CONNECTING THE DOTS

Energy-efficient Adaptable Implantable Body Sensor Networks

Vignesh Raja Karuppiah Ramachandran

Propositions
belonging to the thesis

Connecting the DoTs

Energy-efficient Adaptable Implantable Body Sensor Networks (IBSN)

by

Vignesh Raja Karuppiah Ramachandran
to be defended on 18 July, 2018 at 16.45 hrs.

1. In the near future, full wireless communication between different types of implantable and wearable medical devices will become inevitable (Chapters 2 and 3).
2. A cross-layered medium access control (MAC) protocol, which adapts the duty-cycle of the wireless radio based on link quality not only decreases the number of packets dropped but also the energy consumed (Chapter 4).
3. Instead of directly transmitting the data during a period of poor link quality, using a relay node to forward the data can save a significant amount of energy (Chapters 4 and 5).
4. The not-so-computation-friendly process of machine learning can reduce the overall energy consumption, while improving the quality-of-service (QoS) of wireless communication (Chapter 6).
5. Enabling context-awareness at MAC layer can significantly reduce the energy consumed by the wireless radio (Chapter 7).
6. It is easy to be inspired by natural and biological things, but it is very difficult, if not impossible to replicate them.
7. One human brain is not sufficient to understand The Human Brain.
8. Connecting the dots during the PhD journey is as complex as connecting the dots in an Indian dotted rangoli. If done properly, both looks beautiful!
9. Mutually independent mistakes are the stepping-stones to success.
10. Human intelligence can decipher neither The Natural Superintelligence nor the artificial superintelligence, even when the humans will create the latter.

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Vignesh Raja Karuppiah Ramachandran

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CONNECTING THE DOCS

ENERGY-EFFICIENT ADAPTABLE IMPLANTABLE BODY SENSOR NETWORKS

DISSERTATION

to obtain
the degree of doctor at the University of Twente,
on the authority of the rector magnificus,
Prof. dr. T.T.M. Palstra,
on account of the decision of the graduation committee,
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*Dedicated to My wise-man, beloved Father,
Mr. K. Ramachandran*

*"...to lift a barrel which weighs twice as you,
you can use either a lever or a year-long work-out regimen..."*

— RAMACHANDRAN

ABSTRACT

DURING the last decades, wireless technologies have revolutionized the health-care industry by enabling remote monitoring of physiological signals of the human body through wearable medical sensors connected to the Internet. Currently new medical devices, such as the implantable deep-brain stimulator, are emerging that not only sense the physiological signals but also can deliver targeted disease-specific medical therapy. While traditionally many implantable medical devices have operated in isolation, recently many attempts have been made to connect them and to form a network, the so-called Implantable Body Sensor Networks (IBSN).

In its basic form, IBSN should enable medical devices (both implantable and wearable) to communicate with each other, in and around the patient's body, so that a common consensus on the health-condition of the patient can be reached. This collective knowledge will enable predictive diagnostics for the patient and will be used to deliver a personalized medical therapy based on patient's physiological status.

One of the important challenges of wireless communication in IBSN is that human body, due to its conductive property, heavily attenuates the low-power radio frequency (RF) signals. Due to IBSN node's utmost proximity to the human tissues, transmission power cannot be increased to compensate for the attenuation. Therefore, even a minor human movement frequently disrupts the RF link quality between the nodes. In addition, sensor nodes of IBSN are heterogeneous, i.e. they can sense and/or deliver therapy, generate and/or receive a wide variety of data at the nodes, which requires an adaptive Quality of Service (QoS) to support this heterogeneity. Nodes of IBSN are heavily constrained in power, computation, and memory resources given their size and placement, yet they are expected to operate for a long-time without needing any maintenance. Moreover these nodes must have ultra-low power consumption and very high reliability to ensure their long-term and life-critical functionalities.

In this thesis, we primarily focus on developing energy-efficient and reliable wireless communication schemes for resource-constrained nodes of IBSN that are adaptable to the requirements of variety of medical applications. To this end, we first measure and model the physical wireless channel in and around the body using an animal tissue that closely resembles the human tissue. With this model, we analyze the impact of attenuation caused by the body tissue to the wireless channel by simulating the state-of-the-art network protocols and measuring various network parameters such as throughput and latency at different locations in and around the tissue

and different distances between the implantable nodes. Based on these results and the requirements of advanced medical devices, we develop a cross-layer optimized medium access control protocol called HACMAC (Human ACTivity based Medium Access Control), which is tolerant to frequent link disruptions. The HACMAC protocol uses simple statistical measures to create a RF disruption model for each human activity. Based on this model, it will compute the optimal duty-cycle for the wireless communication and adjust the Medium Access Control (MAC) layer parameters.

However, the RF disruption model, which is developed based on simple statistical measures, cannot cope up with the minor yet frequent disruption caused by variations in human activities. To cope up with this dynamically changing human activity based RF patterns, we use reinforcement-learning principles to further improve the reliability of wireless communication and present a MAC optimization framework called DiNAMAC that is independent of RF disruption-models. Also, we use wake-up radio in addition to the main radio to lower down the overall power consumption of heterogeneous medical devices without affecting the reliability of the wireless communication.

Finally, we develop a context-aware seizure prediction framework for an epileptic use-case, which reduces the amount of raw data transmission by locally processing the brain signals on the IBSN sensor node. In addition, we investigate low-power low-complex signal processing algorithms and machine-learning models capable of being executed on the resource constrained sensor nodes. Based on these models, we develop an active learning-based seizure prediction framework and compare its performance with conventional methods of seizure prediction. To further analyze the feasibility of our optimization framework and seizure prediction framework to be executed on a resource constrained sensor node, we implement the core of our framework on an ARM based Cortex M4 microprocessor to measure the resource consumption values. From our results, it is shown that it is not only feasible to execute our framework on an IBSN sensor node, but also to reduce the overall power consumption of the node without affecting the QoS parameters of the wireless communication.

SAMENVATTING

In de laatste decennia hebben draadloze technologieën een revolutie teweeggebracht in de gezondheidszorg. Draagbare medische sensoren die zijn verbonden met internet stellen ons in staat om fysiologische signalen van het menselijk lichaam op afstand te bewaken. Nieuwe medische apparaten, zoals de implanteerbare neurostimulator, monitoren niet alleen fysiologische signalen, maar kunnen bovendien ook gerichte specifieke medische therapie bieden. Terwijl van oudsher vele implanteerbare medische apparaten op zichzelf opereerden, zijn er onlangs vele pogingen ondernomen om ze te verbinden en om een netwerk te vormen, de zogenaamde Implantable Body Sensor Networks (IBSN), wat vertaald naar implanteerbare sensornetwerken in het lichaam.

In hun basisvorm moeten IBSN medische apparaten (zowel implanteerbaar als draagbaar) in staat stellen met elkaar te communiceren, in en rond het lichaam van de patiënt, zodat een algemene consensus over de gezondheidstoestand van de patiënt kan worden bereikt. Deze collectieve kennis zal voorspellende diagnostiek voor de patiënt mogelijk maken en zal worden gebruikt voor het leveren van een gepersonaliseerde medische therapie op basis van de fysiologische status van de patiënt.

Een van de belangrijkste uitdagingen van draadloze communicatie in IBSN is het feit dat het menselijk lichaam, door zijn geleidende eigenschappen, de laagvermogen radiofrequentie (RF) signalen sterk verzwakt. Omdat IBSN sensor nodes zich zeer dichtbij menselijke weefsels bevinden, kan het zendvermogen niet worden verhoogd om de verzwakking te compenseren. Daarom verstoort zelfs een kleine menselijke beweging vaak de RF-verbindingskwaliteit tussen de sensor nodes. Bovendien zijn IBSN sensor nodes heterogeen, ze kunnen therapieën monitoren en / of afgeven, een grote verscheidenheid aan gegevens bij de sensor nodes genereren en / of ontvangen, hetgeen een adaptieve Quality of Service (QoS) vereist om deze heterogeniteit te ondersteunen.

Door hun kleine omvang en plaatsing binnen in het lichaam, beschikken IBSN sensor nodes over weinig batterij capaciteit, rekenkracht en werkgeheugen. Tegelijkertijd wordt van ze verwacht dat ze lang en betrouwbaar blijven werken zonder onderhoud nodig te hebben. Daarom moeten deze sensor nodes een zeer laag stroomverbruik en een zeer hoge betrouwbaarheid garanderen om hun langetermijn- en levenskritische functies te waarborgen.

In dit proefschrift richten we ons voornamelijk op het ontwikkelen van energie-efficiënte en betrouwbare draadloze communicatie schema's die aanpasbaar zijn aan

de vereisten van verschillende medische toepassingen voor resource-gelimiteerde sensor nodes binnen een IBSN. Daartoe meten en modelleren we eerst het fysieke draadloze kanaal in en rond het lichaam met behulp van een dierlijk weefsel dat sterk op het menselijke weefsel lijkt. Met dit model analyseren we de impact van verzwakking veroorzaakt door het lichaamsweefsel op het draadloze kanaal door de state-of-the-art netwerkprotocollen te simuleren en verschillende netwerkparameters zoals doorvoer en latentie op verschillende locaties in en rond het weefsel te meten en op verschillende afstanden tussen de implanteerbare sensor nodes. Op basis van deze resultaten en de vereisten van geavanceerde medische apparatuur, ontwikkelen we een cross-layer geoptimaliseerd Medium Access Protocol (MAC) genaamd HACMAC (op menselijke (Human) activiteit (Activity) gebaseerde MAC protocol), dat tolerant is voor frequente link verstoringen. Het HACMAC-protocol maakt gebruik van eenvoudige statistische metingen om een RF-verstoring model voor elke menselijke activiteit te creëren. Op basis van dit model zal het de optimale duty-cycle berekenen voor de draadloze communicatie en de MAC-layer parameters aanpassen.

Het RF-verstoring model, dat is ontwikkeld op basis van eenvoudige statistische metingen, kan echter niet overweg met de kleine maar frequente verstoring die wordt veroorzaakt door variaties in menselijke activiteiten. Om het hoofd te bieden aan deze dynamisch veranderende en op menselijke activiteiten gebaseerde RF-patronen, gebruiken we het reinforcement learning principe om de betrouwbaarheid van draadloze communicatie verder te verbeteren. We presenteren een MAC-optimalisatie kader genaamd DiNAMAC dat onafhankelijk is van RF-verstoring modellen. We gebruiken naast de hoofd-radio ook een wake-up radio om het algehele stroomverbruik van heterogene medische apparaten te verlagen zonder de betrouwbaarheid van de draadloze communicatie te beïnvloeden.

Ten slotte ontwikkelen we een framework dat instaat is om epileptische aanvallen te voorspellen. Het framework vermindert de hoeveelheid onbewerkte data die wordt verzonden in een IBSN door lokaal de hersensignalen op de IBSN sensor node te verwerken. Daarnaast onderzoeken we energiezuinige simpele signaalwerkings algoritmen en machine-learning modellen die kunnen worden uitgevoerd op de resource gelimiteerde sensor nodes. Op basis van deze modellen ontwikkelen we een, op het active-learning principe gebaseerd, epilepsie aanval voorspellings framework en vergelijken we de prestaties ervan met conventionele methoden voor de voorspelling van aanvallen. Om de haalbaarheid van ons optimalisatie kader en het kader voor het voorspellen van aanvallen verder te analyseren op een sensor node met beperkte resources, implementeren we de kern van ons framework op een op ARM gebaseerde Cortex M4-microprocessor met als doel de waarden voor het resourcegebruik te meten. Uit onze resultaten blijkt dat het niet alleen haalbaar is om ons framework op een IBSN sensor node uit te voeren, maar ook om het totale energieverbruik van de sensor node te verminderen zonder de kwaliteit van de draadloze communicatie te beïnvloeden.

முகவுரை

கடந்த சகாப்தத்தில், வயர்லெஸ் தொழில்நுட்பங்கள், மனித உடலியல் சமிக்ஞைகளை உடல்மேல் அணியக்கூடிய உணர்கருவிகளின் (**wearable medical devices**) வாயிலாக இணைத்ததின் மூலம் தொலைநிலை கண்காணிப்பு வசதிகளை ஏற்படுத்தி சுகாதார பராமரிப்பு துறையில் புரட்சியை கொண்டுவந்துள்ளது.

உடலின் உட்பொருத்தக்கூடிய மூளை ஊக்குவிப்பான் (**implantable deep brain stimulator**) போன்ற புதிய மருத்துவ சாதனங்கள், உடலியல் சமிக்ஞைகளை உணர்வதுமட்டுமல்லாமல், ஒரு மனிதனுக்கு குறிப்பிட்ட நோயிற்கான மருத்துவ சிகிச்சையை வழங்க முடியும்.

வழக்கமாக, பல உட்பொருத்தப்பட்ட மருத்துவ சாதனங்கள் தனிமையில் இயங்கினாலும், அண்மையில் அவற்றை உடலியல் உணர்கருவிகளுடன் இணைத்து செயல்படவைக்கும் புதிய தொழில்நுட்பம் தான் உடலின் உட்பொருத்தப்பட்ட உடலியல் உணர்கருவிகளின் பிணையம் (**Implantable Body Sensor Networks (IBSN)**).

அடிப்படையில், **IBSN** பிணையமானது, உடலின் உட்பொருத்தப்பட்ட மருத்துவ சாதனங்களையும் உடலியல் உணர்கருவிகளையும் ஒன்றோடொன்று இணைத்து நோயாளியின் மருத்துவ நிலை குறித்த தகவல்களை பரிமாறிக்கொள்வதற்கு வழிவகுக்கும்.

இந்த சாதனங்களின் கூட்டு தகவலானது, நோய்க்குறித்த விஷயங்களை நோயாளிக்கு முன்கூட்டியே தருவதுமட்டுமல்லாது, நோயாளியின் உடல்நிலையின் அடிப்படையில் தேர்ந்தெடுக்கப்பட்ட மருத்துவ சிகிச்சைகளை வழங்க பயன்படும்.

IBSN இன் சென்சார் முனைகள் மிகமிகச் சிறிய மின்சக்தியுடனும், மிகமிக அதிகமான நம்பகத்தன்மையுடனும் செயல்பட்டால் தான் பல வருடங்கள் எந்தவித பராமரிப்புமின்றி மனிதஉடலினுள் இருந்து மருத்துவ சேவைகளை செய்யமுடியும்.

மேலும், உட்பொருத்தக்கூடிய தன்மையின் காரணமாக இந்த சென்சார் முனைகளின் மின்சக்தி, கணக்கீடு மற்றும் நினைவக ஆதாரங்கள் மிகவும் சிறிதாக வடிவமைக்க பட்டாலும், நோயாளிகளின் மருத்துவத்தேவைகளை நீண்ட காலம் உயரிய நம்பிக்கையோடு வழங்கவேண்டியது இந்த சாதனங்களின் முக்கிய கடமையாகும்.

IBSN பிணையத்தின் முக்கியமான சவால் மனிதஉடலின் மின்கடத்தும் தன்மை ஆகும். எந்த ஒரு தகவலையும் ரேடியோ அலைவரிசையில் பரிமாறும் பொழுதும் மனித உடலின் மின் கடத்தும் தன்மை அந்த தகவல் பரிமாற்றத்திற்கு தடங்கலாக அமையும்.

மனிதஉடலினுள் உட்பொருத்தப்பட்டதால் அதிக மின்சக்தியை பயன்படுத்தி தகவல் தொடர்பின் தரத்தை IBSN பிணையத்தில் உயர்த்தமுடியாது.இவ்வாறு செய்வதால் மனித தசைகள் ரேடியோ அலைக்கட்டறையின் தாக்கத்தால் பாதிக்கப்படும். ஆகவே உயிர் சம்மந்தப்பட்ட தகவல்களை பரிமாற்றிக்கொள்ள புதிய ரேடியோ தொழில்நுட்பங்கள் தேவை படுகின்றது.

இந்த ஆராய்ச்சிக்கட்டுரையில் IBSN பிணையத்திற்கு ஏற்றார் போல் புதிய தொழில்நுட்பங்கள் ஆராயப்பட்டு கண்டுபிடிக்கப்பட்டுள்ளது. முக்கியமாக மூன்று முறைகளின் மூலம் குறைந்த மின்சக்தியில் அதிக நம்பகத்தன்மையுடனும் நீண்ட காலமும் IBSN பிணையத்தில் சென்சார் முனைகள் தகவல்களை பரிமாற்றிக்கொள்வதற்கு வழிவகுக்கப்பட்டுள்ளது.

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INTRODUCTION

INNOVATIONS in the health-care industry are continuously emerging. One of these promising innovation is the advent of intelligent and implantable medical devices. While traditionally many implantable medical devices have operated in isolation, recently many attempts have been made to connect them and form a network of implantable medical devices, the so-called Implantable Body Sensor Network (IBSN). In its basic form IBSN should enable these medical devices (both implantable and wearable) to communicate with each other, in and around the patient's body. This thesis is motivated by the challenges in short-range wireless communication of resource-constrained IBSN devices. In this chapter we will present key characteristics of IBSN, requirements of IBSN applications, research objectives and our hypotheses with an overview of this thesis.

பொருள்கருவி காலம் வினையிடனொடு ஐந்தும்

இருள்தீர எண்ணிச் செயல்.

*Resources, tools, time, place and the task –
analyze these beyond doubt, and only then act*

-Thiruvalluvar in Kural 675 Circa 350 BCE

1.1 INTRODUCTION

World population has reached 7.6 billion and it is projected to reach 11.2 billion by 2100 [1]. The global average of human-life expectancy was 71 years in 2015 and is expected to remarkably increase with a six year mark every decade [2]. This rapidly growing population alongside the constantly increasing life expectancy has resulted in new health problems due to various factors such as demographic aging, rapid urbanization, and the spread of unhealthy lifestyles [3].

According to the World Health Organization (WHO), non communicable diseases, such as cardiovascular disease, cancer, diabetes, and chronic lung diseases, have overtaken infectious diseases as the world's leading cause of mortality [4]. Innovations in the health-care industry are continuously emerging to monitor, treat, and reduce the death and disability caused by such non communicable diseases.

One of these promising innovations is the wearable medical devices, which revolutionized the health-care industry. These wearable devices can sense the physiological signals and remotely monitor the health-status of a patient to significantly improve the prognosis, disease-prevention and care-delivery by continuous monitoring and tracking of disease progression, advocating personalized fitness-diet paradigms, and promoting the co-operation between the patients and the health-care professionals [5, 6, 7].

A recent and promising innovation is the advent of Active Implantable Medical Devices (AIMD) which is a broad range of intelligent and implantable medical devices, that can not only sense the physiological signals but also deliver targeted disease-specific medical therapy for a human [8, 9, 10, 11].

While some implantable devices, such as pace-makers, are known already for more than five decades, many new AIMD, such as drug-delivery devices [12], neural-and deep-brain simulators [8], closed-loop pacemakers [10], have only been introduced in the last two decades.

Traditional implantable devices had neither complex computational operations nor wireless-communication capabilities. However, advanced AIMD are incorporated with a wireless communication unit and advanced computing units in addition to physiological sensing and actuation units.

In general, the advantages of AIMD over wearable medical devices include (i) their accurate sensing of a medical symptom with high signal to noise ratio; (ii) being unobtrusive compared to the wearable medical devices; (iii) having minimal impact on the quality-of-life of a patient; and (iv) their ability to deliver a medical therapy localized to a specific part of the human body.

While traditionally many implantable medical devices have operated in isolation, recently many attempts have been made to connect them and form a network of implantable medical devices, the so-called IBSN. In its basic form IBSN should enable these AIMD but also wearable medical devices to communicate with each other, in and around the patient's body, so that a common consensus on the health-condition

of the patient can be reached. This collective knowledge will enable predictive diagnostics for the patient and will be used to deliver a personalized medical therapy.

This thesis is motivated by the challenges that arise when short-range wireless communication of resource-constrained IBSN devices has to take place inside, and around the human body. The main aim of this thesis is to design reliable and energy-efficient wireless communication schemes for IBSN that will meet the requirements of variety of medical applications of the advanced AIMD.

Rest of this chapter is organized as follows. In Section 1.2 key characteristics of IBSN will be elaborated together with the device functionalities. In Section 1.3, important requirements of wireless communication in IBSN will be presented.

Research objectives of the thesis and our hypotheses will be presented in Section 1.4. The main contributions of this work will be summarized in Section 1.5 followed by an overview of the thesis is given in Section 1.6.

1.2 IMPLANTABLE BODY SENSOR NETWORKS (IBSN)

An IBSN is a short-range wireless network of implantable and wearable medical devices that are capable of sensing physiological signals, and delivering targeted and disease-specific medical therapy to a localized part of the human body.

An IBSN is very different from the network of body-worn sensor network, or Body Sensor Network (BSN) because of its special characteristics and requirements. Table 1.1 shows the typical differences between IBSN and BSN.

Figure 1.1: An example of IBSN.

Characteristics	Body-worn sensor networks	Implantable body sensor networks
Network coverage	Up to 50 meters	Up to 3 meters
Types of nodes	Only sensing nodes are present	Sensing and actuation nodes are present
Node functionality	Non-critical, Entertainment, Relays	Life-Critical
Sensor accuracy	Not very accurate	Very accurate and reliable
Size of the node	Wearable size, but not limited in dimensions and bio-compatibility	Should be implantable and very small compared to BSN
Environment	Outside the body, Electromagnetic properties being influenced by the environment	Inside the body, either shallow or deep implant. Electromagnetic properties vary significantly
Event detection	Events are not life-critical, and detection algorithm can be offline and complex	Events are life-critical and detection algorithm should be simple and online
Heterogeneity	Medium in terms of devices, sensing and actuation capabilities	Medium in terms of devices, sensing and actuation capabilities
Security	Security is required but not critical	Security is crucial since the life-critical operations can be fatal if security is compromised
Energy efficiency	Can be recharged. Hence energy constraints can be relaxed	Replacement of the battery is not an option and lifetime of the nodes is in orders of months to years. It has to be highly energy-efficient
Energy availability	Energy is abundant	Energy is scarce and needs to be used with efficiency
Energy harvesting	Energy harvesting is easier from mechanical energy, solar energy, and recharging is also an option	Energy harvesting is very limited, temperature change in the body, chemical changes from glucose and heart vibrations are possible. However, the amount of energy that can be harvested is much lower than the energy harvested from outside the body
Access to nodes	Can be very easily accessed by people and without the help of doctors	Cannot be accessed without the physician and small surgery
Bio-compatibility	Bio-compatibility is not required	Bio-compatibility is of prime importance, since the node are planted inside the body
Context-awareness	Device-level context awareness, i.e. context of the data is not shared among all devices in the network	Network-level context awareness, i.e. context of the data is shared among all the devices in the network
Wireless medium	Mostly air, and surface of the human body	Complex layers of muscle tissues, bones and conducting heterogeneous medium
Connectivity	Should be connected to the Internet	Primarily connected to the base station placed in close proximity to the human and the base station is connected to the Internet
Duty cycling	Very low	Dynamic depending on the application
Interference	Shared with ISM band	Dedicated frequency band for medical applications

Table 1.1: Differences between the requirements of BSN and IBSN

1.2. IMPLANTABLE BODY SENSOR NETWORKS (IBSN)

Figure 1.1 shows an example of an IBSN, where an implantable medical device called Deep Brain Stimulator (DBS)¹, is implanted in the brain. DBS is connected to both wearable and implantable medical devices through a wireless network, in a two-hop extended star topology², where a wearable central-controller is worn on the right-wrist of the person.

The central controller also acts as a wearable heart-rate sensor. Two more implantable sensors are also present. One that measures the blood pressure and core temperature is implanted in the chest cavity and another one that measures the motion and foot pressure is implanted in the left ankle. A wearable medical sensor, which measures the electrical activity of the muscles in the left thigh acts a relay node between the implanted motion sensor and the central controller.

This conceptual example of IBSN might be applied to an epileptic use-case, where personalized stimulation settings for DBS system can be derived from predicting the onset of the seizure by monitoring the physiological signals.

Figure 1.2 shows an example of the closed-loop application of IBSN where DBS is used to treat an epileptic patient. The physiological signals are sensed using either implantable or wearable sensors. The health-status is recorded and is reported occasionally to the base-station that is present external to the human-body.

The onset of seizure is predicted using the physiological signals. Based on prediction results, the stimulation settings of the DBS are recalculated and applied to the patient. The start/stop operation of DBS is notified to the patient in order to ensure that the patient is aware and comfortable during the brain stimulation process. A doctor/physician is always kept in the loop in order to ensure maximum safety for the patient and to take-control in case of an anomaly. This is typical application of IBSN in action.

Figure 1.2: An schematic example of closed loop operation using IBSN.

¹DBS therapy aims to reduce seizures but not necessarily to cure epilepsy. DBS therapy involves implanting electrodes into specific areas of the brain, and then stimulating these areas with small regular electrical impulses.

²also known as Restricted tree topology [13]

1.2.1 DEVICE CLASSIFICATION

A typical IBSN has the following devices:

- **SENSORS** are devices which can measure the physiological data. These devices can either be implanted or body-worn. Number of sensors can vary from one to many, depending on the application of the IBSN. All sensor devices are considered as end-nodes of the IBSN.
- **ACTUATION DEVICES** are the crucial element of the IBSN which delivers the medical therapy. In most cases, these devices are implanted. However, in very specific medical applications, they may be body-worn, for example in case of drug-delivery devices. All actuation devices are considered as end-nodes of the IBSN.
- **CENTRAL CONTROLLER** is a device responsible for configuration of the network, resource-allocation, power-management, and routing-management. It constructs the communication schedule and route according to the requirements of the network devices depending on their functionality. The central controller is always body-worn or in the vicinity of the human-body. In addition to the network controlling part, these devices may also function as a sensing device but can never function as an actuation device.
- **RELAY NODES** is responsible for relaying the information to the central controller from the end node in case of the wireless link disruption. All wearable sensor nodes can act as a relay node, but the implantable nodes can never act as a relay node because of the power-constraints.
- **BASE-STATION** is an external device responsible for connecting the IBSN to external networks such as internet. The base-station is a powerful device which is always-on. The base-station cannot communicate with the end-nodes of IBSN, however it can communicate with the central controller of IBSN. In cases where there the patient is mobile, a mobile phone can also act as a base-station.

1.2.2 SYSTEM FUNCTIONALITY

An IBSN has several functionalities such as monitoring, treating and diagnostics of the health-condition of a patient. The details of the functionalities are described below:

- **SENSING:** The IBSN system should be able to handle the diversity of the implantable and wearable sensors without jeopardizing the quality of the sensor data which may result in the misdiagnosis. These medical sensors output different types of medical data at different rates. An ideal network should be self-adaptive to accommodate different kinds of sensor devices.

Continuous sensing will increase the power consumption of the sensor node. However, discontinuous sensing can lead to missing life-critical data. Each sensor node

of an IBSN system can have a sensing strategy which will handle the trade-off between the power consumption and the reliability of the sensing system efficiently.

- **ACTUATION:** The actuation in IBSN refers to the medical therapy provided by the AIMD, such as a cardiac pace-maker, neural stimulators, and drug-delivery devices. In most case, actuation is pre-programmed.

However, in the context of a closed-loop medical system, the actuation process can be programmed based on the feedback from the sensor nodes. Each actuation node of the IBSN system, can have an actuation strategy which is adaptive to the dynamic and patient centric requirements.

- **POWER SUPPLY** In parallel to battery source, a node can be capable of power scavenging to prolong their lifetime and to enable long-term monitoring, treatment and diagnostics of the patient. Power scavenging is an intermittent source of energy.

A battery is used to store the minimal energy needed for an emergency communication, apart from the routine communication. Energy-efficiency should be guaranteed by IBSN system, which should adapt the power usage of all the nodes without compromising the prime objective of the end-nodes.

- **DATA-HANDLING:** Physiological data is diverse in data density due to various sampling rates depending on the vital sign that is being sensed. For example, a ECG sensor has a high data density and a blood glucose sensor has a low data density. More often than not, the physiological data is also affected by noise due to bio-fouling, motion artifact, and interference.

To improve the reliability of the physiological data, pre-processing can be carried out locally within the network to reduce the presence of noise in raw-data and to achieve uniform information density from diverse physiological signals. Each node in IBSN can pre-process the physiological data within their capability with high reliability but not compromising on the reliability.

- **CONTEXT AWARENESS:** In addition to improving the reliability, pre-processing the physiological data on the node can enable the IBSN node to be contextually aware of the data that is being sensed. Based on this context-awareness, an IBSN node can detect anomalies in physiological data, prognosis of the patient's health-condition, and altering the medical therapy based on the health-condition. Moreover, this context awareness in an IBSN sensor node can reduce the amount of raw data that is sent wirelessly to the base-station, and therefore can reduce the overall resource consumption of the wireless radio in an IBSN node.
- **WIRELESS COMMUNICATION:** The information exchange between the nodes of the IBSN system is achieved using wireless communication. The functionality of the wireless communication is defined based on the following features,

- **MEDIUM OF COMMUNICATION:** Communication in IBSN can happen in three different deployment configurations, namely, in-body to in-body, in-body to on-body, in-body to off-body (eg. a base station or a mobile phone). Depending on the deployment configuration, different physical Radio Frequency (RF) settings have to be chosen according to the international regulations of the spectrum usage. In addition to RF medium, other physical medium such as Ultra Wide Band (UWB), Human Body Communication (HBC) may also be used as the physical channel of communication³.

In order to enable ultra-low power operation at narrow-band RF, two different wireless radios are used in IBSN for implant communication. One is the main radio which uses MICS frequency band to transmit and receive medical data, and another one is the WuR, which operated alongside the main radio at very low power consumption than main radio. WuR reduces the energy-consumption of main radio by switching the main radio to deep-sleep mode when no data is transmitted or received.

- **MEDIUM ACCESS CONTROL:** In addition to the dynamic environment characteristics, an IBSN is prone to interference in the radio channel, collision, overhearing of data, and packet-errors. The quality of the wireless link deteriorates temporally and spatially in the case of IBSN. Access mechanism should be aware of the physical medium of communication and also be optimized based on the application specific requirements.
- **NETWORK TOPOLOGY:** Depending on the number of nodes in an IBSN and the deployment location in and around the human body, the topology of the network can vary. A star topology, where a central controller manages the network configurations of all the end-nodes, can fit to most of the IBSN applications.

In specific use-cases of the IBSN, the link quality between the end-nodes and the central controller is highly deteriorated due to the dynamic human behaviour and rapidly changing environment. In such cases, a one-hop star topology, where the end-nodes relay the information to the central controller through a relay node is used.

- **ROUTING:** Routing within IBSN is plain since the number of nodes in the network is less and topology is simpler than conventional Wireless Sensor Network (WSN). However, the physical channel is highly dynamic due to human behavior and changing environment. A good routing mechanism must be able to handle the dynamic changes of the link quality between the end-nodes and the central controller.
- **SECURITY:** Security is paramount in IBSN as the wireless transfer mainly includes life-critical data and any interference to the data can cause fatalities.

³UWB and HBC can be used only for wearable to wearable communication and cannot be used for implant communication

Devices must be authenticated before wireless communication is engaged and the data generated at the node must be encrypted in life-critical applications.

1.3 REQUIREMENTS OF WIRELESS COMMUNICATION FOR IBSN APPLICATIONS

It is difficult, if not impossible to design a generic wireless communication mechanism for all kinds of IBSN applications due to their diverse requirements and unique design challenges. Contemporary applications of IBSN such as closed loop operation of DBS are continuously emerging, which puts-forth newer requirements to wireless communication between IBSN devices. This severely restricts the use of wireless technologies for life-critical medical devices, where the conventional communication techniques (e.g. near-field magnetic induction) are still relied upon.

In this section we will list some of the important requirements of wireless communication in IBSN, namely:

- **ENERGY-EFFICIENCY**

The implanted sensor nodes have limited power source, most of which is used for delivering the medical therapy. To deliver the levels of comfort and unobtrusiveness required for widespread adoption, IBSN sensor nodes must be small and have energy sources that last for months and years, depending on the application. These sensor nodes have to operate for a very long time ranging from one to fifteen years. Any processing and wireless communication is severely limited by the energy-constraints. Although recharging of these sensor nodes maybe possible with wireless charging, replacement of the power-source is extremely difficult if not impossible after implantation of these devices.

Wearable sensor nodes are rechargeable and the power source is easily replaceable. Although energy is not strictly constrained in these nodes, loss of node-connectivity due to power-outage will directly impact the operation of implantable devices. Most network management activities, such as time slot allocation, routing information, and prioritization are performed by the wearable central controller. By doing so, energy wastage, due to performing such management overheads by the end-nodes of IBSN, is minimized. However, in some of the closed-loop applications of IBSN, the end-nodes are also responsible for such management activities in order to provide high reliability [14].

The implantable sensor nodes of IBSN have very limited computational-power which constraints the implementation of complex algorithms on these devices. Whereas, the wearable sensor nodes have more computational power than the implantable sensor nodes. However, computational-power of wearable nodes is

limited by the physical dimensions of the wearable nodes. Power-hungry algorithms which require large execution time cannot be implemented on these wearable devices due to the energy-constraints.

- **ADAPTABLE QUALITY OF SERVICE (QoS):**

The service of different classes of medical devices in IBSN is shown in Table 1.2. Heterogeneous devices of IBSN requires a variety of QoS requirements.

Device class	Category	Service level	Description
0	Network management	Non-medical services	Non-critical
1	Monitoring	Mixed medical and non-medical services	Usually critical
2	Diagnostic	General health services	Often critical
3	Therapeutic	Highest priority medical services	Always critical

Table 1.2: Application classes and priority services in IBSN. *Inspired from IEEE 802.15.6 standard for wireless communication in medical devices [15].*

In IBSN QoS is defined by three main parameters, namely:

- **LATENCY** The latency requirements varies depending on application scenarios. The typical end-end delay tolerance for monitoring applications lies between few milliseconds to several seconds. For diagnostic and therapeutic applications, data delivery within few milliseconds is required.
- **THROUGHPUT** The throughput requirement of implantable actuation devices varies from 100 kB/s to 150 kB/s depending on the application scenario. The throughput requirements of implantable and wearable sensing device varied from 1 kB/s to 10 MB/s depending on the type of physiological process that is being sensed. For example, a blood glucose monitor requires to transmit 1 byte every few hours whereas an implanted brain-signal sensor needs to transmit 100 kB of data every second [16].
- **RELIABILITY** Every successful wireless communication in an IBSN is directly responsible for diagnostic and/or therapeutic processes that support or sustain human life. Every failed wireless communication will ultimately hinder the primary operation of the device which might result in fatality. Hence, IBSN requires extreme reliability. Fault-tolerance support in deteriorating wireless links of IBSN is needed to guarantee reliability to medical devices. Also, it must be ensured that no devices within IBSN should be down during the operation period. Reliability in IBSN is measured in terms of Packet Delivery Ratio (PDR), which is the ratio of number of successfully received packets to the number of packets transmitted. IBSN is required to have a very high packet delivery ratio.

Unlike the conventional sensor networks, these QoS requirements have to be fulfilled despite two unique challenges of IBSN, namely:

- **HETEROGENEITY:** IBSN is heterogeneous in different forms ranging from heterogeneity in device function, i.e. sensor or actuator to heterogeneity of physiological signals (periodic blood-glucose measurement or continuous heart signal measurement), deployment location (wearable or implantable), and application domains (monitoring, treating, or diagnosing).
 - **DYNAMICITY:** IBSN is dynamic in two forms, i.e., (i) the temporal dynamicity of the physiological data, which varies dynamically over time, and (ii) the temporal and spatial dynamicity of the node-environment which affects the wireless link in both time and space. Node environment not only depends on the deployment location of the nodes, but also the physical location of the patient. For example, a patient can be in a hospital environment or a home environment, which affects the wireless link very differently.
- **SCALABILITY**

AIMD are continuously being evolved in terms of functionalities and device capabilities. Newer functionalities such as predictive diagnostics, advanced therapies, requires these devices to have much faster and broader wireless communication technology. The IBSN must be able to handle the addition of new device to the network architecture without re-modification. The overall objective is to achieve an optimal performance even when the network-size scales up or data generation rate increases.

1.4 RESEARCH OBJECTIVES

The wireless communication in IBSN is very challenging because of its life-critical device functionalities and multiple, sometimes conflicting requirements of its medical applications. Although many wireless technologies exist for low-power sensor networks, contemporary applications of IBSN such as the closed-loop operation of implanted medical devices, largely limits the use of existing wireless technologies. It is clear that wireless technologies for IBSN could potentially be improved in different aspects.

This thesis aims to address the energy-efficiency aspects of the wireless communication for IBSN along with providing adaptable quality of service (QoS) for a variety of medical applications of IBSN.

We intend to enable context-awareness in IBSN nodes at the medium-access layer to support adaptive QoS for wireless communication in IBSN. Finally we explore the optimization of energy-efficiency and reliability of wireless communication, depending on the QoS requirements of the medical applications of IBSN.

The primary research question of this thesis is therefore:

**HOW TO GUARANTEE ENERGY-EFFICIENCY AND QUALITY OF SERVICE (QoS)
PARAMETERS FOR THE WIRELESS COMMUNICATION BETWEEN IMPLANTABLE
AND WEARABLE MEDICAL DEVICES TO FULFILL MULTIPLE AND SOMETIMES
CONFLICTING REQUIREMENTS OF IBSN APPLICATIONS.**

This question can be broken down into various aspects of wireless communication related to the design of Medium Access Control (MAC) protocol, design of low-power physiological signal processing methods, and cross-layer optimization of MAC protocols. To this end, in this thesis we answer the following sub-questions:

RESEARCH QUESTION 1 (RQ1): Can wake-up radio mechanism integrated at MAC layer meet the QoS requirements of IBSN applications and still achieve highly energy-efficient wireless communication?

RQ2: Can the dynamicity information of narrow-band physical channel be leveraged at the MAC layer to improve reliability of wireless communication while achieving high energy-efficiency?

RQ3: Can the context-awareness of the physiological signals in IBSN help improve the reliability and QoS parameters of wireless communication between the heterogeneous sensor nodes, while achieving high energy-efficiency?

RQ4: Can the resource-constrained IBSN sensor nodes use complex signal processing and machine learning algorithms to optimize the QoS requirements of the wireless communication between the heterogeneous and dynamic sensor nodes and still be able to meet reliability requirements while achieving high energy-efficiency?

1.4.1 PROPOSED HYPOTHESIS

To answer the main research question, we start to answer the sub research questions with the following hypotheses.

To answer RQ1 we propose,

HYPOTHESIS 1 (H1): It is possible to achieve high energy-efficiency by using WuR at MAC layer while operating at Medical Implant Communication Service (MICS) frequency band. Adaptive duty-cycle and intelligent relay-establishment with strategically integrated WuR and main radio can significantly reduce the power consumption without affecting QoS requirements of wireless communication in IBSN.

To answer RQ2 and RQ3 we propose,

HYPOTHESIS 2 (H2): Physiological signals processing to enable quality awareness

for the IBSN sensor nodes, use of machine-learning techniques to optimize cross-layer MAC and routing protocol, will address the dynamicity and heterogeneity challenges of the IBSN while meeting the QoS requirements. High energy-efficiency can be achieved by integrating the WuR mechanism at the MAC layer on top of the context awareness and cross-layer optimization.

To answer RQ4 we propose,

HYPOTHESIS 3 (H3): Complex signal processing algorithms can run on the resource constrained IBSN sensor nodes, if properly distributed among the power-surplus sensor nodes. Machine learning algorithms have to be modified in such a way that resource consuming *training* process must be done offline, while *detection or prediction* process can easily be implemented on the resource constrained IBSN sensor nodes.

1.5 CONTRIBUTIONS

In view of the earlier mentioned research objectives, the main contribution of this thesis can be listed as the following:

CONTRIBUTION 1: CHARACTERIZING THE PHY AND WUR BASED MAC FOR IBSN

Medical application requirement of IBSN have diverse characteristics when compared to the generic application requirements of Body Sensor Networks (BSN). Use of WuR have significantly improved energy-efficiency in generic applications of the traditional WSN.

However, the impact of WuR in PHY and MAC layers of the IBSN is not yet clear. In this thesis we at first discuss different network quality metrics, in terms of reliability and QoS parameters, for variety of medical applications of IBSN and characterize the PHY and MAC for these metrics with and without the impact of WuR. This contribution has appeared in [14, 17, 18]:

[14] V. R. K. Ramachandran, B. J. van der Zwaag, N. Meratnia, and P. J. Havinga, "Evaluation of MAC protocols with wake-up radio for implantable body sensor networks," *Procedia Computer Science*, vol. 40, pp. 173 – 180, 2014, fourth International Conference on Selected Topics in Mobile & Wireless Networking (MoWNet 2014)

[17] V. R. K. Ramachandran, B. J. van der Zwaag, N. Meratnia, and P. J. M. Havinga, "Implantable body sensor network MAC protocols using wake-up radio - Evaluation in animal tissue," in *Proceedings of the 9th International Symposium on Medical Information and Communication Technology (ISMICT)*, March 2015, pp. 88–92

[18] V. R. K. Ramachandran, N. Meratnia, K. Zhang, and P. J. M. Havinga, "Towards implantable body sensor networks - performance of mics band radio communication

in animal tissue,” in *Proceedings of the 10th EAI International Conference on Body Area Networks, BODYNETS 2015, Sydney, Australia*. New York: ACM, September 2015

CONTRIBUTION 2: WUR BASED BIO-INSPIRED WIRELESS COMMUNICATION MECHANISM FOR DYNAMIC IBSN

Chronic care is an eminent application of IBSN. Performing physical activities such as walking, running, and sitting is unavoidable during the long-term monitoring of chronic-care patients. These physical activities cripple the radio frequency (RF) signal between the implanted sensor nodes.

This is because various body postures shadow the RF signal. Although shadowing itself may be short, a prolonged activity will dynamically increase the effect of the RF-shadowing. This effect dampens the communication between implantable sensor nodes and hence reduces the reliability of the IBSN.

