However, the proposed scheme has been applied to ad hoc wireless networks and the behavior of the protocol in WSNs and WBANs is yet to be investigated.

In [21], the authors describe channel estimation and power control schemes for WBANs. The authors claim that their proposed algorithm can save up to 25% of energy as compared to a fixed transmission power scheme. The proposed algorithm has been investigated in IEEE 802.15.6 beacon mode [22] with a single hop star topology. In [23], the author investigated transmission power assignment schemes and energy minimization techniques for WBANs. The author used two strategies to assign transmission powers to the on-body sensor nodes; with or without body posture state information. He studied his power optimization approach in a single hop transmission link. However, the proposed transmission power assignment algorithms presented in [21,23] have not been investigated nor evaluated for the specific off-body communication links used in WBANs and their potential impact in a two-hop star topology.

The person or patient who is being monitored cannot always remain stationary, i.e., laying in bed or sitting. Hence, there is a need for mobility algorithms to be implemented into the WBAN so that seamless communication occurs when the nodes are mobile and they move from one access point to another access point. In [24], the authors presented a seamless mobility and handover scheme for WSNs taking into account the sensor mobility from one access point to another. This approach is used as the basis for our own handover implementation described in Section 3.4. The authors in [25] have presented an optimization algorithm for the design of WBANs. The approach is based on a heuristic model and an ant colony optimization method. The authors proposed these algorithms for WBAN design considerations, i.e., network topology and routing, taking into account the variable data rates from individual sensor nodes. The experimental results are promising in terms of quality and computational time as compared to a commercial optimization problem solver. However, the algorithm needs further investigation to improve its performance.

In [26] a robust optimization approach to tackle traffic uncertainty in network design problems was proposed. The described algorithm is a hybrid heuristic approach based on ant colony optimization. The authors compared the proposed algorithm with a commercial optimization problem solver and the experimental results show that their algorithm gave high quality solutions with low optimality gaps. The authors in [26] considered a general network although the impact of their hybrid optimization algorithm in WBAN design applications needs further research. The authors in [27] proposed a global routing protocol for WBANs which targets optimizing the energy consumption at the nodes and increasing the network lifetime. Experimental and simulation results show a significant increase in network lifetime by balancing the energy consumption across all the network. This is quite advantageous in the sense that all nodes can be replaced or recharged at the same time. However, the proposed protocol only takes into account the transmission power for energy optimization. The protocol needs further investigation to take into consideration more parameters in order to better conserve energy.

3. System Model

3.1. WBAN Architecture and Requirements

In this section, we present the WBAN model and the communication tier that has been used in this work. A nursing home has been considered as the application scenario. The real dimensions of the physical space can vary, but for simplicity, we consider a hall 10 m in width and 10 m in length. This area has been logically partitioned into smaller sections, called ‘zones’. Each zone has its own gateway acting as a base station, giving wireless coverage in a $5 \times 5 \text{ m}^2$ area. The gateway is fixed (stationary) at the center of the zone and it is assumed that it has a fixed source of power, i.e., wall power. The nodes in each zone correspond to individual patients. A patient can have multiple sensors fitted or attached to his/her body. All these sensors are sending their data to the central sensor node located at waist height; this central node periodically transmits the collected data to the gateway. This concept is shown in Figure 1.

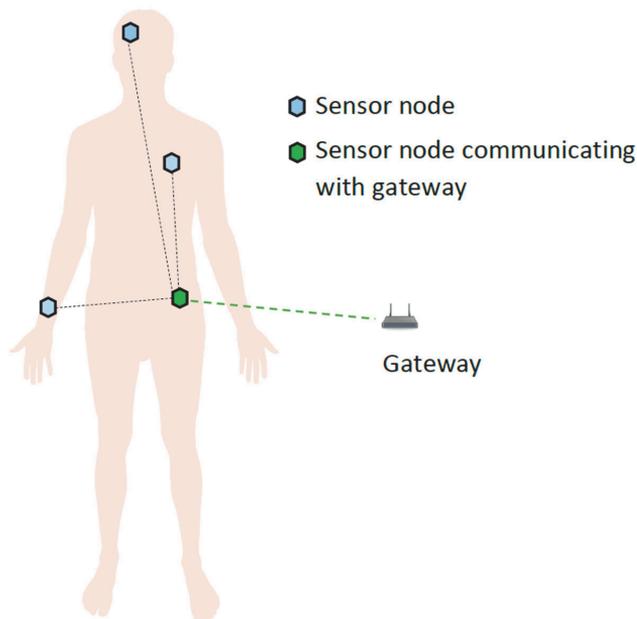


Figure 1. Wireless body area network.

The overall hall, zones, gateways and the corresponding nodes are illustrated in Figure 2 (here at the start of the simulation, right after they have been deployed). In this work, we consider the IEEE 802.15.6 standard that specifically targets WBANs [22]. To accommodate the huge application range of WBANs, this standard defines three physical layer options for WBANs, namely narrowband (NB), ultra-wide band (UWB) and human body communications (HBC) [22]. Each physical layer standard has its own design requirements. In this work, we consider only the NB physical layer on the 2.4–2.483 GHz band. This band is termed the industrial and medical (ISM) band. Each gateway is monitoring this band in the 2.4–2.483 GHz range. Other requirements and features of the system are given in Table 1 [22,28].

Table 1. System features and requirements.

Features	Values
Frequency band	2.4–2.483 GHz
Number of channels	79 (according to ISM band)
Payload	0–2040 bits
Channel bandwidth	1 MHz
Data rates	121.4 Kbps–971.4 Kbps
Modulation Scheme	DBPSK/DQPSK

For simplicity, we use only 20 channels in our simulations. The range of possible data rates for IEEE 802.15.6-compliant WBANs is quite wide (121.4 Kbps–971 Kbps), but to evaluate the system under demanding requirement conditions, we have chosen a data rate of 971.4 kbps in our simulations.

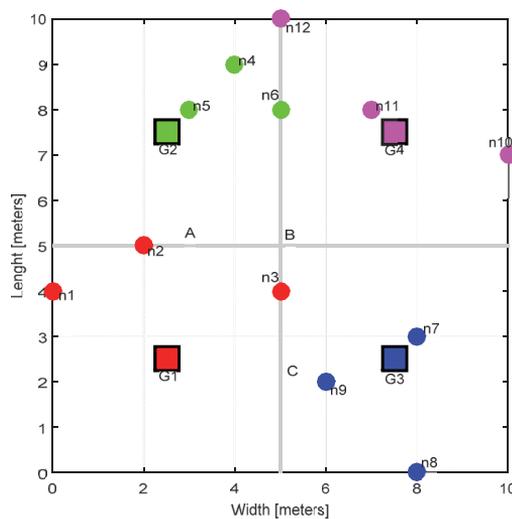


Figure 2. Physical layout and WBANs deployment. The colors show the associations between the nodes and gateways.

3.2. WBAN Network Topology

IEEE 802.15.6 considers WBANs to operate in either a one-hop or a two-hop star topology, with the central node to be located at the center of the body, e.g., at waist level, as shown in Figure 1 [22]. Two types of transmissions exist in the one-hop star topology: (A) transmissions from the sensor device to the gateway and (B) from the gateway to the sensor device. In the two-hop star topology, the sensor nodes connect to the gateway via their peer devices or multi-hopping is used to send data to the gateway [29]. In our system model, the two-hop star topology exists between sensor nodes carried by the patient and the gateway via the central node at the waist (Figure 1). We assume that the data sent by the central node is the collection of data from the other sensors. However, each central node carried by an individual person is connected to the gateway via the one-hop star topology, as shown in Figure 3, where N corresponds to the nodes and they communicate with the gateway. Since our research focuses on the spectrum optimization, the analysis of the individual sensor's data (two-hop star topology mentioned above) is not in the scope of this paper.