To overcome this problem, in this contribution we present a WuR based wireless communication mechanism inspired from the disruption pattern of these activities in the RF link quality. This contribution has appeared in [19]:

[19] V. R. K. Ramachandran, P. J. M. Havinga, and N. Meratnia, “Hacmac: A reliable human activity-based medium access control for implantable body sensor networks,” in *Proceedings of the 13th International Conference on Wearable and Implantable Body Sensor Networks, BSN 2016, California, U.S.A.*, 2016

CONTRIBUTION 3: REINFORCEMENT LEARNING BASED OPTIMIZATION OF BIO-INSPIRED WIRELESS COMMUNICATION MECHANISM TO SUPPORT DYNAMICITY OF IBSN

Although we were able to estimate the RF disruption pattern for simple activities in a controlled environment, in real-world, there can be a number of disruption patterns for the same activity performed by the same person at different points of time and places.

In this contribution, we will explore reinforcement learning approach [20] to optimize the MAC protocol by defining the disruption as a stochastic process with Markov property. With this optimization method, the resource constrained IBSN nodes need not detect each and every disruption pattern of various activities, but optimize the communication protocol in such a way that reliability and QoS is achieved with minimal energy-expenditure. Further optimization is achieved by adding an WuR mechanism on top of the optimized communication mechanism to achieve much higher energy-efficiency. This contribution has appeared in [21]:

[21] V. R. K. Ramachandran, Le Viet Duc, N. Meratnia, and P. J. M. Havinga, “Dinamac: A disruption tolerant, reinforcement learning-based mac protocol for implantable body sensor networks,” in *Proceedings of the 3rd IEEE International Conference on Internet of People, IOP 2017, California, U.S.A.* IEEE Computer Society, 2017

CONTRIBUTION 4: CONTEXT-AWARE WIRELESS COMMUNICATION FOR IBSN - AN ADAPTIVE ACTIVE-LEARNING BASED APPROACH FOR SEIZURE

PREDICTION IN EPILEPTIC USE-CASE UNDER IBSN FRAMEWORK

A context-aware wireless communication, to address the heterogeneity in bio-sensors, by enabling on-node processing of bio-signals and incorporating the signal processing within wireless communication framework.

We presented an active learning based approach for seizure prediction in epileptic use-case for a closed-loop medical application of DBS therapy for epileptic patients. This contribution is under review in [22]:

[22] V. R. Karuppiah Ramachandran, Huibert J. Alblas, Le Viet Duc, and N. Meratnia, "Towards an online seizure advisory system—an adaptive seizure prediction framework using active learning heuristics," *Sensors (Switzerland)*, vol. 18, 2018

CONTRIBUTION 5: RESOURCE CONSUMPTION ANALYSIS OF OPTIMIZATION FRAMEWORKS FOR WIRELESS COMMUNICATION IN IBSN

In this contribution we present an wireless communication framework for the resource constrained IBSN nodes, where our main focus is on evaluating the time, memory and power consumption of various signal processing, machine learning blocks, and additional adaptation mechanisms needed for wireless communication.

We evaluate the power consumption and performance analysis of the newly developed communication and signal processing schemes in a commercially available off-the-shelf hardware for epileptic use-case. Also, we present an overview of the communication schemes in an architectural framework from an hardware perspective.

1.6 ORGANIZATION OF THE THESIS

The remainder of this thesis is organized as follows. Chapter 2 presents the state-of-the-art communication mechanisms that are suitable for IBSN. Chapter 3 characterizes the PHY and WuR based MAC layer of IBSN for various medical applications. Chapter 4 presents the bio-inspired design of communication mechanism for IBSN.

Linked to this, Chapter 5 presents the reinforcement learning based optimization approach of the bio-inspired communication mechanism. The design of quality aware communication mechanism for IBSN to an epileptic use-case is presented in Chapter 6. Followed by an hardware perspective of the overall communication framework in Chapter 7. Finally, Chapter 8 concludes this thesis with a summary and by outlining future research directions. The overall organization of the thesis is shown in Figure 1.3.

Figure 1.3: Thesis organization

MEDIUM ACCESS CONTROL FOR IBSN - A SURVEY

M^{EDIUM} access control (MAC) is crucial to make it possible for several medical devices to communicate using a shared wireless medium in such a way that minimum delay, maximum throughput and long network life-time are guaranteed. MAC protocols designed for implantable devices are still in their infancy and one of their most challenging objectives is to have ultra-low-power consumption. One of the technological solutions to achieve this objective is to integrate the concept of WuR into the MAC design. In this chapter, we present a taxonomy of MAC protocols based on their use of WuR technology and identify their bottlenecks for IBSN applications.

செய்வினை செய்வான் செயன்முறை அவ்வினை
உள்ளறிவான் உள்ளம் கொளல்.

*Who would succeed must thus begin: first let him ask
The thoughts of them who thoroughly know the task.*

—Thiruvalluvar in Kural 677

2.1 INTRODUCTION

Wireless communication between medical sensors and implantable medical devices is essential in the case of IBSN, in which symptoms of the diseases are monitored by sensors that are not placed in close proximity of the therapeutic device. MAC is crucial to make it possible for several medical devices to communicate using a shared wireless medium in such a way that minimum delay, maximum throughput, and long network life-time are guaranteed. To guarantee QoS parameters, the MAC protocols control the main sources of limited resource wastage, namely the idle-listening, packet collisions, over-hearing, and packet loss.

Traditional MAC protocols are not directly applicable to IBSN because of the dynamic nature of the radio channel within the human body and the strict QoS requirements of IBSN applications. Although numerous MAC protocols are available in the literature, the majority of them are designed for BSN and WSN.

Similar to other low-power sensor networks, wireless communication in IBSN suffers from three main problems, which not only affect the power consumption of sensor nodes but also reliability and quality-of-service of wireless communication inside and around the body. These main problems are: (i) idle listening which occurs when the node listens for data-packets while no data-packets are being sent; (ii) overhearing, which occurs when the node is listening to data-packets which are not destined for it; and (iii) packet collision, which occurs when two nodes compete to transfer at the same time through the same channel.

In general, MAC protocols are designed to reduce these problems by regulating the access to the wireless medium. In the case of IBSN, major challenges are faced. For example signal attenuation due to the dynamic movements of the human body, very high attenuation of signals due to the conductive nature of the human tissues, and heterogeneous requirements of different devices that are present in the network.

MAC protocols designed for implantable devices are still in their infancy and one of their most challenging objectives is to be ultra-low-power. One of the technological solutions to achieve this objective so is to integrate the concept of WuR into the MAC design.

The rest of this chapter is organized as follows. We first explain the challenges and requirements of MAC protocols for IBSN in Section 2.2, elucidate its difference from conventional MAC protocols. In Section 2.3, we present the traditional medium access mechanisms and their working principle concerning the IBSN. In Section 2.4, we categorize the existing MAC mechanisms based on their use of wake-up radio and present a taxonomy followed by a comparison between the access mechanism in the classified order. An evaluation of MAC protocols based on the requirements

Part of this chapter has appeared in :
[23]. V. R. Karuppiiah Ramachandran, E. D. Ayele, N. Meratnia, and P. J. M. Havinga, "Potential of wake-up radio-based mac protocols for implantable body sensor networks (ibsn)—a survey," *Sensors (Switzerland)*, vol. 16, 2016

of IBSN is presented in Section 2.4.4. Eventually, we present the open research challenges in designing MAC protocols for IBSN in Section 2.5, then followed by a concluding remark from our study is included in Section 2.6.

2.2 DESIGN CHALLENGES OF MEDIUM ACCESS CONTROL (MAC) IN IBSN

The fundamental task of a MAC protocol is to avoid collision of data packets and to prevent simultaneous transmissions while preserving maximum throughput, minimum latency, communication reliability and maximum energy efficiency [24]. The design of an efficient MAC protocol for IBSN faces a number of challenges, such as interoperability, scalability, QoS, and energy efficient communication.

There are various low-power techniques, such as the fixed duty cycling technique in SMAC [24] and adaptive wake-up slots in TDMA [25] to ensure energy efficient communication in a wireless sensor network. They are, however, not energy-efficient for heterogeneous IBSN and will not suffice. Unlike the supported scenarios by SMAC, the traffic characteristics in a IBSN vary from periodic to non-periodic and vice-versa [14]. Therefore, the concept of the fixed duty cycling technique gives limited answers when it comes to the heterogeneous behavior of autonomous sensor nodes in a IBSN.

The dynamic nature of these nodes does not allow synchronized periodic wake-up periods. Data from some of the sensor nodes, for instance, electrocardiogram (ECG), may be set at a several packets per second to the coordinator, while others such as blood-glucose sensor may send a packet twice a day. Nodes should also have the capabilities to sense and transmit emergency information. The data traffic in IBSN is either normal, on-demand, or burst.

QoS is also an important factor representing a good MAC protocol. In medical applications, a latency of only 125 ms is allowed, whereas in consumer electronics latency can be less than 250 ms [26]. Other important features include adaptability to a dynamic physical medium, maximum achievable throughput in different network scenarios, low jitter in heterogeneous traffic, efficient bandwidth utilization with high payload, safety and security.

Table 2.1 presents major features of MAC protocols for IBSN and their values suggested by the IEEE 802.15.6 [15]. In general, a good BSN MAC protocol should be energy-efficient, reliable even in the presence of heterogeneous traffic, safe and secure, in addition to being QoS-aware [28].

The closed-loop mode of operation of medical devices does not only require these features but also additional features, such as ability to intelligently access the medium in case of emergency events, establishing reliable and low latency communication between nodes and medical devices, and ability to respond quickly within the specific time-frame for a given medical device.

Features	Acceptable value for Implanted medical devices
Throughput	upto 200 kB/s for medical devices upto 4 MB/s for non-medical devices
Latency	upto 100ms in life critical implants upto 2 seconds in monitoring medical devices
Bandwidth	300 kHz MICS band 100MHz in 2.4GHz ISM band 1.74 MHz in 433 MHz ISM band
Duty cycling	less than 0.01 % in MICS band medical devices (no restriction if Listen before talk is incorporated)
Interference mitigation	Cyclic redundancy check, Forward error correction, frequency agility

Table 2.1: Features of MAC protocols as suggested by IEEE 802.15 TG 6 for IBSN [27]

The features of the MAC protocol specified by the IEEE 802.15 TG-6 are common for the in-body and on-body BSNs, however they need to be better specified to suit the requirements of closed-loop medical devices.

In what follows, we describe the main design challenges of MAC protocols for IBSN.

2.2.1 ENERGY CONSTRAINED NODES

To deliver the levels of comfort and unobtrusiveness required for widespread adoption, IBSN sensor nodes must be small and have energy sources that last for months and years, depending on the application. The size requirement obviously limits the size of the batteries that will power the nodes (energy scavenging is another option, but the amount of power available from such techniques is relatively small), so IBSN nodes must be extremely efficient in their energy usage.

IEEE 802.15.6 standard recommends a star topology, in which the coordinator node is rechargeable and is placed outside the body. Most of network management activities such as time slot allocation, routing information, and prioritization are performed by the coordinator node. By doing so, energy wastage due to performing such management overheads by the client nodes is minimized.

However, in some of the closed-loop applications of IBSN, the implanted client nodes are also responsible for such management activities in order to provide high reliability [14]. Furthermore, energy efficiency can be increased by mechanisms that allow sensor nodes to enter a low-power sleep mode for a long time (several beacon

periods) before transmitting/receiving. Low power wake-up radios are required to achieve such long sleep duration without affecting the reliability.

2.2.2 DYNAMICITY

The wireless link between two nodes in IBSN is highly deteriorated by the conductive human tissues and dynamic human activities. Reliability must be ensured in wireless communication where the ratio between the number of successful reception of packets and number of packets transmitted between two nodes, must be always high.

The MAC protocol should have additional mechanisms such as acknowledgement schemes, and beacon synchronization schemes to overcome the dynamic link quality and to increase the reliability [29]. Enhanced reliability, such as integrity and authenticity of the data packets, is achieved by adding redundant information bits in the form of cyclic redundancy check (FCS) and message integrity code (MIC) in IEEE 802.15.6 standard. Thus, there is generally a trade-off between a higher reliability and throughput.

Priority nodes sending medical data should be ensured of reliability as it contains life-critical information in IBSN. An efficient MAC protocol will have an optimum reliability by adapting to the application scenarios and the context of data.

2.2.3 ADMINISTRATIVE OVERHEADS

Prior to communication of useful data, the sensor nodes need to exchange the management packets between each other. The efficient management of packets will ensure that all sensor nodes are aware of other sensor node's resources, schedules of transmission and reception, channel availability information and general information about useful data packets that are to be transmitted.

Management of packets not only creates overheads but also increases the active duty cycle of the sensor nodes. IEEE 802.15.6 requires large range of duty cycle: from 0.1% to 30%. Medium access mechanisms need to be adaptive in terms of their management, access, and communication strategies to meet the duty cycle requirements of variety of medical devices. It is important to note that the duty cycle is set by the spectrum regulating institutions, which limits the duty-cycle of MICS band to 0.01% i.e. approximately 36 seconds of access to the medium in an hour [15].

Alternatively, the regulations allow the nodes to communicate with a *listen-before-talk* mechanism, preventing the nodes to communicate if the physical medium is already occupied by some other device. In this aspect, the amount of overhead data required for link and network management should be minimal and not higher than actual useful data to be transmitted or received.

2.2.4 HETEROGENEITY AND THROUGHPUT

Although flat-fading and inter-symbol interference from multi-path are insignificant in MICS frequency band, low power transmission, dynamic link quality due to human activities deteriorate the effective throughput of the network. Heterogeneous medical devices in IBSN demand dynamic throughput for different applications. For example, a EEG sensor requires much larger throughput (i.e., in the orders of 150 kB/s), where as glucose sensors require much lower throughput (e.g. in the orders of 30 kB/s).

Network throughput is measured by average number of received data bits per seconds. Packets can be lost due to loss of connectivity or collisions among others. In MICS band, the radio channel has been shown to have essentially slow data-rate.

MAC protocols should be able to operate efficiently despite the restrictions set by the spectrum regulations and at the same time meet the dynamic requirements of heterogeneous sensor nodes. Existing MAC protocols are not specifically designed to address such complex application scenarios.

2.2.5 LATENCY

Latency is the delay between sending and receiving data across any two nodes. A heterogeneous IBSN has different medical applications that put a wide range of latency requirements. For example, in case of DBS applications, 100 ms of latency is strictly required. Whereas in long term monitoring applications such as cardiac monitoring, latency upto 1 second is tolerated.

The latency is to be increased when the data is hopped through a relay node between transmitter and receiver. However, IEEE 802.15.6 suggests that the relay node should account for achieving the overall latency of the communication.

A MAC protocol is required to accommodate the relay node and also should be able achieve the latency required by the medical application. For life-critical medical nodes, to achieving both energy efficiency maximization and latency minimization is difficult. A complementary solution needs to be developed instead of resorting only to the regular MAC frame structure.

2.2.6 HARDWARE COMPLEXITY

IBSN sensor nodes have much lesser resources than conventional sensor networks due to their strict size restrictions and bio-compatibility. In such cases, introducing additional hardware only to increase the performance of wireless communication is not an option.

However, with the advent of nano-technology and system-on-chip design, addition of minimal hardware components such as a wake-radio has been made possible without increasing the total surface area of the chip itself [30].

Although the addition of minimal hardware is a viable option, it will have consequences in terms of energy consumption and may even affect performance of the wireless communication.

2.3 MEDIUM ACCESS MECHANISMS RECOMMENDED FOR IBSN

The MAC protocols applicable to IBSN are broadly divided into the following categories:

- Time Division Multiple Access Mechanisms (TDMA)
- Carrier Sense Multiple Access Mechanisms (CSMA)
- Hybrid Access Mechanisms
- Random Access Mechanisms

Each access mechanism has its own advantages and disadvantages. The basic principle of each mechanism is further explained below.

2.3.1 TIME DIVISION MULTIPLE ACCESS (TDMA)

The scheduled access mechanism of the physical medium is carried out either by scheduling the content or carrier. In TDMA-based approaches, scheduled access is carried out by synchronizing all nodes in the network to a specific time-frame and allocating a scheduled time slot for each sensor node.

The advantage of this method is enabling collision-free communication due to time schedules being set up. This will reduce the power consumption and increase the throughput of the network. However, the time schedule needs an accurate time synchronization between the nodes. A deviation in the synchronization will cause the network to operate less efficiently or sometimes even fail to operate.

TDMA is considered to be a suitable candidate for the IBSN for the following reasons:

- Time synchronization is less complex due to the smaller size of the IBSN compared to other WSN applications.
- The star topology is preferred for IBSN where a central network controller (CNC) is always present outside the body in close proximity of the network. This enables simpler coordination between the nodes.
- Collision avoidance is easier with low power consumption.

2.3.2 CARRIER SENSE MULTIPLE ACCESS (CSMA)

The random access of the physical medium is carried out by Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA). In contrast to the IEEE 802.3 standard, which uses collision detection, the IEEE 802.15 (wireless medium) standard uses collision avoidance in order to save some power.

The collision avoidance is performed by setting a back-off counter to a random integer in the range of the maximum allowed contention window (CW), uniformly distributed over the interval $[1, CW]$ where $CW \in (CW_{min}, CW_{max})$. Performance of CSMA/CA in terms of throughput and latency depends largely on the number of sensor nodes present in a network and the amount of data being communicated.

If a node has a large amount of data, it uses the physical channel to send the data, consequently preventing other nodes from gaining access to the medium. This can result in very low reliability for the nodes trying to send high priority medical data. Also, most of the energy is wasted in idle listening, as the nodes have to listen to the medium for the data packets destined for them.

A pure CSMA/CA technique has several limitations, including high energy consumption, high latency, and very low reliability. However, various hybrid CSMA/CA protocols have been developed for BSN applications including health monitoring. Performance of these hybrid CSMA/CA protocols can be improved by incorporating techniques such as scheduling the random access in dedicated time-slots, prioritizing the sensor nodes, and incorporating WuR to wake-up specific sensor nodes before sending data.

2.3.3 HYBRID ACCESS

The hybrid access mechanism uses CSMA for non-realtime data communication and TDMA for real-time data communication. The data is sent in time-slots based on the priority of the nodes generating data.

The time slots can be set depending on the application. The main disadvantages of the hybrid access protocols are resource exhaustion of the client nodes, high energy consumption, and longer beacon-periods for the dynamic allocation of time-slots.

Frequency Division Multiple Access (FDMA) is a complex hybrid access mechanism, in which a full frame of frequency band is made available for communication. This results in the continuous flow of data between the sensor nodes, which improves efficiency of transmission.

In FDMA, each channel is assigned to only one node at a time. Each node shares a channel simultaneously, though transmits at single frequency. FDMA is used with both analog and digital signals [31]. It requires high-performing filters in radio hardware, in contrast to TDMA and CSMA. As each node is separated by its frequency, minimization of interference between nodes is done by sharp filters.

ALOHA is a random access technique in which, whenever a packet is generated, it is transmitted immediately without any further delay. Successful reception of a packet depends only on whether it is collided or not with other packets. At the end of packet transmission, each user knows whether its transmission has been successful or not. If collision occurs, the user schedules its re-transmission to a random time. The randomness is to ensure that the same packets do not collide repeatedly. In the ALOHA technique, the node checks for the availability of data packets to be transmitted. If they are available, then the node transmits them, otherwise the process ends.

Slotted ALOHA is a variant of Pure ALOHA with a channel that is divided into slots. Restriction is imposed on users to start transmission on slot boundaries only. Whenever packets collide, they overlap completely instead of partially. So only a fraction of slots in which the packet is collided is scheduled for re-transmission. It almost doubles the efficiency of slotted ALOHA as compared to pure ALOHA. Successful transmission depends on the condition that only one packet is transmitted in each frame. If no packet is transmitted in a slot, then the slot is idle. Slotted Aloha requires synchronization between nodes which lead to its disadvantage.

The hybrid access is not optimized in terms of energy efficiency but it is optimized in terms of high throughput and reliable packet delivery.

2.3.4 ADAPTIVE LEARNING BASED ACCESS MECHANISMS

Adaptive learning based access mechanisms are improvised hybrid access mechanisms, which are adaptive to the dynamic changes of the system. The underlying working principle of them is based on either contention-free access, contention-based access or both. Unlike hybrid access mechanisms, adaptive access mechanisms incorporate learning techniques to adapt the underlying access mechanisms, based on continuous feedback from the system.

For example, consider a simple frame-based contention access mechanism, in which each node determines its own wake-up schedule based on the real-time requirements of the node. Such a non-fixed adaptive duty-cycle not only improves energy-efficiency, but also improves network performances over time. The node learns about the flow of data over time, and using learning algorithms, the node can teach itself to derive an optimum schedule of duty-cycles.

Also, in the case of IBSN, the dynamicity in the flow of data can be handled easily with adaptive access mechanisms. However, these adaptive access mechanisms are still in their infancy, where learning algorithms require large memory and computing power to operate. In IBSN, the amount of resources is stringent, which widely limited its direct application in MAC protocols for IBSN.

2.4 TAXONOMY OF MAC PROTOCOLS FOR IBSN

2.4.1 IMPACT OF WAKE-UP RADIO ON THE DESIGN OF MAC

In the last decade, the concept of ultra-low-power WuR [32] was introduced. Schematic architecture of the sensor node with WuR is shown in Figure 2.1. WuR operates together with the main radio with much lower power consumption than the main radio.

The WuR reduces the energy consumption of wireless communication by switching the main radio to deep-sleep mode when no data is transmitted or received. It is operated with different duty-cycles and yields a good power budget for the sensor nodes. The WuR can either operate in the same band of the main radio or in a different band.

Figure 2.1: Common architecture of a sensor node with wake-up radio

Different innovative WuR designs already exist, which operate in the power range of nanowatts [30]. It has been shown that WuR reduces the overall power consumption of wireless communication in sensor nodes, provided that the duty-cycle of main radio is carefully selected and synchronized with the duty-cycle of the WuR [33].

The main features of WuR to make it as a suitable technology for MAC protocols of IBSN are its low power consumption, reliable performance in short-range networks, ability to operate out-of-band with main radio, and not requiring complex hardware [34].

By turning the main radio on when it is really needed, WuR limits the power consumed by the main radio for idle listening along with the over-hearing problems preventing data collision from occurring. The data communication is then initiated and completed using the main radio, reducing the total amount of time that the main radio is turned on.

The WuR of the transmitter broadcasts a node-id encoded wake-up signal, which is acknowledged by the WuR of the destined node, indicating that the main radio of the receiver node is actively listening. The main radio of the transmitter is turned on only when the acknowledgment is received for the wake-up signal, hence reducing energy consumption and increasing reliability.

Although WuR based MAC protocols have proven to reduce power consumption without reducing the QoS of the wireless communication, direct application of these protocols is severely limited due to the strict requirements of IBSN.

Figure 2.2: Taxonomy of MAC protocols based on their use of wake-up radio technology

The IEEE 802.15.6 standard suggests the use of WuR-based communication in medical implants. In this context, we classify the existing MAC protocols based on their use of WuR technology. The taxonomy of the access mechanisms based on their use of WuR technology is presented in Figure 2.2.

One should note that, to the best of our knowledge, no MAC protocol has been so far designed specifically for IBSN. However, some of the crucial techniques used in these protocols, such as adaptive sleep mode, and cross-layered access control may meet the requirements of IBSN. Therefore, after providing a brief introduction to them, we study their applicability for IBSN and their ability to meet IBSN requirements. Tables 2.2–2.6 present our analysis of the advantages and disadvantages of these protocols for IBSN applications.

2.4.2 MAC PROTOCOLS WITHOUT WuR

MAC protocols that do not make use of WuR can be classified into the following groups:

2.4.2.1 TDMA-BASED MAC PROTOCOLS FOR IBSN

Marinkovic et. al [35] present an energy-efficient low duty-cycle MAC protocol that enables access to the physical layer for a hierarchical topology consisting of nodes communicating with master nodes, which in turn communicate with the monitoring station. The hierarchy removes the need for sensors to expend power by transmitting to the monitoring station. Also the use of TDMA ensures collision-free transfer and minimization of idle-listening. The protocol is implemented using the Analog Devices 70XMBZ2 platform with ADF7020 RF transceivers. Measurements reveal that the protocol is energy-efficient for streaming and short burst data communications.

A novel TDMA-based protocol called H-MAC, is presented in [36]. This protocol improves energy-efficiency by using the heartbeat rhythm to perform TDMA synchronization, avoiding energy consumption associated with transmitting time synchronization beacons. Power efficiency is also guaranteed in H-MAC as a TDMA-based protocol assigns time slots to each bio-sensor to guarantee collision-free transmission. Simulations show that H-MAC prolongs the network life of sensors dramatically.

In [37], a TDMA-based MAC protocol called BodyMAC is proposed. Three types of bandwidth allocation schemes are devised to cope with different types of data communications, such as periodic data sensing and important event allocation. In conjunction with bandwidth allocation, a sleep mode mechanism is introduced, which turns off a node's radio during beacon, up-link and down-link periods, as much as possible. Simulations results show superior performance of BodyMAC compared to that of IEEE 802.15.4 MAC.

Timmons et. al [28] introduce an adaptive TDMA-based MAC protocol called MedMAC, which incorporates a novel adaptive TDMA synchronization mechanism in which only a multi-superframe beacon has to be listened to by the nodes. An optional contention period is also available for low-grade data, emergency operation and network initialization procedures. Simulations show that MedMAC consumes less power than IEEE 802.15.4 for two classes of medical applications.

In [42] a power efficient MAC protocol is proposed. This work presented a traffic based wake-up mechanism that utilizes the three categories of traffic patterns of the body sensor nodes, namely: normal traffic, on-demand traffic and emergency traffic. The wake-up patterns of all body sensor nodes are organized into a table called traffic-based wake-up table. The table is maintained and modified by a network coordinator according to the application requirements. Based on the body sensor node's wake-up patterns, the network coordinator can also calculate its own wake-up pattern. During normal traffic, both the body sensor nodes and the network coordinator send data based on the traffic-based wake-up table.

A MAC protocol for static BAN is introduced in [39]. A Master Node (MN) collects data from on body nodes and communicates with a Monitoring Station (MS). Received data is being analysed by MS while the on-body network coordination and

protocol	Description	Special feature	Potential drawback
LD-TDMA [35]	Low duty cycle TDMA	2.04 mW at 3 VDC using COTS transceiver. Power consumption is least compared to other protocols.	High latency in the event of a packet failure. Requires accurate synchronization
HDMAC-TDMA [38]	Heartbeat rhythm synchronized TDMA	Increased network lifetime by 15%-300% more than other similar BSN MAC	Suffers from severe single-point of failure problem. No accurate heart rhythm is measured all-over the body, hence use of network coordinator is necessary trading off with energy-efficiency and band-width efficiency.
CF-MAC [39]	Contention-free MAC protocol	Self-stabilizing and does not require a global time reference. The protocol will auto-stabilize for any network change	Cannot handle collision effectively, specially when a new node joins the network. Performance is severely affected on the event of change in network topology
SSD-TDMA [40]	Self-Stabilizing Deterministic TDMA	Energy efficient performance. Self stabilizing in case of dynamic data variations. Can support changes in network topology. Novel two layer approach for data-link creation.	Any slight violation in the assumptions made for the protocol will deviate the performance drastically. Cluster time synchronization is needed, directly proportioning to the performance. Some of the assumptions made cannot be met in real-world implementation
HEH-MAC [36]	Human Energy harvesting MAC	Provides priority differentiation to the sensor nodes and flexibility to the network. Highly adaptive to environmental changes. Energy harvesting rates, network size and packet inter-arrival times are dynamically adapted within the protocol	Throughput, and other QoS parameters are not analyzed and presented. Suffers from global time synchronization issues, failing of which severely hinders the network parameters.
PB-TDMA [41]	Preamble-Based TDMA	Heterogeneous support for dynamic data. Can provide real time guarantee. Very low energy consumption, yet less latency and high throughput is provided.	QoS depends on the preamble and time synchronization.
BodyMAC [37]	Energy efficient TDMA based BSN MAC	BodyMAC uses flexible and efficient bandwidth allocation schemes with dynamic sleep mode.Supports dynamic applications in IBSN . Better performance in terms of the end- to-end packet delay and energy saving	No implementation is done. Results are based on software simulation. Highly accurate global synchronization is required.

Table 2.2: TDMA-based MAC protocols without WuR and their drawback for IBSN

synchronization is being performed by MN. Time slots S1 to Sn are allocated to sensor nodes while time slots RS1 to RS2 are reserved which are being assigned when requested. Number of these extra time slots depends upon targeted packet drop, packet error rate and number of sensor nodes.

2.4.2.2 CSMA-BASED MAC PROTOCOLS FOR IBSN

Authors in [43] presented B-MAC protocol which renders typical properties of a IBSN such as simple implementation on hardware and tolerance to network changes. B-MAC implements asynchronous access mechanism similar to X-MAC. B-MAC has relatively high reliable data packet delivery ratio of 98.5% [44]. B-MAC could be optimized for star topology. However, B-MAC also suffers from hardware constraints such as memory and computational overhead.

In [49], Huq et al. present MEB-MAC, which focuses on the channel access delay reduction for medical emergency traffic with high reliability. No energy efficiency is concerned in implementation and analysis. It has adverse effect on new node insertion and mobility of network.

An energy efficient MAC protocol called O-MAC is presented in [50]. O-MAC has achieved increased energy efficiency by novel receiver scheduling methods such as Staggered On and Pseudo-randomized Staggered On. Theoretical analysis and practical implementation reveals that the protocol is 70% energy efficient than B-MAC, S-MAC and T-MAC.

The CSMA-based MAC protocol presented in [48] is called DISSense. A good analysis of MAC problems in different typologies and the benefits of cross layer optimization are addressed in this paper. Features such as data delivery ratio, latency, duty cycling and adaptability are better than other similar protocols. DISSense can achieve good QoS in small scale networks and proportionately increase with network size. However, the performance of DISSense is traded off with energy consumption. No clear analysis of energy-efficiency is carried out though.

2.4.2.3 HYBRID ACCESS BASED MAC PROTOCOLS FOR IBSN

Otal et. al [51] proposed an energy-saving MAC protocol, called DQBAN as an add-on to the 802.15.6 MAC protocol which suffers from low reliability and limited QoS in real-time environments. The proposed DQBAN is a combination of a cross-layer fuzzy-logic scheduler and energy-aware radio-activation policies. The queuing of access packets and data packets is determined by fuzzy-logic rules, which permit body sensors to find out 'how favorable' or 'how critical' their situation is in a given time-frame.

The logic scheduling MAC protocol optimizing QoS and energy consumption by considering cross-layer parameters such as residual battery lifetime, physical layer quality and system wait time is presented. The authors tested their proposed protocol on two scenarios: a homogeneous scenario of a body sensor network with 5–35

Protocol	Description	Special feature	Potential drawback
CA-MAC [46]	Context Adaptive MAC Protocol	CA-MAC is a novel approach of using a threshold value for deciding whether the packets are transmitted or not, based on the distance to the sink node. Energy efficient implementation for small scale dynamic network topology is achieved with CA-MAC. Latency is reduced by a novel adaptive algorithm based on the context of the packets.	Computational complexity is higher which is a threat to smaller resource constraint nodes and long term network operation. Evaluation of the protocol is limited with theoretical data and ideal assumptions.
PNP-MAC [46]	Preemptive slot allocation and Non-Preemptive transmission MAC	Supports various types of traffics: continuous streaming, periodic data, time-critical emergency alarm, as well as non-periodic data. Highly reliable QoS support. Novel combination of contention-free and contention access mechanisms.	Suffers from severe resource exhaustion. Energy consumption is not considered as a criteria for design. QoS will be traded off with energy efficiency and dynamic network topology.
ULP-MAC [38]	An Ultra-low-power Medium Access Control Protocol for Body Sensor Network	A cross layer design strategy is adopted. Network coordinator and the sensors interact to achieve efficient power management. Variable super-frame structure is adapted. IBSN coordinator can make dynamic adjustment based on the feedback to achieve better performance in energy efficiency and latency.	Optimized for star topology. Suffers from hardware constraints such as memory and real-time guarantee. Simulation is carried out with ideal network conditions.
B-MAC [43]	Berkeley-MAC Versatile Power MAC protocol	BMAC renders properties of IBSN such as simple implementation on hardware, predictable performance parameters, and tolerance to network changes. Highly reliable data packet deliver of 98.5%	Very well suited for star topology networks. In case of change in network topology the protocol hinders performance[44]. Energy efficiency can only be expected when interfaced with different services resulting in cross-layer optimization.
X-MAC [47]	Short Preamble MAC Protocol for Duty-Cycled Wireless Sensor Networks	Low power communication is deployed by a strobed preamble approach that transmits a series of short preamble packets to the target receiver. Truncation the preamble by the target receiver saves energy at both the transmitter and receiver and introduce lower latency [44]. Near-optimal sleep and listen periods are demonstrated. X-MAC out-performs traditional Low-power listening techniques such B-MAC.	High latency in the event of a packet failure.
DISSense [48]	An adaptive, Ultra low-power MAC protocol	Cross layer optimization issues are considered. Features such as data delivery ratio, latency, duty cycling and adaptability are better than other similar protocols. Can achieve good QoS in small scale networks.	Performance is traded off with energy consumption. No clear analysis of energy-efficiency is carried out. Designed for the purpose of large scale and coverage networks.
MEB-MAC [49]	Medical Emergency Body (MEB) MAC	MEB-MAC focuses on the channel access delay reduction for medical emergency traffic with high reliability.	Implementation is done in real-world scenarios. However, no energy efficiency is concerned. It has adverse effect on new node insertion and mobility of network
O-MAC [50]	Ohio State University, Ohio-MAC	Increased energy efficiency by novel receiver scheduling methods such as Staggered On and Pseudo-randomized Staggered On. Theoretical analysis and practical implementation reveals that the protocol is 70% energy efficient than B-MAC, S-MAC and T-MAC.	QoS is not considered, parameters such as latency and throughput are not evaluated.

Table 2.3: CSMA-based MAC protocols without WuR and their drawback for IBSN

homogeneous ECG wireless sensors and a heterogeneous scenario of a body sensor network with wireless ECG sensors and four other sensors for clinical doctor PDA, respiratory rate, blood pressure and endoscope imaging.

In [52], the authors proposed the use of a UWB transmitter for energy-efficient operation of WBANs. Due to the high interference generated by the human body and its environment, one solution to develop low power-output transceivers for radios in the sensor nodes is to optimize the air interface of the network. By creating architectures that exploit features of robust nodes and energy-constrained nodes, low latency and simple network topologies, the authors show that an UWB based architecture is advantageous over narrowband radio communication.

In [38], the slotted ALOHA is employed in the contention access period (CAP) to request the slot allocation. Mini-slot method is designed to enhance the efficiency of the contention. Moreover, sufficient slot allocation in the contention free period (CFP) enables, adaptability to different traffic load conditions.

2.4.2.4 ADAPTIVE LEARNING BASED MAC PROTOCOLS FOR IBSN

Galzarano et al. [53] proposed an adaptive access mechanism called QL-MAC based on the Q-learning technique. In QL-MAC, a simple asynchronous CSMA-CA approach is employed over a frame-based structure. It basically divides the time into discrete time units, i.e., the frames, which are further divided into smaller time units, i.e., the slots. Both frame length and slot number are parameters of the algorithm and remain unchanged at the execution time.

By means of a Q-Learning-based algorithm, each node independently determines an efficient wake-up schedule in order to limit, as much as possible, the number of slots in which the radio is turned on. Such a non-fixed and adaptive duty-cycle reduces the energy consumption over the time without affecting the other network performances.

Authors of [53] compared the performance of QL-MAC with the performance of conventional MAC protocols, such as S-MAC [24] and T-MAC [54] in an OMNETT-based simulation environment. The results show that the adaptive behavior of QL-MAC guarantees better network performances with respect to both the packet delivery ratio and the average energy consumption.

A similar approach is followed in a reinforced-learning-based medium access control protocol called RL-MAC [55]. The distinct feature of the protocol is that both the frame active time and duty-cycle are dynamically modified in accordance with the node's traffic load as well as its incoming traffic characteristics. The RL-algorithm is designed to maximize energy-efficiency and throughput.

Protocol	Description	Special feature	Potential drawback
S-MAC [24]	Sensor MAC	Good energy conserving properties with an ability to make trade-offs between energy and latency according to traffic conditions. The protocol has been implemented efficiently in hardware at real-world scenarios.	Scalability issues are not addressed. Network topology is considered constant with constant number of nodes.
V-MAC [56]	Virtual MAC	VMAC is embedded in BodyQoS to make it radio-agnostic, so that it can control and schedule wireless resources without knowledge of the implementation details of the underlying MAC protocol. BodyQoS adopts an asymmetric architecture, in which most processing is done at the resourceful aggregator while less processing is done at the resource limited sensor nodes.	Energy efficiency is not considered at all. Evaluation of QoS parameters is given more importance than that of the energy concerns.
DQBAN-MAC [51]	Distributed Queuing Body Area Network MAC	High QoS support with limited protocol overhead. Less computational complexity and easy implementation. Novel integration of fuzzy rule scheduling along with TDMA based approach renders a performance oriented cross-layer optimized MAC	Global time synchronization is a limiting factor. Power hungry due to extended operation of cross-layer optimization. Fuzzy logic will become a burden for the sensor nodes in case of dynamic data-load variations.
R-MAC [57]	Reservation Medium Access Control Protocol	Avoidance of overhearing, frequent commutation between sleep and wake up nodes, and data collisions are good results of this novel approach. R-MAC protocol also adjusts the duration of the sleep and active periods according to the traffic load in order to avoid data collisions.	Not very energy efficient in low data rate application. Aimed at high data rate application in large scale networks
UB-MAC [58]	Urgency-based MAC Protocol	Critical nodes packet transmissions are prioritized over non critical nodes packet transmissions.	The proposed protocol is only evaluated mathematically. Network may fail for different network topology and number of nodes in a network is limited
EEE-MAC [59]	Energy Efficient Election based MAC Protocol	Algorithm is good at preserving network topology and connectivity while introducing or reducing extra nodes. Smaller rate of deviation in energy consumption in higher data load conditions. Energy efficiency is good compared to S-MAC and B-MAC	The protocol is not analysed for QoS parameters. It is stated that QoS may hinder the energy efficiency for smaller networks
FE-MAC [60]	Forwarding Election-based MAC protocol	High network lifetime with energy efficiency and load balance. Routing capability of the network layer is also embedded in the protocol. Highly scalable and energy-efficient with more number of nodes	Resource utilization is exhaustive. Requires a relatively large memory and high computational power.

Table 2.4: Hybrid MAC protocols without WuR and their drawback for IBSN

Protocol	Description	Special feature	Potential drawback
Cooperative-MAC [61]	Low duty cycle TDMA	Suitable for highly mobile nodes. Novel combination of TDMA with FDMA deals with the interference and collision caused by the mobile cluster. The collisions brought by the mobile cluster are avoided through different frequencies used in WBAN	Complex hardware is required. Resource utilization is exhaustive rendering less power efficiency
Hybrid-MAC [62]	Hybrid(TDMA+FDMA) MAC Protocol	Reduced interference in the inter cluster and intra cluster communication using novel combination of FDMA and TDMA techniques. Achieves less energy consumption. Fulfills the bandwidth requirement of each node in the sensor network. Here after bandwidth division each node gets channel whose bandwidth is more than the requirement. Implementation is easy.	Less reliable, suffers from high packet drop for higher data load scenarios.
Hy-MAC [63]	Hybrid TDMA/FDMA MAC Protocol	A novel approach which schedules the network nodes in a way that eliminates collisions and provides small bounded end-to-end delay and high throughput. It takes advantage of multiple frequencies available in state-of-the-art sensor node hardware platforms such as MICAZ, TELOS and FireFly. Out-of-band synchronization is effective, rendering TDMA mechanism efficiently	Cannot be implemented in conservative radio band such as MICS where the number of channel available is highly limited. Not efficient in terms of energy
HUA-MAC [38]	Hybrid IBSN-Slot Access MAC Protocol	The special designed mini-slot method increases the contention efficiency,Contention-free data traffic scheme was adopted to guarantee the QoS. Allocation of slots is adaptive to the traffic load. Increased scalability and robustness for a BAN.	Suffers from severe limitations from state-of-the-art hardware. Real world implementation was carried out with ideal assumptions of network parameters. . Energy efficiency is lagging
YNU-MAC [64]	YNU Japan, Ultra-WideBand MAC proposal	Protocol considers SAR or thermal influence to human body by switching cluster mechanism. Positioning or localization of BAN nodes is highly possible	Different supplementary technologies yet to be analyzed. Implementation is not possible with COTS hardware
FM-UWB MAC [52]	CSEM Switzerland, Frequency Modulation - Ultra WideBand MAC proposal	Low energy at the transmitter and also saves energy at the destination node as it does not have to listen to a complete wake-up preamble. Suffers less from overheating.Reduced channel usage and thereby collisions. Improved reliability and reduced latency	Extreme requirement for hardware compared to other mechanisms. No optimal physical layer design is proposed

Table 2.5: Hybrid MAC protocols without WUR and their drawback for IBSN

2.4.3 MAC PROTOCOLS WITH WuR

A TDMA-based scheme combined with wake-up radio can be used to design a power efficient MAC. Authors of [65], [66], [29], have proposed TDMA-based MAC protocols for IBSN with wake-up radio. Use of wake-up radio can minimize the extra power consumption by the RTS-CTS packet exchange which is done by the main radio. The packet inter-arrival parameters are re-configurable values for each node.

For example, in case of a patient, a doctor/nurse or in-charge person can set the packet inter-arrival time for temperature monitor to be 6 h or 21,600s. This will cause the central node controller (CNC) to send a wake-up radio signal to the particular node after the specified intervals and complete the data communication. The node, between two consecutive wake-up periods, can switch off its main radio and go to sleep state to save power. It does not have to contend for data communication.

An ultra low power and traffic adaptive protocol designed for BAN is discussed in [67]. They used a traffic adaptive mechanism to accommodate on-demand and emergency traffic through wake-up radio. Authors of [65] have proposed a MAC protocols which supports dependability and QoS guarantee for the most important life-critical message and majority real time traffic. The protocol can be used with different physical layers UWB, MICS, WMTS, HBC.

A dynamic network size greater than 6 nodes to lesser than 100 nodes per network can be achieved. An improved quality-of-service addressing throughput, access latency, priority. High scalability is realized. Star, cluster-tree and peer-to-peer, are supported in the MAC protocol proposed in [66]. Table 2.6 comprehends the MAC protocols with wake-up radio based on the special feature and potential drawback with respect to the IBSN scenario.

Protocol	Description	Special feature	Potential drawback
NICT-MAC [65]	NICT Japan, Proposal for MAC using wake-up radio	Provides QoS guarantee for the most important life-critical message and majority real time traffic. Can be used in different physical layers UWB, MICS, WMTS, HBC. A dynamic network size from greater than 6 nodes to lesser than 100 nodes per network can be achieved.	Power consumption higher due to high performance. ALOHA is used instead of CSMA/CA which may result in abrupt performance deviation in large network size
IMEC-MAC [66]	IMEC Narrowband MAC proposal	Improved QoS addressing throughput, access latency, priority. High scalability is realized. Star, cluster-tree and the peer-to-peer, are supported.	The design is prone to collision and Low resource efficiency. Energy consumption is very high compared to other similar protocols.
Miller-MAC [68]	A MAC Protocol to Reduce Sensor Network Energy Consumption Using a Wakeup Radio	Supports multiple hop and multiple flow scenarios, outperforming similar protocols in terms of energy and latency.	Additional hardware is required to allow senders to force receivers to wake-up when a specified number of packets are buffered. Extra hardware consumed extra energy, which is not analyzed in the design.
RTWAC-MAC [69]	Radio Triggered Wake-up with Addressing Capabilities MAC	Reduces idle listening and also suppress unnecessary radio wake-ups due to the addressing information included in the wake-up signal. Very less power consumption and low latency than other MAC protocols (SMAC, TMAC and BMAC)	No explicit analysis of QoS with respect to the energy consumption. Further work is needed to integrate with different MAC protocols for data communication using main radio.
PE-MAC [70]	Power efficient MAC using Wake-up radio	Uses TDMA based MAC with wakeup radio that can save a more than 50% of energy used in CSMA/CA while still having a low delay in data transfer	Higher network size is not considered, rather only two nodes were used to evaluate the protocol. QoS and other network parameters such as interference, delay are ideally assumed in the evaluation.
ULPA-MAC [71]	Ultra Low Power Asynchronous MAC Protocol using Wake-Up Radio	This approach can improve up to 82% QoS and 53% energy saving when considering with TIGER [72] protocol for wireless communications.	Suffers from severe data and wake-up beacon collisions in a high traffic network, which reduces the average data received rate by 5.39%.
WuR MAC [73]	Wake-up radio MAC	By eliminating polling for detecting channel activity, this method provides more energy-efficient solutions than B-MAC and S-MAC . Very low per-hop latency and average power consumption	Mathematical analysis is done rather than real world implementation. Real world difficulties are bypassed with assumptions
T-MAC [54]	Adaptive Energy-Efficient MAC Protocol	Handles load variations in time and location by adaptive duty cycle in a novel way. Reduces the amount of energy wasted on idle listening	Throughput is traded off with energy efficiency. Expertimented in static and non-mobile networks
TBCD-TDM [74]	Time-Based Coded Data-Time Division Multiplexing	280 times higher throughput than ZigBee protocol. Simple modulation techniques, requires very less hardware complexity	Ideal case of only one single transmitted data bit per round is used. No real-world implementation is discussed such as effect of environment noise effect.

Table 2.6: MAC protocols with WuR and their drawback for IBSN

2.4.4 COMPARISON OF MAC PROTOCOLS FOR IBSN

We considered more than 30 MAC protocols designed for generic sensor networks and BSN in order to broadly evaluate their use in IBSN. Table 2.7 is a qualitative comparison of different protocols based on network features. We used the results of each protocols as mentioned in the respective article to qualitatively analyze the trade-off made between each requirements such as energy-efficiency, reliability, software overheads, throughput, latency, and hardware complexity. This comparison will present the commonly made trade-offs in the MAC protocols designed for BSN and WSN.

Energy efficiency is the amount of energy consumed to successfully transmit a data packet including the energy consumed by the network management overheads. A (+) for energy efficiency indicates that the MAC protocol is specifically designed to operate at low power application such as BSN. It also indicates that the main aim of the protocol was to improve energy-efficiency and longer network life-time over the performance metrics such as throughput, reliability and QoS. A (–) represents the otherwise.

Reliability is the successful data transfer from the transmitting node to the receiving node. A (+) for reliability indicates that the MAC protocol was designed to deliver reliability even in dynamic physical medium such as the human body environment, where the link quality is highly deteriorated both temporally and spatially. A (–) indicates that the MAC protocol was not designed to provide reliability in highly dynamic link quality.

Overhead is the amount of additional data that is required apart from the payload to successfully establish a link between the transmitting node and the receiving node. A (+) for software overhead indicates that the MAC protocol aim at minimal management phase data communication between the coordinator and still achieves better performance in terms of throughput and reliability. A (–) indicates the otherwise.

Throughput is the amount of information bits received per second at the receiver. A (+) for throughput indicates that the main aim of the protocol was to improve the throughput of the network and a (–) indicates the otherwise.

Low latency is the amount of time required to establish a link before any useful data transfer. A (+) for latency indicates, the MAC protocol is designed to achieve low latency for each transmission and a (–) indicates the otherwise.

Hardware complexity is additional hardware components such as wake-up radio that are required to achieve the intended performance of the MAC protocol. A (+) indicates the MAC protocol requires additional hardware other than the main radio to achieve better performance and a (–) indicates the otherwise.

All MAC protocols mentioned in Table 2.7 are compared based requirements of IBSN applications, while none of them is explicitly developed for IBSN applications. Although some of the protocols are developed for general WSN application, they are

still considered in our comparison since their features meet the requirement of the IBSN applications.

2.5 DISCUSSION

2.5.1 THE NEED FOR WAKE-UP RADIO (WuR)

The operation of WuR is not only simple but also energy efficient. The dual radio architecture is superior because the power consumption of the main communication radio scales up with increasing network traffic. By turning the main radio on when it is really needed, WuR limits the power consumed by the main radio for idle listening along with the over-hearing problems preventing data collision from occurring. The data communication is then initiated and completed using the main radio, reducing the total amount of time that the main radio is turned on.

Consequently, it results in more relaxed synchronization requirements for schedule-based MAC protocols [30]. The energy consumption could be reduced significantly when using appropriate wake-up techniques [33]. The ultra-low-power and performance trade-off can be achieved by creating a proper Tx/Rx link-budget for the main radio. The WuR sets a lower-bound of power consumption in idle state compared with the current available technologies which could be mitigated by applying duty-cycling to the WuR.

Based on our previous research, work reported in [14], the power consumption of WuR-based MAC protocol, synchronous MAC protocol and asynchronous random access protocols is compared. In conclusion, the main features of WuR to make it a suitable technology for IBSN are: its low power consumption, reliable performance in short-range networks, ability to operate out-of-band with main radio, and not requiring complex hardware [34].

MAC Protocol	Features						Access Mechanism
	Energy-Efficiency	Reliability	Overhead	Effective-Throughput	Low-Latency	Hardware Complexity	
CF-MAC [39]Y-2005	+	+	+	-	+	+	TDMA
SSD-TDMA [40]Y-2005	+	-	<i>O</i>	-	+	+	TDMA
DQBAN MAC [51]Y-2009	-	-	+	+	-	<i>O</i>	TDMA
HEH-MAC [36]Y-2007	-	<i>O</i>	-	<i>O</i>	+	+	TDMA
BodyMAC [37]Y-2009	+	+	-	+	<i>O</i>	-	TDMA
UB-MAC [58]Y-2010	-	+	-	+	-	+	TDMA + CSMA
X-MAC [47]Y-2006	<i>O</i>	-	+	-	+	+	CSMA
V-MAC [56] Y-2008	+	-	+	-	+	<i>O</i>	TDMA + CSMA
R-MAC [57] Y-2007	+	+	-	-	<i>O</i>	+	TDMA + CSMA
PNP-MAC [46] Y-2010	<i>O</i>	-	+	+	-	+	TDMA + CSMA
O-MAC [50]Y-2006	+	-	-	-	+	-	TDMA + CSMA
MEB-MAC [49]Y-2012	+	+	+	-	+	-	TDMA + CSMA
EEE-MAC [59]Y-2013	-	+	<i>O</i>	-	+	-	TDMA + CSMA
FE-MAC [60]Y-2007	+	-	+	+	-	-	TDMA + CSMA
P-MAC [75]Y-2013	+	-	+	+	+	<i>O</i>	TDMA + CSMA
CA-MAC [45]Y-2009	-	+	-	<i>O</i>	+	-	TDMA + CSMA
ULP-MAC [76]Y-2005	+	+	-	+	<i>O</i>	+	TDMA + CSMA
BMAC [43]Y-2007	<i>O</i>	+	+	-	+	-	CSMA
BSN-MAC [38]Y-2010	+	-	<i>O</i>	+	+	-	TDMA + CSMA
ULPD-MAC [77]Y-2008	-	+	+	-	<i>O</i>	<i>O</i>	TDMA + CSMA
DISSense [48]Y-2007	+	<i>O</i>	+	-	+	+	TDMA + CSMA
S-MAC [24]Y-2002	-	+	+	-	+	-	TDMA + CSMA
Coop.—MAC [78]Y-2008	+	+	-	+	-	-	TDMA + FDMA
Hybrid-MAC [62]Y-2014	+	-	+	+	-	+	TDMA + FDMA
HyMAC [63]Y-2012	+	<i>O</i>	+	-	<i>O</i>	+	TDMA + FDMA
HUA-MAC [38]Y-2010	+	+	-	-	-	<i>O</i>	Hybrid ALOHA
YNU-MAC [64]Y-2009	-	+	+	+	+	-	CSMA + UWB
FM MAC [52]Y-2009	-	-	-	<i>O</i>	-	+	CSMA + UWB
RL-MAC [55]Y-2006	+	-	-	-	-	+	Adaptive CSMA
QL-MAC [53]Y-2013	+	-	+	<i>O</i>	-	+	Adaptive CSMA
NICT-MAC [65]Y-2014	+	+	-	+	<i>O</i>	+	Slotted ALOHA + WuR
IMEC-MAC [66]Y-2009	-	+	-	-	-	<i>O</i>	ALOHA + TDMA + WuR
Miller-MAC [68]Y-2005	+	<i>O</i>	-	-	-	+	TDMA + CSMA + WuR
RTWAC[69]Y-2009	+	+	+	+	+	+	TDMA + CSMA + WuR
PE-MAC [70]Y-2011	<i>O</i>	-	-	+	-	-	TDMA + CSMA + WuR
ULPA-MAC [71]Y-2013	+	-	+	<i>O</i>	-	+	CSMA + WuR
WuR MAC [72]Y-2004	+	-	<i>O</i>	-	+	<i>O</i>	CSMA + WuR
T-MAC [54]Y-2003	-	-	+	+	-	+	CSMA + WuR
TBCD-TDM [74]Y-2009	+	+	-	+	-	+	TDMA + WuR

Table 2.7: Comparison of MAC protocols. Legends: '+' = Positive; '-' = Negative; 'O' = Neutral.

2.5.2 RESEARCH ISSUES AND CHALLENGES

The amount of energy available for the IBSN sensor nodes is scarce and nodes are expected to last in the order of months to years. The MAC protocols, which are commonly designed for wireless sensor networks do not support high and severe quality-of-service requirements of IBSN applications in terms of high throughput, high reliability and low latency. MAC protocols of generic Body Area Network (BAN) applications focus mainly on monitoring applications. In IBSN, the actuation scenario introduces additional reliability requirements in terms of very low latency and guaranteed packet delivery. In general, existing energy-efficient sensor network applications operate with fixed low duty-cycle. In IBSN scenarios, however, the active duty-cycle is dynamic and may vary through time depending on the medical applications (for example for long-term monitoring of symptoms and time sensitive medical therapy information, such as a cardiac pacemaker).

Although MAC protocols for BAN take into account the body effect on the physical channel, long-term operation and battery life, their use in life-critical medical application is questionable. Significant improvements in MAC protocol to achieve the ultra-low-power consumption are to be made.

To ensure reliability in highly dynamic sensor network topology, MAC protocols may be designed with redundant acknowledgment schemes and extensive link quality assessment, which often are not energy-efficient. Conventional methods to ensure reliability can be improved significantly by complementing it with bio-inspired design, benefiting from the predictable patterns of link deterioration caused by everyday human activities such as walking and running. Furthermore, reliability can be improved in an energy-efficient manner by utilizing bio-signals for synchronization and acknowledgment purposes.

Generally, MAC protocols of BSN are designed to support devices which are intended only for sensing. In IBSN, nodes can also be actuator which have different characteristics than sensing devices. In such cases, the MAC protocol should be able to provide the QoS support for actuation and sensing devices to support heterogeneous data communication. Apart from priority, these medical actuation devices also require real-time communication to accurately prognose and diagnose the medical condition with strict time constraints.

Existing MAC protocols for BSN are largely adaptable to different environmental and sensing conditions. They are however not adaptable to the dynamic changes required in the flow of information within the IBSN for different medical applications. For example, in the complex closed-loop operation of DBS for epileptic patients, predicting the onset of seizure requires input from different bio-sensors within the network at different time stamps. A MAC protocol designed for long-term monitoring applications of BAN cannot adapt to such complex requirements of the closed-loop medical devices. The level of adaptability in existing MAC protocols is very limited. For example, in hybrid access mechanisms, either time-slots are adaptive or the con-

tention window is adaptive according to the traffic load. In dynamic networks, such as IBSN, more than one dimension of the MAC aspect has to be adaptive.

Conventional MAC protocols are streamlined to send data to the physical medium as soon as possible. In some protocols, the link quality is predicted at the MAC layer before initiating any communication. This greatly improves the performance of the MAC layer in terms of energy-efficiency. In IBSN, the bio-signals and their characteristics, such as periodicity, can help reduce the synchronization overheads and consequently improve the performance of MAC protocol. Additionally, by knowing the type of bio-signal and the destination node to which its data will be sent, data packets may be prioritized and adapted to increase the reliability.

Adaptive MAC protocols are capable of learning additional information about the type of data that are being communicated. However, the learning algorithms for MAC protocols are not designed for medical applications but are designed for conventional sensor network applications which do not have life-critical applications. Accuracy of these learning-based MAC protocols should be demonstrated for medical purposes, and error free implementation of these algorithms is yet to be studied. Incorporating WuR to these adaptive MAC protocols can greatly reduce the power consumption, where nodes can benefit from the low power operation of WuR when establishing newer wake-up schedules. Use of WuR for the learning phase of these adaptive MAC protocols will have significant improvement in terms of energy-efficiency and QoS performance.

Furthermore, co-optimization of MAC and the PHY layer between the main radio and WuR can improve energy-efficiency in dual radio IBSN devices. Incorporating WuR at the MAC level rather than using only the wake-up interrupt will improve the reliability of the data communication.

2.6 CONCLUDING REMARKS

In this chapter, we analyzed various existing MAC protocols considered suitable for IBSN application. The requirements for developing an MAC protocol for IBSN are presented in this work. IEEE 802.15.6 standard recommendations were used to define the requirements for IBSN. Crucial improvements that could be amended to the standard were discussed. The design requirements of the IBSN communication scheme are based on a specific IBSN scenario.

Several existing MAC protocols are explored and compared for the given IBSN application scenarios. TDMA and contention-based mechanisms could be used for developing MAC protocols, however, they suffer from synchronization, low reliability, high latency and memory overhead. A comparative study is also done, to identify the most applicable access mechanism for the implant communication. In addition, we presented the research challenges that exist in the design of MAC protocols for implant communication. Based on this study, we recommend the imple-

mentation of a collaborative WuR and main communication radio in deploying a MAC protocol for IBSN.

CHARACTERIZATION OF PHY AND MAC FOR IBSN

W^{IRELESS} communication in IBSN takes place in and around the human body. Tissues in the human body are heterogeneous and have dynamic conductivity and permittivity. The physical layer (PHY) characteristics including the channel model depends on different tissue properties, the environment, the hardware components used such as antenna and matching circuit as well as the operating frequency, and the hardware losses. In this chapter, we will characterize the PHY through rigorous empirical measurements. Based on these empirical PHY parameters, we will characterize few of the existing MAC protocols with and without wake-up radio (WuR), to understand the impact of WuR in IBSN channel. Moreover, these robust PHY and channel model parameters will be used in all our future experiments and simulations.

ஆற்றின் வருந்தா வருத்தம் பலர்நின்று
போற்றினும் பொத்துப் படும்
On no right system if a man toil and strive,
Though many men assist, no work can thrive
—Thiruvalluvar in Kural 468

3.1 INTRODUCTION

Reliable wireless communication inside the human body is crucial for the design of IBSN. The tissues in human body are heterogeneous and have dynamic conductivity and permittivity, which make the modeling of the wireless channel challenging. The design of upper layers of the network stack requires knowing the physical layer (PHY) characteristics including the channel model.

The channel model characteristics depends on the hardware components used such as antenna and matching circuit as well as the operating frequency, which are not taken into account by the existing channel models for implant communication. Moreover, hardware losses and different tissue characteristics have not been taken into account in the link budget of the existing channel models.

The approach used in this chapter pays special attention to the losses introduced by hardware components of the implant itself and the physical medium. Having this in mind we will mathematically model the parameters of PHY and its impact on the IBSN's radio channel. A comparison will be made between these measured characteristics and the existing channel characteristics provided by the IEEE 802.15.6 standard.

With the newly measured PHY parameters, we will analyze the impact of Wake-up Radio (WuR) on commonly used MAC protocols and evaluate the performance of three MAC protocols with and without WuR. Energy efficiency, reliability in terms of packet delivery ratio, and end-to-end delay for each node are considered as the evaluation criteria for measuring the performance of MAC protocols with and without WuR.

Parts of this chapter have appeared in :

- [17] V. R. K. Ramachandran, B. J. van der Zwaag, N. Meratnia, and P. J. M. Havinga, "Implantable body sensor network MAC protocols using wake-up radio - Evaluation in animal tissue," in *Proceedings of the 9th International Symposium on Medical Information and Communication Technology (ISMICT)*, March 2015, pp. 88–92
- [18] V. R. K. Ramachandran, N. Meratnia, K. Zhang, and P. J. M. Havinga, "Towards implantable body sensor networks - performance of mics band radio communication in animal tissue," in *Proceedings of the 10th EAI International Conference on Body Area Networks, BODYNETS 2015, Sydney, Australia*. New York: ACM, September 2015

The rest of this chapter is organized as follows.

In Section 3.2 channel model proposed by the IEEE 802.15.6 standard is summarized and its characteristics are described.

Section 3.3 explains the characterization of the PHY layer including the channel model. Also, PHY configurations and choices of evaluation parameters are presented, followed by results and a comparison between the simulations of IEEE 802.15.6.

Based on the results from Section 3.3, the simulation of network parameters with three different MAC protocols with and without WuR is explained in Section 3.4. Also, results are explained, elaborating on the impact of WuR on MAC protocol for IBSN.

Finally, concluding remarks from observation made from our characterization experiments on the PHY and MAC are presented in Section 3.5.

3.2 IEEE 802.15.6 COMMUNICATION CHANNEL

Reliability of wireless communication largely depends on the environment and the communication medium. The medium in the case of IBSN is the body itself, which is conductive with varying permittivity and permeability and largely affects the propagation of the electromagnetic waves.

In order to standardize the wireless communication in, on, and around the body (not limited to humans), the IEEE 802.15 task group 6 has been set in 2007 [15]. The task group aims to standardize wireless communication with a dedicated radio spectrum, ultra-sound, and ultra-wide-band communication, and an in-body communication channel. The immediate use of ultra-sound, ultra-wide-band and in-body communication channel in IBSN is not feasible due to the lack of reliable technology to have it implanted inside the body.

The physical layer (PHY) and the medium access control layer (MAC) of implant communication are standardized by the IEEE 802.15 task group 6 [15]. A frequency band called Medical Implant Communication Service (MICS) is introduced, which operates at 402-405 MHz for implant communication [15].

MICS band is allocated only for the use of implantable medical devices by various telecommunication regulatory agencies such as the U.S. Federal Communications Commission (FCC) and the European Telecommunications Standards Institute (ETSI).

The antenna used for IBSN is limited in size and the RF propagation is not trivial inside the body [79]. The communication channel inside the body is completely different from that in the free space because of the tissue properties. Furthermore, the directivity of the antenna introduces a challenge because the properties of the body tissues influence the antenna radiation pattern.

Channel characteristics provided in the IEEE 802.15.6 standard do not clearly indicate the characteristics of the antenna in the path loss model. Furthermore, it is

unclear whether antenna matching has been applied when obtaining the channel model in the IEEE 802.15.6 standard [79].

The human body model of IEEE 802.15.6 is based on frequency dependent biological material and is claimed to have an accuracy of 2mm in tissue properties [79]. The received signal strength is calculated for a grid of points within a cylinder area around the body.

The resulting data is then filtered for 2 scenarios, i.e., (i) in-body propagation (channel model 1 (CM1)): set of points that completely reside inside the body, (ii) in-body to on-body (body surface) propagation (CM2): set of points that reside within a certain distance (i.e., 2mm, 10mm, 20mm, 50mm) from the body surface.

The reference path loss $PL(d_0)$ is calculated using the formula shown in Eq. 3.1, where G_T , P_T , P_R represent the gain of receiving antenna, the transmission power, and the receiving power, respectively.

$$PL(d_0) = \frac{G_R \cdot P_T}{P_R(d_0)} \quad (3.1)$$

The path loss is expressed in terms of log normal distance as shown in Eq. 3.2, where d_0 , $PL(d_0)$, and n are reference distance, path loss at the reference distance d_0 , and the path-loss exponent, respectively.

$$PL(d) = PL(d_0) + 10n \log_{10}\left(\frac{d}{d_0}\right) + S \quad (3.2)$$

S is a Gaussian random variable with zero mean and standard deviation of σ_s accounting for the losses due to tissue layers. When there is a direct line of sight between the sender and the receiver, a free space path loss can be added to CM2 to account for the additional loss that the signal sent by the implant will go through once it leaves the body.

The unique characteristics which differentiate the implantable medical devices from the non-medical and body-worn medical devices are shown in Table 3.1.

Parameter	Value
Antenna position	2 cm beneath tissue surface (in-body) 0-300 cm away from the tissue (off-body)
Transmission distance	0-16 cm (in-body), 0-300 cm (in air)
Antenna orientation	Parallel to the body surface
Transmit power	25μW EIRP (or) -15dBm
Operating frequency	403.5 MHz center frequency with 3 MHz bandwidth

Table 3.1: PHY and channel parameters from IEEE 802.15.6 [15]

3.2.1 LIMITATIONS OF THE EXISTING CHANNEL MODEL

Although different works in modeling the radio propagation in computer based simulation [80, 81, 82] have been done, the amount of research work estimating the empirical path loss response of the real biological tissue in MICS band communications is not adequate.

In order to evaluate these electro-magnetic (EM) parameters in *in-vitro* conditions, an environment that has a close resemblance to tissue is required. For instance, a body phantom can be used to simulate the characteristics of tissues in human body [83, 84]. However, the phantoms cannot simulate the heterogeneous layered structure of human tissue.

To the best of our knowledge, all existing empirical results addressing human channel modeling are related to communication between sensors placed on the surface of the body (i.e. communication between on-body sensors) and communication between in-body and on-body sensors [85, 86, 87].

The empirical channel modeling related to the communication between in-body sensors are still in infancy. To this end, EM properties such as relative permittivity, and conductivity of 57 different human tissues were analyzed for RF and microwave frequencies (10 Hz — 20 GHz) in [88].

A few investigations have been reported to determine the effect of human body as a radio channel in wireless medical communication [89]. To the best of our knowledge, there are not any empirical measurements of the channel that are made using the animal tissue in MICS band communication.

3.3 CHARACTERIZATION OF PHY USING ANIMAL TISSUE

A complete channel model, which includes shadowing, fading model, delay profile, and spatial properties, is not the aim of this chapter. We aim to measure the deviation in path-loss model by measuring the received power at various transmission distances and power. This will ensure the reliability of the computer-simulated model by including the environmental losses which have to be considered in addition to the losses caused by the tissues.

To understand the layered characteristics of the tissue, an animal tissue, which has close resemblance to human tissue can be used. From literature the most resemblance to the human tissue is found with the tissue of swines (pigs) [90]. Hence the performance of radio communication in a layered tissue structure can be obtained from tissue extracted from a pig.

ANIMAL TISSUE

Our test environment for the implant communication is a piece of muscle tissue extracted from the thigh of the pig including the (layers of) skin. Anatomically, the

Figure 3.1: A cross section of animal tissue showing different layers including skin. [93]

Figure 3.2: A dissected part of pig tissue used for experimenting with implant communication.

near-surface implantable devices are implanted in between the dermis and subcutaneous layer of the skin [9, 91, 10]. The dermis layer, as shown in Figure 3.1, is just below the epidermis which forms the outer layer of the skin.

The animal tissue is chosen for various reasons such as elimination of difficulties and complexities of test processes using real human tissue, not being dependent on the human phantoms with static EM properties, and identification of practical limitations faced using real tissues.

It is important to note that different layers of skin have different conductivity (μ) and permittivity (ϵ). These values change dynamically with body mass, structure, and diet, which cannot thoroughly be validated using simulations. Therefore, the animal tissue over computer simulations or phantoms is preferred to validate the performance of the radio.

Figure 3.2 illustrates the tissue used for experiments dissected from the thigh of a pig. It was extracted from the animal immediately after euthanization. The experiments were conducted on the tissue within 30 minutes of the euthanasia. We used a biological safety cabinet to prevent any contamination while carrying out the experiments. The ethical codes [92] were carefully followed during the experiments.

LOG-DISTANCE PATH LOSS MODEL

In order to obtain a realistic prediction of the received signal strength of in-body communication, we employ the log-distance path loss model [79], in which the received signal strength (in dBm) at a distance d (in meters) from the transmitter ($PL_R(d)$) is expressed as:

$$PL_R(d) = PL_R(d_0) + 10n\log_{10}(d) + S_R, \quad (3.3)$$

where $PL_R(d_0)$ represents the mean (expected) signal strength at a distance of $d_0 = 1\text{cm}$ from the transmitter and is calculated using Eq. 3.1, and n is the path loss exponent.

S_R represents a Gaussian random variable with zero mean and standard deviation of σ_s dB [79] contributing to the loss due to the channel characteristics. In the Eq. 3.3, $PL_R(d)$ is the path loss calculated at a random distance d .

This model takes into account the different obstacles present in multiple transmitter-receiver paths having the same separation (also known as log-normal shadowing). The parameters (n, σ_s) define the statistical model and are known to be heavily dependent on the environmental characteristics [94].

Measurements in the literature have reported empirical values for n in the range between 4.22 (near tissue implants) and 6.26 (deep-tissue implants), while values for σ_s usually fall into the [6.81,9.05] dB interval [15].

HARDWARE

While designing an implant two important requirements, namely longer lifetime and compactness, should be taken into account. In terms of ultra low-power radios, there are different radio chips available in the market which can comply with the requirements of the medical implant. The implant we used for experiments is shown in Figure 3.3.

Figure 3.3: CC430 based implant used in experiments

Figure 3.4: Paraffin coated implant for testing

It comprises of a CC430 chip set from Texas Instruments, a ceramic antenna matched to operate at 400 MHz band, and an accelerometer. The implant has a UART and a SPI connection through which the software is loaded and the output will be debugged.

The main features making the CC430 suitable for evaluation are its ultra-low power radio operation - $160\mu\text{A}/\text{MHz}$, its ability to operate in the MICS band (402-405 MHz), clear channel assessment, configurable access to PHY, configurable MAC layer, 16 bit CPU with 50ns instruction cycle time, memory (32 kB of flash and 4 kB of RAM).

Casing for the hardware The purpose of the casing is two-fold. One is to prevent any contact with the conductive tissue, which would cause a short circuit on the board. The other one is to ensure bio-compatibility of the sensor node. The casing is often made up of bio-compatible ceramic, glass, or polymers [95] depending on the application. These casing provide transparent RF window and do not attenuate the signal [95]. For our experiments, it was sufficient to encapsulate the node in a paraffin cover just to prevent any contact with conductive tissues.

3.3.1 EXPERIMENTAL SETUP

The PHY parameters to be examined are transmission power, data rate, and frequency of operation. In addition to these parameters, transmission distance and antenna orientation will influence the performance of in-body communication. To this end, we perform experiments with the following parameters:

3.3.1.1 TRANSMISSION (Tx) POWER

Transmission power is the power at which the radio signal is delivered from the antenna. If the antenna is matched with the impedance of the channel, the power delivered at the antenna should ideally be equal to the transmission power. The PHY specification of the IEEE 802.15.6 group recommends $25\mu\text{W}$ effective isotropic radiated power (EIRP), which limits the transmission power to be at -15dBm [15].

3.3.1.2 TRANSMISSION (Tx) RATE

Transmission rate is the rate at which data is sent from the transmitter to the receiver. The IEEE 802.15.6 group recommends a minimum data rate of 57.5 kB/s when operating in the MICS band of frequency [15].

3.3.1.3 TRANSMISSION FREQUENCY

High frequencies have lower the propagation inside the body. The in-body communication as mentioned earlier is standardized to operate in the MICS band.

3.3.1.4 DISTANCE

The distance between Tx and Rx will change the radio performance. IEEE 802.15.6 recommended a maximum single-hop coverage distance of 3 meters in the MICS band communication [27].

3.3.1.5 ANTENNA ORIENTATION

This parameter refers to the orientation of the antenna inside the tissue with respect to the receiver. The Tx antenna and Rx antenna can be placed horizontally (0°

Set of parameters	Evaluating parameters
Set of physical parameters	Transmission power (dBm)
	Transmission distance (cm)
	Antenna orientation (degrees)
Set of network parameters	Data rate (kB/s)
	Packet length (bytes)

Table 3.2: Evaluation of hardware with two different sets of physical and network parameters.

- posterior plane of the Tx antenna faces the posterior plane of the Rx antenna, 0°
- posterior plane of Tx antenna faces the anterior plane of the Rx antenna) or vertically (90°) with reference to the 2D surface of the tissue.

For the MICS band, the near-field of the antenna is less than 16 cm [96]. The hardware used in our experiments has an isotropic antenna, which radiates uniformly in all directions and is affected by the near-field reflections for distances less than 16 cm.

This effect may induce attenuation and signal loss, which will also be taken into account in our path-loss model. There will be no significant difference in RSSI due to antenna orientations in CM2, because of the relatively larger distances between the transmitter and the receiver.

3.3.2 EVALUATION METHODOLOGY

The values of the PHY parameters are chosen statistically based on the values presented in Table 3.2. The parameters are divided into two groups, i.e., physical and network parameters. The physical parameters are directly related to the EM propagation such as transmission power, distance, and orientation of the transmitting and receiving antennas, whereas the network parameters are related to the performance of the radio in terms of data rate and packet length with respect to the packet delivery ratio (PDR).

In order to simplify the measurement process, a UART interpreter is developed. The radio has to be reset for every change in the physical parameters. Radio resets will put the radio into sleep mode [97]. Thus for every change, the implant has to be initialized with physical parameters before sending any data. In CM2 scenario, the RSSI at larger distances is limited by the receiver sensitivity of CC430 radio. Optimum values for the physical parameters are found out before experimenting with the network parameters.

3.3.2.1 SETTING THE PHYSICAL PARAMETERS

In case of CM1 scenario, the nodes are placed within the tissue at a distance of at-most 16 cm. The characterization of the channel when devices communicate in such close distance is crucial for the design of the topology of an IBSN [14].

Evaluation parameters	Values
Antenna orientation	0°,90°,180°
Transmission power	5, 0, -10, -15, -30 dBm
Transmission distance	CM1 : 0, 2, 4, 8, 16 cm CM2 : 0, 25, 50, 75, 100, 150, 225, 300 cm

Table 3.3: Set of physical parameters. Repeated for CM1 and CM2

In case of CM2 scenario, larger distances are used, where an implant could communicate to a device placed outside the body. We increase the distance gradually from 25cm to 3m to understand the channel characteristics through RSSI information varying in distance. The values of the physical parameters are shown in Table 3.3.

3.3.2.2 SETTING THE NETWORK PARAMETERS

We vary the network parameters and measure the packet delivery ratio for each possible combination of parameter values. This will help in finding the optimum settings for network parameters. The values of the network parameters are shown in Table 3.4.

Evaluation parameter	Values
Packet length	5, 20, 40, 60, 80, 100 bytes
Data rate	5, 20, 40, 60, 80, 100, 150 kB/s

Table 3.4: Set of network parameters. Repeated for CM1 and CM2

The network parameters are set through the UART interpreter of the implant. Received packet information is read back through the UART interpreter and stored in a local PC for further analysis with MATLAB. The results from that data analysis are discussed in Section 3.3.3.

3.3.3 RESULTS AND DISCUSSIONS

In our experiments, we collected 150 data points as shown in Figure 3.5 - Figure 3.6 for each combination of the physical parameters.

The scatter plot of CM1 in Figure 3.5, shows how RSSI information varies with the transmission distance. The mean value of the received power has an impact over the path loss exponent (n) which is shown in a regression line in the scatter plot.

The value of path loss exponent (n) from the IEEE 802.15.6 simulation model is expressed in a regression line, which has $n=4.22$ [15]. Whereas the empirical estimation of the path-loss exponent (n) is 6.16, which is much higher than the estimated

value from path loss model of IEEE 802.15.6. The CM2 scenario also has variation as shown in the Figure 3.6. The deviation in CM2 is not as much as when the communication takes place completely inside the tissue.

Figure 3.5: RSSI as a function of distance (Tx=-15dBm) CM1

Figure 3.6: RSSI as a function of distance (Tx=-15dBm) CM2

Figure 3.7: Probability density of RSSI(CM1 and CM2 combined) Tx=-15dBm

Figure 3.7 shows the probability density of RSSI of CM1 and CM2 combined, which indicates that the received signal strength will be close to -105 dbm most of the times. In such situations, the receiver has to operate at high sensitivity by consuming more power. When operating at high sensitivity, the radio receiver provides reduced data rate [97].

3.3.3.1 EVALUATION OF PHYSICAL PARAMETERS

Validation results of the set of physical parameters are shown in Figure 3.8 - 3.10. Generally speaking, RSSI is linearly decreasing with distance. This can be formu-

lated as:

$$RSSI (dB) \propto \log_{10} \left(\left(\frac{k}{Distance} \right) \cdot (\mu \cdot Tx power) \right), \quad (3.4)$$

,where k and μ are statistical constants.

In order to match to the standards of the MICS band, the transmission power should not be higher than $25\mu W$. By referring to the data-sheets of antenna and CC430 radio chip [97], we found out that at a transmitting power of $-15dBm$, the EIRP of the node will not exceed $25\mu W$.

Additionally, by lowering down the power further below $-15dBm$, we were not able to communicate at distances larger than $5cm$ with a packet delivery ratio higher than 95% . Experimenting with larger distances resulted in very low signal strengths as shown in Figure 3.6. Having lower RSSI values may result in higher error rates in data transmission, which is not desirable for in-body communication.

Figure 3.8: RSSI vs Distance at 0 degree antenna orientation

As far as CM1 scenario is concerned, the attenuation of signal is very high even for short distances. The plot shown in Figure 3.8 illustrates that with 0 degree antenna orientation (which implies that the antennas are placed facing each other in line of sight), even at $2cm$ separation, a transmission sent by $5 dBm$ is received as $-20 dBm$. This attenuation is persistent in all set of repeated experiments, which indicates the presence of large reflection of signals in the near field of the antenna.

Figure 3.9: RSSI vs Distance at 90 degree antenna orientation

Figure 3.10: RSSI vs Distance at 180 degree antenna orientation

A linear decrease in RSSI is expected as the distance increases. However, experimental results show that the decrease in RSSI is not linear at larger distances. An additional path-loss due to NLOS communication is also accounted together with the statistical path-loss model in our experiments.

3.3.3.2 EVALUATION OF NETWORK PARAMETERS

Both CM1 and CM2 scenarios were used to evaluate the set of network parameters. The data rate is varied from the minimum of 2 kB/s to 150 kB/s and the corresponding PDR is measured. The PDR indicates how many packets are successfully received. For most of the application in CM1 and CM2 scenarios, the tolerable packet error rate has been set to at-most 10% for a 256-byte payload with a packet delivery ratio of 95% [98, 99]. Different packet sizes will help to identify the number of re-transmissions required in case of larger packet lengths. Upon exceeding the maximum number of re-transmissions, the receiver will ignore the packet. However, in our experiments, we do not use any re-transmission and as soon as a packet fails, it is considered as a dropped packet.

Using the CM1 scenario, as the packet length increases, the packet delivery ratio decreases even for higher data rates as shown in Figure 3.11. This indicates that large packet length allows the implant to communicate for a longer time. The failure of a packet can also occur if a frame is corrupted due to very low RSSI. It is also conversely found that higher data rates will not increase the packet delivery ratio in case of large packet length. For a fixed packet length, the PDR increases as the data rate increases. An important observation is that the PDR is almost constant at higher data rates for a fixed packet length.

Using the CM2 scenario, as the packet length increases, the packet delivery ratio is decreased even for higher data rates as shown in Figure 3.12. This behavior is sim-

Figure 3.11: Tx Rate vs Packet delivery ratio evaluated with fixed packet length.
Measured in CM1

Figure 3.12: Tx Rate vs Packet delivery ratio evaluated with fixed packet length.
Measured in CM2

ilar to that of the CM1. The data rate is directly proportional to the packet delivery ratio; however it changes with that of the packet length. As the packet length increases, PDR is decreased. PDR increases, as the data rate increases. This indicates that small packet length and higher data rates are required to maintain the reliability of the network.

PL parameters	CM1		CM2	
	Simulation	Empirical	Simulation	Empirical
$PL(d_0)$ dB	40.94	56.65	49.81	61.32
n	4.99	6.18	4.22	6.06
σ_s	9.05	10.65	6.81	9.56

Table 3.5: Comparison of our empirical results and simulation results from [79]

Small packet length with twice the data rate will have better performance in case of both CM1 and CM2 scenario. Sending packets at a faster rate will reduce the congestion in the network.

3.3.3.3 COMPARISON OF EMPIRICAL RESULTS AND SIMULATION MODELS

The deviations in the simulated model and the empirical results are shown in Table 3.5. The differences in the statistical constants is large and the empirical results are not in line with the values from the computer simulated models of IEEE 802.15.6. Even though simulations may exhibit a good network performance, this does not guarantee good performance of the radio in a network setup under practical scenarios. It can be seen that the path loss from our measurements includes the additional losses, which can be due to the indoor propagation losses and multipath effects. In addition to the free space path loss, indoor path loss has to be accounted for. From the results, it can be assumed that the radio waves are partially scattered to the air medium when a transmitting from inside the body. The scattered signal picked up by the receiver has multipath characteristics such as fading and a delay profile which are not explicitly shown in the results. This study shows that the existing channel model from computer simulations is not accurate and does not reflect the real-world operating conditions.

3.3.3.4 CONCLUSION

Two different channel model scenarios were chosen for evaluation of PHY parameters and characterization of the performance of radio in animal tissue. From the results, it is shown that the attenuation of radio communication is very high inside the tissue. The path loss exponent inside the animal tissue deviates from that of the IEEE 802.15.6 results.

Based on our experiments, the optimum physical and network parameters are presented in Table 3.6. These channel model parameters will be used also in our future experiments and simulations when validating the network performance of IBSN.

Parameter	Value
Tx power	-15 dBm
Tx distance	CM1 :16 cm CM2 :100 cm
Packet length	20 bytes
Data rate	40 kB/s
Modulation	BPSK

Table 3.6: Optimum values of physical and network parameters obtained from experiments

3.4 CHARACTERIZATION OF MAC FOR IBSN

IBSNs are life critical. Therefore, nodes must neither fail due to energy deficiency nor report unreliable data at any point in time within the lifespan of the network. Every single access to the wireless medium is expensive in terms of energy.

Therefore, access protocols need to be designed carefully meeting the communication reliability and energy efficiency requirements of the network. In this section we briefly describe six conventional MAC protocols with and without WuR in three different categories, i.e., contention-free, contention-based, and hybrid. These protocols will be used in our analysis being reported in Section 3.4.2.

3.4.1 CONVENTIONAL ACCESS MECHANISMS FOR IBSN

3.4.1.1 CONTENTION-BASED ACCESS MECHANISM

The contention-based access mechanism investigated in this study is Berkeley MAC (B-MAC) for low-power sensor networks [43]. It features low-power listening (LPL) and two random back-off periods without control packets such as receive to send (RTS), clear to send (CTS) and acknowledgment (ACK). One drawback of Carrier Sense Multiple Access (CSMA) is the delay: the sensor node has to wait to occupy the channel with a random back-off, thereby eliminating any real-time guarantee. The main disadvantage of B-MAC is the preamble, which creates large overheads. The effect of WuR can be studied by implementing a wake-up feature in B-MAC, reducing the delay by shortening the LPL mode and preambles.