The time division multiple access (TDMA) technique is used for medium access. Each node is assigned one time slot; hence, all nodes' data are combined into a superframe for transmission from the gateway to the backend network for further data processing and/or diagnosis purposes.

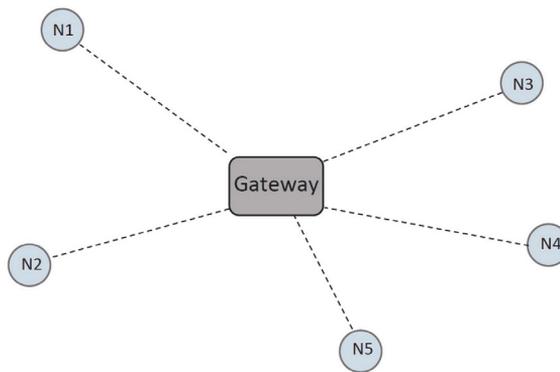


Figure 3. Network topology.

3.3. Channel Model

The IEEE 802.15.6 standard document defines the channel models for the WBANs [10]. Figure 4 shows these channels (termed CM1–CM4). As mentioned previously, this paper only addresses the off-body communication, i.e., between the central node (on waist, see Figure 1) and the gateway (Figure 3). This channel is referred to as Channel Model 4 (CM4) in the IEEE standard document [10]. In WBANs, there are many factors which affect and deteriorate the signal quality, e.g., shadowing, reflections, diffractions, interferences, etc. Shadowing is a key factor which causes signal degradation due to the body environment; body movements and postures can also cause shadowing. Therefore, the node is either in direct line of sight (LOS) with the gateway or in non-line of sight (NLOS) at any instant. This also creates additional complications to create an accurate mathematical model for CM4. The IEEE standardization document presents the measured values for the channel model [10] but no concrete mathematical model is included. From these measured values, we have formulated a mathematical channel model for the CM 4 using MATLAB, as shown in Equation (1):

$$\text{pathloss} = ax^3 + bx^2 + cx + d, \quad (1)$$

which is a third degree polynomial equation modelling CM4. The identified values for the constants a , b , c and d are given in Table 2.

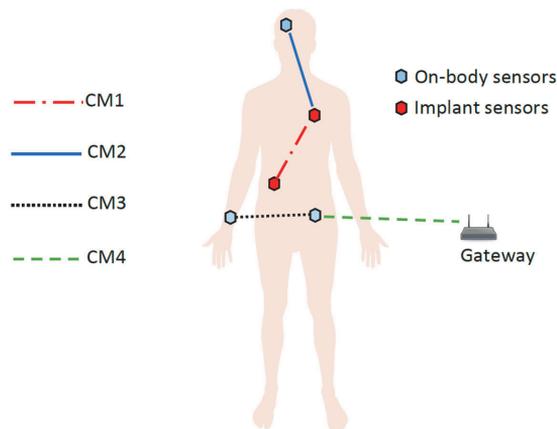


Figure 4. IEEE 802.15.6 Channel Models.

Table 2. Channel model values of the polynomial constants.

Constants	LOS	NLOS
a	2.45	3.673
b	−17.99	−30.61
c	43.95	76.94
d	16.05	9.48

Our mathematical model for CM4 takes the shadowing caused by body orientation as well as LOS and NLOS into consideration. This mathematical model gives realistic channel properties for CM4 and is in compliance with the values presented in [10].

3.4. Mobility and Handovers

The permissible radio range of CM4 is ~5 m (as indicated in the IEEE standard itself [10]). This is the motivation for dividing the coverage area into smaller partitions, i.e., zones of $5 \times 5 \text{ m}^2$. This inspiration of dividing the physical location into smaller regions comes from the cellular networks (e.g., micro or femto cells).

The positions of the gateways are fixed, i.e., at the center of each zone, while the nodes are randomly deployed. All nodes (patients) can freely and randomly move in all directions across all zones, at a constant speed of 1 m per second. The gateways are installed in such a way that when a node crosses the coverage of one gateway, it enters into the other gateway coverage zone, and handover is taking place. A simple distance-based handover algorithm has been implemented to facilitate the movement of all nodes freely across all zones and providing seamless vital data transfer while moving from one access point (gateway) to another [24,30].

3.5. Channel Allocations

The gateway is the master node or base station which undertakes the spectrum-related tasks along with data processing and routing. The nodes are sensors which sense and transmit data. Each gateway assigns the transmission channels to its governed nodes. We propose that spectrum management algorithms shall be hosted by the gateway, as it can have a constant power source (e.g., mains). On the other hand, the nodes, which are mainly battery operated, can have only limited functionality related to sensing the data and transmitting it to the gateway. This saves the node's battery to a great deal and is very desirable for many applications of sensor networks.

We have previously proposed a dynamic channel allocation algorithm for cognitive radio networks [31]. To turn the WBAN into a cognitive body area network (C-BAN), we have revised the algorithm and made it more dynamic and robust for the resource limited computational platform.

3.5.1. Reinforcement Learning—Channel Assignment Algorithm (RL-CAA)

The RL-CAA is based on reinforcement learning, which itself comes from the field of artificial intelligence and machine learning. The RL-CAA builds upon a Bernoulli distribution and its internal architecture is based on the Bernoulli random variables and probabilities. This internal part of the algorithm is called the Bernoulli logic unit [32,33]. The algorithm works following an unsupervised learning approach and interacts with the target environment and considers the feedback. The algorithm interaction with the environment is based on feedback and M input signals. An input signal x is biased by the weighting factor w , which are real vectors containing input variables for the algorithm and their corresponding weights. The inputs and their weights are combined as per Equation (2) in a scalar quantity z :

$$z = \sum_{i=1}^M w_i x_i \quad (2)$$

where M is total number of channels; z is then subjected to a Bernoulli logistic function given in Equation (3):

$$p = f(z) = \frac{1}{1 + e^{-z}} \quad (3)$$

Then the algorithm updates its internal probabilities and context variables (i.e., x and w) based on that feedback. A probability bias σ is added to p so that it may not converge to 0. Based on the feedback signal, a decision is made according to the context in which RL algorithm is being used. The feedback is termed reward signal $r(t)$ in the RL terminology. The instantaneous reward signal in our simulation domain is given in Equation (4):

$$r(t) = \begin{cases} 0, & \text{if Throughput} < TH \text{ or SNR} < 0 \text{ or interference} > I_{Th} \\ \overline{\text{SNR}}, & \text{otherwise} \end{cases} \quad (4)$$

where the throughput threshold, i.e., TH , depends upon the total number of nodes at the gateway (Table 4) and I_{Th} is the interference threshold. The reward value is the average signal to noise ratio (SNR) of the channel. The output of the algorithm is a Bernoulli random variable (Equation (5)). At the start of the simulations, each gateway executes the RL-CAA in order to find the optimal channel allocation for the data transmission. The RL-CAA traverses all the available channels; the channel(s) which meet the criteria given in Equation (5) are then selected:

$$y = \begin{cases} 0, & \text{if } r(t) \leq 0 \\ 1, & \text{if } r(t) > 0 \end{cases} \quad (5)$$

The probability mass function representing the probability p of output y is described in Equation (6):

$$g(y, p) = \begin{cases} 1 - p, & \text{if } y = 0 \\ p, & \text{if } y = 1 \end{cases} \quad (6)$$