EFFECT OF WUR: The channel can be pre-occupied by a node of the same network or by an external interference sharing the same spectrum. By using WuR, the main radio can sleep if it is not communicating, allowing the channel to be free of internal interference. The WuR will eliminate the idle listening by waking up only the intended receiver with encoded wake-up signals [100]. As a result, the main radio can transmit without waiting for the free channel and receiver can sleep without over hearing. The implementation of CSMA with WuR follows the Sub Carrier Modulated MAC protocol as reported in [100].

3.4.1.2 CONTENTION-FREE ACCESS MECHANISM

The contention-free access mechanism or Time Division Multiple Access (TDMA) enables the access to communication channel with guaranteed time slots (GTS). The real-time guarantee can only be achieved by time synchronization between the nodes with large and regular beacons shared within the network. These beacons consume additional bandwidth and power before any data is communicated. The implementation of Time Division Multiple Access (TDMA) protocol in this study follows Preamble-Based MAC as reported in [41]. The analysis of this protocol will explicitly show the efficiency of WuR in reducing the overheads of TDMA and thereby reduce the duty cycle of the main radio of [41].

EFFECT OF WuR: The use of WuR reduces the overheads in TDMA by reducing the large preambles prior to the transmission of the useful data. GTS for the main radio communication can still be achieved with shorter beacons containing synchronization, priority, and slot information as shown in [101]. The idle listening period of the main radio can be largely reduced with the use of WuR in TDMA mechanisms as well, which again decreases the power consumption. In order to evaluate the effect of WuR in TDMA, the implementation in this study follows On-Demand MAC as reported in [101].

3.4.1.3 HYBRID ACCESS MECHANISM

The hybrid access mechanism uses CSMA for non-real-time data communication and TDMA for real-time data. The data is sent based on priority and the GTS can be set depending on the application. One such hybrid MAC protocol which meets the requirements of IBSN is PNP-MAC [46]. The disadvantages of [46] are resource exhaustion in client nodes, high energy consumption and longer beacons, as it is not optimized for energy efficient performance.

EFFECT OF WuR: The effect of WuR in the hybrid access mechanism in terms of energy consumption, delay and reliability will be studied by comparing the PNP-MAC [46] with the Power-Efficient MAC which reduces the power consumption by shorter beacons in TDMA and shorter delay in the CSMA-based protocol reported in [70].

3.4.2 EVALUATION OF MAC PROTOCOLS WITH AND WITHOUT WuR

3.4.2.1 NETWORK SETUP

After characterization of the hardware, we formed a network to evaluate the performance of the communication between the sensor nodes using software simulation. OMNeT++ was used for software simulation. We used a star topology network composed of a central coordinating node and five client nodes. We used discrete event simulation with the PHY models obtained from characterization of radio channel in Section 3.3.3.

Figure 3.13: Overview of delays for dual radio communication

Simulation was repeated for different values of Inter Packet Arrival Time (IPAT), while observing parameters such as delay, power consumption, packet drop ratio and duty cycle. IPAT is defined as the time between adjacent packets to arrive at the receiver. It is a commonly used parameter to evaluate network performance, as it is directly affected by dynamic wireless channel.

3.4.2.2 EVALUATION BY THEORETICAL ANALYSIS AND SIMULATIONS

In order to evaluate the performance of MAC protocols with wake-up radio, three important parameters are considered: *delay*, *packet delivery ratio*, and *power consumption*. The operation of the MAC protocol with wake-up radio is shown schematically in Figure 3.13. The sensor node is assumed to have a main radio and a wake-up radio allowing parallel radio transmissions.

A MAC protocol with wake-up radio is expected to reduce the delay of communication in the main radio and the energy consumption of the wireless communication without affecting the packet delivery ratio. In this section we formalize these assumptions and analyze the performance based on them. We verify the validity of the formulas with simulations performed using the channel model developed from the characterization.

Delay The delay in a sensor network is defined as the time taken for a set of data to travel from the source to the destination without any errors. Let $D_{data-wur}$ be the overall delay for communicating the data packet using the access mechanism with wake-up radio as shown in Equation (3.5). Figure 3.13 gives an overview of delays in data communication, where,

- τ_{d_1} is the time taken for communication between the CPU of the sensor node to the wireless module,
- τ_{d_2} is the time taken for successfully waking up the destined node by the transmitter,
- τ_{d_3} is the time taken to wake up the main radio after receiving the appropriate wake-up signal,
- τ_{d_4} occurs after receiving acknowledgement for the wake-up signal from the receiving node, and
- τ_{d_5} is the time taken for the main radio communication including the time taken for the mechanisms prior to accessing the channel such as random back-off, clear channel assessment, and synchronization.

Equations (3.6) and (3.7) represent the delay in TDMA and CSMA respectively, where $\tau_{d_{csma}}$ and $\tau_{d_{tdma}}$ are the time taken for the backing-off procedure in CSMA and the time taken for synchronization in TDMA.

$$D_{data-wur} = \left(\tau_{d_1} + \tau_{d_2} + \tau_{d_3} + \tau_{d_4} + \tau_{d_5} \right) \quad (3.5)$$

$$D_{data-csma} = \left(\tau_{d_1} + \tau_{d_{csma}} + \tau_{d_5} \right) \quad (3.6)$$

$$D_{data-tdma} = \left(\tau_{d_1} + \tau_{d_{tdma}} + \tau_{d_5} \right) \quad (3.7)$$

For a MAC protocol with wake-up radio to have less total delay than a MAC protocol without wake-up radio, $(\tau_{d_2} + \tau_{d_3} + \tau_{d_4})$ must be less than $(\tau_{d_{csma}}, \tau_{d_{tdma}})$. From literature [101][34][100], it is found that the above condition is met for different access mechanisms in body sensor networks.

The time taken for the wake-up radio to wake-up the main radio and acknowledge the sender is less than the back-off period in CSMA and the beacon interval in TDMA, given the fact that internal interference and overheads are higher for the main radio. In our evaluation, experiments will be conducted to measure the delay in the network and verify the validity of the condition for the given IBSN scenario.

Measured values of the parameters τ_{D_1}, τ_{D_5} correspond to the values found in the hardware's data-sheet [97]. Values for the rest of the delay parameters, $\tau_{D_2}, \tau_{D_3}, \tau_{D_4}$ could not be measured directly and were therefore taken from the data-sheet.

The graph in Figure 3.14 confirms that $(\tau_{d_2} + \tau_{d_3} + \tau_{d_4}) < (\tau_{d_{csma}}, \tau_{d_{tdma}})$, i.e., the delay of the main radio without wake-up radio is higher than that of the main radio with wake-up radio. Furthermore the results show that the CSMA mechanism without wake-up radio has the highest delay and hybrid access mechanism with wake-up radio has the lowest delay. Even though the network size is smaller, the nodes suffered from collision in CSMA access mechanism without wake-up radio.

The delay in TDMA access mechanism is almost the same for MAC protocols with and without wake-up radio, since there is no change in time schedule. However, the

Figure 3.14: IPAT vs end-to-end delay

effect of longer and continuous beacons in TDMA is reduced, increasing the effective throughput. There were few missed emergency data communications from high priority nodes during the experiment which is not encouraged in IBSN.

Hybrid access mechanism with wake-up radio has no issues in delay and has better delay performance than CSMA and TDMA without missing any emergency data from high priority nodes and no collisions. In terms of delay, TDMA has a higher performance but due to the limitation in handling high priority data, the hybrid access mechanism with wake-up radio has a lower delay as shown in Figure 3.14.

Duty cycle and power consumption Duty cycle is the proportional duration for which the radio is turned on for useful data communication. The power consumption can be predicted using the duty cycle and the values of current and voltage of the radio hardware according to the data sheet of the radio hardware used.

The duty cycle of the main radio is reduced by introducing the wake-up radio, which detects the wake-up packet and allows the main radio to turn on from deep sleep state. This makes the main radio to remain turned off for a longer period of time without losing any useful data from being transmitted or received.

Let C_{M_0} be the duty cycle of the main radio without wake-up radio, C_{M_1} the duty cycle of the main radio with wake-up radio, and C_W the duty cycle of the wake-up radio. In order to relate the power consumption with the duty cycles, let P_0 be the power consumed for wireless communication without wake-up radio and P_1 the power consumed for wireless communication with wake-up radio.

Similarly, let P_{Mon} be the power consumption of the main radio when turned on, and P_{Moff} the power consumption of the main radio when turned off. We then have

$$P_0 = C_{M_0} \cdot P_{Mon} + (1 - C_{M_0}) \cdot P_{Moff} \quad (3.8)$$

$$P_1 = C_{M_1} \cdot P_{Mon} + (1 - C_{M_1}) \cdot P_{Moff} + C_W \cdot P_{Won} + (1 - C_W) \cdot P_{Woff} \quad (3.9)$$

This power calculation is to show that the longer the sleep mode, the shorter the duty cycle and hence the lower the power consumption. The power consumed by the main radio is higher than that of the wake-up radio. Hence for a system without wake-up radio to be power efficient, $P_1 < P_0$ has to be achieved. Applying the condition to Equations (3.8) and (3.9), we obtain

$$C_{M_1} < C_{M_0} - \frac{C_W \cdot P_{Won} + (1 - C_W) \cdot P_{Woff}}{P_{Mon} - P_{Moff}} \quad (3.10)$$

From Equation (3.10), we observe that the duty cycle of the main radio with wake-up radio is always lower than the duty cycle of the main radio without wake-up radio, considering (by design) that the power consumption of the main radio is much higher than that of the wake-up radio.

Figure 3.15: IPAT vs duty cycle

The duty cycle of CSMA without wake-up radio is highest among other access mechanisms indicating higher power consumption due to back-off and higher num-

ber of re-transmissions. Wake-up radio has reduced the duty cycle of CSMA, however it is still higher than other access mechanisms with and without wake-up radio.

TDMA without wake-up radio has higher duty cycle than the CSMA with wake-up radio because of longer and continuous beacons sent for synchronization within the network. The use of WuR reduced the need of continuous beacons and shortened the beacon during the main radio communication.

This has significantly reduced the duty cycle of the node when TDMA access mechanism with WuR is used. However, the hybrid access mechanism with WuR overcomes the drawbacks of these access mechanisms by reducing the longer back-offs and numerous re-transmissions, shortened beacons and synchronization. As mentioned earlier shorter duty cycles of main radio can save a lot of energy consumption, enabling longer network life and battery-life. The hybrid access mechanism with WuR has the shortest duty cycle of all the access mechanisms as shown in Figure 3.15.

Packet delivery ratio The packet delivery ratio (PDF) is the ratio of the total number of packets successfully reached at the receiver to the total number of packets sent from the sender. PDR is an important parameter to analyze the network performance with different physical layer parameters for a specific network topology. In case of IBSN the network topology is fixed, however, the IPAT can vary due to the highly varying physical properties of the human body as a medium.

Figure 3.16: IPAT vs packet delivery ratio

In a delay-sensitive network like IBSN, a packet will be considered not successful if it has not been received within the threshold time period. Packet delivery ratio

is low, i.e. the number of successfully received packets at the receiver end is low, for CSMA without WuR because of collisions and weak signal-to-noise ratio. Emergency data packets were lost when the time threshold for the data packets was exceeded. However, the CSMA with WuR was able to communicate with higher PDR but still not higher than other access mechanisms as shown in Figure 3.16.

TDMA with WuR has higher PDR at shorter IPAT but was out-performed by the hybrid access mechanism with WuR at higher IPAT. At higher IPAT, TDMA packets were lost due to longer preambles without the use of WuR, whereas TDMA with WuR increased the PDR considerably benefiting from the shorter beacons.

In medical scenarios, the loss of emergency packets cannot be tolerated under any circumstances. From the results, we demonstrate that the higher PDR is achieved in lossy environment like IBSN, when WuR was used in addition to the hybrid access mechanisms. In general, the use of WuR increased the PDR thereby increasing the reliability of the network.

3.5 CONCLUDING REMARKS

In this chapter, we characterized the physical layer and MAC sub-layer. We carried out rigorous experiments with different parameters of PHY and characterized the performance of the radio with animal tissue. Two different channel-models, in-body – in-body and in-body – on-body, were chosen for evaluation.

The empirical results show that the attenuation of radio communication is very high inside the tissue. The path loss exponent inside the animal tissue deviates from that of the IEEE 802.15.6 results.

Based on our experiments, we developed an optimum physical and network parameters that closely resemble the real-world scenarios of IBSN application. These channel model parameters were used to evaluate the impact of WuR in the performance of MAC protocols.

Results obtained from experiments with animal tissue and from simulations show that the hybrid access mechanism outperforms CSMA and TDMA for IBSN, because it combines the advantages of CSMA and TDMA. The disadvantages of those MACs are mitigated by using WuR.

Using WuR has a positive impact on the performance of hybrid access mechanisms for IBSN as it decreases both packet-loss and latency. The power consumed for duty cycling will also be less when WuR is used, because the power consumed by the WuR is much lower than that of the main radio.

BIO-INSPIRED MEDIUM ACCESS CONTROL FOR IBSN

CHRONIC care is an eminent application of IBSN. Performing physical activities such as walking, running, and sitting is unavoidable during the long-term monitoring of chronic-care patients. These physical activities cripple the radio frequency (RF) signal between the implanted sensor nodes. This effect dampens the communication between implantable sensor nodes and hence increases the chance of missing life-critical data. To overcome this problem, a link quality-aware MAC protocol called HACMAC is proposed in this chapter. We further optimized the HACMAC using wake-up radio (WuR) technology to reduce its power consumption, without affecting its reliability and latency. Our results show that, WuR based HACMAC is 30% more reliable and 20% faster and 44% energy-efficient than conventional MAC protocols suggested by the IEEE 802.15.6 standard.

உற்றான் அளவும் பிணியளவும் காலமும்
கற்றான் கருதிச் செயல்

*The habitudes of patient and disease, the crises of the ill
These must the learned think over well, then use his skill.*

—Thiruvalluvar in Kural 949

4.1 INTRODUCTION

In the past decade, health-care organizations underwent steep rise of pressure to provide improved health-care as the number of chronic disease patients increases every year world wide [3]. Chronic diseases such as heart and lung diseases require real time, continuous, and long-term follow-up from medical personnel. Energy-efficient medical sensors and devices, both wearable and implantable, are suitable for this purpose [102] [11] [12].

IBSN is capable of improving the therapeutic significance of the long-term treatments by collective-diagnosis, in which different symptoms of the chronic care patients are continuously monitored using subcutaneously implanted sensors. This diagnostic information is used as a feedback to adapt the treatment delivered by medical devices such as pacemakers and deep brain simulators (DBS) in real-time, resulting in the closed-loop operation of medical devices.

For example, in the case of epileptic patients, physiological information from sensors such as Electroencephalogram (EEG) and Electrocardiogram (ECG) together with physical information from sensors such as accelerometers, sweat, and breathing can be used to predict the onset of epileptic seizures with better accuracy [103]. In the such medical scenarios, wireless communication between the medical sensors and devices is inevitable. Wireless communication is the most power hungry part of such medical devices and any wireless communication should be energy-efficient and reliable.

As seen earlier, the propagation behavior of the RF signal in and around the human-body is highly reliant on the environment, characteristics of the human body and the hardware components, which directly affects the wireless communication. MAC protocols are mainly engineered to improve the reliability of wireless communication by:

(i) reducing collision (i.e., two nodes accessing the medium at the same time) and the data loss caused by it, (ii) lowering energy consumption by reducing idle-listening (i.e., a node listening for data-packets while no data-packets are being sent), and (iii) over-hearing (i.e., a node receives data-packets which are not destined for it).

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Advanced MAC protocols are designed to adapt to the quality of the physical medium. This adaptation means that communication is initiated only when quality of the RF link (calculated based on received signal strength information (RSSI)) between the sender and receiver is sufficient to successfully transmit and receive the data.

In this chapter we aim to develop a MAC protocol which is adaptive to RF link-quality and also provide reliable wireless communication between the nodes.

The rest of the chapter is organized as follows, in Section 4.2 we elaborate on the problem of link quality deterioration in IBSN by explaining the effect of human-activities in RF signal quality. A MAC protocol called Human ACTivity based MAC (HACMAC) protocol is presented in Section 4.3, followed by an explanation of its design and simulation.

In Section 4.4 we incorporate WuR into the design of HACMAC to further reduce the power consumption of sensor nodes. Through simulations we show that the power consumption of HACMAC is greatly reduced with the introduction of WuR without affecting the reliability of the wireless communication. Finally we conclude the chapter in Section 4.5 with remarks we observed from the experiments.

4.2 IMPACT OF HUMAN ACTIVITIES IN RF LINK QUALITY

4.2.1 INTRODUCTION

According to the European Telecommunications Standards Institute (ETSI) and IEEE 802.15.6 recommendation, The transmission power of the sensor nodes in IBSN must not exceed $25\mu\text{W}$ in order to ensure a safe operation within the human body [15, 27]. Also, the RF signal is heavily attenuated by the conductive tissues which deteriorates the wireless link quality. In general, a lower link quality will result in unreliable communication and unwanted wastage of energy in wireless communication.

The received signal strength information (RSSI) at the receiver end is a common method to estimate link quality. Link quality estimation (LQE) is another parameter used to estimate whether the communication between the nodes will be successful. LQE is a proprietary metric of Texas Instruments, which calculates the link quality at the chip by comparing the received frequency of bits with the expected frequency of bits according to the modulation schemes used by the chip. Other popular link quality metrics such as estimated number of transmission (ETX) [104], requested number of packets (RNP), and 4 bit (4B), use packet reception information to calculate the link quality.

In addition to the impact of channel characteristics, link quality between IBSN sensor nodes suffer greatly from signal attenuation caused by simple human activities such as walking, running, sitting, and standing. These physical activities cripple the radio frequency (RF) signal between the implanted sensor nodes. This is because

various body postures shadow the RF signal. Although shadowing itself may be short, a prolonged activity will significantly increase the effect of the RF-shadowing.

Impact of human activities on the RF link quality has been studied before and it has been shown that each activity has its unique pattern influencing the RF spectrum [105]. Use of RSSI value to calculate the link quality is a common method in designing MAC protocols aiming to ensure high PDR [106] [107].

For example in BANMAC [108], authors predict an opportunistic time window (OTW) by recording the RSSI values with a central controller in a network of 5 nodes. They achieve a high PDR of 96% at a very low transition power of -21dBm, simply by transmitting only during the predicted OTW. This achieved PDR is considerably high compared to the 73% of PDR achieved by the IEEE 802.15.4 MAC. Accurate estimation of the opportunistic time window (OTW) as done in the BANMAC requires complex calculations, which require a powerful central controller such as mobile phones to be always connected to the network. Such complex calculations cannot be performed by computationally primitive nodes of IBSN. Also the external nodes in IBSN have less computational power than mobile phones and cannot support extremely-long (in terms of months) wearable periods between charging cycles.

In BATMAC [109], authors used relay nodes to communicate between the transmitting node and the receiving node, when the wireless link between the sender and the receiver was shadowed by human body while performing different activities. BATMAC calculates the link quality using the PDR of the acknowledgement packets sent and received by the nodes, and forwards the packets through a relay if the calculated PDR is lower than the expected PDR. There are different methods to quantify the human activity from RSSI data, for example using band-pass filter followed by a fast Fourier transformation (FFT) [107] to extract the human activity information from RSSI in the frequency domain. Less complex analysis in time domain and statistical domain also exist [110] [111], which are easier to be implemented on resource-constraint IBSN nodes.

4.2.2 IMPACT OF HUMAN ACTIVITY ON LINK-QUALITY

In contrary to the existing works, we define the human activity in which the human is not only physically active (e.g. walking and running) but also idly active for example while sitting, sleeping, and standing. We measured RSSI data while performing different activities using the CC430 based on-body sensor nodes which is described in [14]. We made these measurements between two on-body sensor nodes placed on the ankle and on the waist, while the person was in an indoor-office environment.

The measurements were made without MAC implementation and RSSI was recorded every 100 ms, which was sufficiently longer to record the impact of the activities in RF signal. Transmission power was set to -12 dBm at the ankle-node and waist-node was receiving continuously (for details about hardware specifications refer [14]).

Figure 4.1: Boxplot of RSSI data while performing different activities

Figure 4.2: Time vs RSSI. The colormap shows the distribution of PDR during each activity

Our initial study shows that even idle activities greatly influence the RF signal. The magnitude of attenuation caused by different activities can be seen from Figure 4.1, in which mean and standard deviation of the RSSI during different activities are illustrated. It can be seen that each activity has its own particular deviation with respect to the RSSI values. Additionally, activities such as sleeping, sitting, and standing have constant attenuation for long period of time which results in very low RSSI and hence low packet delivery ratio (PDR). Figure 4.2 shows distribution

of RSSI and PDR while performing different activities. It can be understood from the figure how the RF signal is affected by different activities. A high PDR means a favorable link quality.

The RSSI value is clipped in the range of -65dBm and -90 dBm specifically to show (i) the effect of low RSSI and (ii) that low RSSI does not always result in a low link quality. This is because the link quality also depends on the RF noise level and multi-path effect of the environment. Figure 4.2(e), shows a clear indication of walking pattern of a person walking at a speed of 4 km/h with each step lasting about 1.2 seconds.

It can be seen that at very low RSSI, PDR is still high for a short duration of time between each step indicating the line of sight between ankle and waist nodes. Figure 4.2(d) shows the running activity, in which the person is running at a speed of about 14 km/h with each step lasting about 0.6 seconds. It can be observed that the pattern repeats with the same periodicity for a long period of time.

Figures 4.2(a) and (c) show during standing and sitting activities, the link quality is good and constant with high PDR. However, depending on the posture of sitting or standing, the quality of link will vary. Sleeping activity can be disrupted when the human rolls towards the bed and there is no direct line-of-sight between the transmitter and receiver. A huge difference in the PDR is seen during the sleeping activity due to the complete shadowing of the RF signals by the body for a significantly longer periods of time, as shown in Figure 4.2(b).

Finding a time window for such dynamic events, if not impossible, is a complex-process to be implemented on resource constraint IBSN nodes. Idle activities like sleeping can occur with longer duration in the same posture, causing constantly low RSSI and link quality between the nodes. The frequency of the occurrence of human activity is not always predictable and to enable the radio communication only while a favorable link-quality exist is challenging for the MAC protocol design.

The time window prediction is useful for activities such as walking and running, in which periodicity is expected, and transmitting only during favorable link quality will ensure high reliability. It is, however, not very useful and energy-efficient in case of idle activities such as sleeping, sitting, or standing.

Use of relay nodes will improve the PDR during idle activities by hopping the information through an intermediate node which is not shadowed by the body posture. Also, use of relay nodes is feasible in IBSN, as the maximum number of hops required is at most two, due to the short distance between the nodes [112].

However, introducing relay nodes will increase the power consumption [112] particularly because of (i) improper design of routing and (ii) unwanted use of relay nodes, which are the same reasons for not recommending the use of relay nodes in MICS band communication by the IEEE 802.15.6 standard [27].

By considering a combination of both physically active and idle activities and their effect on the RSSI, we will design a link quality-aware MAC protocol called the Human ACTivity Medium Access Control (HACMAC). We will follow the regula-

tions (i) set by ETSI for the physical layer parameters of active medical implants and (ii) as suggested by the IEEE 802.15.6 standard for MAC layer parameters for medical implant communication service (MICS).

4.3 HUMAN ACTIVITY BASED MEDIUM ACCESS CONTROL (HACMAC)

HACMAC is an hybrid access mechanism based on the IEEE 802.15.6 MAC layer specifications and is intended to operate in MICS band communication [27]. The main aim of the HACMAC is to enhance the reliability of wireless communication when the RF spectrum is distorted by human activities without compromising on the energy-efficiency of the sensor nodes.

Despite the poor channel characteristics and ultra-low transmission power of $25\mu W$, HACMAC ensures reliability in IBSN by using:

- Hybrid access mechanism to support reliable transmission of high priority medical data
- Modified IEEE 802.15.6 MAC protocol to support long term monitoring with medical implants
- Adaptive scheduling
- Fault tolerant link management to overcome RF shadowing effect while performing different activities

Figure 4.3: Location of IBSN nodes in simulation set-up

We assume that resource-constrained BN nodes of IBSN are implanted subcutaneously in the human body with one external body-worn coordinator node (BNC). An example of IBSN is shown in Figure 4.3, where the red node is BNC and coffee-colored nodes are implanted subcutaneously in the body.

The BN nodes can also act as a relay node (BNR) to hop information with the same mechanism as described in the IEEE 802.15.6 standard [27]. According to this

standard, nodes are classified into two categories, namely priority nodes and non-priority nodes.

IEEE 802.15.6 MAC uses super-frame of duration n time units, within which BNC allocates three different phases namely, exclusive access phase (EAP) in which the nodes can only send emergency medical data in contention based fashion, random access phase (RAP) in which all nodes can contend to send medical-data, managed access phase (MAP) in which the BNC allocates either carrier sense multiple access with collision avoidance (CSMA/CA), slotted aloha, polled allocation, or scheduled time division multiple access mechanism (TDMA) for each BN node to send the medical data. The super-frame structure is shown in Figure 4.4.

Figure 4.4: Super-frame specified by the IEEE 802.15.6 standard [27]

HACMAC is operated in beacon mode, in which a beacon frame B is transmitted from BNC to the BN nodes at the start of each super-frame period to facilitate the network management, including the coordination of medium access phases, duty-cycle of the BN nodes connected the BNC, and clock synchronization information. HACMAC uses TDMA during the MAP phase for transmitting the non-emergency data which applies to continuous monitoring of medical symptoms. It uses CSMA/CA during the EAP phase for sending emergency data, which can be an anomaly in the medical data. This processed is shown in Figure 4.5

Figure 4.5: BNC and BN communication processes as specified by IEEE 802.15.6 standard [27] ($BN1$ is an emergency-node, and $BN2$ is a non-emergency node.)

It was discussed in Section 4.2 that the PDR drops substantially depending on the body posture during the activities. This results in poor reliability and energy wastage. HACMAC uses RSSI information and PDR information to detect the human activity and benefits from the periodicity and dynamicity of human activities to improve the reliability and energy-efficiency of the wireless communication.

In HACMAC, BNC performs minimalistic operations to adapt the super-frame for reliable communication. BNC does not require additional packets to carry out these operations because the required information, such as RSSI and PDR, are derived from the data-packets transmitted previously. BNC propagates the adaptive super-frame structure to the BN nodes through the beacons, which makes HACMAC simple yet powerful.

The BN nodes determine their position, link quality, relay mechanism, and periodicity, through the beacon frame of the BNC, based on which the BN node determines the access mechanism, time slot and the relay to transmit the information to BNC.

HACMAC is designed based on two important metrics, i.e., RSSI and PDR. Although these metrics are noise-prone, careful pre-processing is done to ensure the credibility of these parameters during the run-time of the network.

(i). RSSI sensing function

RSSI sensing function is implemented only on the BNC. Before the network initiation, RSSI values between each BN node and the BNC are calibrated and stored in a table, for different activities of a person.

The calibration process will identify the mean ($\mu = \frac{1}{N} \sum_{i=1}^N x_i$) and standard deviation ($\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2}$) of RSSI, for different activities. The mean and standard deviation are used for simple rule-based identification of different physical activities.

Since the location of nodes are fixed in IBSN, the calibration remains valid for longer periods of time. Periodicity of the activity is determined by peak-detection using *mean crossing rate* and deriving the time stamps for each of the RSSI values which crosses a threshold of the mean value. Upon network initiation, the RSSI sensing function will buffer RSSI after each super-frame period, as per the requirements of HACMAC schemes.

(ii). PDR sensing function

BNC calculates PDR using number of successful reception of packets within minimum number of re-tries. We use the acknowledgment scheme of IEEE 802.15.6 standard to calculate the PDR by sensing the sequence number and the acknowledgment of a packet, which is similar to the *Expected Number of Transmissions (ETX)* [104] method of estimating the link quality.

4.3.1 SCHEMES OF HACMAC

HACMAC uses three main schemes, namely, (i) qualitative time-slot allocation, (ii) m-period interleaving, and (iii) adaptive relay establishment to function robust against RF shadowing caused by the human activities irrespective of their dynamicity and non-periodicity. In what follows we elaborate on each of these three schemes.

Figure 4.6: HACMAC schemes - Flowchart

(i). Qualitative time-slots allocation

As shown in Figure 4.2(d) and Figure 4.2(e), the periodic activities performed by human beings have sufficient time periods of favorable link quality. On the BNC node, RSSI values of the BN nodes are buffered for T_n time period in a buffer of n_{buf} , after each super-frame period n . As soon as the buffer is full, the BNC node calculates the mean and variance of the RSSI values, which are unique for each periodic activity.

Average periodicity of each activity is calibrated for a specific person and pre-stored on the BNC. The BNC adapts the time-slot allocated to the BN node such that the node transmits only when favorable RSSI is sensed.

By doing so, even if the RSSI value is lowered down over time because the person moves in different environments while performing different activities, the signal to noise ratio will still be high when the link between the BN and the BNC nodes is not shadowed by the human body. Such high signal to noise ratio will result in a good PDR.

(ii). M-periodic interleaving

If the RSSI values do not exhibit any periodicity, the BNC assumes that the person is idle and distributes the time slot equally between all BN nodes. However, a person can be static in a body posture, but the link between a BN node and BNC maybe shadowed.

We will use the RSSI sensing function of the BNC explained before to allocate time slots for the BN nodes such that for the BNs node with the highest shadowing, additional redundant time-slots will be allocated. This time-slot allocation will be constant for a period of m super-frames until the RSSI sensing function detects periodicity.

Sequentially, the PDR sensing function will accumulate packet delivery information for all BN nodes. If PDR of a specific BN node decreases during the m-periodic interleaving, a relay node (BNR) between the BNC and the BN has to be instantiated to relay the packet to guarantee the required PDR. If a relay node is instantiated, the adaptive time slot allocation is reset immediately, reverting back to the equally distributed time-slot allocation.

(iii). Adaptive relay establishment

As explained above, the prolonged shadowing effect of RF link between the BN and the BNC nodes can be improved by selecting a relay node between them.

The mechanism of connecting the relay node in HACMAC is inspired by the IEEE 802.15.6 standard [27]. Prolonged shadowing of the BN increases the possibility of missing life-critical medical events and also may increase the latency. As the transmission power cannot be increased in the MICS RF band, temporary use of relay nodes is an optimal solution to overcome this situation.

Moreover, in HACMAC the relay node is used only when a low PDR is detected and is disabled otherwise. This reduces the unnecessary wastage of energy on the BN node.

The location of nodes in IBSN is fixed once implanted, which makes the selection of relay nodes simple.

Time-slot of the relay node will be compensated by an additional time-slot allocation in which the relay node can transmit its own data. The RSSI and PDR sensing functions of the BNC will decide about the duration for which the relay node has to function.

4.3.2 OPERATION OF BN AND BNR

The BN node receives the beacons and identifies the duration of each phase and the time slot allocated for it. If there is no data to be sent, the BN node transmits the no-data frame and goes to sleep, otherwise it transmits on the time slot allocated to it.

Figure 4.7: Operation of BN

Figure 4.8: Operation of BNR

In case of a emergency event or an anomaly in the sensed medical data, the BN node contends to send data in the consecutive EAP phase with reference to the latest received beacon. BN node does not have to send any additional packets for the operation of HACMAC. Figure 4.7 presents the flow chart of the BN operation.

In case of the relay initiation, BN node which acts as the BNR will encapsulate the data in its frame and transmit it to the BNC in the additional time-slot allocated for it. It is important to note that emergency nodes cannot be allocated as relay nodes to prevent any ambiguity in selection of relay. This process is similar to the relay mechanism as described in IEEE 802.15.6 standard [27]. Figure 4.8 present a flow chart of the BNR operation.

The choice of selecting a BN node as a relay node is pre-determined based on the location of the node. For example, in Figure4.3, the BN node on the ankle, uses BN node on the thigh as the relay node. Since the location of these two nodes is fixed, the choice of relay node is easily pre-determined and the relay-topology for each BN node is pre-stored in the BNC.

4.3.3 EVALUATION OF HACMAC

For the purpose of evaluation, we use simulations in an OMNeT++ based simulator called Castalia v3.2 [113]. Castalia simulator has good implementation of temporal variations of the physical channel and is modifiable in the simulator.

We measured the RSSI values between each BN node and the BNC in a round-robin fashion, during each activity in an indoor environment. We model 5 different

activities namely, sitting, standing, sleeping, walking and running, since these activities cover both the periodic and non-periodic activities.

The BN nodes were sending a dummy packet of 40 bytes to the BNC every 10 ms (optimal for measuring the impact of human activities in RSSI [112]), with which the BNC calculates the RSSI and PDR, while the human was performing each activity.

Algorithm 1 Pseudocode of HACMAC operation

```

1: procedure HACMAC(BNC,BN,BNR)
2:    $BNC \leftarrow \text{Calibrate\_Activities\_RSSI}$ 
3:    $\text{Init\_IBSN}$  ▷ PHY & Topology fixed
4:    $\text{Init\_802.15.6\_MAC}$ 
5:   for  $\text{SuperFrame\_BNC}$  do
6:      $n_{buf} \leftarrow \text{Accumulate\_RSSI}$ 
7:     if  $n_{buf} > \text{MAX\_BUF\_SIZE}$  then
8:        $(\mu(n_{buf}), \sigma(n_{buf}), \delta_{peak}(n_{buf}))$ 
9:       if  $(\text{RSSI} \rightarrow \text{PeriodicActivities})$  then
10:         $\text{Adaptive\_Time\_Slot}(\delta_{peak})$ 
11:       else if  $\text{PDR} < \text{Req\_PDR}$  then
12:         $\text{Adative\_Relay\_Est}$ 
13:       else
14:         $M - \text{Periodic\_Interleaving}(\mu, \sigma, \delta_{peak})$ 
15:       end if
16:       go to 6:
17:     end if
18:   end for
19: end procedure

```

These RSSI values are translated to temporal variations as mentioned in [113]. In addition to our measured data, we also used the data from [112] and [110] to simulate the temporal variations of the physical channel caused due to the human activities.

For the simulation of MAC protocols, we used the PHY parameters as listed in Table 4.1. We simulated 5 BN nodes which are located on two limbs, thigh, chest and back-shoulder, and one BNC connected in a star topology, as shown in Figure 4.3. This topology is suitable for most of the medical applications [14].

Parameter	Value	
Channel bandwidth	300	kHz
Reception current	7	mA
Transmission current (main)	11	mA
Idle current (main)	3	mA
Sleep current	3	μA
Slot time (TDMA)	500	μs
Number of retries (CSMA)	10	–
Goodput	40	kB/s

Table 4.1: Simulation parameters

Note that the thigh node is a potential relay node between the ankle BN node and the BNC. We vary the data generation rate for each node in order to simulate the heterogeneity of the IBSN nodes that generate the medical data at different rates,

for example in case of a blood-glucose sensor and a heart rate sensor. In Algorithm 1, the pseudo-code of the implementation of HACMAC is presented.

In order to compare the performance of HACMAC with existing MAC protocols, we simulate IEEE 802.15.6 MAC without wake-up radio [27], BANMAC [108] which uses OTW to access the wireless medium, and BATMAC [109], which uses relay nodes to transmit data with variable super-frame period, in the same physical channel described in [14].

We use specifications of the Microsemi ZL70102 radio [114] to evaluate the power consumption of the BNC, BN, and BNR nodes. However, it has to be noted that the actual power consumption depends on the hardware design of the sensor nodes and the overheads caused by the additional hardware to support the functioning of the wireless radio.

4.3.4 RESULTS AND DISCUSSION

Simulation results related to reliability, latency, and power consumption are shown in Figures 4.9-4.13. Figure 4.9 illustrates the average PDR of the network calculated on the BNC node.

Figure 4.9: Offered load vs Packet delivery ratio

The IEEE 802.15.6 MAC without wake-up radio has the lowest success in terms of packet-delivery ratio because of lack of any mechanism to compensate for the high attenuation caused by the human activities. At high data generation rates, the IEEE 802.15.6 MAC has around 20% packet loss. This indicates, the need for a mechanism which can compensate for the attenuation caused by the human activities.

BANMAC protocol predicts OTW to compensate for the periodic activities like walking and running, hence it outperforms the IEEE 802.15.6 MAC at higher data

generation rates. However, it still has 15% packet loss at higher data rates, which is not desirable for IBSN. Such high packet loss is due to the lack of any mechanism to compensate for the prolonged attenuation caused by idle activities such as sleeping and sitting.

BATMAC uses relay nodes to compensate for long attenuation but it cannot compensate for high attenuation caused by periodic activities. BATMAC has the worst performance with almost 25% packet loss because it does not take into account the short periods of favorable links at higher data generation rates. In contrary, HACMAC has the lowest packet loss of 10% even at higher data generation rates, due to the fact that it compensates for the prolonged attenuation caused by idle activities and benefits from the shorter periods of favorable link quality to achieve better performance in all the scenarios.

Figure 4.10: Offered load vs Application level latency of IBSN

Application level latency is the difference in time at which the packet is generated and the time at which packet is received at the receiver. BATMAC which uses purely time-slot allocation with adaptive super-frame structure has more delay when more packets are generated. Measurements of application level latency are shown in Figure 4.10.

On an average, the hybrid MAC protocols, IEEE 802.15.6, BATMAC, and HACMAC have uniform distribution of latency, which is due to their uniform super-frame duration. OTW prediction in BANMAC adds overhead packets to be transmitted which significantly increases the latency of successful communication. IEEE 802.15.6 MAC has no such mechanism but still suffers from temporal variations in the wireless channel, which results in a slightly higher latency compared to HACMAC.

HACMAC has pre-stored information, which can overcome temporal variations in the channel and perform better in latency than the rest of the MAC protocols.

The power consumption evaluation results of the MAC protocols are illustrated in Figure 4.11- 4.13. The power consumed is calculated by measuring the periods at which the BNC, BN and BNR are transmitting, receiving, idly listening (radio is turned on but not in receive mode) or sleeping (radio is turned off). Note that, each mode of radio operation has different power consumption as mentioned in Table. 4.1.

Figure 4.11: Power consumption - BNC

The power consumption of the BNC is vastly reduced in HACMAC due to the fact that it does not listen for a long period and transmits no extra beacons to calculate the PDR. HACMAC benefits from the characteristics of the human activities and pre-predicting the activity and its attenuation characteristics. On the other hand, BANMAC requires additional receiving and transmitting periods to effectively calculate the OTW.

BATMAC suffers from repeated transmissions to decide the super-frame period and the selection of the relay nodes. It wastes extra power to decide on the relay nodes when the topology is fixed, which results in additional power consumption at higher data generations rates.

The IEEE 802.15.6 MAC has no mechanism to compensate for the attenuation at all, which results in higher number of retries in prolonged attenuation periods, than the rest of the MAC protocols. The difference between power saving mechanisms in HACMAC and BATMAC on the BN nodes is quite small, because both of them use similar process in selecting the relay nodes.

The only difference between the two MAC protocols is that, in HACMAC the BN nodes are excluded from the process of deciding the relay nodes in longer attenu-

Figure 4.12: Power consumption - BN

Figure 4.13: Power consumption - BNR

ation periods. In BANMAC, the BN nodes have higher power consumption due to the additional reception and transmission required for the OTW prediction. In the IEEE 802.15.6 MAC, the BN nodes have the highest power consumption since they suffer from higher number of re-transmissions to ensure reliability.

BANMAC has no relay mechanism to compare the power consumption of the relay nodes. We used BATMAC and IEEE 802.15.6 MAC with 1 hop extended star-topology to compare their power consumption with HACMAC. In BATMAC, the BNR nodes continuously listen for the packets and re-route the packets depending on the link quality to the BNC. This process requires the BNR to be always in the receive mode when it is not transmitting, making the BNR power hungry.

To improve this process, in HACMAC the BNC selects the BNR nodes by calculating the link quality after each super-frame duration which enables the BNR nodes to be in idle mode in most of the super-frame duration, and BNR enters the receive mode only in the scheduled time slot. Energy-efficiency of HACMAC over BATMAC is realized in higher packet generation rates as shown in Figure 4.13.

In the IEEE 802.15.6 MAC, the BNR nodes try to poll the source BN node for any remaining data and have no pre-stored information about the topology. This requires additional packets to be sent between BNR and BNC so that an agreement can be made regarding the relay mechanism. These additional packets can consume extra power when the channel is dynamically varied in terms of link quality and higher number of retries are required for a successful reception of the packet.

4.3.4.1 CONCLUSION

We presented the HACMAC protocol, which complies with the IEEE 802.15.6 regulations and adapts dynamically to different human activities in order to guarantee a high reliability of wireless communication being distorted by shadowing effect. We compared the performance of HACMAC in terms of packet loss through simulation

and demonstrated the need to handle dynamic attenuation caused by different kinds of human-activities. Power consumption of the wireless radio decreased greatly with HACMAC when compared to the IEEE 802.15.6 MAC, BANMAC, and BATMAC.

However, at low packet generation rates there is no reduction in power consumption of the relay nodes in HACMAC compared to BATMAC. In IBSN the packet generation rates are highly dynamic, i.e. the number of packets generated will vary from few packets per second to hundreds of packets per second. HACMAC however is not very energy-efficient in low packet generation rates. BATMAC, which has only the relay mechanism, has similar power consumption as HACMAC. To overcome this problem, we will incorporate WuR technology into HACMAC in the following section.

4.4 WAKE-UP RADIO BASED OPTIMIZATION OF HACMAC

HACMAC has excellent performance in terms of reliability while operating in an IBSN based environment. Thanks to its adaptive mechanism, which takes into account the dynamic temporal channel deterioration. We were able to accomplish a maximum of 20% increase in packet delivery ratio while achieving 15% reduction in latency.

However, BN nodes of HACMAC consume 15% more energy than BATMAC at low packet generation rates. Power consumption of BNR nodes in HACMAC is similar to BATMAC. In real world scenarios, this power consumption will be drastically increased rendering the HACMAC unusable for IBSN nodes.

In this section, we will strategically introduce Wake-up radio (WuR) in addition to the main radio of HACMAC to reduce its power consumption. Also, we will investigate whether the packet delivery ratio is affected while using WuR and whether the addition of wake-up radio introduces any delay in the HACMAC performance.

4.4.1 WUR IN HACMAC

As seen in Chapter 3, use of WuR can reduce the power consumption of conventional access mechanisms. WuR will operate in addition to the main radio in a different frequency band. The power consumption of WuR is negligible compared to that of the main radio due to two important factors, i.e., its modulation method and data-bandwidth. This reduces the amount of information that need to be sent through WuR.

Various WuR designs that are available in both literature and commercially off-the-shelf. We select one of the most power-efficient designs of the WuR, which operates in 433 MHz with On-Off Keying (OOK) modulation as presented in [115]. This WuR design is intended for very short range of operation that can cover upto 20 meters.

Figure 4.14: Functional blocks of WuR design based on [115]

The OOK modulator in [115] is also designed in such a way that WuR receiver is always in ultra-low power idle mode and will enter full reception mode only when it decodes a unique device ID from OOK signal. By doing this, no power is wasted in idle listening mode and the OOK decoder consumes merely 9nW. To compare it with our main radio, which has an idle mode power consumption of 3mW, WuR in [115] consumes very negligible amount of power in idle mode.

In addition to the unique device ID, OOK decoder can also deliver short messages called Wake-up Beacon (WuB). The WuB are appended to the device ID in such a way that the intended device which is full reception mode can only decode the WuB message. The functional blocks of the WuR design is shown in Figure 4.14. The characteristics of the WuR that will be used for this study are shown in Table 4.2.

Parameter	Value
Channel bandwidth	20 kHz
Reception current	0.27 μ A
Transmission current (main)	1 mA
Data rate	10 kB/s
Frequency of operation	433.9 MHz
Sensitivity	-51 dBm

Table 4.2: Simulation parameters

In case of HACMAC, we have a hybrid access mechanism which will use CSMA/CA for emergency data communication and TDMA for non-emergency data communication. Also, as shown in Figure 4.6, three main schemes called the qualitative time slot allocation, M-periodic interleaving, and adaptive relay establishment are used to extract information about the channel deterioration. In addition to these schemes, nodes in WuR-based HACMAC will have a WuR that will operate in addition to the main radio. By this, we assume the following,

- Main radio will be switched off on BNC, BN and BNR all times except the when useful data needs to be transmitted or received between the nodes.
- WuR in BNC will be always in reception mode except when it needs to wake-up a certain BN node.

- WuR in BN and BNR nodes will always be in sleep mode except for periodic idle mode listening which is pre-determined globally throughout the network by the BNC.

The operation of BNC in WuR based HACMAC is almost similar to that of the normal HACMAC. The WuR only replaces the idle mode operation of BNC and rest of the operation of BNC is same as HACMAC. However, the operation of BN and BNR is changed, as will be explained in the following subsections, in order to achieve maximum energy-efficiency.

4.4.1.1 OPERATION OF BN NODE

The BN nodes in WuR based HACMAC aim to reduce power consumption by switching off the main radio when there is no data to be sent from the node. The BN node will continuously monitor for any emergency events locally on the sensor node.

In case of an emergency event, the BN node first checks if it needs a relay node for sending the emergency information to the BNC. If a relay node is not needed, it sends an WuB to BNC requesting for a time-slot in the following MAC frame. Once a acknowledgement for the WuB request is received, the main radio is turned for the specified time slot and the data is sent.

If a relay node is needed, the BN node sends an WuB request to BNC for initiating the emergency relay node. Since the topology is apriori known in IBSN, the BNC wakes up the relay node corresponding to the requesting BN node. Once the relay_active WuB is received from the BNC, the BN node will turn on the main radio and transmit the emergency data.

The non-emergency data is sent periodically to the BNC similar to the HACMAC scheme. However, instead of predetermined time-slot WuR based HACMAC requests the time-slot needed for the corresponding data transmission. By doing this the BNC will know the time required for a BN node to send all its non-emergency data. The appropriate time slots are allocated and the BN node is acknowledged by BNC through WuB, indicating the time-slots allocated. BN node will now turn on the main radio for non-emergency data transmission.

In cases when BNC needs to wake-up a BN node, a WuB is continuously transmitted across the network. Once a BN node decodes the device ID and if it matches with its device ID, the main radio is turned on for data communication, otherwise it ignores the WuB and goes to sleep mode. The WuR of the BN node will be again be awake only at the beginning of the next super-frame.

The operation of BN node in WuR-based HACMAC is shown in Figure 4.15

Figure 4.15: Operation of BN

4.4.1.2 OPERATION OF BNR NODE

The BNR node in IBSN has more energy resource than a BN node. BNR nodes are deployed in such a way that no emergency event will occur in its location. However, the BNR node will be monitoring physiological signals and reporting to BNC.

The main radio is always off except when the BNR node has to communicate to BNC node or relay information from another BN node to BNC. The WuR of BNR operates in a duty-cycle, in which it wakes-up for every super-frame period to listen for any initiate_relay request from BNC. If there is no relay request, the BNR node goes back to sleep mode.

If there is any relay request, the BNR checks if it is an emergency_relay request. In case of an emergency relay request, the BNR will send an WuB requesting for a time-slot allocation. Once the time-slot allocation request is acknowledged by BNC, the BNR will turn on its main radio to communicate in the allocated time slot.

If the relay_request is non-emergency transmission, then BNR node will wait till its next frame period to turn on the main radio for data communication. During the next super-frame, the BNR will send the data using main radio in managed access phase determined by the BNC.

Figure 4.16: Operation of BNR

Once transmission of all the data queued up for transmission is complete, BNR node will turn off the main radio and returns the WuR to idle mode of operation. Operation of BNR is shown in Figure 4.16.

4.4.2 EVALUATION OF WUR-BASED HACMAC

We simulate the WuR-based HACMAC in a similar simulation set-up as explained in Section 4.3.3. The characteristics of the WuR as mentioned in Table 4.2 are used to create a separate radio hardware in Castalia [113]. All the sensor nodes simulated have a packet_generation unit, main radio and a WuR .

Dynamic temporal deterioration of the channel is simulated using the pre-recorded RSSI valued measured during different human activities. Also, to compare the performance of the WuR-based HACMAC, we used IEEE 802.15.6, HACMAC, BATMAC and BANMAC as described earlier in Section 4.3.3.

It is important to note that these MAC protocols only have one radio, in other words no additional WuR to optimize the power consumption. Main radio of these three MAC protocols are never completely turned off, i.e. the main radio will be listening periodically in idle mode of operation, consuming less power than reception or transmission mode.

4.4.3 RESULTS AND DISCUSSION

Simulation results of WuR-based HACMAC protocol are shown in Figures 4.17-4.21. Reliability of the WuR-based HACMAC is measured using PDR, which is the ratio between number of packets successfully received at the receiver and number of packets transmitted.

Figure 4.17: Offered load vs Packet delivery ratio

As shown in Figure 4.17, the use of WuR in HACMAC positively improves the packet delivery at lower packet generation rates. This is mainly due to the optimized time-slot allocation, where prior to the actual data transmission BNC knows the amount of time required to send the data. This *â*priori time-slot allocation improves the PDR at lower packet generation rates.

However, there is no further improvement in PDR when packet generation rates are high. At such high generation rates, WuR-based HACMAC performs similar to that of HACMAC. Performance of other MAC protocols are shown for comparison.

As shown in Figure 4.18, the application level latency is reduced in WuR-based HACMAC at lower packet generation rates. However, at higher packet generation rates, the latency is slightly increased than HACMAC. This is mainly due to the fact that the main radio has to be turned on for larger duty-cycle, in addition to the WuR

In addition, more beacons from WuR has to be sent to BNC for additional time slot allocation. It is important to note that this increment in latency can be reduced by switching of the WuR in long periods of continuous data transmission. However, the latency of WuR-based HACMAC is still lower than other MAC protocols compared.

Figure 4.18: Offered load vs Application level latency of IBSN

Power consumption of WuR-based HACMAC is shown in Figures 4.19-4.21. The power consumed by main radio is calculated by measuring the periods at which the BNC, BN and BNR are transmitting, receiving, idly listening (radio is turned on but not in receive mode) or sleeping (radio is turned off). The power consumed by WuR is calculated by measuring the period at which BNC, BN, and BNR are transmitting, and receiving through WuR . Note that, each mode of operation in WuR and main radio has different power consumption as mentioned in Table 4.1 and 4.2.

Figure 4.19: Power consumption - BNC

The power consumption of BNC in WuR-based HACMAC is vastly reduced because of the always-on ultra-low power wake-up radio. The main radio is completely turned off, which eliminates the power wastage that happens due to the idle mode listening. Although WuR is always-on, the power consumed by the WuR is negligible when compared to the main radio.

Figure 4.20: Power consumption - BN

Figure 4.21: Power consumption - BNR

We were able to achieve a maximum of 44% reduction in power consumption of BNC through WuR-based HACMAC. Results of other MAC protocols are shown for comparison. In BN and BNR nodes, WuR-based HACMAC has vastly reduced the power consumption at low packet generation rates. However, at higher packet generation rates the power saving is not very high. This is due to the fact that larger packet generation rates fill the data queue faster and the main radio has to operate at larger duty-cycle, where the use of WuR has very little impact on energy-efficiency. However, we achieved the best possible energy-efficiency possible than other MAC protocols with WuR-based HACMAC without affecting the reliability and latency performance.

4.5 CONCLUDING REMARKS

In this chapter, we studied impact of human activity on the RF link quality. The patterns of temporal channel-deterioration caused due to dynamic human activities such as walking, running and sleeping was used to develop an adaptive MAC protocol called HACMAC. Reliability and latency of the wireless communication were significantly improved compared with the state-of-the art MAC protocols. However no improvement was observed in terms of power consumption of the sensor nodes.

To address this problem, we strategically introduced WuR in the design of HACMAC, such that the main radio was turned-off all the time except when useful com-

munication took place between the nodes. Power wastage due to idle-listening was significantly reduced in all the BNC, BN and BNR nodes. WuR-based HACMAC had similar performance as HACMAC, in terms of reliability and latency. Through simulation we showed that the WuR-based HACMAC has the optimal power consumption and still can provide reliable wireless communication with very low latency than the state-of-the-art MAC protocols.

DISRUPTION-TOLERANT REINFORCEMENT- LEARNING BASED MAC

LINK quality between the nodes of IBSN is heavily disrupted even by normal human activities such as walking and running. These disruption patterns are unpredictable since the patient can carry out random activities at any time. The activity pattern is also dynamic since, for example, patients walk in different patterns resulting in very different RF disruption models for the same activity. To this end, we propose Disruption tolerant reinforcement learning-based MAC (DiNAMAC) protocol, which uses reinforcement learning technique to adapt the MAC scheduling based on channel conditions and to prioritize data transmission and availability. In addition, we design DiNAMAC as a model-free learning technique to make it more practical in real-world applications. Our simulation results show that DiNAMAC performs better than conventional MAC protocols in terms of latency and throughput.

கற்க கசடறக் கற்பவை கற்றபின்
நிற்க அதற்குத் தக.
So learn that you may full and faultless learning gain,
Then in obedience meet to lessons learnt remain.
—Thiruvalluvar in Kural 391

5.1 INTRODUCTION

Inevitable day-to-day activities such as walking, running, and sleeping cause severe disruptions in the wireless link among IBSN sensor nodes, resulting in temporary shadowing of wireless signals. These disruptions in the wireless link not only reduce the reliability of the network but also increase the power consumption.

This is mainly due to the very low isotropically radiated power of $25\mu W$ set by the spectrum regulations. Additionally, at such low power transmission, fading and shadowing of RF signal is very frequent due to the conductivity of human body [116].

Therefore, one of the important requirements for the MAC protocol is the capability to deal with unreliable wireless links and to handle the enormous temporal variations in the wireless link quality caused due to the day-to-day activities such as walking, running, sleeping, and sitting of a patient [23].

These temporal variations are very unpredictable since the patient can carry out random activities at any time [19]. Moreover, the pattern of activity by itself is dynamic, for example, patients walk in different patterns resulting in very different RF disruption models for the same activity. Modelling such highly dynamic RF disruption, if not impossible, is a complex process since it is both patient and environment centric.

In Chapter 3, we investigated the possibility to detect simple activities such as walking, running, sleeping, sitting and standing based on the RF signal strength of the sensor nodes in IBSN and their disturbances. Although we were able to define an RF disruption pattern for these simple activities in a controlled environment, we found that in the real-world, there can be a number of disruption patterns for the same activity performed by the same person at different points of time and places.

This will lead to inability to anticipate the correct influence and disruption of the activity on the RF signal and will consequently greatly decrease the efficiency of the MAC protocol to adapt its duty-cycle according to the disruption pattern.

Part of this chapter has appeared in :

- [19] V. R. K. Ramachandran, P. J. M. Havinga, and N. Meratnia, "Hacmac: A reliable human activity-based medium access control for implantable body sensor networks," in *Proceedings of the 13th International Conference on Wearable and Implantable Body Sensor Networks, BSN 2016, California, U.S.A.*, 2016
- [117] V. R. K. Ramachandran, L. V. Duc, N. Meratnia, and P. J. M. Havinga, "Dinamac: A disruption tolerant, reinforcement learning-based mac protocol for implantable body sensor networks," in *3rd IEEE International Conference on Internet of People 2017*, 2017

Also, this will also result in increased number of re-transmissions and thereby will reduce the throughput and energy-efficiency of the network. Therefore, we aim to adapt the duty-cycle of wireless radio according to the disruption pattern, without compromising on the throughput, latency and energy-efficiency, as the optimization problem of our MAC protocol. In this chapter, we will explore a reinforcement learning technique [20] to optimize the MAC protocol by defining the disruption as a stochastic process with Markov properties.

The rest of this Chapter is organized as follows. In Section 5.2, we present the mathematical background of the disruptive wireless channel, the choice of link quality metric, and the reinforcement learning framework. We define the dynamic disruption as a stochastic process with Markov property, thereby defining the problem of achieving disruption tolerance as a Markov Decision Process (MDP)

In Section 5.3, we present and explain the near-optimal disruption tolerant MAC protocol called DiNAMAC based on our reinforcement learning based framework. The simulation setup and the evaluation methods are explained in Section 5.3.3, followed by discussion of the results in Section 5.3.4.

In Section 5.4 we incorporate WuR into the design of DiNAMAC to further reduce the power consumption of sensor nodes of IBSN. Through simulations we show that the energy expenditure of DiNAMAC is greatly reduced with the introduction of WuR without affecting the reliability of the wireless communication.

Finally we conclude the Chapter in Section 5.5 with remarks we observed from the experiments.

5.2 DISRUPTION TOLERANCE AS A MARKOV DECISION PROCESS

The optimization problem of the MAC protocol is a classical issue in any wireless sensor networks. Majority of existing work deals with optimizing the duty-cycle to ensure maximum throughput, minimum latency, and maximum energy-efficiency [24].

It is a well established fact that the power consumption of the wireless radio is decreased by reducing the duty cycle of the radio in MAC protocol. Adapting duty cycle to ensure high throughput and low power consumption is a common optimization problem of MAC protocols.

Use of machine learning framework to solve the optimization problem of duty-cycle have also been investigated earlier. One such approach is presented in [118], where authors developed a near-optimal transmission strategy using Reinforcement Learning (RL) technique that chooses the optimal modulation level and transmit power while adapting to the incoming traffic rate, buffer condition, and the channel condition.

In case of IBSN, the modulation level and transmission power are heavily constrained by the regulations in order to ensure the safety of the patient through preventing the overheating of tissue around the antenna, and data integrity in the wireless communication of medical implants [15].

Authors of [55] introduced RL-MAC, which uses RL mechanism to achieve high throughput and low power consumption for a wide range of traffic conditions, by inferring the current state of other nodes and adapting the duty cycle based on the data generation rate of the sensor node.

Similarly, authors of [53] introduced QL-MAC, which uses RL mechanism to find an efficient radio schedule on the basis of the node's own traffic and the traffic load of its neighbours. The simulation results show that the adaptive behaviour of QL-MAC guaranteed better network performances with respect to both the packet delivery ratio and the average energy consumption.

Both RL-MAC and QL-MAC are not disruption tolerant, since the model of the RL technique is based only on the data throughput and energy-efficiency and they had not included the link quality information in the RL optimization framework.

Most of MAC protocols do not consider the disruptions in the wireless channel, which causes temporal variations in the link quality between the sensor nodes. Since temporal fluctuations in the RF link quality was not considered by these protocols, the optimization of duty-cycle significantly drops when they are exposed to the dynamic temporal link quality [18]. Moreover, there is no mechanism to handle the increased Packet Error Rate (PER), which is caused by the fluctuations in RF link quality.

To the best of our knowledge, DiNAMAC framework is the first to explore reinforcement learning technique at the MAC layer to handle the link disruptions caused due to human activities in IBSN.

5.2.1 DISRUPTIVE WIRELESS CHANNEL MODEL

Let us assume an IBSN network of N nodes deployed in a stochastic wireless channel that has Markov property. The physical interpretation of the communication link between two nodes in such wireless channel is given by the complement of the information outage probability between any pair of nodes for a given data rate x in bits [119], and is represented as follows,

$$P_{out}(SNR, x) = P_r(\log_2(1 + SNR \times |h|^2) > x) \quad (5.1)$$

,where h is the channel transfer coefficient The average signal to noise ratio (SNR) is related to the path loss component η such that $SNR \propto r_{ij}^{-\eta}$, where r_{ij} is the relative distance between the nodes i and j .

Typically $\eta > 4$ in the case of implant communication, as reported in our previous studies [17]. We consider Rayleigh fading model and that all channels are statistically independent [15]. Since the number of nodes in IBSN is less than conventional sensor

networks and due to the fact that the IEEE 802.15.6 standard for medical implant communication requires channel to be accessed at node's destined time frames, we assume that the intra-network interference is not present in IBSN.

Notation	Description
$\mathcal{P}_P$	Packet error ratio
n_{rx}	No. of successfully received packets
n_{frx}	No. of corrupted packets
$\mathcal{N}_{eff}$	$n_{rx}/(n_{rx} + n_{frx})$
τ_{slot}	Duration of one time slot
τ_{on}	Duration of ON time within a time slot
τ_d	Duration of disruption window
τ_{fad}	Duration of fading window
τ_{Tx}	Duration of transmit time
τ_{Rx}	Duration of receive time
α	Learning rate
γ	Discount factor
η	Weighing factor
Δ	Temporal difference of $Q_i(s, a)$ and $Q_{i+1}(s, a)$
N_{bits}	Number of bits in a packet
$\mathcal{R}$	Data rate in bits per second
$\mathcal{S}$	State space
$\mathcal{A}(s)$	Action space
$r_i(s, a)$	Reward policy in i^{th} iterative index
ϵ	Probability with which the agent executes the action with highest Q value

Table 5.1: RL notations used in text and derivations

(All the mathematical notations used throughout this Chapter are gathered in Table 5.1.)

Hence, the connection probability between node i and node j separated by a relative distance r_{ij} is given by

$$H(r_{ij}) = e^{-\beta r_{ij}^\eta} \quad (5.2)$$

,where β is responsible for the characteristic connection distance between two nodes such that $r = \beta^{-1/\eta}$.

According to [119], this connection probability has two sources of randomness, i.e., (i) random node positions and (ii) random link formation based on the channel fading model controlled here by η . In the limit of $[\eta \rightarrow \infty]$, the link between two nodes is no longer probabilistic. We will later make use of this randomness to model the reward function of MAC design in the reinforcement learning based framework.

5.2.1.1 LINK QUALITY METRIC IN STOCHASTIC WIRELESS CHANNEL

In highly random wireless channels, received signal strength do not completely represent quality of the link, as it does not include noise information in the channels. Another commonly used link-quality metric is Signal to noise ratio E_b/N_0 , where E_b

is the signal energy of each transmitted bit and N_0 is the noise spectral density in the channel.

Although SNR contains the information of noise density, direct instantaneous measurement of SNR on IBSN is not practical. This is because the approximation of noise floor of the human body channel is not only dependant on the bandwidth, but also on internal body temperature of the human, composition of the tissues and bones and location of the sensor nodes on the human body [120], [94].

Moreover SNR of the wireless channel does not directly represent the successful packet delivery, as the use of intelligent carrier modulation techniques will result in a higher PDR even in a lower SNR.

To this end, we will use packet error rate $\mathcal{P}_P$ as a link quality metric, since it carries information about bit error rate $\mathcal{P}_B$, which in turn carries information about the signal to noise ratio $SNR = E_b/N_0$. Packet error rate is expressed as,

$$\mathcal{P}_P = 1 - (1 - \mathcal{P}_B)^{N_{bits}} = \mathcal{N} \operatorname{erfc}(\sqrt{E_b/N_0}) \quad (5.3)$$

,where N_{bits} is the number of bits transmitted in a packet and $\mathcal{N}$ is the modulation coefficient which depends on the type of modulation used in transmission.

There are two main advantages in choosing $\mathcal{P}_P$ as a link quality metric. Firstly, in IBSN, the client nodes always carry out uplink communication and central controller always carries out the downlink communication. An exception to this is for control packets, which are a small fraction of the sensor data. Since, central controller is responsible for optimization of MAC protocol, need for client nodes to be aware of link quality is non-existent.

Most of the up-time, the central controller, which is also the receiver, will be carrying out error detection mechanisms to verify the integrity of the data. This procedure implicitly enables the central controller to measure the link quality after each packet is received, eliminating the need for any additional calculation or measurement schemes.

Secondly, $\mathcal{P}_P$ also contains accumulated information of SNR for a time duration at which the packet was in the physical medium. This will include even the minimal variations of temporal noise of the channel and will enhance the Markov property of the wireless channel.

5.2.2 OPTIMIZATION PROBLEM AS MARKOV DECISION PROCESS

The objective of our work is to decrease $\mathcal{P}_P$ in a highly disruptive and stochastic wireless channel, by finding an optimal latency and energy-efficiency. To achieve this, we design a MAC agent, which predicts the $\mathcal{P}_P$ in the consecutive time-frame and allocates a time slot to a node. We define this allocation of an optimal time-slot to the node, without compromising on latency and energy efficiency as a Markov Decision Process (MDP) of the RL model.

A MDP of the RL model is defined as a tuple $(S, A, \{P_{sa}\}, \gamma, R)$, where S represents the *state* space $\{s_1, s_2, \dots, s_n\}$, A represents the *action* set $\{a_1, a_2, \dots, a_n\}$, P_{sa} represents the transition probability function. For each state $s \in S$ and action $a \in A$, P_{sa} is a distribution over the state space, $\gamma \in [0, 1)$ is called the *discount factor*, and R is the *reward function* such that $R : S \times A \mapsto R$.

Also, the decision policy is defined as π , which maps the state set to an action set such that $\pi : S \mapsto A$. At an event i , the RL agent is at state $s_i \in S$, it selects an action $a_i \in A$, according to the defined policy $\pi(a_i)$.

This action-state policy will interact with its environment and state s_i will now transit to state $s_{i+1} = s' \in S$ with a transition probability of $P_{s_i a_i}$. The environment now provides the RL agent with a feedback reward of $r_i(s, a)$.

This whole process is repeated for all event iterations. The goal of the RL agent is to maximize the policy or the value function $V^\pi(s)$ [20]

$$V^\pi(s) = E \left[\sum_{i=0}^{\infty} \gamma^i r_i(s_i, a_i) | s_0 = s, \pi \right] \quad (5.4)$$

,where $E[\cdot]$ represents the expected return when starting from a state s and following the policy π .

Given a fixed policy π , the equation 5.4 can be rewritten as the Bellman equations [20],

$$V^\pi(s) = R(s, a) + \gamma \sum_{s' \in S} P_{sa}(s') V^\pi(s') \quad (5.5)$$

,where $R(s, a) = E[r(s, a)]$ is the mean value of the reward $r(s, a)$, the immediate reward that we get rightaway simply for starting in state s . The second term is the expected sum of future discounted rewards.

In our framework, we define the $\mathcal{P}_P$ as the state, and allocation of time-slot T_s as well as deploying a relay node between controller and client node R_n as the actions such that, $[\mathcal{P}_P] \in S$ and $[T_s, R_n] \in A$. In addition, transition from state $\mathcal{P}_P$ to state $\mathcal{P}'_P$ has a probability of P_{sa} , such that $P_{sa} \in \{P_{sa}\}$.

In practical scenarios, the transition probabilities $\{P_{sa}\}$, reward function R , and the model of the environment are unknown. In such cases, Temporal Difference (TD) based RL is commonly used [20, 118, 55]. TD methods can learn directly from raw experience without a model of the environment's dynamics.

In our case the environment is stochastic and dynamics of the channel is unknown. TD learning will adapt the duty-cycle and allocate the time slots based on the predicted outcome of the environment based on the previous knowledge of the environment.

5.2.2.1 Q-LEARNING BASED REINFORCEMENT LEARNING

Since our goal is to train DiNAMAC in the absence of transition probability and reward function, we propose to use an off-policy TD-based control algorithm known as Q-learning, which is a model-free technique learning from delayed reinforcement to determine an optimal policy [20].

In Q-learning, policies and the value function are represented by a look-up table indexed by state-action pairs. Formally, for each state s and action a , we define the Q value under policy $\pi(a)$ to be:

$$Q^\pi(s, a) = R(s, a) + \gamma \sum_{s' \in S} P_{sa}(s') \mathcal{V}^\pi(s') \quad (5.6)$$

From Eq. 5.6, it is known that the expected discounted reward starting from s , will take an action a from A and thereafter follow the policy π . Therefore, the value function of an optimal policy π^* , denoted by V^* , can be defined as:

$$\mathcal{V}^*(s) = \mathcal{V}^{\pi^*}(s) = \max_{\pi} \mathcal{V}^\pi(s) \quad (5.7a)$$

$$\mathcal{V}^*(s) = \max_{a \in A} \left(R(s, a) + \gamma \sum_{s' \in S} P_{sa}(s') \mathcal{V}^*(s') \right) \quad (5.7b)$$

Let us assume that $Q^*(s, a)$ be the optimal action function under the π^* , then

$$Q^*(s, a) = R(s, a) + \gamma \sum_{s' \in S} P_{sa}(s') \max_{a \in A} Q^*(s', a) \quad (5.8)$$

The Q-value is updated by a learned action value function, by iterating the value of Q^* . The updating rule is defined based on the temporal difference method, which is given by,

$$Q_{i+1}(s, a) = \begin{cases} Q_i(s, a) + \alpha \Delta & \text{if } s_i = s, a_i = a \\ Q_i(s, a) & \text{otherwise} \end{cases} \quad (5.9)$$

,where α is the learning rate and Δ is the temporal difference defined by,

$$\Delta = r_i(s, a) + \gamma \max_{a \in A} Q_i(s', a) - Q_i(s, a) \quad (5.10)$$

From Equation 5.8 and 5.10, it is clear that the state-value function will make the agent to always learn to maximize its reward. To make the agent achieve our objective, it is important that the reward function must truly indicate the objective to be accomplished. In other words, reward function should not directly define the duty-cycle or enable a relay node, rather it should encourage the MAC agent to learn

from the environment and derive value-policies for different states of packet error ratio ($\mathcal{P}_P$).

In the following section, we present the design of DiNAMAC and explain the reward function and optimization policies to achieve our goal of increasing the throughput and decreasing the latency, thereby increasing the energy efficiency in a wireless channel with a high $\mathcal{P}_P$.

5.3 DISRUPTION TOLERANT REINFORCEMENT LEARNING BASED MAC (DiNAMAC)

DiNAMAC is an hybrid access mechanism based on the IEEE 802.15.6 MAC layer specifications and is intended to operate in MICS band communication [15]. We assume that the client nodes (BN) of IBSN are resource-constraint and are implanted subcutaneously in the human body with one external body-worn coordinator node (BNC).

Figure 5.1: Location of IBSN nodes in simulation set-up

An example of IBSN is shown in Figure 5.1, where the red node is BNC and coffee-colored nodes are implanted subcutaneously in the body. The BN nodes can also act as a relay node (BNR) to hop information with the same mechanism as described in the IEEE 802.15.6 standard [15].

The super-frame structure as defined by IEEE 802.15.6 standard for medical implants has three different phases:

- (i). Exclusive access phase (EAP) in which the nodes can only send emergency medical data in contention free fashion,
- (ii). Random access phase (RAP) in which all nodes can contend to send medical-data,
- (iii). Managed access phase (MAP) in which the BNC allocates either carrier sense multiple access with collision avoidance (CSMA/CA), slotted aloha, polled allocation, or scheduled time division multiple access mechanism (TDMA) for each BN node to send the medical data.

The super-frame structure is shown in Figure 5.2.

Figure 5.2: Superframe of IEEE 802.15.6

DiNAMAC is operated in beacon mode, in which a beacon frame B is transmitted from BNC to the BN nodes at the start of each super-frame period to facilitate the network management, including the coordination of medium access phases, duty-cycle of the BN nodes connected the BNC, and clock synchronization information.

DiNAMAC uses TDMA during the MAP phase for transmitting the non-emergency data which applies to continuous monitoring of medical symptoms. It uses CSMA/CA during the EAP phase for sending emergency data, which can be an anomaly in the medical data.

In DiNAMAC, BNC performs minimalistic operations to adapt the super-frame for reliable communication. BNC does not require additional packets to carry out these operations because the required information, $\mathcal{P}_P$, is derived from the data-packets transmitted previously. BNC propagates the adaptive super-frame structure to the BN nodes through the beacons, which makes DiNAMAC simple yet powerful.

The BN nodes determine their position, link quality, relay mechanism, and periodicity, through the beacon frame of the BNC, based on which the BN node determines the access mechanism, time slot and the relay to transmit the information to BNC.

The goal of DiNAMAC is to maximize highly reliable communication by minimizing the $\mathcal{P}_P$ in an disruptive environment. The unique feature of DiNAMAC is that there is no need for a priori knowledge of the environmental changes which cause the disruption of wireless channel, rather it is predicted at each iteration of the super-frame duration.

This posteriori knowledge of the wireless channel will enable DiNAMAC to handle a wide range of dynamic disruptions, resulting in a disruption tolerant communication.

5.3.1 SCHEMES OF DiNAMAC

5.3.1.1 ACTION POLICY

In order to achieve the goal of DiNAMAC we define our action policy π with two main actions that has to be taken in different instances of disruption, namely the ON time allocation and Relay node establishment.

Definition 5.3.1. *ON time τ_{on} is the duration in which a node is actively transmitting within the time slot τ_{slot} allocated to it in the i^{th} super-frame.*

Figure 5.3: Time vs RSSI. The color-map of the surf-plot shows the distribution of PDR in different activities

As shown in Figure 5.3(d) and Figure 5.3(e), the periodic activities performed by human beings have sufficient time periods of favorable link quality, which is expressed by the PDR (%). If the duration and position of τ_{on} is perfectly allocated to match with when the signal quality is high, represented by PDR crests in Figure 5.3(d) and Figure 5.3(e), optimal throughput and energy-efficiency will be achieved.

Our DiNAMAC aims at optimizing τ_{on} allocation in terms of location and duration to archive optimal throughput and energy-efficiency. By doing so, DiNAMAC is able to yield high PDR even when the link quality varies over time because the movement of the person.

Definition 5.3.2. *Relay node BNR is a temporary node placed between the shadowed BNC and the BN to deal with severe shadowing of the RF link.*

If the RF link between the BN and the BNC is shadowed for a prolonged period of time as shown in Figures 5.3(a), (b) and (c), the BN increases the possibility of missing life-critical medical events and also will increase the latency.

As the transmission power cannot be increased in the MICS RF band, DiNAMAC temporarily uses relay nodes to overcome this problem. By doing so, DiNAMAC is able to assure high PDR even when the link between the BN and the BNC nodes is constantly shadowed by the human body.

5.3.1.2 RL REWARD FUNCTION FOR DiNAMAC

Designing the reward function is crucial for the RL learning process of the MAC agent. Since our goal is to maximize the throughput and minimize the energy consumption, we design our reward function based on these values.

For the energy efficiency, the node is supposed to accurately predict the disruption windows $\{\tau_d^i, \tau_d^{i+1}, \dots, \tau_d^n = \mathcal{T}_d\}$ in the wireless channel, and allocates ON time τ_{on} , as an exclusion function of $\mathcal{T}_d$, i.e. $\{\tau_{on} \cap \mathcal{T}_d = \emptyset\}$. In IBSN it is not desirable to decrease the energy consumption without considering the expected throughput, i.e., a node should not be allocated longer ON time to increase the throughput. Therefore, the reward of ON time allocation has to be a function of effective package receiving times ratio, denoted by $\mathcal{N}_{eff} = n_{rx} / (n_{rx} + n_{f_{rx}})$, where n_{rx} is the number of successfully received packets in a receive time τ_{rx} , and $n_{f_{rx}}$ is the number of corrupted packets in the transmission time τ_{tx} .

In addition, the fading between BNC and BN is constant and strong over a period of time τ_{fad} , which is greater than the slot time τ_{slot} . In such cases, MAC agent establishes a relay node BNR between BNC and shadowed BN node, in the next time slot allocated for the BN within the super-frame duration. Since the node position is fixed in IBSN for any duration of time, the selection of BNR is predetermined and the one-hop route information from any BN to BNC through an optimal BNR node is already known to the BNC. This establishment of BNR at continued shadowing will further improve the $\mathcal{N}_{eff}$ in addition to the ON time allocation.

For the throughput, the packet error ratio at the start of the next frame, denoted by $\mathcal{P}'_P$ is a valid indicator of the effectiveness of the allocated ON time in the previous frame. Hence, the effectiveness of the ON time window is expressed as a function of the packet error rates $\mathcal{P}_P$, $\mathcal{P}'_P$, and the throughput. We refer the term throughput as the data rate $\mathcal{R}$ at which the node is transmitting is in bit/s. To this end, we incorporate these two rewards in a reward function defined by

$$r_i(\mathcal{P}_P) = \begin{cases} \frac{(n_{rx}+n_{frx})(\mathcal{N}_{eff})^{n_{hop}}}{\tau_{slot}-\tau_{on}} - \eta \frac{\mathcal{P}'_P - \mathcal{P}_P}{\log_{N_{bits}}(\mathcal{R})} & \text{if } \mathcal{P}_P \neq 0, \mathcal{P}'_P > \mathcal{P}_P \\ \frac{(n_{rx}+n_{frx})(\mathcal{N}_{eff})^{n_{hop}}}{\tau_{slot}-\tau_{on}} & \text{if } \mathcal{P}_P \neq 0, \mathcal{P}'_P \leq \mathcal{P}_P \\ -\eta \frac{\mathcal{P}'_P - \mathcal{P}_P}{\log_{N_{bits}}(\mathcal{R})} & \text{if } \mathcal{P}_P = 0, \mathcal{P}'_P \neq 0 \\ 1 & \text{if } \mathcal{P}_P = 0, \mathcal{P}'_P = 0 \end{cases} \quad (5.11)$$

,where n_{hop} is the number of hops that is made in the last frame (in IBSN it is usually either 0 or 1) and η is the weighing factor.

5.3.1.3 Q-LEARNING ALGORITHM

In our learning process, at the end of each frame, the RL agent evaluates the temporal difference Δ , updates the Q-value and selects the next action according to the ϵ -greedy method [20].

Using this approach, with probability $1 - \epsilon$, the agent executes the action with the highest Q value, and with probability ϵ the agent randomly chooses an alternative action. This is done to balance exploitation of presumed optimal state-action pairs and exploration of novel policy modifications.

Naturally, when n_{frx} increases due to high $\mathcal{P}_P$, one would expect the allocation of ON time to have an overlap with the disruption window τ_d . Also, since the traffic load and the networking condition vary in our case, we adopt a constant learning rate $\alpha = 0.1$ as recommended in [20] in order to adapt to the non-stationary environment.

We further note that if the shadowing due to fading effect is constant over a relatively long period of time, the $\mathcal{P}_P$ will always not change abruptly, hence the learning process is accelerated. This accelerated learning will further improve the energy-efficiency. The learning algorithm is presented in Algorithm 2.

5.3.2 OPERATION OF BN AND BNR

The BN node receives the beacons and identifies the duration of each phase and the time slot allocated for it. If there is no data to be sent, the BN node transmits the no-data frame and goes to sleep, otherwise it transmits on the ON time slot allocated for it. In case of a emergency event or an anomaly in the sensed medical data, the

Algorithm 2 RL optimization framework

```

1: procedure RL_OPTIMIZE_MODULE( $\alpha, \gamma, \epsilon$ )
2:   Init[ $A(s)$ ]  $\forall s \in S$ ;
3:   BNC  $\leftarrow$  Assign ( $\alpha, \gamma, \epsilon$ )
4:   Init [IBSN]  $\leftarrow \langle Tx_{\text{power}}, \mathcal{R}, (\text{BNC} \leftarrow \text{BNR} \leftarrow \text{BN}) \rangle$   $\triangleright$  PHY & Topology fixed
5:   Init [802.15.6 MAC]  $\leftarrow \langle \mathcal{B}, \tau_{\text{on}}, \tau_{\text{slot}}, \mathcal{N}_{\text{eff}}, \mathcal{P}_P \rangle$ 
6:   Init  $_Q(s, a) = 0 \forall s \in S, \forall a \in A(s)$ 
7:   for Every  $i^{\text{th}}$  SuperFrame_BNC do
8:     Observe  $\mathcal{P}_P$ 
9:      $\mathcal{N}_{\text{eff}} \leftarrow (n_{rx} / (n_{rx} + n_{frx}))$ 
10:    Perform  $a_i = (t_{\text{on}} || \text{BNR})$   $\triangleright$  in  $s_i = \mathcal{P}_P$  based on  $[\epsilon \{Q(s, a)\}]$ 
11:     $i++$ ;
12:  end for
13:  Reward [MAC]  $\leftarrow r_i(\mathcal{P}_P)$ 
14:   $\mathcal{P}_P \leftarrow$  Update  $\mathcal{P}_P$ 
15:   $\Delta \leftarrow r_i(s, a) + \gamma \max_{a \in A} Q_i(s', a) - Q_i(s, a)$ 
16:  if  $s_i == s, a_i == a$  then
17:     $Q_{i+1}(s, a) = \{ Q_i(s, a) + \alpha \Delta \}$ 
18:  else
19:     $Q_{i+1}(s, a) = Q_i(s, a)$ 
20:  end if
21: go to 7:
22: end procedure

```

BN node contends to send data in the consecutive EAP phase with reference to the latest received beacon.

BN node does not have to send any additional packets for the operation of DiNAMAC. In case of the relay initiation, BN node which acts as the BNR will encapsulate the data in its frame and transmit it to the BNC in the additional time-slot allocated for it. This process is similar to the relay mechanism as described in IEEE 802.15.6 standard [27]. The choice of selecting a BN node as a relay node is pre-determined based on the location of the node.

For example in Figure5.1, the BN node on the ankle, uses BN node in the thigh as the relay node. Since the location of these two nodes is fixed, the choice of relay node is easily pre-determined and the relay-topology for each BN node is pre-stored in the BNC.

5.3.3 EVALUATION OF DiNAMAC

For the purpose of evaluation, we use simulations in an OMNeT++ based simulator called Castalia v3.2 [113]. Castalia simulator has a good implementation of temporal variations of the physical channel and is modifiable in the simulator.

We recorded the RSSI values between each BN node and the BNC in a round-robin fashion, during each activity in an indoor environment. The BN nodes were sending a dummy packet of 40 bytes to the BNC every 10 ms (optimal for measuring

the impact of human activities in RSSI [112]), with which the BNC calculates the RSSI and PDR, while the human was performing different activities.

These RSSI values are translated to temporal variations as mentioned in [113]. In addition to our measured data, we also used the data from [112] and [110] to simulate the temporal variations of the physical channel caused due to the human activities. The packet error rate is calculated after the packet is received at the receiver.

Parameter	Value	
Channel bandwidth	300	kHz
Reception current	7	mA
Transmission current (main)	11	mA
Idle current (main)	3	mA
Sleep current	3	μ A
Slot time (TDMA)	500	μ s
Number of retries (CSMA)	10	–
N_{bits} Packet size	40	bytes
$\mathcal{R}$ Data rate	20	kB/s
α Learning rate	0.1	–
γ Discount factor	0.5	–
η Weighing factor	5.5	–

Table 5.2: Simulation parameters

For the simulation of MAC protocols we used the PHY parameters as listed in Table 5.2. We simulated 5 BN nodes located on two limbs, thigh, chest and back-shoulder, and one BNC connected in a star topology, as shown in Figure 5.1, which is suitable for most of the medical applications [17].

Note that the thigh node is a potential relay node between the ankle BN node and the BNC. We vary the data generation rate for each node in order to simulate the heterogeneity of the IBSN nodes that generate the medical data at different rates, for example a blood-glucose sensor and a heart rate sensor.

In order to compare the performance DiNAMAC with existing MAC protocols, we simulate RL-MAC which has no relay mechanism but uses RL framework to adapt to the dynamic traffic load [55], and HACMAC [19], which uses a priori knowledge of the disruption window, adapts the duty cycle and establishes relay nodes for different disruption patterns as the need be for a given disruption.

All MAC protocols are evaluated based on the same physical channel described in Chapter 3. We use specifications of the Microsemi ZL70102 radio [114] to evaluate the power consumption of the BNC, BN, and BNR nodes. However, it has to be noted that the actual power consumption depends on the hardware design of the sensor nodes and the overheads caused by the additional hardware to support the functioning of the wireless radio.

5.3.4 RESULTS AND DISCUSSION

Simulation results related to reliability and power consumption are shown in Figure 5.4-5.8. Figure 5.4 illustrates the average PDR of the network calculated on the BNC node. The RL-MAC without relay mechanism has the lowest success in terms of packet-delivery ratio because of lack of any mechanism to compensate for the dynamic disruption in the link quality.