To simplify, y is a two action learning outcome of the RL process. The learning of the agent can be condensed in the weighting vector so that at each time step t , the agent learns by updating its weighting vector using Equation (7) and any instantaneous change in the individual weight is calculated by Equation (8):

$$w(t) = w(t - 1) + \Delta w(t) \quad (7)$$

$$\Delta w_i(t) = \alpha(t)[r(t) - \bar{r}(t - 1)][y(t - 1) - p(t - 1)]x_i(t - 1) \quad (8)$$

where $\alpha(t) > 0$ is called the learning rate, $r(t)$ is the reward returned by the environment at any instant (step) of time t , and $\bar{r}(t)$ is the average reward which is obtained as shown in Equation (9):

$$\bar{r}(t) = \beta r(t) + (1 - \beta)\bar{r}(t - 1) \quad (9)$$

where $0 < \beta \leq 1$ is called the reward memory factor of the RL. Low values of β assures enough memory of the past rewards. Decreasing the learning rate α with the RL steps improves the convergences speed of the algorithm. Thus, the learning rate is linearly decreased as given in Equation (10):

$$\alpha(t) = \alpha(t - 1) - \Delta \quad (10)$$

where Δ should be small enough to assure a smooth transition between steps and negative values for α should be avoided.

If any channel is giving a throughput below the target throughput, or if the channel is experiencing co-channel interference, the reward function returns zero (Equation (4)) and the RL-CAA discards that

channel and continues its exploration. Once the algorithm has converged, the set of optimal channels is known (Equation (11)): duplicated number

$$Y = \{y_1, y_2, \dots, y_M\} \quad (11)$$

where y_i represents the outcome of the RL-CAA for an individual channel. These channels are subsequently assigned to the sensor nodes and the gateway starts receiving data from the nodes. At any instant, due to the change in throughput requirements (either the target throughput has been changed or the traffic load has changed in the zone due to handovers) the particular gateway executes the RL-CAA to look for the new optimal channel allocations to satisfy its governed nodes. Some of the key parameters of the RL-CAA are presented in the Table 3. The key steps of the RL-CAA are listed in Algorithm 1 (note that this is a revised version of [34] with more focus on QoS requirements and co-channel interference).

Table 3. RL-CAA simulations parameters.

RL-CAA Parameters	Values
RL Evaluation Steps	500
RL Convergence Steps	50
α (RL learning rate)	100
β (reward memory factor)	0.01
σ (probability bias)	0.05

Algorithm 1: The key steps of the RL-CAA.

1. **REPEAT UNTIL** RL Convergence **OR** RL Evaluation steps
 2. Sense the available channels' conditions, i.e., SNR, interference
 3. Calculate instantaneous reward, $r(t)$, as per Equation (4)
 4. Update average reward, $\bar{r}(t)$, as per Equation (9)
 5. **FOR** $i = 1$ to M
 6. Update: x, w, p
 7. **END FOR**
 8. **FOR** $i = 1$ to M
 9. **IF** $p_i > 0.5$
 10. $y_i = 1$, i.e., assign the channel
 11. **ELSE**
 12. $y_i = 0$, i.e., do not assign the channel
 13. **END IF**
 14. **END FOR**
 15. **END REPEAT**
 16. **FOR** $i = 1$ to M
 17. $C_i = \text{Channel_Capacity}(y_i)$
 18. **IF** $\text{TotalTH} < \text{Req_TH}$
 19. $\text{TotalTH} = \text{TotalTH} + C_i$
 20. **ELSE**
 21. $y_i = 0$
 22. **END IF**
 23. **END FOR**
-

3.5.2. Static Channel Assignment (SCA)

In order to evaluate (later in Section 4) the performance of the proposed RL-CAA, we compare it to the SCA even selection algorithm [35]. The algorithm has been modified in order to comply with our application domain. The operation of the algorithm is as follows. The gateway monitors the available

channels. The channels are assigned in an increasing order based on the gateway ID, irrespective of the channel conditions, e.g., SNR, interference, etc. For example, if Gateway 1 needs to allocate a channel and if Channel 1 is currently assigned, then Channel 2 will be assigned to Gateway 1 and Gateway 2 will take Channel 3 and so on.

3.6. Transmission Power

WBANs are distributed networks and often a large number of networks have to co-exist close to each other. Each network has its own transmission power and it is practically very hard to maintain cooperation among all the WBANs to avoid co-channel interferences. Traditionally assigned transmission powers are not very optimized, so there is a big room for power optimization in WBANs. These traditional transmission power algorithms can generate tremendous amounts of interferences in the neighboring WBANs [21,36]. We propose a novel power allocation algorithm to reduce the interference among gateways (which are acting as base stations for all control operations for the individual WBANs). Each gateway is governing various WBANs in its vicinity. The primary convergence criteria for the power optimization is interference minimization.

The transmission power is calculated based on the desired interference level at the boundary of the WBAN, i.e., edge of a zone. The algorithm is derived from the convex optimization and is based on the illumination problem [37]. To calculate the transmission power, the interference boundary, i.e., perimeter of the zone, is divided into equally spaced linear small k patches. The interference received at any patch should not be greater than I_{des} , which is known as the interference threshold to avoid any interference to the neighboring WBANs. Equation (12) states the received power/interference level, I_k , at the center of each patch of interference boundary:

$$I_k = \sum_{j=1}^m a_{kj} P_T, \quad (12)$$

where m is the number of transmitters (base stations). Since there is only one gateway serving the zone, here $m = 1$ and P_T is the optimal transmission power of the transmitter. a_{kj} is the propagation losses between transmitter and the receiving path k , where the interference level is calculated. a_{kj} is calculated from the path loss and channel model presented in Section 3.3. Since the interference threshold, I_{des} , is known (it is determined empirically), the algorithm calculates the transmission power meeting this interference criterion for the given gateway. For optimization purposes, the objective function is formulated as shown in Equation (13):

Minimize:

$$\max_{k=1, \dots, n} |\log I_k - \log I_{des}|, \quad (13)$$

Subject to:

$$0 \leq P_j \leq P_{max}, \quad (14)$$

4. Simulation Results

In this section, simulation results for our proposed algorithms are presented. At the beginning of the simulation, the WBANs are deployed, i.e., the gateway and the nodes are placed in an area of $10 \times 10 \text{ m}^2$. Each zone of $5 \times 5 \text{ m}^2$ starts with an equal number of nodes. In the cases when mobility is also considered, the nodes can move across all the zones freely and randomly. The key simulation parameters are listed in Table 4.

Table 4. Simulation parameters.

Simulation Parameters	Values
Frame size	2040 bits
Transmission power (fixed power case)	3 dBm
Node Throughput	971.4 Kbps
Total Nodes per Gateway	3
Zone Area	25 m ²
Total Region	100 m ²
Maximum distance between a node—gateway (before handover may occur)	3.54 m
Total Simulation Time	600 s
Simulation statistics averaging period	10 s

We have performed the simulations for various scenarios modeling realistic nursing home activity patterns. These scenarios are modeled from the idlest time (when all nodes are stationary) to the busiest activity time, i.e., all nodes are mobile. These scenarios are:

- Case A: All the nodes are stationary. This case depicts that all patients are sleeping at night. They are not moving so there is no traffic change during this time.
- Case B: This corresponds to 100% mobility. All the nodes are moving. This situation corresponds to the busy working hours when all patients have to perform routine tasks.
- Case C: In this case, eight nodes are moving and four nodes are stationary.
- Case D: In this case, four nodes are moving and eight nodes are stationary.