Figure 5.4: Offered load vs Packet delivery ratio

Optimization framework of RLMAC focuses on improving the throughput by rewarding the mac agent based on the number of packets queued at the transmitter. Figure 5.4 proves that rewarding based on the packets queued will not work efficiently in a highly disruptive environment. At high data generation rates, the RL-MAC has around 20% packet loss.

HACMAC protocol presented in Chapter 4 predicts *ON time* based on a priori knowledge of the disruption to compensate for the periodic activities like walking and running. Although it outperforms the RL-MAC at lower data generation rates, as it goes higher, the HACMAC is under performing than the RL-MAC. This is due to the lack of any mechanism to cope up with higher data generation rates and limitation of priori knowledge of the disruption patterns. However, it still has 15% packet loss at higher data rates, which is not desirable for IBSN.

In contrary, DiNAMAC has the lowest packet loss (less than 10%) even at higher data generation rates, due to the fact that it compensates for the disruption in link quality by an active learning mechanism, which includes packet error ratio as the observable metric. Since packet error rate is a function of modulation technique and bandwidth used by the transmitter, the higher data generation rates are implicitly accounted for in the learning mechanism.

Application level latency is the difference in time at which the packet is generated and the time at which packet is received at the receiver. HACMAC has no learning mechanism, which fails to handle the latency at higher data generation rate in a disruptive environment.

Figure 5.5: Offered load vs Application level latency of IBSN

In addition, if the disruption patterns are not known to HACMAC, adaptability of the MAC protocol fails. This results in high number of re-transmissions before the packet is received. Such re-transmissions tremendously increase the latency and in cases of higher data generation rates, the latency is worst and clearly visible in Figure 5.5. In addition, it underperforms RL-MAC in case of higher data generation rates.

RL-MAC has constant increase in terms of latency for higher data generation rates as the disruption in link quality changes dynamically. On average, the latency is lower than HACMAC for higher data generation rates and higher for smaller generation rates.

It is clear from the results that the reward function of DiNAMAC is highly optimizing the MAC agent such that it achieves the lowest latency when compared with HACMAC and RL-MAC. Also, from Figure 5.5, it is observed that the prediction of disruption and learning rate is optimal, as the latency stays constant, after considerable packets are generated.

The power consumption evaluation results of the MAC protocols are demonstrated in Figure 5.6- 5.8. The power consumed is calculated by measuring the periods at which the BNC, BN and BNR are transmitting, receiving, idly listening (radio is turned on but not in receive mode) or sleeping (radio is turned off). Note that, each mode of radio operation has different power consumption values as mentioned in Table 5.2.

Figure 5.6: Power consumption - BNC

The power consumption of the BNC is greatly reduced in DiNAMAC due to the fact that it does not carry out additional transmission to support the optimization framework. DiNAMAC benefits from the continuous and rigorous learning rate of the Q-learning, which enables the BNC of the DiNAMAC framework to have the lowest power consumption when compared to HACMAC and RL-MAC.

Moreover, HACMAC requires the BNC to have extra receiving periods to effectively decide between adapting the duty cycle or establishing a relay node. This gets worse if the disruption features are not known and data generation rates of the BN are higher. Also, at lower data generation rates, the power consumption is less because HACMAC adapts faster to the changing time. Although the complexity of the HACMAC grows at higher data generation rates and causes high energy consumption, in lower data generation rates and HACMAC is energy efficient than RL-MAC.

In RL-MAC, there is no mechanism to compensate for the disruption in link quality at all, which results in a higher number of retries in prolonged attenuation periods, than the rest of the MAC protocols. This results in higher power consumption. However in average, power consumption is reduced at higher data generation rates, because the optimization framework learns to improve the throughput and energy-efficiency.

The power consumption of BN node in RL-MAC is higher because of the additional compensation that the MAC agent has to undergo for the failed transmission. The client node is partly responsible for handling the congestion in network traffic, which requires the BN node to be in the receiving mode and monitor the data flow from neighbouring nodes.

In HACMAC, the BN nodes do not perform additional compensations. However, the BN nodes have to perform a number of re-transmissions in the case of unknown

Figure 5.7: Power consumption - BN

Figure 5.8: Power consumption - BNR

disruption patterns. The difference between power saving mechanisms in HACMAC and RL-MAC on the BN nodes is quite small, because both of them require directly or indirectly to be aware of the network conditions.

In the case of RL-MAC, BNC is solely responsible for handling the network traffic and disruptive link quality. As seen from previous results, the robust learning framework eliminates the need for BN to re-transmit the data packets. This enables the BN node to carry out the normal transmission, which makes the BN node of DiNAMAC have the least power consumption than HACMAC and RL-MAC.

We used HACMAC and DiNAMAC with 1 hop extended star-topology to compare the BNR power consumption. RL-MAC has no relay mechanism so that we cannot compare the power consumption of the relay nodes. In DiNAMAC the BNC selects the BNR nodes by calculating the link quality after each super-frame duration which enables the BNR nodes to be in idle mode in most of the super-frame duration, and BNR enters the receive mode only in the scheduled time slot.

However, allocated time window of BNR can overlap with disruption window resulting in a large number of failed transmitted packets. This will require BNR to re-transmit not only their own packets, but also the relayed packets. Thus power consumption of BNR increases largely in higher data generation rates.

In DiNAMAC, the intuitive learning process creates state-action policy to be efficient to considerably reduce the number of re-transmissions required by the BNR to achieve the maximum throughput. It is evident from the results, the BNR of DiNAMAC has a lower power consumption.

5.3.4.1 CONCLUSION

We presented the DiNAMAC protocol that is able to handle the disruption in link quality caused due to different human activities. In addition, our DiNAMAC protocol is model-free so that it is practical for most real-world applications. DiNAMAC also complies with the IEEE 802.15.6 regulations.

In particular, DiNAMAC optimizes the MAC protocol by using a reinforcement learning technique to incrementally learn the optimal action policy with regards to dynamic environment, through updating the long-term value of packet delivery ratio.

Hence, DiNAMAC guarantees high reliability of wireless communication in the presence of shadowing effect. We compared the performance of baseline MAC protocols such as HACMAC in terms of packet loss through simulation, and demonstrated the need to handle the dynamic disruption in link quality caused by different kinds of human-activities. The power consumption of the wireless radio decreases with DiNAMAC when compared with that of RL-MAC, and HACMAC.

In order to further reduce the energy-expenditure of DiNAMAC, we will incorporate WuR in the design of DiNAMAC. We elaborately explain the WuR-based DiNAMAC and present the results in the following section.

5.4 WUR-BASED DiNAMAC

The DiNAMAC is adaptive to dynamic temporal variations in link quality. Also, it can effectively learn the disruption patterns caused due to different human activities in different environments. The optimization framework of DiNAMAC is based on reinforcement learning technique, which requires no prior knowledge of the activity based RF disruption models. To this end, DiNAMAC is a model-free adaptive MAC protocol, which makes it practical to be deployed in real-world scenarios.

Although the power consumption of DiNAMAC is lower than that of the HACMAC, we hypothesize that use of Wake-up radio (WuR) will further reduce the power consumption. In this Section, we will present the optimization of DiNAMAC using WuR such that the power consumption of the sensor nodes are reduced without reducing the reliability and latency of the wireless communication.

5.4.1 WUR IN DiNAMAC

The reinforcement learning based optimization framework of DiNAMAC is executed on the BNC controller of IBSN, which is assumed to have more energy and computational resources than BN and BNR nodes. Introducing WuR in DiNAMAC will not affect this optimization framework, however the operation of main radio is changed in accordance with the WuR . As elaborated in previous Chapters, the power consumption of WuR is negligible when compared to that of the main radio.

WuR operates in two modes namely, the low-power receiving mode and a transmitting node, in a different bandwidth and modulation method than the main radio. This ensures that the WuR and main radio do not have internal interference with each other while transmitting and receiving.

Also WuR cannot send useful data due to the limited bandwidth, however it can send small beacons called the Wake-up Beacon (WuB). All the useful communication

Parameter	Value
Channel bandwidth	20 kHz
Reception current	0.27 μ A
Transmission current (main)	1 mA
Data rate	10 kB/s
Frequency of operation	433.9 MHz
Sensitivity	-51 dBm

Table 5.3: Simulation parameters

within IBSN will take place using main radio. In summary the characteristics of the WuR are presented in Table. 5.3.

In order to incorporate WuR in the design of DiNAMAC we assume the following:

- Main radio will be switched off in BNC, BN and BNR all the times except the when useful data needs to be transmitted or received between the nodes
- WuR in BNC will be always in reception mode except when it needs to wake-up a certain BN node
- WuR in BN and BNR nodes will always be in sleep mode except for periodic idle mode listening which is pre-determined globally throughout the network by the BNC

5.4.1.1 OPERATION OF BN AND BNR

The BN and BNR nodes periodically wake up at every super-frame duration to update BNC about its current status. If there is non-emergency medical data, the BN node will inform BNC about the non-emergency medical data and request for time-slot allocation in the following super-frame duration.

Upon receiving the acknowledgement from BNC, BN will turn on the main radio and send the non-emergency medical data to the BNC through main radio. Once the data buffer is empty for the BN node, the main radio is completely turned-off and the periodic WuR scanning is carried out.

In an emergency event, the BN nodes will inform BNC about the event through WuB and request the BNC for immediate allocation of time-slot for data transmission. Upon receiving the acknowledgement from BNC, the BN node will turn on the main radio to send the useful data through main radio to BNC. Once the transmission of the data is complete, BN node will turn off the main radio and periodic WuR scanning is carried out by BN node.

The BNC node is always in the low-power reception mode, actively searching for WuB sent from BN and BNR nodes. In IBSN the shadowed BN nodes are deployed

in close proximity of a non-shadowed BNR node which will relay the information to the BNC. This topology will remain fixed during the life-time of the IBSN.

Establishment of BNR node to a particular BN node is known to BNC since the topology is fixed. Upon receiving the initiate_relay request from BN, the BNC will send the request to the appropriate BNR node to relay the information.

On receiving the acknowledgement, the BN node will turn on the main radio and start to communicate via the BNR node. Once all the data have been transferred, the BN node will turn off the main radio and goes into periodic WuR scanning mode.

5.4.2 EVALUATION OF WUR-BASED DiNAMAC

We simulate the WuR-based DiNAMAC in a similar simulation set-up as explained in Section 5.3.3. The characteristics of the WuR as mentioned in Table 5.3 are used to create a separate radio hardware in Castalia. All sensor nodes simulated have a packet_generation unit, main radio and a WuR .

Dynamic temporal deterioration of the channel is simulated using the pre-recorded RSSI valued measured during different human activities. Also, to compare the performance of the WuR-based DiNAMAC, we used RL-MAC, WuR-based HACMAC, and DiNAMAC. This comparison will help us to understand the impact of WuR in DiNAMAC optimization and overall power savings achieved when compared with HACMAC.

It is important to note that RL-MAC protocol only have one radio do not have an additional WuR to optimize the power consumption. Also RL-MAC does not have any relay mechanism to cope up with the shadowing effect of BN nodes during various human activities.

Main radio of RL-MAC is never completely turned off, i.e. the main radio will be listening periodically in idle mode of operation, consuming less power than reception or transmission mode. On the other hand, WuR-based HACMAC and DiNAMAC will use two radios and have an one hope relay mechanism to cope up with the shadowing effect caused due to different activities.

5.4.3 RESULTS AND DISCUSSION

Simulation results of WuR-based DiNAMAC is shown in Figures 5.9-5.13. Reliability of the WuR-based DiNAMAC is measured using PDR, which is the ratio between number of packets successfully received at the receiver and number of packets transmitted.

As shown in Figure 5.9, the use of WuR in DiNAMAC did positively improve the packet delivery at lower packet generation rates. However, at higher packet generation rates WuR-based DiNAMAC has almost similar performance to that of the DiNAMAC.

The PDR performance results from RL-MAC and WuR-based HACMAC are shown to compare the results with WuR-based DiNAMAC. As mentioned earlier, WuR-

Figure 5.9: Offered load vs Packet delivery ratio

based HACMAC suffers from dynamicity problem when link quality deterioration are not known apriori.

As shown in Figure 5.10, the application level latency of WuR-based DiNAMAC is similar to that of the DiNAMAC. Latency was not significantly affected due to the addition of WuR in DiNAMAC. Negligible increase in latency at higher packet generation rates are observed. This was due to the repeated wake-up request to send long queues of non-emergency data.

It is important to note that this negligible increase in latency can be eliminated by switching off the WuR optimization at higher packet generation rates. By doing so, the BN nodes can operate in DiNAMAC mode without the use of WuR. During lower packet generation rates, the WuR optimization can be switched on again to reduce power consumption. This process can be set based the requirements of the application, i.e. depending on the packet generation rates of the application of IBSN.

Power consumption of BNC, BN and BNR nodes in WuR-based DiNAMAC is shown in Figures 5.11-5.13. The power consumed by main radio is calculated by measuring the periods at which the BNC, BN and BNR are transmitting, receiving, idly listening (radio is turned on but not in receive mode) or sleeping (radio is turned off). The power consumed by WuR is calculated by measuring the period at which BNC, BN, and BNR are transmitting, and receiving through WuR. Note that, each mode of operation in WuR and main radio has different power consumption as mentioned in Table 5.2 and 5.3.

The power consumption of BNC in WuR-based DiNAMAC is vastly reduced because of the always-on ultra-low power wake-up radio. The main radio is completely

Figure 5.10: Offered load vs Application level latency of IBSN

Figure 5.11: Power consumption - BNC

turned off, which eliminates the power wastage that happens due to the idle mode listening. Although WuR is always-on, the power consumed by the WuR is negligible when compared to the main radio.

We were able to achieve a maximum of 53% reduction in power consumption of BNC through WuR-based DiNAMAC. Results of BNC node in other MAC protocols are shown for comparison. RL-MAC without 1 hop mechanism has the highest power consumption since the BNC has to re-transmit data packets when they are lost in shadowing caused due to temporal deterioration.

Figure 5.12: Power consumption - BN

Figure 5.13: Power consumption - BNR

BN and BNR nodes in WuR-based DiNAMAC has vastly reduced the power consumption at low packet generation rates. However, at higher packet generation rates the power saving is not very high.

BN nodes of RL-MAC has the highest power consumption of all the MAC protocols. This is due to the larger on-time of the main radio and continuous re-transmission that occur due to packet loss.

WuR-based HACMAC has similar power consumption as RL-MAC in lower packet generation rates. Adaptability of HACMAC is minimized due to the dynamic link deterioration and resulting in higher power consumption of the HACMAC even when optimized with WuR.

This is due to the fact that larger packet generation rates fill the data queue faster and the main radio has to operate at larger duty-cycle, where the use of WuR has very little impact on energy-efficiency. However, we achieved the best possible energy-efficiency possible than other MAC protocols with WuR-based DiNAMAC without affecting the reliability and latency performance.

WuR-based DiNAMAC not only benefited from the reinforcement learning based optimization framework, but also benefited from WuR mechanism which improved the reliability and latency while reducing the power consumption of the BN, BNR and BNC nodes of IBSN.

5.5 CONCLUDING REMARKS

In this chapter, impact of dynamic human activity on the RF link quality is studied. Selecting the proper duty-cycle based on the channel condition was defined as the optimization problem. Channel deterioration due to different human activities was modelled as Markov decision process, and Q-learning approach of reinforcement learning was used to optimize the duty-cycle. A Disruption tolerant Reinforcement leArning based MAC protocol called DiNAMAC was developed, which

optimizes the duty-cycle based on the dynamicity of the human activity based RF disruption patterns.

Reliability and latency of the wireless communication were significantly improved using the DiNAMAC when compared with the state-of-the art MAC protocols. DiNAMAC is designed to be model-free MAC protocol such that DiNAMAC is more practical than HACMAC in real-world scenarios. However there was not improvement in the power consumption of the sensor nodes.

To address this problem, we strategically introduced WuR in the design of DiNAMAC, such that the main radio is turned-off all the time except when useful communication takes place between the nodes. Power wastage due to idle-listening was significantly reduced in all the BNC, BN and BNR nodes. Also, WuR-based DiNAMAC did not reduce the performance of DiNAMAC, in terms of reliability and latency, yet consumed less power than DiNAMAC.

Through simulation we showed that the WuR-based DiNAMAC has very low power consumption and still can provide highly reliable wireless communication with very low latency in real world scenarios.

CONTEXT AWARENESS IN IBSN — AN EPILEPTIC USE-CASE

NODES of IBSN are resource constrained, yet are commissioned to continuously monitor physiological signals and deliver life-critical medical therapies. An important requirement for these heterogeneous IBSN nodes is to be contextually aware of the data and communicate only-when-necessary to the base-station. In this chapter, we present an Epileptic use-case in which the IBSN nodes have to continuously monitor Brain signals (ECoG) and predict seizures with reasonable accuracy. We develop an active-learning based seizure prediction framework, which aims to reduce the raw data transmission to the base-station by locally pre-processing the ECoG and on-the-node execution of pre-trained machine learning models. Through simulations we show the amount of raw ECoG data required for our prediction framework is reduced by 80% compared with conventional prediction frameworks, but still predicts the seizures with high accuracy.

எப்பொருள் எத்தன்மைத் தாயினும் அப்பொருள்
மெய்ப்பொருள் காண்பது அறிவு.
*Whatever thing, of whatsoever kind it be,
'Tis wisdom's part in each the very thing to see.*
—Thiruvalluvar in Kural 355

6.1 INTRODUCTION

According to the WHO, chronic diseases kill 40 million people each year, contributing to 70% of the global mortality rate [3]. Epilepsy is one of the chronic neurological disorders characterized by the occurrence of sudden and recurrent abnormal neuronal activity in the brain called seizures [121].

The seizures may vary from being undetectable episodes to long episodes of vigorous shaking of the body [122]. The morbidity and mortality of epilepsy are largely associated with the sudden loss of consciousness, fatal injuries caused by unforeseen seizures, and *status epilepticus*, where a life-threatening seizure lasts for more than five minutes [123].

Advanced Implantable Medical Devices (IMD) such as DBS [124] and Vagus Nerve Stimulator (VNS) [125] have been extensively researched and developed to significantly reduce the seizure frequency for the patients who do not respond to Anti-Epileptic Drugs (AED) [123, 126, 127]. IMDs deliver electrical impulses through brain-implanted electrodes to a specific target area in the brain in order to reduce the seizure frequency.

For the last 80 years, analyzing the electrical signals from the brain, namely ElectroEncephaloGraph (EEG) and ECoG, is used as a well established method to describe the physiological process of the seizure development and its impact over different parts of the brain [128].

EEG is a non-invasive method of measuring the electrical signals with electrodes that are placed on the surface of the scalp, whereas ECoG is an invasive method with electrodes that are placed directly on the exposed surface of the brain [129]. The advantages of ECoG over EEG are its high Signal-to-Noise Ratio (SNR) and non-obtrusiveness in daily-life when the patient has to be monitored over long periods of time. Nonetheless, these physiological signals are highly patient-specific and require expert medical intervention to analyze these signals.

Applying the principles of statistics to automate the analysis of these physiological signals and to predict the onset of seizure has been researched since 1970 [130, 131]. In the last two decades, extensive use of machine learning algorithms to detect the onset of seizure based on EEG & ECoG recordings have been reported. Machine learning algorithms such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are used to detect seizure events, given the patient-specific EEG data analysis [132, 133]. The outcome of these algorithms can be effectively used as physiological feedback to the IMDs, which will then expectantly operate in a closed-loop fashion. As a result, the efficacy of the treatment will be improved by delivering intense targeted stimulation [132].

Part of this chapter will appear in :

[22] V. R. Karuppiiah Ramachandran, Huibert J. Alblas, Le Viet Duc, and N. Meratnia, "Towards an online seizure advisory system—an adaptive seizure prediction framework using active learning heuristics," *Sensors (Switzerland)*, vol. 18, 2018

Figure 6.1: Example of a schematic flow of closed loop operation of DBS process. Inclusion of the expert is always in loop before any treatment is applied locally. *Picture adapted under CC BY 3.0 license from [134].*

In conventional seizure prediction systems, brain signals are continuously sensed through EEG and/or ECoG sensors and are wirelessly transmitted in their raw form to a power-surplus base station that can perform large complex computations [8, 9, 16]. At the base station, the raw signals are processed and analyzed to predict the onset of seizure.

It is important to note that, the continuous wireless transmission of highly dense raw EEG/ECoG data requires a high bandwidth and power. Although highly complex computations cannot be executed on the resource constrained IBSN sensor nodes, less complex computations such as band-pass filtering and thresholding can be fairly executed.

Moreover, state-of-the-art micro-processors such as ARM cortex M4 [135] requires relatively less power consumption to locally process and store megabytes of data-packets than to transmit it through a wireless radio such as TI's C1100 [114, 136]. Such ultra-low power embedded devices are completely capable of executing pre-trained machine learning models [136]. However, these embedded machine learning models must be trained using pre-recorded EEG/ECoG data in a computationally powerful processing system, and the resulting machine learning model can be executed on these low-power embedded devices.

Towards this end, we propose an active-learning based seizure prediction framework, which is capable of being executed on a resource constrained IBSN sensor node. Our framework will enable IBSN sensor nodes to be context-aware of the status of the brain signals by locally processing the ECoG data. As a result, IBSN sensor nodes will not transmit raw ECoG signals to the base station but will only transmit the nature of the brain signal, i.e. if it is a preceding a seizure or not.

In addition, our framework enables expert intervention in cases where particular set of ambiguous ECoG signals cannot be classified using machine learning models. Such expert knowledge will be used to re-train the machine learning model on a computational powerful base station. This new model will be updated in the IBSN sensor node to ensure high prediction accuracy.

The rest of this chapter is organized as follows. In Section 6.2, we explain the nature of the brain signals of an epileptic patient, the main challenges of the online seizure prediction systems, and the related work. In Section 6.3, we explain the principles of our seizure prediction framework and its active learning heuristics. In Section 6.4, we explain simulation settings, followed by the validation metrics used to validate our framework. In Section 6.5, we present and discuss the results obtained. Finally, we conclude our work in Section 6.6.

6.2 PRELIMINARY BACKGROUND

In this section we briefly explain the nature of brain signals of an epileptic patient, the main challenges in seizure prediction, and the related work.

6.2.1 ECoG SIGNAL

ECoG is a type of electrophysiological monitoring that measures the electrical activity on specific locations in the brain by implanting a surface-electrode-array through invasive brain surgery [129].

Each electrode in the array is considered as a *channel* of the measurement. Each channel is sampled at a constant sampling rate producing a constant number of ECoG samples per second. For example, a sampling rate of 400 Hz will produce 400 samples per second on each channel. We will study ECoG of 16 channels. As shown in Figure 6.2, the ECoG is categorized into four periods, namely ictal period, pre-ictal period, post-ictal period, and inter-ictal period [137].

Figure 6.2: Four states of ECoG of an epileptic patient [137]. A snapshot of data captured from an array of 16 brain implanted electrodes of an epileptic patient with generalized tonic-clonic seizure. The sampling rate is 500Hz and is recorded for a total duration of 40 hours(snapshot of ECoG signal obtained from iEEG viewer [138]).

The ictal period is when the actual seizure occurs. The post-ictal is the period shortly after the ictal period when significant spikes in ECoG occur sparsely. The pre-ictal is the period before the seizure occurrence when a patient feels visual auras. The inter-ictal is the seizure-free period between two seizure events [130].

The seizure events are *detected* in the ictal period. To *predict* the onset of the ictal period, it is important to *detect* the pre-ictal period from the inter-ictal period. By doing so, the clinical measures to reduce the impact of seizure events can be taken.

Typically, the pre-ictal period may vary from 10 minutes to 1 hour depending on different seizure and patient types, however there is no straightforward way to define a unique pre-ictal period for future data [139].

By well-established conventions, the *Seizure Occurrence Period (SOP)* is the time period within which a seizure is expected and the *Seizure Prediction Horizon (SPH)* is the time period between the onset of *prediction* alarm and the SOP [16, 140, 141, 142, 143].

A seizure prediction framework should analyze real-time ECoG and must generate a time series of binary data classification of pre-ictal denoted by (1) and inter-ictal denoted by (0).

These binary classifications can be translated into a seizure warning, and consequently a necessary medical treatment can be provided in real-time before the onset of a seizure event. Note that SPH is clinically unknown but it has to be longer than pre-ictal period [140].

Ideally, the SPH can be consistently set to the upper bound of the standard pre-ictal period, i.e. 1 hour duration, so that SPH will be persistent even for shorter pre-ictal periods say 5 or 50 minutes.

6.2.2 CHALLENGES IN SEIZURE PREDICTION

Although there exist numerous research results in the area of the seizure prediction, most of them are not suitable for real-time detection and execution on low-power devices. It is a well-established convention that ECoG data will be collected at a power-deficient sensor node, and the processing of signal will be carried out on a power-surplus base station.

Recently, this convention is evidently changing. With the rapid development of the IMDs, the need for seizure prediction algorithms being able to locally run on such resource constrained environment is paramount.

Most of the existing work on seizure prediction arena will neither fit in these resource-constrained hardware platform nor are able to meet the requirements for clinical applications. To this end, we summarize the limitations of seizure prediction concerning the ultra-low power IMDs as follows.

6.2.2.1 PERFORMANCE REQUIREMENTS

As the IMDs are continuously shrinking in size, the need for highly reliable data processing techniques is growing stronger. The physical limitation of resources such as power and computational capability, are barriers to run complex algorithms locally on the IMDs.

Also, newly developed algorithms are computationally complex and require more resources to achieve high reliability. An optimum design should intelligently compromise the power consumption and the performance metrics such as reliability and accuracy.

Neural networks and deep learning have the potential to detect particular seizure related patterns, by extracting and learning features from ECoG data without requiring a priori knowledge of the seizure structure.

However, the use of these advanced learning algorithms on the IMDs is severely limited due to their large power-hungry computation. With advances in computer architecture such as neuro-morphic computing [144], which mimics the human brain in computations, complex computations with very low power consumption were proven to be possible.

Nonetheless, these hardware platforms are still under development to be used for life-critical medical applications. This limits the immediate use of these learning algorithms on the IMDs.

6.2.2.2 UNCERTAINTY OF BRAIN SIGNALS

The underlying cause of seizure dynamics in the brain is still not clear. However, the brain has its own regulatory mechanism which could stabilize any abnormal activity in the brain [145]. Because of this, deterministic seizure prediction will not be capable of accurately predicting the onset of seizure, as the seizure event could have been regulated by the brain itself.

To address this issue, authors in [146] suggest utilizing a more probabilistic approach such as regression, in which brain signals are continuously filtered through a probability model of seizure events. Moreover, EEG and ECoG are highly uncertain and are susceptible to noises from other parts of the brain which may closely resemble seizure events.

The use of other bio-markers such as heart rate and blood pressure has been shown to improve the prediction accuracy [147].

6.2.2.3 EXPERT INTERVENTION IS BOTH CONSTRUCTIVE AND DESTRUCTIVE

In life-critical seizure prediction systems, in which the brain signals are very heterogeneous and uncertain, an expert intervention is needed to overview the outcome of such systems.

However, such personalized care with close monitoring of the patient by an expert is unscalable to large size of patient groups. This destructs the purpose for autonomous seizure prediction system, when the outcome of each event has to be monitored by an expert.

Nonetheless, when such an autonomous system can detect the ambiguity in the signal with high confidence, an expert can intervene to assist the system with a further course of action. Minimal intervention can be constructive in cases like generic seizure prediction systems.

6.2.3 RELATED WORK

A substantial amount of work has been done in detecting the ictal epochs over the last six decades [148]. It was not until recent years that the focus of research is being shifted to detect the pre-ictal epochs, which is proven to be more helpful in prediction of seizure [16].

A significant number of algorithms have been proposed for seizure prediction at a crowd-sourced seizure forecast competition in *Kaggle*, set up in the year 2014 by American Epilepsy Society [148].

A similar approach has been followed by the University of Melbourne together with American Epilepsy Society in 2016 using a different data-set available in [149]. Most of the top 10 performing algorithms in these competitions used SVM based classifiers and frequency domain features. The description and performance of the top 10 performing algorithms are described in [148].

All these algorithms are designed to perform well on patient-specific data and with an abundance of labeled data in the pre-ictal class. These algorithms, however, do not focus on the problem of data insufficiency and scalability to large patient groups, but rather focus on the high detection accuracy using patient-specific models.

In a practical setting, it is difficult, if not impossible, to collect a large amount of such categorized data in advance for an epileptic patient. Other seizure prediction algorithms which aim to be adaptive in their seizure prediction are summarized in Table 6.1.

One of the major disadvantages of these adaptive seizure prediction algorithms is that they do not have any direct mechanism to handle the ambiguous data which cannot be confidently classified into either pre-ictal class or inter-ictal class.

These algorithms aim at changing classifier's properties such as the distance threshold from the classification plane to improve the classification accuracy. In case of the seizure prediction, in which there is an abundance of ambiguous samples, a simple increase or decrease in classifier's threshold will not only decrease the accuracy but also increase the misclassification rate of the minority class.

The first use of active-learning heuristics to handle the ambiguous data was presented by the authors of [150], where they presented an outlier detector over the

Name of the work	Machine learning method	Data-set used	Feature used	Validation method	Sensitivity
Cook et.al. [16]	Decision Tree, kNN	Private data	Average energy, Teager-Kaiser energy, line length	Comparison with random predictor based on ground truth	(65 – 100)%
Shiao et.al. [140]	SVM, intuitive data segmentation	Kaggle.com, iEEG.org	Band pass filtered power density, Power of FFT bin. correlation matrix	Ground truth	(89 – 100)%
Xiao et.al. [141]	Adaptive LDA, Adaptive Naive Bayes	Private data	Lyapunov exponent, pairwise euclidean distance, T-statistic, Pearson correlation, temporal pattern	Comparison with random predictor based on ground truth	(72 – 82)%
Parvez et.al. [142]	Least square-SVM,	Freiburg	Customized phase correlation	Comparison with six existing methods based on ground truth	(91 – 95) %
Aarabi et.al. [143]	Rule based classification	Freiburg	Lempel-Ziv complexity, Lyapunov exponent, nonlinear interdependence, correlation dimension, correlation entropy, noise-level,	Ground truth	(86.7 – 92.9)%

Table 6.1: A selective summary of adaptive seizure prediction methods

results of SVM classifier and selected the samples that were far away from classification boundary.

In [151], Gupta et. al. compared different techniques for active selection and proposed a novel output-based active selection (OAS) method for active learning framework. In OAS a meta-classifier called Bernoulli-Gaussian Mixture Model (BGMM), which combines the base classifier’s uncertainty along with base classifier’s outputs, is generated. The resulting BGMM model has a mixture of distributions consisting of feature set distribution, crisp label distribution, and soft label distribution. The sub-population of ambiguous feature set is considered as a hidden variable and identified from the overall population of feature set by estimating the parameters of feature set distribution with respect to crisp and soft label distribution. The set of features with the highest ambiguity is selected using the BGMM.

One of the main advantages of using BGMM over other active selection methods is that it combines the prediction uncertainty with the actual prediction outcome of the classifier to effectively mitigate the querying of morbid samples to be labeled by an expert [151].

The authors applied this algorithm for the task of ensemble classification with an array of re-trainable classifiers using active learning heuristics.

To complement their work, we aim to develop a seizure prediction framework that is capable of handling the ambiguous samples by seeking feedback from an expert. We will adapt the BGMM to be used for the task of binary classification of pre-ictal and inter-ictal periods from ECoG signals under active learning heuristics.

The core of our active learner is based on this BGMM block, which will determine the feature samples that have the most ambiguity. In the following section we present the seizure prediction framework of which our major contribution is the active learner block and its integration with the machine learning classifier in a closed-loop fashion.

6.3 SEIZURE PREDICTION FRAMEWORK

The main aim of our seizure prediction framework is to predict the seizure events with minimum number of labeled data, and to be scalable for large patient groups. Also the complexity of the framework will be kept minimal so that it can be operated on a resource-constrained embedded platforms.

As shown in Figure 6.3, our prediction framework receives the raw ECoG signal over which the set of features will be extracted. Obtained feature set is forwarded to a classification model, which will classify the feature samples into two different classes of labels, i.e. pre-ictal and inter-ictal, with a degree of certainty.

During initialization of our framework, the classification model is obtained from minimal labels that are generic to large patient groups. This prevents longer initial training periods to obtain a patient-specific classifier model. We locally store the features samples and label-set along with the classification certainty.

Figure 6.3: Schematic flow of our seizure prediction framework. The base classifier is expected to output both soft label (or degree of certainty) which is used to determine the certainty of the classification and crisp label (or label) to know the class.

A *thresholding* block accumulates the results of the classifier for a time-period of 1 hour and applies a threshold of 70% on the class labels, i.e. 70% of the class labels should be classified as pre-ictal state. If the outcome is above this threshold, a seizure alarm is triggered. Otherwise the feature set, together with the stored labels and their certainty are forwarded to the active learner block, which operates with a core of Bernoulli-Gaussian Mixture Model (BGMM).

Labels for the ambiguous samples are obtained from an expert, and the classifier model is updated accordingly. This feedback loop through an active learner will improve the accuracy of the classifier with minimum number of initial training labels and also the patient-specific accuracy is improved over time. In what follows we elaborate on the functionality of the main building blocks of the framework.

6.3.1 FEATURE EXTRACTION

The typical approach to analyze the ECoG data using machine learning algorithms is to pre-process the raw signal by computing *features* and use these features as inputs to the classifiers. Using features would enhance the classification accuracy and reduce the computational burden.

We aim to analyze the ECoG signals in the time-domain rather than in the frequency-domain in order to achieve low-complexity for running on IBSN nodes. This is because the signal conversion from time-domain to frequency-domain consumes substantial amount of power and considerably high processing-time.

To this end, we selected eight features which can closely represent the pre-ictal epileptiform discharges in time-domain [152]. The features selected are *area*, *normalized decay*, *line length*, *mean energy*, *peak amplitude*, *valley amplitude*, *normalized peak number*, *peak variation*.

All these features reduce a static number of consecutive raw ECoG samples into one value. The static number of consecutive samples correspond to a specific duration in time called the *window size*, based on the sampling rate of each electrode. For example, a window size of 20 seconds of ECoG will have 8000 raw samples when sampled at 400Hz. Increasing the number of samples in this window is directly proportional to the accuracy and computational cost [153].

These time domain features will be extracted from every channel of the ECoG, so that for each window-time instance we will extract 128-dimensional (16 channels * 8 features) feature for non-overlapping 20-second time-window of raw ECoG signal, collectively denoted as set_t features.

We also use another set of input features representing the power-in-band properties of the ECoG signal in the commonly studied Berger's frequency bands, Standard Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz), Gamma (30-100 Hz).

We filter 20 seconds of ECoG data using band-pass filter (2nd order Butterworth) into 5 frequency bands and find the power spectral density by squaring the signal (based on Plancherel theorem to skip the calculation of FFT over ECoG signals).

Then, we extract a set of 80 dimensional (16 channels * 5 features) features from non-overlapping 20-second time-window of raw ECoG signal, collectively denoted as set_f features.

6.3.2 CLASSIFICATION MODEL

The classifier is an integral part of the prediction framework as shown in Figure 6.3. We focus on binary classification problem to classify the pre-ictal data and inter-ictal data from patient-specific ECoG.

The classification model is generated based on patient-specific ECoG signals. One of the crucial criteria for selecting the classification method is the memory required and the classification time. We selected 7 classifiers namely,

- k-Nearest neighbour (kNN) with $k = 3$
- k-Nearest neighbour (kNN) with $k = 5$
- Support Vector Machine (SVM)
- Logistic regression
- Naive Bayes
- Linear Discriminant Analysis (LDA)
- Quadratic Discriminant Analysis (QDA)

The choice of 3 and 5 neighbors in kNN is to generate distinct class boundaries, as larger k makes boundaries between the classes less distinguishable.

Implementation of these classifiers are fairly standard in MATLAB. The classifiers are trained with features extracted over 20-second non-overlapping time windows of ECoG signals.

6.3.3 THRESHOLDING

The main aim of threshold block in our seizure prediction framework is to temporally analyze the output of the classifier over a time-period and to decide if the signal is pre-ictal or inter-ictal.

For this, we use the segmentation of classifier's outcome in one hour blocks, i.e. for each 20 seconds of the raw ECoG signals, the classifier model outputs the class, either pre-ictal or inter-ictal, to which the sequence belongs.

This outcome is accumulated for 1 hour of raw ECoG contributing to 180 classification labels. A threshold of 70% is set, i.e. 126 out of the 180 classification labels should be classified as pre-ictal to trigger a seizure alarm.

If it cannot be achieved, the feature set is forwarded to the active learner block together with the soft labels (certainty of the prediction) and crisp labels (prediction of the class) from the classifier.

The choice of 70% will result in improving the classification accuracy and it is empirically selected for our data-set. In real-world scenarios, this threshold is patient-dependant and must be changed according to the requirements of the disease condition.

6.3.4 ACTIVE LEARNER

In general, all pre-ictal signals are believed to be unique for each seizure, so it is impossible to capture all the expected pre-ictal signal types in a patient's lifetime [16].

Re-training process without new labels will not improve the accuracy of the classifier model for unknown pre-ictal signals. Expert's knowledge is constantly needed to maintain the high accuracy in seizure prediction throughout patient's lifetime.

The advantage of applying the active-learning heuristic to the output of classifier is twofold. One is to improve the prediction accuracy by dynamically updating the classifier model, and the other is to make it scalable by constantly updating the classifier model to achieve patient-non-specific detection of pre-ictal periods.

Updating the classifier model requires additional labels and a training phase to derive a model based on the newly obtained labels.

Figure 6.4: Schematic flow of active learner block based on Bernoulli-Gaussian model. This model takes the ambiguous samples along with the base classifier's label prediction with its certainty as inputs.

In an active learning framework, these additional labels are provided by an expert (otherwise known as *oracle* w.r.t active learning terminologies) by observing the ambiguous samples. The process of labeling by the expert and updating the classifier model through training is repeated until a stopping criterion is met.

An important aspect of active learning in addressing the issue of expensive labeling over other semi-supervised learning is that, active learning explores the instances

with most ambiguity or least confidence, whereas the latter explores the instances with least ambiguity or most confidence.

However, selecting the samples to be labeled by the expert is a crucial task, which determines the success of the active learning framework.

There are various techniques, such as the uncertainty-based selection [154], the margin information density criterion [155], and the importance weighting technique [156], to select the ambiguous samples to be labeled.

The total number of labeled pre-ictal samples is often lower than the number of the available inter-ictal samples. Outlier based ambiguous sample selection for active learning will select *morbid samples* to be classified in a multi-dimensional feature space, which results in high misclassification.

A *morbid* set of samples is defined as the set of most uncertain samples which would belong to the same class as predicted by a classifier model, but in reality belongs to two different classes.

Selecting this morbid set of samples to be labeled by an expert will not only increase the labeling cost but also show no significant improvement in the detection accuracy.

6.3.4.1 BERNOULLI-GAUSSIAN MIXTURE MODEL

To prevent morbid samples from being selected to be labeled by an expert, we use BGMM as the active selector block. BGMM will create a mixture of three probability distributions namely, ambiguous-samples and their label distribution as a Gaussian distribution and their certainty distribution as a Bernoulli distribution.

New sample's ambiguity will be estimated by identifying the probability of the new sample to belong to either pre-ictal or ictal class. The sample with the least probability will be selected to be labeled by an expert.

In what follows, we will explain the mathematical modelling of the BGMM block with respect to our problem of ambiguous pre-ictal sample selection from ECoG signals.

Let the feature space be defined by $\mathbf{X} \subseteq \mathbb{R}^d$, where d denotes the feature dimension and $\mathbb{R}$ denotes the measurable set of ECoG signals. Let the binary output space be defined by $Y \subseteq \mathbb{Y}$.

We consider the problem of estimating the joint probability density $P_{\mathbf{X}\mathbf{Y}}$ given a set of input ECoG observations $\{x_j\}_{j=1}^N$ and output seizure labels $\{y_j\}_{j=1}^L$, where L is the total number of available labels and N is the total number of observed ECoG samples.

In our case the available number of labels does not fully represent the observed samples, i.e. $0 < L < N$, which makes the estimation of $P_{\mathbf{X}\mathbf{Y}}$ to be semi-supervised [151].

Hence, the uncertain labels of seizure are defined as $\{y_j\}_{j=L+1}^N$. Input ECoG observation x_j is represented as a marginal 2-component Gaussian mixture distribution, i.e. the inter-ictal epoch and the pre-ictal epoch, and is defined as follows.

For $c = \{0, 1\}$,

$$(x_j|y_j = c) = \mathcal{N}(x_j; \mu_c, \Sigma_c) \quad (6.1)$$

, where μ_c & Σ_c represents the mean and co-variances of the distribution.

The BGMM model also includes the augmented observations $\{u_j\}_{j=1}^L$ and $\{v_j\}_{j=1}^L$ where $\{u_j\} \in \mathbb{Y}^K$ and $\{v_j\} \in \{0, 1\}^K$, representing the crisp and soft labels (normalized confidence probability) of the classifier's outcome, respectively.

K is the maximum number of times an expert can be queried for the label and is determined based on the application requirement. The distributions of (u_j, v_j) are defined as follows.

For $c = \{0, 1\}$ and $m = \{0, 1\}$,

$$(u_{jk}|y_j = c) \sim \mathcal{B}(u_{jk}; \pi_{ck}) \quad (6.2)$$

$$(v_{jk}|y_j = c, v_{jk} = m) \sim \mathcal{N}(v_{jk}; \lambda_{cmk}, \sigma_{cmk}^2) \quad (6.3)$$

, where u_{jk} and v_{jk} represent the k^{th} component of u_j & v_j , respectively and $\mathcal{B}(z; \pi)$ denotes a Bernoulli distribution for variable z with success probability π .

From these individual distributions, the joint distribution of BGMM is defined as $p(x, y, u, v)$ with parameters $c = \{0, 1\}$, $m = \{0, 1\}$, α_c (mixture proportion), $\Sigma_c \in \mathbb{R}^{d \times d}$, $\mu_c \in \mathbb{R}^d$, $\pi_c \in [0 \leq \pi \leq 1]$, $\lambda_{cmk} \in \mathbb{R}^{K \times 2}$, $\sigma_{cmk} \in \mathbb{R}^{K \times 2}$.

The estimation of these parameters is carried out using a Expectation-Maximization (E-M) algorithm [151] by considering the variables $\{y_j\}_{j=L+1}^N$ as hidden variables.

The cost function is defined as the error in classification due to non-optimal classifier model, i.e.,

$$\epsilon(\hat{\theta}) = \mathbb{E}(Y, \hat{\theta}(X)) - \mathbb{E}(Y, \theta(X)) \quad (6.4)$$

, where $\mathbb{E}$ is the expectation operator with respect to the probability measure P_{XY} , θ is the optimal classifier model and $\hat{\theta}$ is an estimate of the optimal classifier.

The estimation of parameters $\theta = (\alpha_c, \mu_c, \Sigma_c, \pi_c)$ is done by a E-step and a M-step.

The E-step creates a function for the expectation of the log-likelihood using the current estimate for the parameters. The M-Step computes the parameters by maximizing the expected log-likelihood of the parameters estimated on the E-step.

The E-step is generally defined as,

$$Q(\theta, \theta^t) = \sum_{j=1}^N \sum_{c=0}^1 \gamma_{j,c}^{(t)} \left[\log(\alpha_c) - \frac{1}{2} \log |\Sigma_c| - \frac{1}{2} (x_j - \mu_c)^T \Sigma_c^{-1} (x_j - \mu_c) \right] \quad (6.5)$$

while, in our case $N = L + U$, $\gamma_{j,c}^{(t)}$ is defined by,

$$\gamma_{j,c}^{(t)} = \begin{cases} I(y_j = c), & \text{if } 1 \leq j \leq L \\ T_{j,c}^{(t)}, & \text{if } (L + 1) \leq j \leq N \end{cases} \quad (6.6)$$

and the $T_{j,c}^t$ is given by,

$$T_{j,c}^{(t)} = \frac{\mathcal{N}(\tilde{x}_j; \mu_c, \sigma_c) \mathcal{B}(u_j; \mu_c^{(t)}) \alpha_c^{(t)}}{\sum_{c=0}^1 \mathcal{N}(\tilde{x}_j; \mu_c, \sigma_c) \mathcal{B}(u_j; \mu_c^{(t)}) \alpha_c^{(t)}} \quad (6.7)$$

The M-Step is given by,

$$\pi_c^{(t+1)} = \frac{\sum_{j=1}^N \gamma_{j,c}^{(t)} u_j}{\sum_{j=1}^N \gamma_{j,c}^{(t)}} \quad \mu_c^{(t+1)} = \frac{\sum_{j=1}^N \gamma_{j,c}^{(t)} \tilde{x}_j}{\sum_{j=1}^N \gamma_{j,c}^{(t)}} \quad (6.8)$$

$$\Sigma_c^{(t+1)} = \frac{\sum_{j=1}^N T_{j,c}^{(t)} [\tilde{x}_j - \mu_c^{(t+1)}] \left[(\tilde{x}_j - \mu_c^{(t+1)})^T \right]}{\sum_{j=1}^N T_{j,c}^{(t)}} \quad \alpha_c^{(t+1)} = \frac{\sum_{j=1}^N \gamma_{j,c}^{(t)} u_j}{\sum_{j=1}^N \sum_{c=0}^1 \gamma_{j,c}^{(t)}} \quad (6.9)$$

The output from the BGMM is then forwarded to a *selector* block, which selects the samples with least confidence or most ambiguity, to be labeled by an expert. The least confident sample $\phi_{LC}\{x_j\}$ is selected by $\phi_{LC}\{x_j\} = (1 - P_\theta(y_j|x_j))$ [157].

6.3.4.2 STOPPING CRITERION

The vital step in active learning is to know when to stop querying the expert, because more querying will typically increase the labeling effort and renders the system unscalable for large patient groups. The active learner must be aware of when to stop the expert querying.

For this, we monitor the confidence samples that are observed after the *selector* block in the active learner (Figure 6.4). This confidence samples are used as active feedback to exhibit the confidence in classification accuracy and to stop the active learner to query the expert.

In order to achieve this, the confidence samples are monitored for each iteration of the active learner block. Querying the expert is stopped when the confidence samples remain the same for consecutive iterations of the active learner block.

This constant confidence sample directly reflects the accuracy of the base classifier model i.e. the new labels from the expert have improved the classifier model

and there is no ambiguous samples to be labeled by an expert. Thus querying the expert must be stopped immediately.

Algorithm 3 Pseudo-code of individual functions

<pre> 1: function EXTRACT FEATURE($S_{\text{ecog}}, \mathcal{X}$) input: $S_{\text{ecog}} = 20$ seconds; all channels output: $\mathcal{X} \in \mathbb{R}^K$ 2: $\mathcal{X} = \{x_1, x_2, \dots, x_N\}$ 3: end function 4: function CLASSIFY($\mathcal{X}, \mathcal{Y}, \mathcal{V}, \mathcal{U}$) input: $\mathcal{X} \in \mathbb{R}^K$ output: $\mathcal{Y}, \mathcal{V}, \mathcal{U}$ 5: for each sample in $\mathcal{X}$ do 6: $(\mathcal{Y}, \mathcal{V}) = \theta(\mathcal{X})$ (acquire soft and crisp labels) 7: end for 8: return $\mathcal{U} = \{\mathcal{X} \mid P_{\mathcal{Y} \mathcal{V}} < 80\%\}$ (obtain ambiguous samples) 9: end function </pre>	<pre> 10: function THRESHOLD($\hat{\mathcal{Y}}, PA$) 11: if 70% of $\hat{\mathcal{Y}}$ is classified as pre-ictal state then 12: return $PA = 1$ 13: else 14: return $PA = 0$ 15: end if 16: end function 17: function ACTIVE LEARNER($\mathcal{X}, \mathcal{U}, \mathcal{Y}, \mathcal{V}, \mathcal{A}$) input: $\mathcal{X}, \mathcal{U}, \mathcal{Y}, \mathcal{V}$ output: $\mathcal{A}$ 18: $\theta_{\text{BGMM}} = \text{BGMM}(\mathcal{X}, \mathcal{U}, \mathcal{Y}, \mathcal{V})$ (Obtain BGMM model) 19: for each sample in $\mathcal{U}$ do 20: $(\mathcal{Z}, p(\mathcal{Z})) = E_M[\theta_{\text{BGMM}}(\mathcal{X}, \mathcal{Y}, \mathcal{V})]$ 21: end for 22: $\mathcal{A} = (\text{Samples in } \mathcal{Z} \text{ with smallest } p(\mathcal{Z}))$ 23: end function </pre>
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6.3.5 SEIZURE PREDICTION FRAMEWORK

Our prediction framework is implemented using four main functional blocks described in Section 6.3.1 - Section 6.3.4, namely,

- (i) EXTRACT FEATURE ($S_{\text{ecog}}, \mathcal{X}$): where, the n dimensional feature-set ($\mathcal{X}$) is extracted over 20 second time window of raw ECoG signals (S_{ecog})
- (ii) THRESHOLD($\hat{\mathcal{Y}}, PA$): where, a prediction alarm PA is set, if 70% of the accumulated labels ($\hat{\mathcal{Y}}$) are classified as pre-ictal state.
- (iii) CLASSIFY($\mathcal{X}, \mathcal{Y}, \mathcal{V}, \mathcal{U}$): where, a trained semi-supervised classifier model is used to obtain the set of soft-labels ($\mathcal{Y}$) and crisp-labels ($\mathcal{V}$), from the input feature-set ($\mathcal{X}$). Also, the set of uncertain feature samples ($\mathcal{U}$) is obtained based on the soft and crisp-labels of the classifier model
- (iv) ACTIVE LEARNER($\mathcal{X}, \mathcal{U}, \mathcal{Y}, \mathcal{V}, \mathcal{A}$): where, a BGMM model based on the feature-set ($\mathcal{X}$), uncertain sample-set ($\mathcal{U}$), soft-label set ($\mathcal{Y}$), and crisp-label set ($\mathcal{V}$) is generated.

E-M algorithm is used to obtain the sample-set ($\mathcal{Z}$), where the confidence of classification of each sample is determined by the probability $p(\mathcal{Z})$. Active sample ($\mathcal{A}$), is selected from the samples of $\mathcal{Z}$ which has the smallest $p(\mathcal{Z})$. Pseudo-code of these individual functional blocks are shown in Algorithm 3.

Algorithm 4 Pseudo-code of seizure prediction framework

```

1: procedure PREDICTION( $S_{\text{ecog}}, PA$ )
2:   input:  $S_{\text{ecog}}$ 
3:   output:  $PA$  (prediction alarm)
4:   repeat
5:     for every 20 second window of  $S_{\text{ecog}}$  do
6:        $\mathcal{X} = \text{EXTRACT\_FEATURE}(S_{\text{ecog}})$ 
7:        $(\mathcal{Y}, \mathcal{V}, \mathcal{U}) = \text{CLASSIFY}(\mathcal{X})$ 
8:     end for
9:     while !(time == 60 mins) do
10:       $\hat{\mathcal{Y}} = \mathcal{Y}$  (accumulate the labels for 1 hour)
11:    end while
12:    if !(THRESHOLD( $\hat{\mathcal{Y}}$ )) then
13:       $\mathcal{A} = \text{ACTIVE\_LEARNER}(\mathcal{X}, \mathcal{U}, \hat{\mathcal{Y}}, \mathcal{V})$ 
14:       $\mathcal{Y} = \text{expert}\{\mathcal{A}\}$  (Obtain labels)
15:      update  $\theta(\mathcal{X})$  (Update base classifier model)
16:    else
17:      return  $PA$ 
18:    end if
19:  until End of  $S_{\text{ecog}}$ 
20: end procedure

```

As shown in Algorithm 4 our prediction framework sequentially utilizes these functional blocks such that for every 20 second time-window of raw ECoG signals, the $\text{EXTRACT_FEATURE}(S_{\text{ecog}}, \mathcal{X})$ function generates the feature-set. This feature set is input to the $\text{CLASSIFY}(\mathcal{X}, \mathcal{Y}, \mathcal{V}, \mathcal{U})$ function, to obtain the soft and crisp-labels together with the uncertain feature-subset.

Based on these labels, $\text{THRESHOLD}(\hat{\mathcal{Y}}, PA)$ function triggers a *prediction alarm* (PA) if more than 70% of the samples are labeled as pre-ictal state. If less than 70% of the labels are classified as pre-ictal, the feature-set together with soft and crisp-labels are forwarded to the active learner.

The $\text{ACTIVE_LEARNER}(\mathcal{X}, \mathcal{U}, \mathcal{V}, \mathcal{A})$ function, then selects the samples with most ambiguity and obtains the label from an expert.

The classifier model ($\theta(\mathcal{X})$) is updated based on the newly obtained label and the whole procedure is repeated until the end of ECoG signal.

6.4 SIMULATION SETUP

6.4.1 DATA-SET

The ECoG data used in our work is an open-access data, obtained from Mayo Systems Electrophysiology Laboratory (MSEL) [158] and iEEG database [138].

The ECoG data is segmented and labeled as pre-ictal or inter-ictal by human experts. Data is obtained in segments of 10 mins sampled at 400 Hz and the total duration of available data is summarized in Table 6.2.

Subject	Sampling rate in Hz	# of Inter-ictal segments #(h)	# of Pre-ictal segments #(h)	# of lead seizures	%of pre-ictal segments	%of inter-ictal segments	Total duration of labeled data (h)
Dog1	400	480 (80 Hours)	24 (4 Hours)	8	4.8%	95.2%	84 (hours)
Dog2	400	500 (83)	42 (7)	40	7.8%	92.2%	90
Dog3	400	1440 (240)	72 (12)	18	4.8%	95.2%	252
Dog4	400	804 (134)	97 (16)	27	10.8%	89.2%	150
Dog5	400	450 (75)	30 (5)	8	6.2%	93.8%	80
Patient1	5000	50 (8)	18 (3)	4	26.5%	73.5%	11
Patient2	5000	42 (7)	18 (3)	6	30.0%	70.0%	10

Table 6.2: Data characteristics used in our study accessed from [158]. Source: [148]

Epileptic data is obtained from five canine and two human subjects. The canine epileptic data reflects continuous long-term recordings of dogs with naturally occurring epilepsy.

The human patients’ medication was lowered to promote seizures for 7 - 14 days and the ECoG signals are recorded for a much lower duration in time than the canine subjects. The canine epilepsy is claimed to be an excellent analog for naturally occurring epilepsy in humans [140].

Canine subjects data-set contains 16 channels of raw data from implanted electrodes, and human subject Patient 2 has 24 channels of ECoG. Lead seizures are seizures that are recorded without a preceding seizure for more than 7 days for canine subjects and more than 4 hours for human subjects.

Although inter-ictal data is chosen randomly from a much longer recording, contamination of inter-ictal data by the pre-ictal data is prevented by choosing inter-ictal epochs a week away from the pre-ictal epochs in canine subjects and more than 4 hours away from pre-ictal epochs of human subjects.

6.4.1.1 IMBALANCED DATA-SET AND CLASSIFICATION MODEL

It is important to note that the long hours of data has a very small percentage of pre-ictal segments and a large percentage of inter-ictal segments. As shown in Table 6.2, the data-set has imbalance ratio ranging from 20:1 (Dog1 and Dog5) to 2:1 (Patient2) for inter-ictal to pre-ictal data.

Modelling a classifier on this imbalanced data-set will result in highly biased classification results towards the majority class, which is inter-ictal. However, an efficient approach to overcome this problem in modelling an SVM classifier with unbalanced ECoG data-set is presented in [140], which we utilize here

We train the classifier using the unbalanced data-set, whereas the validation and model selection will be done using an artificially balanced data-set as explained in the following text. As we explained earlier, we follow a 1 hour time window for seizure prediction based on pre-ictal data.

So we split available data into blocks of 1 hour and iterate the validation for the number of available pre-ictal blocks available, as shown in Table 6.3. For example, in Dog1 data-set we have four blocks of pre-ictal data, so the classifier is validated by four-fold cross-validation and iterated for four times as shown in Table 6.3.

Subject	Training set		Validation set	
	Inter-Ictal	Pre-Ictal	Inter-Ictal	Pre-Ictal
Dog1 (Iteration1)	2-80	2,3,4	1	1
Dog1 (Iteration2)	1,3-80	1,3,4	2	2
Dog1 (Iteration3)	1,2,4-80	1,2,4	3	3
Dog1 (Iteration4)	1-3,5-80	1,2,3	4	4

Table 6.3: Separation of 1 hour blocks of data for a fair training and validation for Dog1.

Each number represent the sequence number of the 1 hour blocks [140]. Tables [6.4-6.9] present the separation of 1 hour blocks of data for each subject. However, all iterations are not shown due to their repetitiveness

Subject	Tra.-set		Val.-set	
	I. I	P.I	I.I	P.I
Dog2 (It.1)	2-83	2-7	1	1
Dog2 (It.2)	1,3-83	1,3-7	2	2
	...			
Dog2 (It.7)	1-6,8-83	1-6	7	7

Table 6.4: Dog2

Subject	Tra.-set		Val.-set	
	I. I	P.I	I.I	P.I
Dog5 (It.1)	2-75	2-5	1	1
Dog5 (It.2)	1,3-75	1,3-5	2	2
	...			
Dog5 (It.5)	1-4,6-75	1-4	5	5

Table 6.7: Dog5

Subject	Tra. - set		Val. - set	
	I. I	P.I	I.I	P.I
Dog3 (It.1)	2-240	2-12	1	1
Dog3 (It.2)	1,3-240	1,3-12	2	2
	...			
Dog3 (It.12)	1-11,13-240	1-11	12	12

Table 6.5: Dog3

Subject	Tra. - set		Val. - set	
	I. I	P.I	I.I	P.I
Patient1 (It.1)	2-8	2,3	1	1
Patient1 (It.2)	1,3-8	1,3	2	2
Patient1 (It.3)	1,2,4-7	1,2	3	3

Table 6.8: Patient1

Subject	Tra. - set		Val. - set	
	I. I	P.I	I.I	P.I
Dog4 (It.1)	2-134	2-16	1	1
Dog4 (It.2)	1,3-134	1,3-16	2	2
	...			
Dog4 (It.16)	1-15,17-134	1-15	16	16

Table 6.6: Dog4

Subject	Tra. - set		Val. - set	
	I. I	P.I	I.I	P.I
Patient2 (It.1)	2-7	2,3	1	1
Patient2 (It.2)	1,3-7	1,3	2	2
Patient2 (It.3)	1,2,4-7	1,2	3	3

Table 6.9: Patient2

This will ensure, validation is always performed on an out-of-sample data-set, yet each classifier model is validated on its own data-set. Also, the accuracy of the model will be validated based on individual test segments of 1 hour rather than extremely short segments, which is clinically relevant [140].

6.4.2 VALIDATION METRICS

The validation process has three main goals: (i) to evaluate performance of the classifiers; (ii) to evaluate the performance of the active learner, and (iii) to evaluate the overall seizure prediction accuracy of the framework.

6.4.2.1 PERFORMANCE METRICS FOR THE CLASSIFIER

Classic evaluation of the classifier performance is performed using the False Positive Rate (FPR) and False Negative Rate (FNR). Since the goal of the classifier is to classify the pre-ictal class from inter-ictal class, *true positive* means correctly classified pre-ictal epoch and *true negative* means correctly classified inter-ictal epoch.

So, FPR corresponds to the number of inter-ictal epochs incorrectly classified as pre-ictal epochs, which also results in overall reduction in accuracy of seizure prediction. FNR corresponds to the incorrectly classified pre-ictal epochs as inter-ictal epochs, which also contributes to the overall accuracy but it is clinically desirable to have very low FNR at the expense of high FPR [140].

The FPR and FNR are calculated over 1 hour time period, in order to match the constraint of prediction horizon and pre-ictal period, i.e. $SPH(3 - 16 \text{ hours}) > \text{pre-ictal period}(1 \text{ hour})$ (*SPH of 3- 16 hours is based on the range of pre-ictal data available for different patients [refer Table 6.2].*).

Nevertheless, we also evaluate performance of the classifiers in terms of the accuracy ($\mathcal{A}$), which is defined as the ratio of the sum of true positives (correctly classified pre-ictal epoch) and true negatives (correctly classifier inter-ictal epoch) to the sum of real positives (number of pre-ictal epoch) and real negatives (number of inter-ictal epoch).

6.4.2.2 PERFORMANCE METRICS FOR THE ACTIVE LEARNER

The performance of the active learning process is measured in terms of accuracy ($\mathcal{A}$) of the base classifier, or its complement, error rate (ϵ), with respect to the number of available labels. This is known as the *label complexity* [151]. In general, an ideal active learner will have a label complexity of $O(\ln \frac{1}{\epsilon})$.

In our case, the drop in accuracy of classification occurs when the ambiguous feature-samples close to the hyperplane are selected improperly for the active-labeling process.

To evaluate the performance of our active learner with the minimum number of labels, we validate the trained classifier model slightly differently from the method of evaluating the performance of the base classifier as shown in Table 6.10. It is important to note that the base classifier model is not generic for all patients.

A personalized training of base classifier model is carried out with each individual subject. Validation of this base classifier model with the active-learning block is carried out still with balanced data, but using different *label fractions* as shown in Table 6.10. The expert in our evaluation case is a *database* of labeled feature samples of pre-ictal class, which was not used for training the model.

So every time the active learner block is triggered, the database is queried for labeling the unknown samples. In reality, this database will be a trained medical expert. A label fraction is the ratio of the labeled data and the sum of labeled and unlabeled data that is used for validation.

In general, if there are n pre-ictal epoch available for a subject, a bench-marking of the classifier model is done using n pre-ictal epochs, and $(n - 1)$ iterations of validation is carried out using sequentially decreasing label fractions. This way, label complexity is measured as a function of classifier accuracy ($\mathcal{A}$).

Subject	Training set		AL-Validation set	
	Inter-Ictal	Pre-Ictal	Inter-Ictal	Pre-Ictal
Dog5 (benchmark)	1-75	1,2,3,4,5	71,72,73,74,75	1,2,3,4,5
Dog5 (Iteration1)	1-74	1,2,3,4	75	5
Dog5 (Iteration2)	1-73	1,2,3	74,75	4,5
Dog5 (Iteration3)	1-72	1,2	73,74,75	3,4,5
Dog5 (Iteration4)	1-71	1	72,73,74,75	2,3,4,5

Table 6.10: Selection of data blocks for validating active learner

Misclassification can occur in the base classifier model with real-world data. This misclassification of the base classifier is considered as the noise to the input of active learner.

The sensitivity of the active learner in presence of such random noise in the data-set is measured using *noise sensitivity* [151]. Noise sensitivity is the measure of error rate ϵ as a function of noise rate η for a fixed label fraction.

In case of subject *dog5*, we will choose the iteration 3 in Table 6.10 as the validation case, where out of 5 pre-ictal epoch only 2 pre-ictal epochs are used for training and 3 pre-ictal epochs are used for validation. In general, if there are n pre-ictal epoch available for a subject, $\frac{n}{2} - 1$ ($\frac{n+1}{2} - 1$ if n is odd) is used for training and the noise sensitivity is calculated on the remaining epochs by adding random noise.

6.4.2.3 PERFORMANCE METRICS FOR SEIZURE PREDICTION FRAMEWORK

As mentioned earlier the seizure alarms are generated after the classification based on the threshold of 70% of the 20-second epochs in 1 hour period is classified as the pre-ictal epochs. To compare the performance of our framework with random prediction we used Poisson prediction scheme [141].

This Poisson prediction scheme will issue the seizure warning according to an exponentially distributed random time interval with a fixed mean λ_{ran} , which is chosen for each subject based on the available data-set according to the time-interval between the lead seizures.

For example, in a period of 5 hours if a patient has three events of lead seizure occurring at 1.4, 2.3 and 3.6 hours, then $\lambda_{\text{ran}} = 1.1$ (averaged inter-seizure duration). With this Poisson prediction scheme we assume that a priori knowledge of the seizures can be compared with our prediction framework and measure how accurate our prediction results are compared to a random prediction system.

To evaluate the performance of the prediction framework, we will use the *sensitivity* and *specificity* measures. Sensitivity is defined as the ratio between the total number of correctly predicted seizures and the total number of seizures.

The specificity of the prediction framework is defined as the total number of falsely predicted seizure in the total duration of the ECoG signals for each subject.

It is important to note that the specificity does not reflect the correctly prediction inter-ictal period, which is true negative.

By measuring the sensitivity and specificity of the framework with the minimum number of labels will emphasize the impact of the active learner in seizure prediction framework.

6.4.2.4 PLATFORM FOR EVALUATION

All our algorithms were implemented and validated using existing machine learning libraries in MATLAB2017a installed on a Windows 7 laptop with Intel Core i7 4800MQ @ 2.7GHz CPU and 8 GB RAM. We used the machine learning classifiers with their default implementation and no optimization of individual classifiers was done, as our work focuses on the relative performance evaluation and not on individual classifiers' performance. It is important to note that the reported absolute accuracy of the classifier may not be the best possible outcome and can be improved further by optimizing the implementation of the classifiers.

6.5 RESULTS AND DISCUSSION

6.5.1 FEATURE SELECTION

We selected two sets of features representing the time-domain characteristics and spatial-domain characteristics of the ECoG signals. We compared the performance of seven classifiers with three different feature sets, set_t , set_f , and a combination of sets t and f , where set_t corresponds to time domain features, set_f corresponds to frequency domain features as explained in Section 6.3.1.

It is apparent from the results shown in Figure 6.5, that the combination of the feature sets has the highest accuracy in all the classifiers. However, set_t has low performance when compared to the features of set_f .

For further evaluation of our seizure prediction framework, we intend to use set_t , mainly for two reasons. Firstly, to measure the impact of the active learner on classifier accuracy. With low accuracy, the results of classifiers are not always reliable. With this empirical results, it is known that these features are not completely capable of representing the ECoG signal in higher dimensional feature space, which will result in large number of ambiguous feature samples near to the classifier's hyper-plane. Secondly, the calculation of these features is less complex than other two sets. These features can be implemented on ultra-low power hardware and the power consumption can be greatly reduced when compared to the implementation of other feature sets [159].

Figure 6.5: Performance of classifier for different sets of features

6.5.1.1 FEATURE EXTRACTION ON THE DATA-SET

The feature extraction is done on non-overlapping 20-second time windows of raw ECoG signals. Due to the decision of non-overlapping time windows, it is possible that various window sizes will have a significant impact on the classification accuracy ($\mathcal{A}$).

We compared the impact of different window sizes on the classification accuracy with different window sizes ranging from 1 second till 100 seconds in steps of 10. Accuracy in Figure 6.6 is calculated using a balanced data-set with respect to pre-ictal duration, in a 2 fold cross-validation setting. A SVM classifier with linear kernel (cost $C=5$) is used with features from set_t to evaluate the performance of time windows. This accuracy measure is not to reflect the classifier performance, instead to reflect the impact of different choices of window sizes ranging from 1 to 60 seconds on the classifier performance for different data-sets.

We found out that with our selection of features the classification accuracy of the selected classifiers did not improve after 20 seconds as shown in Figure 6.6. Based on these results, we select the 128 dimensional (set_t) feature vector which is obtained over 20 second time window for further evaluation of classifier and active learning framework.

6.5.2 EVALUATION OF CLASSIFIER

In this section we present and discuss the evaluation and selection of the base classifier model for our seizure prediction framework.

Figure 6.6: Accuracy ($\mathcal{A}$) of a linear SVM classifier as a function of time.

6.5.2.1 TIME AND MEMORY CONSUMPTION

We evaluate the performance of 7 classifiers with the feature set set_t in terms of classification time, i.e. the total time required to classify 1 hour block of raw ECoG signals, using the *tic* and *toc* functions of MATLAB. This timing method includes the overhead of the laptop's background process; however, profiling of all classifiers is carried out at the same time, with an assurance that the overheads are commonly present during all timing measurement.

From Figure 6.7, it can be seen that k-NN classifiers require the least time for the classification process because of the minimal computation, but they have the most memory usage. Most suitable classifier among the list is SVM as it requires less memory and has the least classification time. Based on this result, for further evaluation of the prediction framework we choose SVM classifier with set_t as the feature set extracted from 20 seconds of non-overlapped ECoG signals.

In SVM, together with the crisp-label, a degree of certainty, i.e. probability of the output, is also extracted after the classification process using the Platt's scaling method [160]. In this way, the classifier block outputs a *soft-label* and a *crisp-label* after each iteration of the feature set. These labels are forwarded to a threshold block in our prediction framework, which decides either the classification outcome is eligible for a seizure alarm and can be used for post-processing or the classifier model needs to be retrained through an active-learning framework.

Figure 6.7: Classification time for 20(s) of ECoG data from 16 channels using set_t feature set. Timing with Dog5 data.

6.5.2.2 EVALUATION OF BASE CLASSIFIER MODEL

In order to evaluate the performance of the classifier with respect to our segmented data, we calculate the performance in each class (pre-ictal and inter-ictal) separately. This ensures the performance of the classifier is valid for each class. Also, in this way we will be able to know how much data from each class is classified as *unknown* for each subject. For this performance evaluation, we used the segmented data as shown in Table 6.3. We discuss the results from all iterations for *Dog5* data-set in this section.

Iteration	Classifier Performance		Feature samples (%)	
	FPR (%)	FNR (%)	Clear	Ambiguous
Dog5 (Iteration1)	2.30	23.2	52	48
Dog5 (Iteration2)	3.62	20.7	63	37
Dog5 (Iteration3)	2.45	13.8	37	63
Dog5 (Iteration4)	1.54	22.5	46	54
Dog5 (Iteration5)	4.47	31.3	22	78

Table 6.11: Performance of SVM classifier with Dog5 Pre-ictal data-set using set_t feature set

In Table 6.11, FPR and FNR are calculated for one hour period to match our assumption of prediction horizon. The feature samples that have a degree of certainty of more than 80% in either class is considered clear samples. These samples can be

classified with high confidence into one of the classes. The remaining samples which have a lower degree of certainty are grouped as ambiguous samples.

Although a perfect classifier model will have a high degree of certainty and less ambiguous samples near the hyper-plane, with this superstitious certainty requirement, we intentionally increase the amount of ambiguous data. This setting will replicate the real-world scenario, where the amount of pre-ictal epochs used for training the classifier will be less than the inter-ictal epochs, naturally increasing the amount of ambiguous data or unknown class.

From Table 6.11, it is observed that each iteration using Dog5 data-set with different validation data has different error rates. Also, the FPR is always lower than the FNR because of the large amount of inter-ictal data used for training the classifier. Iteration 5 has the most number of ambiguous samples, and it is also reflected in the FPR and FNR. The number of ambiguous samples is very high i.e. 78% of the whole validation data used is grouped as ambiguous data. We choose the classifier model which is developed based on the iteration5 for further evaluation of the active learner block.

In Table 6.12, we present the performance of the classifier for inter-ictal data-set, with similar metrics. It is evident that the abundance of inter-ictal data has a positive influence on the classifier performance in terms of FPR and FNR, i.e. only negligent amount of samples are misclassified in the inter-ictal class.

Also, most of the samples are clear and very few samples are ambiguous in all iterations. It is observed from these results that all classifier models derived from all 5 iterations have almost similar performance for inter-ictal class. Therefore, we choose the classifier model based on the pre-ictal performance, which is the model Iteration5 for the subject Dog5.

Iteration	Classifier Performance		Feature samples (%)	
	FPR (%)	FNR (%)	Clear	Ambiguous
Dog5 (Iteration1)	0.01	0.12	92	8
Dog5 (Iteration2)	0.41	0.21	93	7
Dog5 (Iteration3)	0.21	0.87	91	9
Dog5 (Iteration4)	0.14	1.01	97	3
Dog5 (Iteration5)	0.37	0.91	96	4

Table 6.12: Performance of SVM classifier with Dog5 Inter-ictal data-set using set_t feature set

6.5.2.3 CLASSIFIER MODEL FOR EACH SUBJECTS

A similar process as explained above is used to obtain base classifier model for each subjects. The number of iterations for each subject depends on the number of available one hour pre-ictal segments.

For example, the subject Dog4 has 16 pre-ictal segments, so the classifier model has been iterated for 16 fold cross-validation to find the classifier model with the most ambiguous samples as shown in Tables [6.4-6.9].

We present only the iteration which has the most ambiguous samples and its corresponding FPR and FNR are presented in this section. The results of the classifier using data-set of all subjects are presented in Table 6.13.

Subject	Classifier Performance		Feature samples (%)	
	FPR (%)	FNR (%)	Clear	Ambiguous
Dog1	4.15	34.2	29	71
Dog2	3.74	26.7	24	76
Dog3	3.45	25.8	21	79
Dog4	3.88	29.8	26	74
Dog5	4.47	31.3	22	78
Patient1	8.24	38.5	16	84
Patient2	10.47	41.3	12	88

Table 6.13: Performance of SVM classifier for all the subject's pre-ictal data-set using set_t feature set. Classifier performance of only the best iteration is shown

It is important to note that subjects Patient1 and Patient5 has the highest error rate because of the highest scarcity in pre-ictal data. We selected the classifier model which has the most number of ambiguous data in the pre-ictal class.

We also report the performance of the same classifier model with inter-ictal class in Table 6.14. As explained in the case of Dog5 data-set the abundance of data in the inter-ictal class has no influence on the selection of classifier model, which is true for all other subjects.

Subject	Classifier Performance		Feature samples (%)	
	FPR (%)	FNR (%)	Clear	Ambiguous
Dog1	0.19	0.18	94	6
Dog2	0.12	0.23	95	5
Dog3	0.02	0.11	98	2
Dog4	0.25	0.62	97	3
Dog5	0.37	0.91	96	4
Patient1	0.54	1.45	91	9
Patient2	0.47	1.32	90	10

Table 6.14: Performance of SVM classifier for all the subject's inter-ictal data-set using set_t feature set. Classifier performance of only the best iteration is shown

6.5.3 EVALUATION OF ACTIVE LEARNER

To compare the performance of BGMM-based active learner, we used the SVM classifier with semi-supervised setting (or passive setting) and the SVM with just our uncertainty sampler as shown in Figure 6.8.

The classifier model selected for each subject is validated with different label fractions and the label complexity is presented for each subject separately as shown in Figure 6.9. The ratios of different label fractions are derived as shown in Table 6.10.

Figure 6.8: Label complexity of three different settings of SVM classifier. In each setting, the error rate is measured as a function of label fraction.

The model selected from the evaluation of the classifier performance is used to evaluate the active learner block. The error rate is the complement of accuracy $\mathcal{A}$ of the classifier. The performance of an ideal active learning in terms of error-rate ϵ should be close to $\mathcal{O}(\ln \frac{1}{\epsilon})$, whereas in the semi-supervised case it is $\mathcal{O}(\frac{1}{\epsilon})$.

From Figure 6.9, it is evident that for all the subjects, the active learner was able to achieve a much lower error rate than the semi-supervised SVM classifier.

In Figure 6.9(a), BGMM based SVM was able to achieve 37% lower error rate than semi-supervised SVM, with just 10% of the labels. Although uncertainty sampler has reduced the error rate by 17% with just 10% of the labels, the complexity is still close to $\mathcal{O}(\frac{1}{\epsilon})$, which is not desirable.

It is evident that the BGMM-based active selection has a clear improvement in the classification error when the number of labeled data is very less. Also, the case of BGMM-based SVM, the error rate saturates at around 1% because of the limitation of the selected classifier model. This complexity is close to $\mathcal{O}(\ln \frac{1}{\epsilon})$

Figure 6.9: Label complexity of three different settings of SVM classifier. Error rate as a function of label fraction.

As explained earlier, the base classifier is prone to misclassification because of the nature of pre-ictal distribution in ECoG signals. We added misclassification noise, i.e. randomly distributed label proportion, to the output of the base classifier.

We used the base classifier model that was chosen to have the highest ambiguous sample, and the label fraction was fixed in a way that the number of labeled data segments used for training is always lesser than the number of labeled segments used for validation.

In order to evaluate the performance of the active learner block in presence of such misclassification, we measure the accuracy of the base classifier with three different settings as shown in Figure 6.8. We measure accuracy of the classifier as a function of different noise proportions η . In presence of noise, the base classifier in a semi-supervised setting has poor performance. Also, the uncertainty sampler did not improve the accuracy in the presence of noise.

BGMM-based SVM classifier has a significant stability to the misclassification noise. The ability of the BGMM to select the active samples based on the estimation probability distribution results in clear isolation of the random noise added to the classification results.

It is evident that the misclassification costs can be lowered by BGMM model; however, choice of classifier model is important to achieve high accuracy. Also, at very high noise proportion of above 80%, all settings of the base classifier have similar accuracy in classification.

Figure 6.10: Noise complexity of three different settings of SVM classifier. Accuracy as a function of noise rate (η).

6.5.4 EVALUATION OF SEIZURE PREDICTION FRAMEWORK

To compare the seizure prediction performance of our framework, we used the set_t features, 20% labeled data with an SVM classifier which has the least memory consumption and execution time. This setting is a valid representation of a low-power low- complex classifier with minimal training phase. Also, in a practical setting, a seizure prediction framework is expected to work with such a constrained setting.

We compare our seizure prediction framework with a Poisson random predictor in terms of sensitivity and specificity. The prediction horizon is the time period between a true positive seizure warning and the actual seizure episode.

Subject	Random Poisson predictor			Active learning Predictor		
	Sen	Spe	Prediction horizon	Sen	Spe	Prediction horizon
Dog1	0.25	0.98	8 (minutes)	0.88	0.12	14.5 (minutes)
Dog2	0.13	0.96	94	0.95	0.08	20.3
Dog3	0.17	0.94	62	0.94	0.11	15.6
Dog4	0.15	0.99	4	0.88	0.03	18.2
Dog5	0.13	0.97	12	0.88	0.13	36.2
Patient1	0.25	0.98	30	0.75	0.30	20.2
Patient2	0.16	0.97	60	0.83	0.16	23.2

Table 6.15: Performance of SVM classifier for all the over-all data-set using set_t feature set

The performance of the random predictor and our seizure prediction framework is presented in Table 6.15. The sensitivity is very low for the Poisson predictor as it sends the seizure warnings randomly for the seizure occurrence.

However, with the minimal a priori knowledge, our seizure prediction framework has an average sensitivity of 87%. Also, in case of subject Dog3 which has the highest number of seizure events, sensitivity is very high at 94%.

The prediction horizon of the Poisson predictor is completely random. As the time to throw a seizure warning can be at any random time within inter-ictal periods. This results in very high specificity, which reflects the incorrectly predicted seizure event through the pre-ictal period.

Also, with random Poisson predictor the prediction horizons are completely random reflecting the random seizure events. In our seizure prediction framework, the specificity is very low reflecting the falsely predicted seizure events, and the prediction horizon is averaged at 21.7 minutes for all the subjects.

6.6 CONCLUDING REMARKS

In this chapter, we presented a low-power less-complex seizure prediction framework, which was able to achieve almost 95% sensitivity in seizure prediction with only 20% of the labeled data. A SVM classifier coupled with active learning heuristics is used as the core of the prediction framework. We showed that a scalable *expert-in-the-loop* operation of life-critical medical devices is possible through our framework.

We used openly available intra-cranial ECoG data-set and compared a set of temporal, spatial and a combination of temporal and spatial features to evaluate the performance of 7 different classifiers. We selected the best performing classifier with the lowest execution time and memory usage and used active learning principles to improve the accuracy of the classification with only 20% of the initial labeled data. Finally, a simple threshold-based prediction framework, which leverages the expert knowledge through active learning principles, to improve the classification accuracy was presented and compared with a random seizure predictor.

The active selection method eliminates the random need of expert knowledge thereby promising the scalability of our framework. Although we did not evaluate this framework in a clinical setting, we ensured clinical reprehensibility is achieved through the different choices of data-segmentation, prediction horizon, and feature selection during the development of our seizure prediction framework.

It is clear from this chapter that resource constrained IBSN sensor nodes can be made contextually aware of the brain signals. With 80% reduction in the amount of raw ECoG data needed to achieve high prediction accuracy, our seizure prediction framework will have low power consumption. In order to investigate the practical feasibility of our framework on a resource constrained sensor node, we will evaluate our framework on a ARM cortex M4 device in the following chapter. We will also

show that the power consumption of the sensor node is reduced with our context-aware seizure prediction framework, by locally processing the ECoG data and reducing the amount of raw ECoG data transmitted through a wireless radio.

RESOURCE CONSUMPTION ANALYSIS OF THE OPTIMIZATION FRAMEWORKS

OPTIMIZATION of wireless communication for energy-efficiency while improving its reliability is achieved through our newly developed algorithms. With carefully designed simulations, these optimization algorithms are proven to be suitable for IBSN applications. To further explore the feasibility of our algorithms to be executed on a resource constrained IBSN sensor node, we will investigate the time, memory and power consumption by implementing our algorithms in a commercially off-the-shelf low-power platform. Our main focus in this chapter is to measure the impact of our optimization algorithms in overall resource consumption of an IBSN sensor node. Our results show that our optimization algorithms significantly reduced the over-all power-consumption, however minor increase in memory usage and execution time is observed.

பீலிபெய் சாகாடும் அச்சிறும் அப்பண்டஞ்
சால மிகுத்துப் பெயின்

*With peacock feathers light, you load the wain;
Yet, heaped too high, the axle snaps in twain.*

—Thiruvalluvar in Kural 475

7.1 INTRODUCTION

In the last decade the computation capabilities of embedded μ processors have increased enormously and the power consumption of these devices has been largely reduced [161]. Several new μ processors are commercially available that can perform large complex computations with high accuracy at low-power consumption [135, 162, 163]. Although these devices have very low power consumption, implementation of complex software that require large computations will not only increase the power consumption but also decrease the functional accuracy of these devices.

On IBSN sensor nodes, several life-critical functional units are present in addition to the μ processor. As shown in Figure 7.1, sensor, actuator, wireless communication unit, memory unit together with the processing unit has to function based on the power from a tiny battery source. An IBSN node should be aware of the power availability and may have to trade off between performing computations and wireless transmission, without affecting the sensing and actuation functions. A typical IBSN sensor node is shown in Figure 7.1.

Figure 7.1: A common architecture of IBSN sensor node. (Dotted lines indicate power connection and solid lines indicate data connection.)

A central processing unit, in most cases a low-power high-performance μ processor controls all individual units of the node and performs mathematical operations over the data that is flowing through these individual units. A power unit, which mainly comprises of battery sources, supplies power to all the components of the sensor node as controlled by the central processing unit. A sensing and/or actuation unit is present depending on the function of the sensor node. A local memory unit is always present to store critical data throughout the life-time of the node.

Wireless unit comprises of a main radio which operates at 400 MHz in MICS frequency band and a wake-up radio which operates out of band of the main radio at 433 MHz. Additional hardware components such as analog-to-digital converter, switched mode power supply, voltage regulators, etc., which are not shown in the figure are implicitly present in these individual units.

We have elaborately explained the functionalities of these units together with their requirements in Chapter 1. In the Chapter 4 and 5, we developed new low-power wireless communication techniques to reduce the power consumption of these sensor nodes and to increase their reliability and quality-of-service parameters. As we presented in Chapter 5, DiNAMAC had improved the reliability and latency of wireless communication requiring much lower power consumption in our simulations.