Cases C and D correspond to the situations when some patients are resting and some of them are moving around, for example during the first hours of the working day, after lunch, or evening before bedtime. To evaluate the performance of our proposed RL-CAA, we compare its results with the classical static channel assignment scheme SCA. The RL-CAA is also analyzed based on various QoS requirements. The analysis of the simulation results are done on the basis of three performance parameters; (i) bit error rate (BER), which is the average bits in error received at the gateway; (ii) throughput, average throughput in bits per second (bps) available at the gateway; and (iii) dissatisfaction probability. The data involved in the WBANs can be quite critical depending upon the nature of the application, so the users (nodes) must have sufficient quality of service (QoS) to transmit their data properly. Dissatisfaction can give an indication of the QoS at any given time. Here, the dissatisfaction probability is defined as the percentage of time in which the users' QoS (i.e., user throughput) is below the target (user) throughput. This target throughput is often referred as satisfaction throughput. Here the satisfaction throughput is chosen as 971.4 kbps, i.e., the maximum allowed by the IEEE 802.15.6 standard.

4.1. Case A

In this case, all nodes are stationary. Figure 5a shows the averaged BER per gateway for the SCA and Figure 5b shows the average BER for the RL-CAA. The average error rate for SCA is a little over 10%, whereas it is less than 10% for each gateway with the RL-CAA. The average throughput per gateway provided by both algorithms is quite similar, as shown in Figure 6a,b.

All the users have acceptable QoS so no dissatisfaction is observed (probability = 0). The SCA is a static algorithm whereas the RL-CAA is a dynamic and robust algorithm (i.e., it can promptly act on any change in the network parameters and can adjust accordingly to provide sufficient QoS), and it is suited for scenarios with changing traffic requirements. In case of a static scenario, there are no much benefits with the RL-CAA.

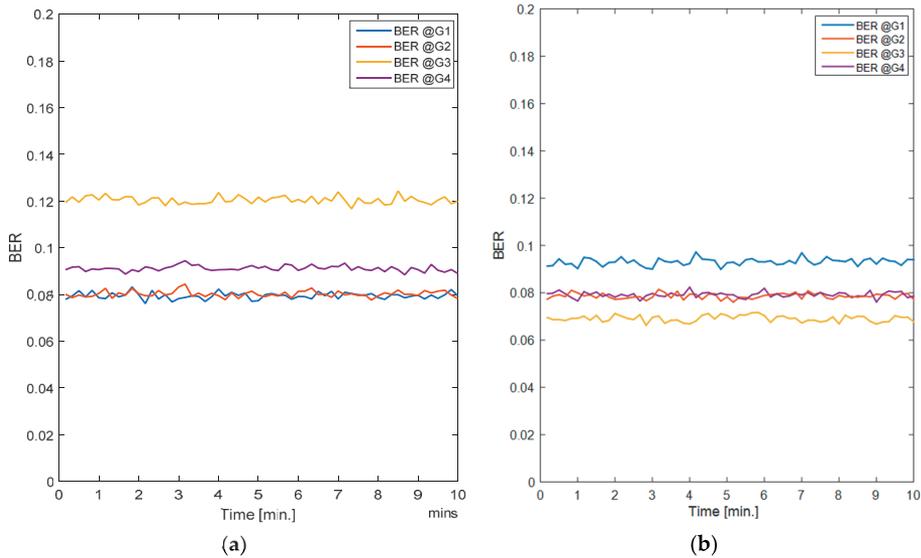


Figure 5. (a) Average BER for the SCA algorithm; (b) Average BER for the RL-CAA algorithm.

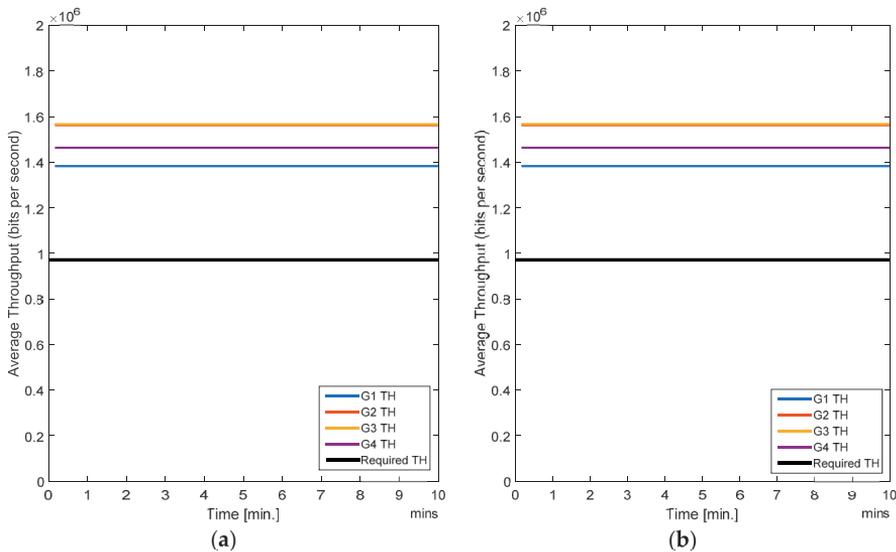


Figure 6. (a) Average throughput for the SCA algorithm; (b) Average throughput for the RL-CAA algorithm.

4.2. Case B

In this case, all the users (i.e., nodes) are moving. Since handovers are allowed from one zone to another, the users move freely and randomly across the entire region. Traffic load is also changing randomly as the nodes are entering or leaving a zone. The RL-CAA is a dynamic and robust algorithm which can confront the traffic change instantly, but it has a downside. More dynamics mean that the RL-CAA will undergo exploration of new channels as soon as the throughput goes below the throughput threshold. The RL-CAA is computationally complex and it has a learning curve before

it can converge to new channel assignments. Hence, there is a tradeoff between the impact on the desired QoS and the RL-CAA execution overheads. We do not require too frequent execution of the RL-CAA, so we set a 5% margin in throughput requirements. As the gateway throughput falls 5% below the target throughput, the RL-CAA is executed by the gateway and the new channels are then assigned. Figure 7a,b show the average BER of the SCA and the RL-CAA, respectively.

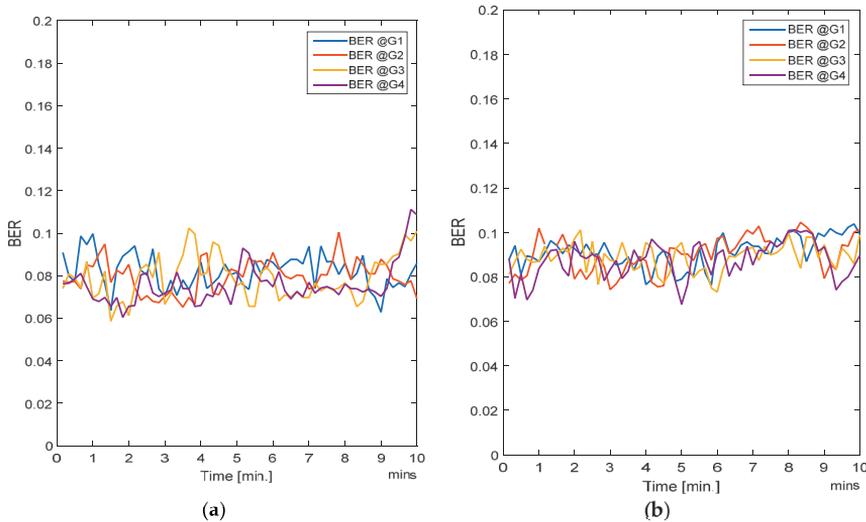


Figure 7. (a) Average BER for the SCA algorithm; (b) Average BER for the RL-CAA algorithm.

The RL-CAA is giving much consistent BER under 10% while SCA is fluctuating around 10%. The average throughput available at each gate for the SCA and the RL-CAA are shown in Figure 8a,b, respectively. The RL-CAA provides better distributed and higher throughput performance (reaches over 7 Mbps instantaneous throughput). The dissatisfaction probabilities, as experienced by the individual nodes, are given in Figure 9a,b for the SCA and RL-CAA, respectively.

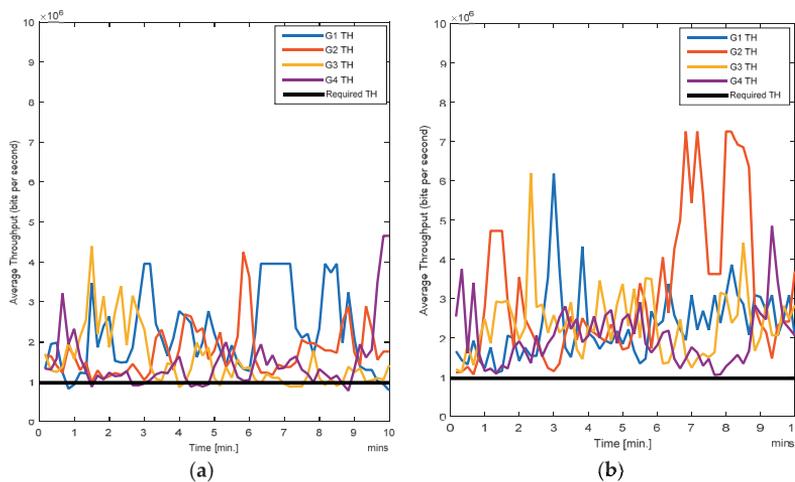


Figure 8. (a) Average throughput for the SCA algorithm; (b) Average throughput for the RL-CAA algorithm.

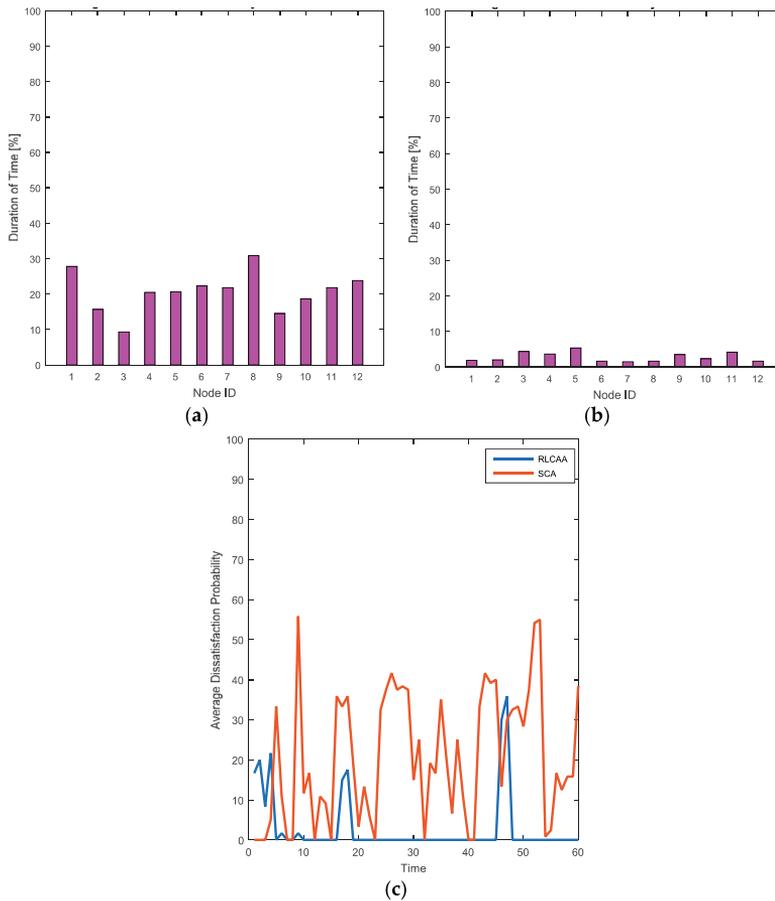


Figure 9. (a) Individual nodes dissatisfaction probabilities for the SCA algorithm; (b) Individual nodes dissatisfaction probabilities for the RL-CAA algorithm; (c) Comparison of the RL-CAA and SCA based total dissatisfaction probabilities averaged over time.

The RL-CAA is giving much consistent BER under 10% while SCA is fluctuating around 10%. The average throughput available at each gate for the SCA and the RL-CAA are shown in Figure 8a,b, respectively. The RL-CAA provides better distributed and higher throughput performance (reaches over 7 Mbps instantaneous throughput).

The dissatisfaction probabilities, as experienced by the individual nodes, are given in Figure 9a,b for the SCA and RL-CAA, respectively. The RL-CAA provides better QoS satisfaction as compared to the SCA. This can also be seen from Figure 9c, where the total dissatisfaction probabilities averaged over time for all nodes is presented for both algorithms. The RL-CAA provides, on average, a QoS satisfaction to individual nodes 97.2% of the time, while the SCA can only provide, on average, QoS satisfaction 79% of the time. These results consolidate the hypothesis that the proposed RL-CAA is highly effective in traffic changing environment and can accommodate handovers.

4.3. Case C

In this scenario, eight nodes are moving while four are stationary. The average BER, as observed at each gateway, is shown in Figure 10a,b for SCA and RL-CAA, respectively.

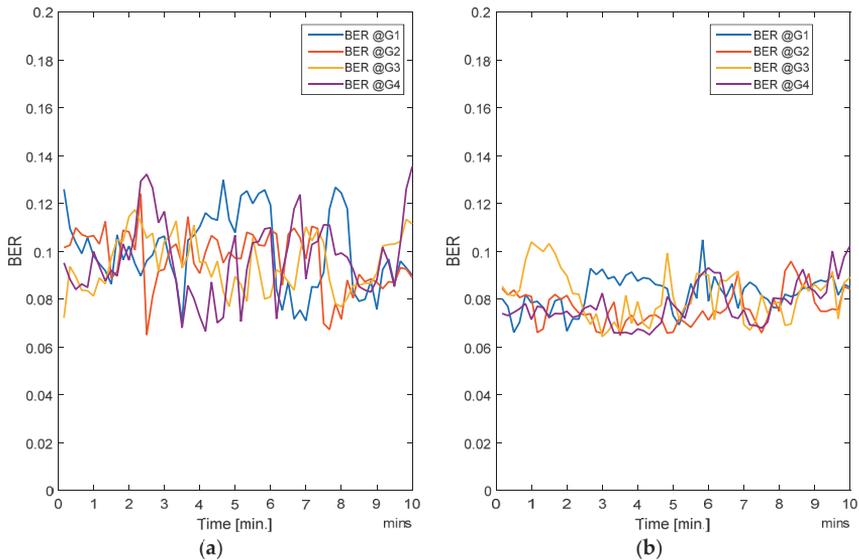


Figure 10. (a) Average BER for the SCA algorithm; (b) Average BER for the RL-CAA algorithm.

The RL-CAA is giving a below 10% error rate on average and a few fluctuations giving an error rate over 10%. The SCA's BER is over 10% for all gateways. The RL-CAA is providing better throughput per gateway as compared to SCA. For a short period, G4 experiences a throughput over 7 Mbps (Figure 11a,b). From Figure 12a,b, it is clear that RL-CAA provides better QoS satisfaction and little dissatisfaction is observed. From Figure 12c, it can be observed that there are short periods when the total system faces dissatisfaction. The RL-CAA in general provides better user QoS satisfaction.

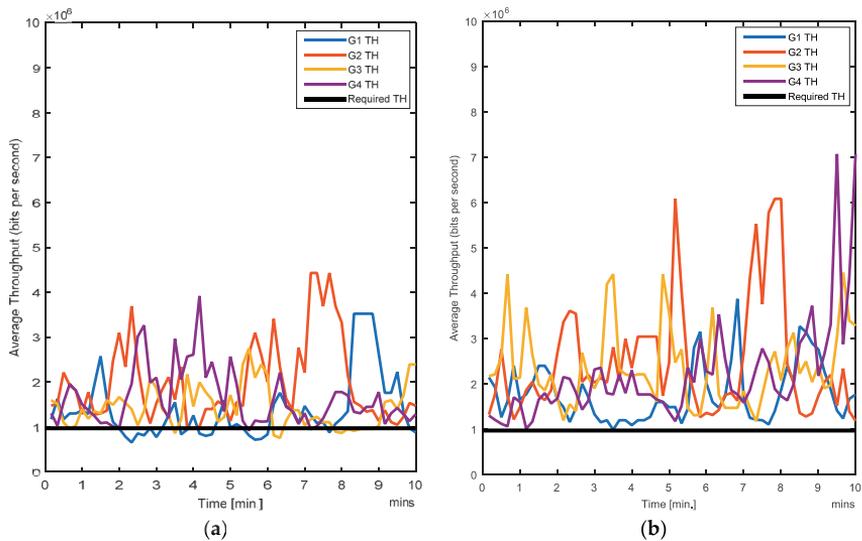


Figure 11. (a) Average throughput for the SCA algorithm; (b) Average throughput for the RL-CAA algorithm.

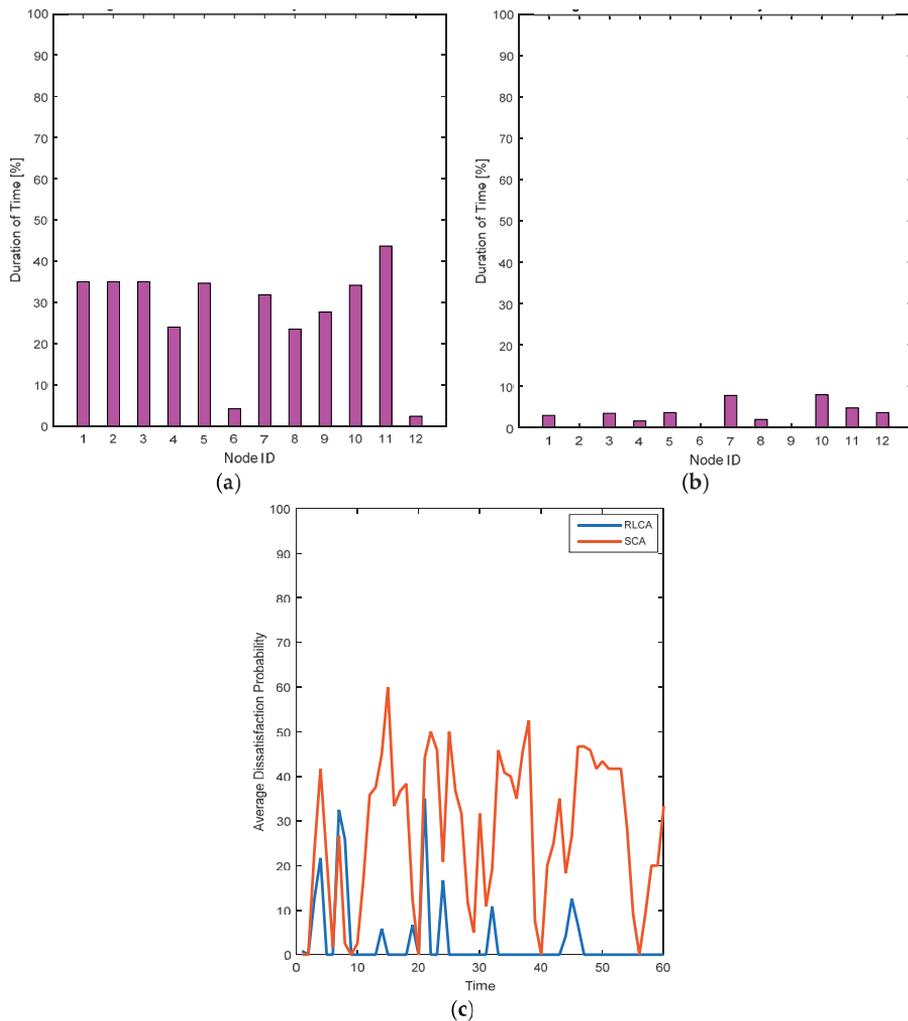


Figure 12. (a) Individual nodes dissatisfaction probabilities for the SCA algorithm; (b) Individual nodes dissatisfaction probabilities for the RL-CAA algorithm; (c) Comparison of the RL-CAA and SCA based total dissatisfaction probabilities averaged over time.

4.4. Case D

In this scenario, four users are mobile while eight users are stationary. The average BER values, shown in Figure 13a,b, illustrate that the RL-CAA is consistent in providing a ~10% error rate while SCA is giving slightly more than 10%. Since few nodes are mobile, less handovers are occurring, therefore throughputs observed at each gateway are more consistent, as shown in Figure 14a,b.

The RL-CAA provides a better overall throughput, e.g., at G2 and G3 the average throughput is over 3 Mbps. The individual dissatisfaction probability for the RL-CAA is almost zero (Figure 15b). The SCA provides poor QoS and the nodes are dissatisfied. The total average system dissatisfaction probabilities of the RL-CAA and the SCA are compared in Figure 15c. The overall dissatisfaction for the RL-CAA is negligible.

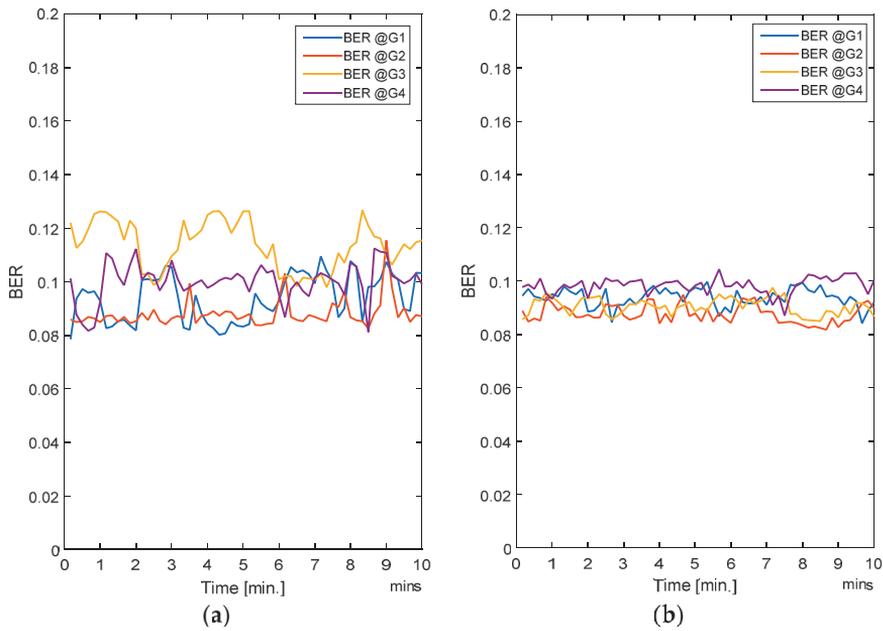


Figure 13. (a) Average BER for the SCA algorithm; (b) Average BER for the RL-CAA algorithm.

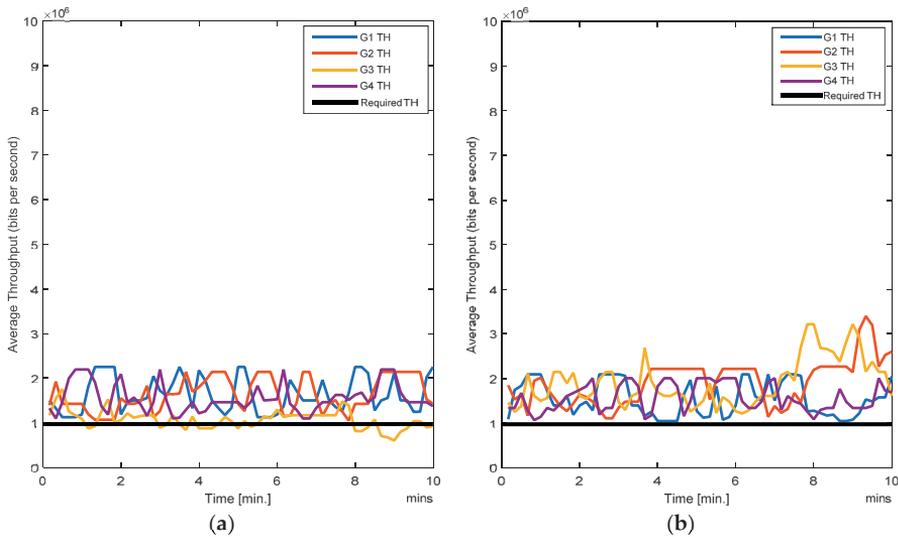


Figure 14. (a) Average throughput for the SCA algorithm; (b) Average throughput for the RL-CAA algorithm.

As previously discussed, the RL-CAA is a computationally expensive algorithm. We managed to minimize its execution time in a traffic-changing environment by introducing a throughput margin for the acceptable throughput. The lower the throughput margin, the higher the number of executions of the RL-CAA in a given amount of time. There is a tradeoff between QoS requirements and the acceptable throughput margin. The results presented above correspond to a 5% margin for the throughput.

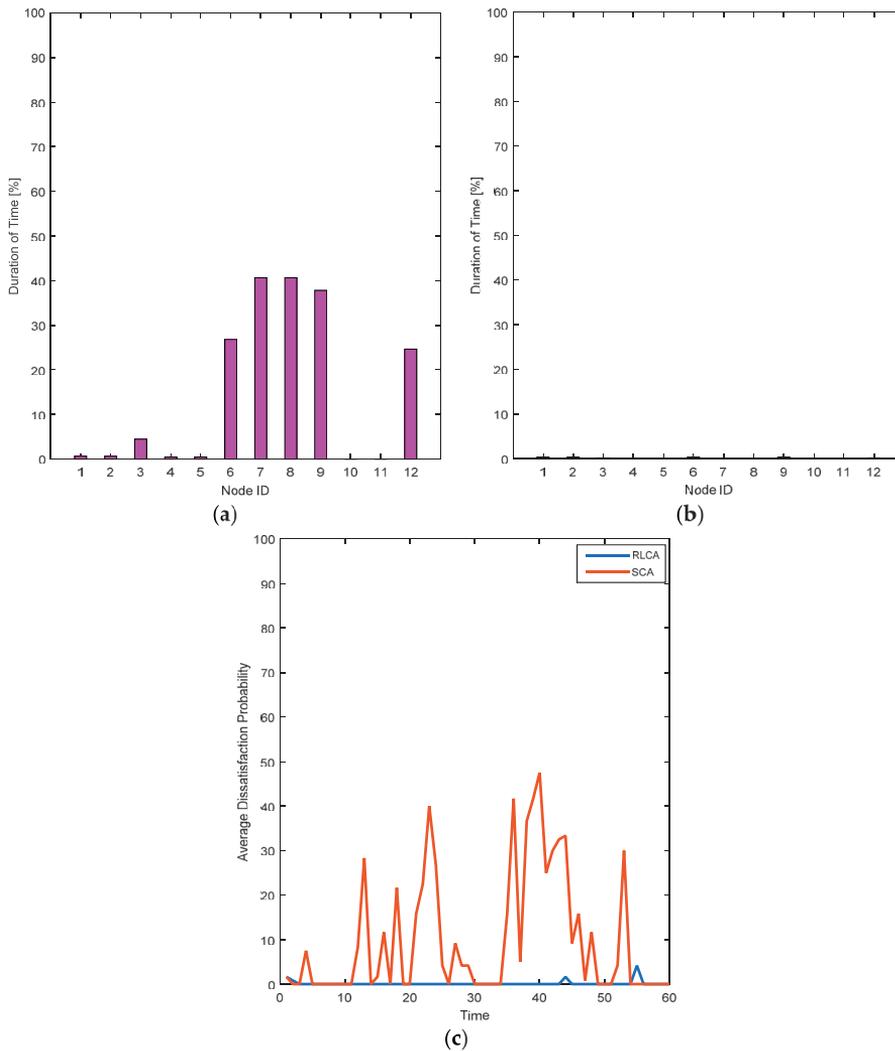


Figure 15. (a) Individual nodes dissatisfaction probabilities for the SCA algorithm; (b) Individual nodes dissatisfaction probabilities for the RL-CAA algorithm; (c) Comparison of the RL-CAA and SCA based total dissatisfaction probabilities averaged over time.

Based on these simulated results, the proposed RL-CAA gives an overall better performance. In terms of BER, the RL-CAA performs slightly better than the SCA; we can summarize that the RL-CAA and the SCA exhibits similar behaviors. However, the RL-CAA gives better performance in terms of throughput and dissatisfaction probabilities, which is the main aim in this work.

We analyze the results of the RL-CAA with different throughput margins. Case B is the most dynamic with the highest mobility, handovers and changing traffic, hence it is the most challenging case for the algorithm in terms of complexity, dynamism and robustness. The RL-CAA is analyzed only for the QoS satisfaction for the case B, for 5%, 10%, 25% and 50% throughput margin. It is evident from Figure 16a that the 5% margin gives the best individual nodes' QoS satisfaction, i.e., the individual dissatisfaction probability is lowest.

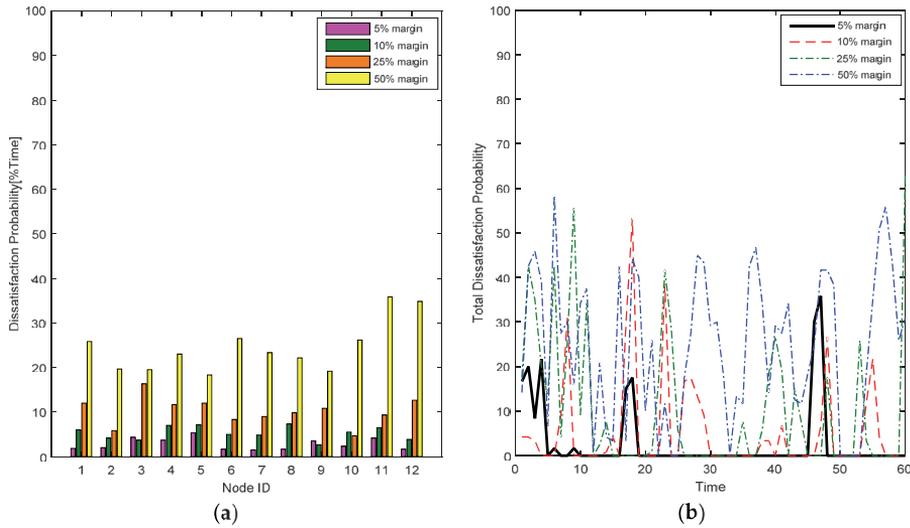


Figure 16. (a) Comparison of individual dissatisfaction probabilities of 5–50% throughput margin values; (b) Comparison of total averaged dissatisfaction probabilities for 5–50% throughput margin values.

This aspect can also be presented in the form of the total averaged dissatisfaction probability of all the margin values, as plotted in Figure 16b. The 5% margin shows the lowest dissatisfaction probability among all. The 50% throughput margin yields almost the same dissatisfaction probability as the SCA (refer to Figures 8 and 9). The results show that for the presented experiments, the RL-CAA yields the best results for channel allocation in a highly dynamic environment and that a 5% margin is good tradeoff to achieve the benefits of unsupervised learning and making the WBAN as C-BAN.

To evaluate our power optimization algorithm, we take the example of Zone 1 with gateway G1. We use three reference users located at A, B and C (Figure 2). These users are located at the edges of their zones, which is also the edge of Zone 1. This is the closest point where these users can come into the coverage radius of G1. The available transmission power ranges from -13 to 3 dB (Table 1). In a conventional power assignment scheme, the maximum available power (3 dBm) is assigned to the base station, i.e., the gateway. For simplicity, let's only take the case of direct LOS; the users at location A, B and C are receiving interference of -46.7688 dBm, -49.5413 dBm and -46.7688 dBm, respectively. With our power optimization algorithm, the same users receive -51.266 dBm at location A, -54.0386 dBm at location B, and -51.266 dBm at location C, when they are in direct LOS with G1. These results illustrate that our power optimization algorithm improve the performance when co-channel interferences exist and the users receive much less interference from neighboring zones. Our proposed algorithm sets the transmission power to -1.4973 dBm for G1. This gives 4.479 dBm lower interference at these reference points.

5. Conclusions

In this paper, a cognitive and dynamic channel algorithm named RL-CAA has been presented. An optimized channel can give better throughput and QoS as shown by our simulation results. In static environments, where the sensor nodes are not much mobile, computationally expensive algorithms are not much required as can be seen in our simulation results for Case A. In highly demanding environments, which can be due to the change of the throughput requirements on the run or due to the sensor nodes' frequent handovers, the RL-CAA is a better choice for C-BANs. The static channel assignment algorithm cannot keep up with the requirements of volatile network conditions. However,

the RL-CAA has high computational overheads, i.e., complexity, memory requirements, execution time, etc. Hence, it is recommended to use it in an application where the throughput and QoS requirements must not be compromised.

Our proposed RL-CAA presented here is evaluated for a specific health related application, but it is largely application-independent. It can be used in other types of sensor networks applications with little or no modification to the internal structure of the algorithm. Due to its unsupervised learning approach, the RL-CAA is well suited for distributed WSNs where there is no need for a central controller or coordinator to supervise spectrum sharing.

The power optimization algorithm gives better performance by reducing the transmission power and better performance in terms of interference. The radio module is one key component which drains the batteries of the sensor nodes. Our proposed power optimization algorithm saves up to 4.4973 dBm in transmission power. Reducing the transmission power can increase the battery life of the sensor nodes. The algorithm is most suited for base stations or gateway nodes, which are not mobile or not changing their positions over longer periods. It is not computationally intensive so it is quite suitable for resource-limited platforms. The downside of the algorithm is that it requires the path loss matrix to be calculated and stored in memory before executing the power optimization algorithm.

6. Future Work

The work presented in this paper can be seen as a starting point towards the research and development of C-BANs. This work can be extended toward more diverse scenarios and applications of WBANs. Considering the pace of development in modern technologies, it is expected that the size of the sensors will reduce dramatically. Hence, it will be possible in the future to carry or wear many more sensor nodes on the body. Such dense deployment of the sensor nodes in a WBAN will create new challenges in terms of spectrum management, e.g., interference, QoS, etc. Traditional approaches will no longer be very effective to encounter such challenges. The cognitive capabilities in the C-BANs will be suitable candidate to combat these challenges. Since most of the WBANs are proposed or designed for the ISM band and with growing diverse services in this unlicensed band, more cognitive functionalities will be required at various layers in the C-BANs.

Interference is a major hindrance for the QoS of the WBANs. With the introduction of C-BANs, efficient and opportunistic spectrum management algorithms can be proposed. In this work, inter-gateway interference avoidance has been proposed through power control. In the future, inter-WBAN and beyond-WBAN interferences could be avoided with cognitive capabilities of future C-BANs.

Channel modeling has been a tough subject for WBANs' researchers. Off-body and body-to-body channel modeling has been very little investigated in the literature. In this work, an off-body mathematical channel model has been proposed based on the body postures and shadowing resulting from various factors. A more comprehensive model of the off-body channel link based on the antenna design and position could be a future investigation task.

Finally, the algorithm presented in this work (i.e., the RL-CAA) has been proposed for channel allocation and simulation results show it as a promising candidate for future C-BANs. However, hardware implementation and design considerations for resource constrained platforms (in particular their computational power and energy conservation issues) remain to be investigated; for this, further modifications and optimizations to the proposed approach would be needed to improve the matching between the algorithms and architecture.

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Education

Educational Institution	Year	Education
Tallinn University Of Technology	2014 – 2017 (expected)	PhD, Electronics and Telecommunication
Harbin Engineering University China	2008 – 2010	MSc, Information and Communication Engineering
University of Engineering and Technology Peshawar Pakistan	2002 – 2006	BSc, Computer Systems Engineering
FG Sir Syed College Rawalpindi Pakistan	1999 – 2001	Pre-Engineering (High-school education)

Language competence

Urdu: Native

English: Fluent

Spanish: Intermediate

Russian: Basic

Professional employment

2013 – till day: Project Manager at Mayfly Marketing Ireland

2012 – 2013: Search Engine Optimization at OES SPAGO Spain (Google Map Search Engine evaluation, correction and optimization)

2010 – 2012: Research Associate at Technical University of Catalunya (UPC) Barcelona Spain.

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Hariduskäik

Haridusasutus	Aasta	Haridus
Tallinna Tehnikaülikool	2014 – 2017 (eeldatav)	PhD, elektroonika ja telekommunikatsioon
Harbiini Inseneeria Ülikool, Hiina	2008 – 2010	Magister, info- ja kommunikatsiooni tehnoloogia
University of Engineering and Technology Peshawar Pakistan	2002 – 2006	Bakalaureus, arvutisüsteemid
FG Sir Syed College Rawalpindi Pakistan	1999 – 2001	Keskharidus

Keelteoskus

- Urdu: emakeel
- Inglise: kõrgtase
- Hispaania. kesktase
- Vene: algtase

Teenistuskäik

- 2013 – ... Projektijuht, Mayfly Marketing, Iirimaa
- 2012 – 2013: Otsingumootori optimeerimine (Google'i kaardid), OES SPAGO, Hispaania
- 2010 – 2012: Teadur, Kataloonia Tehnikaülikool,(UPC). Barcelona, Hispaania

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