In Chapter 6, we showed that our context aware seizure prediction framework has reduced the amount of raw data, which is required for accurate seizure prediction, by pre-processing the physiological signals using simple machine learning models. We have studied the performance of our techniques through carefully designed software simulations that accurately replicate the real-world scenarios.

However, simulations cannot accurately represent the actual execution of the algorithms in real hardware. To this end, in this chapter we will evaluate the context-aware seizure prediction framework together with our cross-layer optimized WuR based DiNAMAC protocol, on a commercially off-the-shelf hardware.

The main aim of this evaluation is to investigate the time, memory, and power consumption of our prediction framework and its associated algorithms and feasibility of their execution on a computation and power constrained IBSN hardware platforms. Evaluating our algorithm in a medical scenario, i.e. animal testing or human testing, is out-of-scope of this thesis.

The rest of this chapter is organized as follows. In Section. 7.2, we will present our chosen hardware platform and explain its characteristics. In Section. 7.3, we will investigate time, memory, and power consumption of our context-aware seizure prediction framework together with its performance in terms of accurately predicting the seizures.

In Section. 7.4, we will evaluate the time, memory, and power consumption of our reinforcement learning based optimization framework for wireless communication. Finally we conclude this chapter with our findings in Section. 7.5.

7.2 HARDWARE COMPONENTS OF IBSN SENSOR NODE

In our evaluation, we focus on time, memory, and power consumption of our newly developed algorithms. Therefore, sensing and actuation units of the sensor node are not included in our evaluation. Moreover power consumed by these sensing and actuation units is in the range of hundreds of nano-Watts, which is negligible compared to the processing and wireless units [164, 165].

We will use a sensor node which has a commercially off-the-shelf general purpose μ proc-essor, a main radio and a wake-up radio. In what follows, we will elaborate on the characteristics of the μ processor and wireless unit used in our evaluation.

7.2.1 MICROPROCESSOR

There are several general purpose μ processors available off-the-shelf from different manufacturers [135, 162, 163]. We selected the μ processor for our evaluation based on three main criteria.

- Firstly, the ultra-low power consumption in active mode i.e. while processing data, and sleep mode i.e., while being idle. Although many general purpose μ processors exists, only a few of them are ultra-low power, i.e. in the range of hundreds of μ Watts per MHz (μ W/MHz) during active mode and couple of n Watts during sleep mode.
- Secondly, capability to support fast signal processing algorithms through ultra-low power floating-point engines. Fixed-point implementation will only decrease the accuracy of our algorithm and might consume more power and memory than actually required. Not many μ processors have built-in low-power floating point engines that can support fast digital signal processing.
- Third, ability to operate at adaptable clock frequencies. In general, higher clock frequency requires more power, as the power and clock-frequency are directly proportional. Our algorithms consists of both processes that require quick and sporadic computations and processes that require slow and continuous computations. For example, thresholding of physiological data is a slow and continuous computation, whereas applying a machine-learning model is a quick and sporadic computation that is not always needed.

	Clock frequency(Hz)	Memory (bytes)	Power consumption (Watts)	Peripherals
Kinetis ⁵ K66 Cortex M4f [135]	24-180 MHz Our platform: 180 MHz	upto 256 kB SRAM upto 2 MB Flash (ROM) upto 8Gb SD card storage Our platform has highest possible memory	hundreds of micro-Watts	Limited to UART, I2C, USB
Core i7 [166]	1.8-4 GHz Our laptop: 2.7 GHz	upto 128 Gb DRAM upto 16Tb HD storage Our laptop: 8Gb RAM and 1TB HD storage	hundreds of Watts	Present, but not limited to PCIe, SATA, USB, UART

Table 7.1: Comparison between the μ processor on a Laptop and the μ processor on IBSN sensor nodes

To this end, we selected Kinetis[®] K66 ARM based Cortex M4f μ processor [167], which has ultra-low power consumption, floating point support with adaptable clock-frequency. Characteristics of the Kinetis[®] processor is presented in Table 7.1. Also to compare the resources of our platform with a general purpose personal computer, we list the characteristics of an Intel Core i7 processor range [166] in Table 7.1. The development board for our μ processor is shown in Figure 7.2, which has on-board SD card slot, a micro USB connection and accessible input and output pins for interfacing the wireless radio. The development board has on-board voltage regulator and voltage supply pins which will supply 3.3V DC that can be used to power-up the wireless unit.

Figure 7.2: Development board of the μ processor used in our evaluation

7.2.2 WIRELESS UNIT

We selected wireless radio based on two main criteria.

- Firstly, the ultra-low power consumption. The significant part of power consumption in wireless radio is the sensitivity of receiver and the transmission power. In IBSN, the transmission power is fixed at $-25 \mu\text{W}$ effective isolated radiated power (EIRP), equivalent to -16 dBm , in order to meet the safety regulations for the implant communications. This is the least transmission power setting in most commercial off-the-shelf wireless radios, and at such low transmission power, over-all power-consumption of the wireless radio is reduced. On the other hand, at such low power transmission, the receiver sensitivity must be very high for the receiver node to successfully receive a data-packet. Higher receiver sensitivity is ensured by additional techniques such as error correction, which will only increase the power consumption.
- Secondly, the ability to fully customize the PHY and MAC layer of the wireless radio. In some radios, PHY and MAC layer are not accessible through software such the Microsemi's ZL70103 [114]. Any software to control PHY and MAC will be executed on top of the hard-coded native PHY and MAC of the radio. These hard-coded settings precedes the software control in such radios. Selecting a wireless radio for both main radio communication and wake-up communication must be customizable at PHY and MAC layers of the radio.

To this end we selected, Texas instruments' CC1101 400 MHz radio [169] as main radio which can transmit at -16 dBm with customizable PHY and MAC. It has a

	Transmission power	Bandwidth	Power consumption	Data-rate	Operating frequency
IEEE 802.15.6 based wireless radio [27]	-16dBm (max ERP)	3MHz (10 channels of 300 kHz each)	μ W range (years of operation)	up to 150 kb/s	400 MHz (less reactive to conductive tissue)
IEEE 802.15.1 based Bluetooth radio [168]	20dBm (max ERP)	80 MHz (40 channels of 2 MHz each)	mW range (weeks of operation)	up to 3 MB/s	2.4 GHz (highly reactive to conductive tissue)

Table 7.2: Comparison between resource constrained IEEE 802.15.6 radio and IEEE 802.15.1 Bluetooth radio.

receiver sensitivity of -116 dBm. For wake-up radio, we selected RFM69CW 433 MHz ISM radio [170] as Wake-up radio, which can transmit at -16 dBm. It has a receiver sensitivity of -116 dBm with customizable PHY and MAC. Characteristics of wireless unit used in our evaluation is presented in Table 7.2. Also, to illustrate the limitations of IEEE 802.15.6 based wireless radio from high performance general purpose radios such as Bluetooth, we list their characteristics in Table 7.2.

Figure 7.3: Development board of 433MHz WuR with quadruple wire antenna (16.5 cm)

Figure 7.4: Development board of 400 MHz main radio with ceramic antenna

The development board of the main radio and WuR is shown in Figure 7.3 and 7.4, respectively. Although there are micro-controllers on these development boards, they are bypassed and a direct connection is made between the radio chip and our μ processor. This direct connection is made via the inter-integrated circuit (I2C) port, through which the control-commands, the data to be transmitted, and the received data are transmitted to and from the radio and μ processor.

7.2.3 EVALUATION SETUP

In order to evaluate the resource consumption, we will connect the sensor nodes to a laptop for power supply and data connection as shown in Figure 7.5.

Our development board has an on-board voltage regulator and current measurement set-up through which power-consumption of different software blocks on the μ processor will be measured. In our evaluation, we focus on worst-case analysis of the implementation, where the software blocks are not optimized for best performance but rather implemented using standard signal processing libraries from Cortex Microcontroller Software Interface Standard (CMSIS) [171]. Further optimization of individual software blocks for low-power and high performance is still possible, but that is not the main focus of our implementation.

Figure 7.5: Evaluation setup. (Dotted lines indicate power-flow and solid lines represent data-flow)

The μ processor is programmed via a micro-USB connection from the laptop through open-GCC environment [172]. The data present in the memory of the μ processor is also read through this connection. The memory (RAM and ROM) usage and execution time of the software blocks on the μ processor are read through an UART connection. The μ processor supplies the power to the wireless unit powering up both main and wake-up radios. A constant 3.3 V is drawn by wireless radio from the μ processor and depending on the usage current consumption of the radio is varied. We will measure this variation in current consumption during the execution of different programs through a shunt resistor as shown in Figure 7.6

Figure 7.6: Measurement of power in Wireless unit

7.3 HARDWARE EVALUATION OF CONTEXT-AWARE SEIZURE PREDICTION FRAMEWORK

We have presented context-aware seizure prediction framework in Chapter 6. The framework has different functional blocks namely feature extraction, machine-learning classifier, thresholding and an active-learner block as shown in Figure 6.3. In this section, we will evaluate the implementation of these blocks and measure the time, memory, and power consumption of individual functional blocks on its execution on the sensor node. This will provide an overview of the resource consumption of the individual functional blocks of the framework when it is executed on an IBSN sensor node.

7.3.1 FEATURE-CALCULATION

In our evaluation, we stored 10 minutes of 16 channels of ECoG signal in a SD card connected to the μ processor of the sensor node. 10 minutes of ECoG signal will be divided into 30 segments of 20 second-long ECoG signal. As discussed in Chapter 6, Section 6.3.1, 8 time-domain and 5 frequency-domain features were extracted over this 20 second time-window of ECoG signal. In the end, 3840 time-domain features (set_t) ($\{16\text{channel} * 8\text{features} * 30\text{segments}\}$) and 2400 frequency domain features (set_f) ($\{16\text{channel} * 5\text{features} * 30\text{segments}\}$) are extracted over the 10 minute ECoG signal. The resulting feature-set is stored in the on-board SD card.

We implemented the feature extraction on the μ processor using DSP library for Cortex M4 processors called CMSIS DSP library [171]. Time, memory, and power consumption of the feature extraction are measured from the moment when μ processor fetches the first 20 second segment of ECoG signal from the SD card until it computes and stores the feature sets in the SD card. The resource consumption values for computing features over 20 second ECoG signal sampled at 5 kHz are shown in Table 7.3.

From Table 7.3, it is clear that frequency domain feature, FFT requires most of the memory when implemented on the μ processor. However, other time domain features consume relatively less memory. Implementation of feature calculation pro-

Feature	Time required for processing (mS)	RAM used (bytes)	ROM used (bytes)	Power consumption (mW)
Area under the curve	280	128845	1274	73
Line-length	220	158741	1232	62
Mean-energy	220	132541	1121	73
Peak-amplitude	210	112548	854	66
Valley amplitude	230	121457	427	74
Normalized peak number	310	132512	978	72
Peak variation	340	125142	1232	86
Band-pass filter	320	192012	1214	83
Power spectral density	360	185214	1214	81
FFT [16384 point]	540	221325	1124	93

Table 7.3: Resource consumption analysis of computing time-domain and frequency-domain features in an embedded platform.

gram is stored on the ROM and in general the memory usage for storing the program is couple of kilo-bytes. However, the ECoG data is fetched from SD card and it is stored in RAM along with the intermediate results of the calculation, which explains the large usage of RAM to calculate the time and frequency domain features.

Calculation of both time and frequency domain features did not have big impact on the power-consumption. However, a slight increase can be seen while computing frequency domain features. FFT has the highest power consumption among all the feature calculation.

FFT took the highest time to compute among all the features, whereas other time domain features have rather similar execution times. The calculation of time domain feature do not require intermediate steps but only require simple calculation over set of data. This is the reason for constant time-consumption to compute all time-domain features.

These results corresponds well with our findings in Chapter 6, in which time domain features had less memory usage and took less time than frequency domain features to be calculated. Therefore, we will use time-domain features for further evaluation of our machine learning classifier model.

7.3.2 MACHINE-LEARNING CLASSIFIER

Although we evaluated the resource consumption of 7 different machine learning classifiers in Chapter 6, Section 6.3.2, the execution capability of the low-power μ processor for these machine learning models were not studied. To this end, we will investigate time, memory, and power consumption of these 7 classifiers namely, kNN (k=3), kNN (k=5), SVM, Logistic regression, Naive Bayes, LDA and QDA. These machine learning models are trained offline using a powerful laptop based on the ECoG signal as mentioned in Chapter 6.

For the classifier evaluation, the time domain feature set set_t will be used as input to the pre-trained classifier models. These features are calculated over 10 minutes of

ECoG signal on the μ processor as explained in Section 7.3.1. The computed features are stored locally in SD card and is fetched in batches of 128 corresponding to the 20 second segments of ECoG signals. We used CMSIS math library [171] to implement these models. The time, memory, and power consumption of the classifier models are measured from the moment when μ processor fetches first batch of feature-set until the classified labels are stored in the SD card. The resource consumption values of the μ processor corresponding to the execution of feature-extraction and classifier models are presented in Table 7.4. It is important to note that these resource consumption values also indicate the resource consumption of feature-calculation block together with the machine learning models.

Machine learning model	Time required for processing (mS)	RAM used (bytes)	ROM used (bytes)	Power consumption (mW)
kNN (k=3)	3245	184571	11412	101
kNN (k=5)	3457	174587	12541	112
SVM	3264	165784	14455	101
Logistic regression	3254	186547	12147	114
Naive Bayes	5254	187458	18741	102
LDA	3124	194527	17943	93
QDA	3223	195475	18144	91

Table 7.4: Resource consumption analysis of executing Machine-learning classifier models in an embedded platform.

From Table 7.4, it can be seen that the memory usage has increased from feature-calculation block but no memory-overflow has happened while executing machine learning models on the μ processor. In linear classifiers like LDA and QDA, the classifier model is simply a feature vector which categorically separates the feature-point between the classes. ROM usage is significantly increased because of these feature-vectors that are stored in ROM along with the classifier program. Classification is basically calculation of the linear relationship between the feature point to be classified and the feature-vector. In such cases, the program size increases as the size of the feature-vector increases. As the size of feature-vector increases, more non-volatile memory, i.e. ROM is required. This is evident from the results of ROM usage.

Time consumed to classify 10 min of ECoG signal is on average 3.2 seconds, which corresponds to 53 milliseconds(3.2/600) to process 1 second of ECoG sample. This is a reasonable time for using any classifier models on ECoG signals in real-world embedded applications [141]. However, it is important to note running another set of features and classifier model on the same platform may require different time for classifying 10 min of ECoG data.

Power-consumption of the μ processor is at its highest while the classifier models were executed. Logistic regression has the highest power consumption because of it recursive calculation of multiple linear regression models. LDA and QDA have the

least power consumption because of their minimal run-time to classify large feature points.

The time and memory usage results from Chapter 6 corresponds to the results presented in Table 7.4. SVM has the moderate memory usage and average power consumption compared with other machine learning classifiers. Since our aim is not to develop or optimize machine learning models for seizure prediction, we did not evaluate the accuracy of the classifier model in this chapter. However, we will evaluate the overall prediction accuracy of our framework on the embedded platform in Section 7.3.4.

7.3.3 ACTIVE LEARNER BLOCK

The implementation of our active learner block follows Figure 6.4 from Chapter 6 Section 6.3.4. We selected SVM classifier model with time-domain feature-set as the base classifier. The BGMM model will be implemented on top of the classifier model. For this evaluation, the intermittent results of feature-extraction and classifier labels from each segment are stored in SD card. Active learner fetches accumulated results of the classifier model and applies the BGMM based active selection on them for selecting samples with least classification accuracy. Since we only store 10 minute of ECoG signal in SD card of the μ processor, we will evaluate the resource consumption of active learner over the entire 10 minute ECoG signal. The resource consumption values of active learner are presented in Table 7.5.

	Time required for processing (mS)	RAM used (bytes)	ROM used (bytes)	Power consumption (mW)
Active learner	4245	175475	16548	105

Table 7.5: Resource consumption analysis of Active-learner block in an embedded platform.

From Table 7.5, it can be seen that the memory usage has not increased significantly, because the active learner block additionally stores only the soft and crisp labels in RAM and no large data is required to be stored along with the program in ROM. The power consumption is already at the maximum because of execution of the classifier models, and addition of active learner block did not increase the power consumption significantly, only few mW. For the active learner block to process 10 min long ECoG on an embedded platform took 4.2 seconds, 1 second more in addition to the classifier model execution.

7.3.4 SEIZURE PREDICTION FRAMEWORK

In order to measure the overall resource consumption of the framework, we will execute all individual functional blocks as shown in Figure 6.3. 20 second ECoG

segments are input to the feature-extraction block, which extracts 128 feature points. These 128 feature points are used as input to the classifier model to obtain the soft and crisp labels. The ECoG signal itself is not stored on the SD card, but the features extracted together with the soft and crisp labels are stored on the SD card. These soft and crisp labels are forwarded to the active learner block when 10 minute segment of the ECoG signal has been processed through machine learning models. The active learner block determines the confidence of these labels and determines if the segment is preceding a seizure or not. If it is preceding, a seizure warning is sent via UART to the laptop, otherwise the corresponding feature-set together with the labels are sent to the laptop. The resource consumption of our seizure prediction framework to process 10 minute of 16 channel ECoG signal sampled at 5kHz is shown in Table 7.6.

	Time required for processing (mS)	RAM used (bytes)	ROM used (bytes)	Power consumption (mW)
Seizure Prediction Framework	5112	224512	19254	119

Table 7.6: Resource consumption analysis of Seizure prediction framework in an embedded platform.

From Table 7.6, it can be seen that entire seizure prediction framework can be fit to the available memory. Moreover out of 256 kB of RAM only 220 kB is used for the execution of our seizure prediction framework. Also, seizure prediction framework with its allocated memory for intermediate variables consumed about 18 kB out of the 2 MB of ROM (flash) memory. Power consumption is at the maximum of the processor due to its continuous execution of functional blocks of our prediction framework.

The time taken for processing 10 minutes of ECoG signal is 5.1 seconds which also includes the overheads of accessing data from the SD card to the RAM for processing. In a real-world scenario, where the ECoG signal is sensed continuously, processing of signals will take much less time than what we recorded. This is because of the additional overheads in accessing/storing the data from/to SD card takes enormous amounts of CPU time in such low-power embedded platform [135]. This resource analysis shows that our prediction framework can be executed on low-power platform.

In order to measure the accuracy of our seizure prediction framework, we will use randomly selected 2 hours of 16 channel ECoG signal such that at-least 1 seizure episode is present in the segment. The characteristics of this ECoG signals are elaborated in Chapter 6, Section 6.4, Table 6.2. The 2 hour ECoG signal is too large to be stored locally on the SD card. Therefore, we will use serial communication to transfer segments of 20 second ECoG signals. An UART handler at the μ processor

receives the data and forwards it to the prediction framework. The performance of our seizure prediction framework for individual subjects is shown in Table 7.7.

Subject	Actual number of seizures	Predicted seizures	ROM used (bytes)	Power consumption (mW)
Dog1	5	3	19564	115
Dog2	3	1	19874	114
Dog3	4	2	19552	116
Dog4	1	0	19954	118
Dog5	2	1	19454	118
Patient1	1	1	14654	119
Patient2	2	0	15745	118

Table 7.7: Performance of seizure prediction framework executed in a low-power embedded platform

From Table 7.7, we show the prediction accuracy, ROM usage and power consumption. It is not possible to accurately measure RAM usage while continuously transmitting through UART peripheral of the μ processor. Also, additional overhead due to the UART interpreter will dynamically increase the RAM usage. Similarly, accurate time consumption cannot be measured.

The ROM usage is different for each subject due to the unique classifier model that is trained separately based on individual ECoG signal. Moreover, the processor always consumed highest power and it took on average 20 minutes to process 2 hours of data. We observed significant rise in temperature of the chip due to the continuous execution of software blocks.

The seizure prediction framework is not as accurate as it was shown in Chapter 6 through MATLAB simulations. Seizure episodes of the subjects Dog4 and Patient2 were not predicted at all, but in other subjects at-least 1 of the seizure was predicted. One of the main reasons for this could be the lack of optimization in the embedded implementation our framework, as we translated and implemented the MATLAB codes purely based on the standard CMSIS library and individual functional blocks were not optimized for prediction accuracy. However, this reduction in accuracy could easily be improved with careful optimization of individual functional blocks.

Also, the 10 minute segmentation of the original ECoG data on the flash memory and abrupt processing of individual 10 minute segments might have significantly reduced the seizure prediction accuracy. It is important to note that segmentation of the ECoG signal directly affected the accuracy of the machine learning classifier (as mentioned in Chapter 6, Section 6.5.1.1). This reduction in accuracy could easily be improved with efficient techniques of storing and recalling the original ECoG signals. Moreover, in real applications, the need for recalling the stored ECoG signals will be minimal since the incoming signals are processed before it is stored to the memory, but except for cases where the original ECoG signal has to be sent to the base-station.

By this we can safely assume that the reduction in accuracy is not due to the accuracy of our algorithm, but it is caused by the lack of optimized implementation, improper segmentation of ECoG signals and inefficient store-and-recall functions. Optimizing our implementation to improve the accuracy caused by these phenomena is out of the scope of our study. In this study we focused on worst-case analysis, and the results show that it is feasible to implement our seizure prediction framework on a low power embedded platform, and further optimization will not only assure the accuracy but will also reduce the resource consumption.

7.4 OPTIMIZATION FRAMEWORK FOR WIRELESS COMMUNICATION IN IBSN — HARDWARE EVALUATION FOR AN EPILEPTIC USE-CASE

In addition to the complex on-node processing of seizure prediction framework, our newly developed reinforcement learning based optimization framework of MAC protocol also requires processing of physical channel quality before transmitting any data packets. In this section, we will evaluate the time, memory, and power consumption of wireless unit while executing the reinforcement learning based optimization framework for wireless communication in IBSN.

It is important to note that the previous optimization framework is aimed at reducing the amount of data that is wirelessly transmitted to a base-station and this optimization framework is to improve the wireless communication between the nodes. In real application, we envision these frameworks to be executed side-by-side on an IBSN node for a specific application. In our thesis, we will consider the epileptic use-case, in which the reduction of ECoG signals will be ensured by the active-learning framework and quality-of-service in wireless communication will be ensured by the reinforcement learning based optimization framework.

7.4.1 CONCEPTUAL OPEN SYSTEMS INTERCONNECTION (OSI) MODEL FOR IBSN

One of the major contribution of this thesis is the reinforcement-learning based cross-layer optimization of MAC layer for IBSN. Another contribution is the characterization of PHY and MAC layer for IBSN in Chapter 3 based on the IEEE 802.15.6 standard. Based on these, we conceptualize a new OSI model for IBSN as shown in Figure 7.7. Unlike conventional OSI models, our model has no strict boundaries between layers and can dynamically communicate the feedback between each layer to enable adaptability and accommodate different application requirements and channel conditions. For example, duty-cycle is dynamically adapted based on the disruptions in channel-quality and relay establishment in case of poor channel-quality for prolonged periods of time.

Figure 7.7: A conceptual OSI model for IBSN

As shown in Figure 7.7, most of the functional blocks in each layer carry-out well established functions in wireless communication such as, transmission power and modulation frequency control in physical layer, carrier sensing in CSMA/CA and time-synchronization in TDMA in data-link layer, and routing-table management in network layer. Resource consumption of these functions are fairly standard across different sub-GHz wireless platforms. However, in our OSI model, additional blocks such as reinforcement-learning based adaptive controller and RF link quality manager in data-link layer, relay management at network layer and data fragmentation in application layer are unprecedented in the conventional design of OSI model.

Through simulations we presented in Chapter 3, 4, and 5 that these additional blocks have significantly improved the performance of wireless radio in terms of high packet delivery ratio, with very low latency. In addition to the reliability and adaptability, our algorithms significantly reduced the power consumption of the MAC protocol. However, resource consumption of these additional blocks was not studied in our simulations. To this end, we will implement our DiNAMAC optimiza-

tion framework on top of IEEE 802.15.6 PHY and MAC functions on a μ processor. We will investigate the resource consumption of IEEE 802.15.6 PHY and MAC layer with and without our optimization framework.

7.4.2 REINFORCEMENT LEARNING (RL) BASED OPTIMIZATION

In general, RL based adaptation of DiNAMAC has three main functional components as explained in Chapter 5. Firstly, the link quality estimation function, which continuously records the signal strength and packet error rate (PER) after each packet reception (as explained in Section 5.2.1.1). Secondly, the RL optimization framework, which has a reward function for setting the duty-cycle of the main radio and establishing relay node based on PER information (as explained in Section 5.3). Finally the action policy table, which continuously stores the action taken and recalculates the reward based on the PER information. Mathematical formulas of these functions are explained clearly in Chapter 5, and are implemented on the general purpose μ processor. The radio control-commands to wireless radio is sent from the μ processor through an I2C connection made between the μ processor and the wireless radio.

7.4.2.1 RESOURCE CONSUMPTION OF WIRELESS RADIO AND μ PROCESSOR

For our evaluation, DiNAMAC optimization framework is implemented on top of the PHY and MAC of IEEE 802.15.6 [27] standard for medical implant communication. Two sensor nodes, one acting as transmitter node and another acting as receiver node are used for evaluation. There are no other devices in the network, hence they can send whenever the transmitter has data to send, following the WuR-based DiNAMAC approach.

For our resource consumption measurement, we will continuously transmit 10 min ECoG segments stored in SD card of the Transmitter node. The data will be transmitted in 20 second blocks. The receiver will receive and process the data-packets to retrieve and store the ECoG signal on to its SD card. The IEEE 802.15.6 wireless stack and the RL based optimization framework are implemented on the μ processor.

Time consumed by the μ processor to process and to send one data-packet through wireless radio is measured as the time required for processing. The overhead in processing time caused due to the optimization framework is studied through this measurement. RAM and ROM used by the μ processor to process one data-packet with the IEEE 802.15.6 protocol stack and RL optimization framework is measured. This measurement will show if the RL optimization framework can be fit to the low-power IBSN platform.

In our case the 10 min of ECoG signal is approximately 65 MB¹ of data and the data rate of the radio is 150 kB/s. We also report the time taken to transfer 65 MB of data from Tx node to Rx node along with their power consumption. It is important to note that these values report the overall power-consumption of the sensor node and not individual radios and the μ processor. Resource consumption of the transmitter node and the receiver node when communicating over IEEE 802.15.6 standard with and without the optimization framework is shown in Table 7.8.

	Time required for processing (mS)	RAM used (bytes)	ROM used (bytes)	Power consumption (mW)
IEEE 802.15.6	Tx node: 0.12 Rx node: 0.22	Tx node: 22402 Rx node: 33412	Tx node: 2345 Rx node: 1225	Tx node: 380 mW Rx node: 220 mW Transfer time: 6.5 min @ 150 kB/s
RL optimization framework based IEEE 802.15.6	Tx node: 0.4 Rx node: 0.6	Tx node: 142402 Rx node: 143412	Tx node: 12215 Rx node: 12425	Tx node: 420 mW Rx node: 270 mW Transfer time: 7.9 min @ 150 kB/s

Table 7.8: Resource consumption of IEEE 802.15.6 with and without RL optimization framework in an embedded platform.

From Table 7.8, the time required for the processing of one data-packet with RL optimization framework is approximately 2 times more than the plain IEEE 802.15.6 protocol stack. This increase is mainly due to the implementation method in our evaluation, i.e. we used an I2C port to connect the μ processor and radio. Signal strength values and channel quality metrics has to be read from the radio, stored and processed before adapting the duty-cycle, which requires additional overheads than the processing of the framework. These overheads will simply be removed if the RL-optimization framework is built within the radio-chip.

It can also be seen that the RL optimization framework used more ROM than plain IEEE 802.15.6 stack because of the additional program memory and initialization variables needed. Also, RAM usage is higher than the plain IEEE 802.15.6 because of continuous calculations during the run-time execution. These usages can be reduced with optimized implementation of the framework within the radio-chip.

Power consumption values are very high for the RL optimization framework, mainly because of two reasons. Firstly, we send continuous 10 min data (65MB)

¹ECoG signal has 16 channels each sampled at 5kHz, which produces 80k samples per second (16*5000). 10 minutes of ECoG signal will have 48M samples (600*80k). Sampled values are stored as float which takes 4 bytes in memory.

between two nodes at very low data-rate (150 kB/s). The data-rate is very low to accommodate such large file, and the μ processor has to continuously process large chunks of data. Secondly, although there is no channel quality disruptions during our measurement, RL optimization framework is implemented in such a way that it continuously assesses the channel before sending any data. This requires both main and WuR radios to be consequently active for prolonged periods of time in addition to the μ processor, which also executes the framework continuously.

We have not optimized this implementation because in IBSN scenarios, in addition to the continuously transmitting nodes there might be other low-power devices which need to communicate within the network. In such cases, the RL optimization framework should be continuously assessing the channel for such requests. With our results, it is clear that RL optimization framework takes more power, time and memory than the plain IEEE 802.15.6 for long and continuous transmissions between two nodes. In what follows, we will implement our seizure prediction framework on top of the RL optimization framework to reduce the long and continuous transmission by locally processing the data.

7.4.3 SEIZURE PREDICTION FRAMEWORK WITH OSI MODEL OF IBSN

We focus on two main objectives in this section: (i) to investigate the feasibility of our optimization frameworks to be executed in a low-power embedded platform, and (ii) to explore how much power can be saved to process the data locally than to send it to a base station by continuous and prolonged wireless transmission. It is important to note that in this section, we do not measure the accuracy of the seizure prediction framework and the wireless properties such as latency and throughput. Towards this end, we implemented and compared IEEE 802.15.6 PHY and MAC together with RL optimization framework and seizure-prediction framework as shown in Figure 7.8.

7.4.3.1 RESOURCE CONSUMPTION OF WIRELESS RADIO AND μ PROCESSOR

Two sensor nodes acting as transmitter node and receiver node are used for evaluation as shown in Figure 7.5. 2 hour long ECoG signal will be sent to transmitter node through serial port of the laptop. We will process the 20 second segments of ECoG signal on the transmitter node and transmit only the outcome of the prediction framework, i.e. a seizure alarm packet is sent if the ECoG segment is preceding a seizure. Local processing of the seizure prediction framework is carried out as explained in Section 7.3.4.

The main radio of the transmitter node is turned on to transmit the packet and is returned to sleep mode once the transmission is complete. The WuR of the transmitter node will send out Wake-up Beacon (WuB) if there is any data in the transmit buffer. The main radio of the receiver mode is always in sleep mode and WuR of the receiver node is always in receive mode. The WuR and the main radio follow the

Figure 7.8: Our optimization frameworks on top of IEEE 802.15.6 PHY and MAC

WuR-based DiNAMAC mechanism to communicate with each other as explained in Section 5.4. The resource consumption values transmit and receive mode are presented in Table 7.9.

From Table 7.9, it is clear that overall power consumption of the sensor node is significantly reduced with our optimization framework. From row 2 and 3, it is clear that local processing requires less power than transmitting raw and continuous data for prolonged periods of time.

However, RAM and ROM are heavily used, i.e., out of 256 kB of available RAM memory 238 kB is used and out of 2 MB of available ROM memory, 1.4 MB is used by our frameworks. This is the worst-case memory foot-print of our newly developed frameworks. The general purpose chips, as used in our evaluation do not have any hardware accelerators for signal processing or dedicated PHY and MAC hardware for wireless radio. It is clear that we could fit our framework in resource-constrained platform and with further optimization and hardware-software co-design we could achieve reduced memory usage.

The time required for processing the seizure prediction framework with RL optimization framework is around 5 seconds for 10 minutes of ECoG data. Although it is still reasonable for a seizure prediction, this prolonged continuous processing on the

	Time required for processing (mS)	RAM used (bytes)	ROM used (bytes)	Power consumption (mAh)
IEEE 802.15.6	Tx node: 2 Rx node: 4 Transfer time: 6.5 min @ 150 kB/s	Tx node: 112402 Rx node: 113412	Tx node: 1245 Rx node: 1225	Tx node: 380 mW Rx node: 220 mW
RL optimization framework based IEEE 802.15.6	Tx node: 4 Rx node: 6 Transfer time: 7.9 min @ 150 kB/s	Tx node: 142402 Rx node: 143412	Tx node: 12215 Rx node: 12425	Tx node: 420 mW Rx node: 270 mW
Seizure prediction framework + RL optimization framework based IEEE 802.15.6	Tx node: 5121 Rx node: 4 Transfer time: 30 ms @ 150 kB/s	Tx node: 246852 Rx node: 154875	Tx node: 1432654 Rx node: 1132425	Tx node: 154 mW Rx node: 127 mW

Table 7.9: Resource consumption of our optimization frameworks for wireless communication in an IBSN sensor node

μ processor increase the temperature of the μ processor. In IBSN this temperature increase is neither suitable for the implantable devices, nor for the wearable. Although our framework is feasible to be executed on general purpose low-power platform, it is clear from these results that further optimization of the algorithm is necessary and specific hardware optimization can reduce the time and memory usage.

Most importantly, the power consumption of sensor nodes is definitely decreased with our frameworks and local processing processing is more favorable than wireless transmission in IBSN sensor nodes.

7.5 CONCLUDING REMARKS

In this chapter, we evaluated the resource consumption of algorithms on low-power embedded platform. We selected an off-the-shelf low-power general-purpose μ processor and a low-power customizable wireless radio to evaluate time, memory, and power consumption of our newly develop seizure prediction framework and reinforcement learning based optimization framework for wireless communication in IBSN. We investigated individual functional blocks of our algorithm and also integrated them into a framework. A conceptual OSI model for IBSN was presented based on their algorithms. From the results we show that power consumption of the IBSN sensor nodes can be significantly reduced by local processing of physiological signals following our framework. However, time required and memory used by our framework is slightly high. Accuracy of the local-processing was moderate and careful optimization in hardware and software implementation is needed.

CONCLUSIONS AND FUTURE WORK

***I**N this thesis, we focused on energy-efficient and reliable wireless communication schemes for resource-constrained nodes of IBSN to meet the requirements of a variety of medical applications. In this chapter, we will outline our contributions, conclusions derived from our work, and future research directions for the IMPLANTABLE BODY SENSOR NETWORKS.*

வினையான் வினையாக்கிக் கோடல் நனைகவுள்
யானையால் யானையாத் தற்று.

*By one thing done you reach a second work's accomplishment;
So furious elephant to snare its fellow brute is sent.*

—Thiruvalluvar in Kural 678

8.1 SUMMARY OF THE RESEARCH

The main focus of this thesis is on energy-efficiency and reliability of wireless communication between the resource-constrained sensor nodes of IBSN. Radio-frequency (RF) links between the IBSN nodes are heavily disrupted due to the conductive nature of human-body and therefore simple human movements, such as walking, deteriorates the wireless communication between the sensor nodes. In addition, the sensor nodes of IBSN are heterogeneous, i.e. they can sense and/or deliver therapy, generating and/or receiving a wide variety of data at the nodes, which require an adaptive support for varying Quality of Service in wireless communication. We addressed the following research question:

**HOW TO GUARANTEE ENERGY-EFFICIENCY AND QUALITY OF SERVICE (QoS)
PARAMETERS OF THE WIRELESS COMMUNICATION BETWEEN IMPLANTABLE AND
WEARABLE MEDICAL DEVICES TO FULFILL MULTIPLE AND SOMETIMES
CONFLICTING REQUIREMENTS OF IBSN APPLICATIONS.**

In this thesis, we answered this research question with the following five main contributions:

CONTRIBUTION 1: CHARACTERIZING THE PHY AND WuR BASED MAC FOR IBSN

In Chapter 2, we did an extensive literature survey on the existing wireless technologies for IBSN application, presented a taxonomy of MAC protocols based on WuR radio technology, and identified important limitation of existing wireless technology for IBSN. Following the survey, in Chapter 3 we carried out experiments with different parameters of physical layer and characterized the performance of the wireless radio with an animal-tissue. Two different channel-models, in-body – in-body and in-body – on-body, were evaluated.

From the empirical results, we identified and modelled the attenuation parameters of the radio in the animal tissue and developed a channel model for wireless communication in IBSN. Based on this channel model, we evaluated the impact of WuR on the performance of conventional MAC protocols and identified that: (i) Hybrid access mechanisms which uses TDMA for emergency communication and CSMA/CA for non-emergency communication are best suited for IBSN applications, (ii) WuR has a positive impact on the performance and significantly reduces the power consumption of hybrid MAC protocol.

CONTRIBUTION 2: WuR BASED BIO-INSPIRED WIRELESS COMMUNICATION MECHANISM FOR DYNAMIC IBSN

In Chapter 4, we investigated the impact of human activity on the RF link quality. We extracted patterns of temporal channel-deterioration caused due to dynamic human activities such as walking, running and sleeping. We used these patterns to develop an adaptive MAC protocol called HACMAC. Through carefully designed simulations, based on the channel model resulted from Contribution 1, we showed that

reliability and latency of the wireless communication were significantly improved compared with the state-of-the-art MAC protocols.

To further reduce the power consumption of our HACMAC protocol, we strategically introduced WuR in the design of HACMAC, such that the main radio was turned-off all the time except when useful communication took place between the nodes. Power wastage due to idle-listening was significantly reduced. Through simulation we showed that the WuR-based HACMAC has the optimal power consumption and still can provide reliable wireless communication with very low latency than the state-of-the-art MAC protocols.

CONTRIBUTION 3: REINFORCEMENT LEARNING BASED OPTIMIZATION OF BIO-INSPIRED WIRELESS COMMUNICATION MECHANISM TO SUPPORT DYNAMICITY OF IBSN

The RF disruption model for simple activities resulted from Contribution 2 was obtained from a controlled environment. In real-world, there can be a number of disruption patterns for the same activity performed by the same person at different points of time and places. To address this problem, we further developed a reinforcement learning approach to optimize the MAC protocol by defining the disruption as a stochastic process with Markov property.

Disruption tolerant Reinforcement learning based MAC protocol called DiNAMAC was developed, which optimizes the duty-cycle based on the dynamicity of the human activity based RF disruption patterns. Reliability and latency of the wireless communication were significantly improved using the DiNAMAC when compared with the state-of-the-art MAC protocols. DiNAMAC is designed to be model-free MAC protocol such that DiNAMAC is more practical in real-world implementation than HACMAC.

To further reduce the power-consumption of DiNAMAC, we integrated WuR in the design of DiNAMAC, such that the main radio is turned-off all the time except when useful communication takes place between the nodes. Power wastage due to idle-listening was significantly reduced. Through simulation we showed that the WuR-based DiNAMAC has very low power consumption and still can provide highly reliable wireless communication with very low latency in real world scenarios.

CONTRIBUTION 4: CONTEXT-AWARE WIRELESS COMMUNICATION FOR IBSN - AN ADAPTIVE ACTIVE-LEARNING BASED APPROACH FOR SEIZURE PREDICTION IN EPILEPTIC USE-CASE UNDER IBSN FRAMEWORK

We developed an active learning based approach for seizure prediction in epileptic use-case with intra-cranial ecog recordings.

A low-power low-complex seizure prediction framework, which was able to achieve almost 95% sensitivity in seizure prediction with only 20% of the labelled data was developed. A SVM classifier coupled with active learning heuristics is used as the core of the prediction framework. We showed that a scalable *expert-in-the-loop* operation of life-critical medical devices is possible through our framework.

Although we did not evaluate this framework in a clinical setting, we studied its clinical reprehensibility through the different choices of data-segmentation, prediction horizon, and feature selection during the development of our seizure prediction framework.

It was shown in Chapter 6 that resource constrained IBSN sensor nodes can be made contextually aware of the brain signals. With 80% reduction in the amount of raw ECoG data needed to achieve high prediction accuracy, our seizure prediction framework has low power consumption.

CONTRIBUTION 5: RESOURCE CONSUMPTION ANALYSIS OF OPTIMIZATION FRAMEWORKS FOR WIRELESS COMMUNICATION IN IBSN

In this contribution we presented wireless communication framework for the resource constrained IBSN nodes, in which we mainly focused on evaluating time, memory and power consumption of various signal processing, machine learning blocks, and additional adaptation mechanisms needed for wireless communication.

In order to investigate the practical feasibility of our framework on a resource constrained sensor node, we evaluated our framework on an ARM cortex M4 device as explained in Chapter 7. We presented that the power consumption of the sensor node is reduced with our context-aware seizure prediction framework, through local processing of the ECoG data, reducing the amount of raw ECoG data transmitted through a wireless radio. Our optimization framework and its constituting algorithms were shown to be implementable with minimal memory footprint such that it can be executed in an ARM cortex M4 device. Also, constrained clock frequency of the ARM cortex M4 device did not increase the latency of either the prediction algorithm or the optimization algorithm. As a result, we showed that our framework and its corresponding algorithms can be executed on resource constrained IBSN nodes.

8.2 LESSONS LEARNED

During our research we learned the following lessons,

- *No one solution fits all:* Wireless communication technologies, both hardware and software, are continuously evolving and are driven by variety of application requirements put-forth by different industrial sectors such as, health-care, aviation, automotive, agriculture, construction, manufacturing etc. The existing wireless communication protocols cannot always be directly applied to specific applications. Exploring the limitations of existing protocols for a specific application requirement is a crucial step in developing energy-efficient and reliable wireless communication protocols.
- *Knowledge of physical medium is essential:* Reliability of wireless communication protocols largely depends on physical medium and the wireless hardware. Therefore, it is important and essential to analyze the characteristics of physical channel,

such as radio propagation and path-loss, and to address their limitations in the design of communication protocols.

- *Cross-layer optimization improves reliability and energy-efficiency:* In short-range small-scale networks like IBSN, in which reliability and energy-efficiency are crucial, strictly defining the boundaries of network layer functions will reduce the performance of the network protocols. For example, in IBSN defining a rigid duty-cycle at MAC layer for all transmissions will significantly reduce the successful packet delivery and consequently increase the power-consumption. If the duty-cycle (a MAC layer function) is adapted based on the RF signal quality (a PHY layer function), then reliability can be ensured even with ultra-low power consumption. Similar cross-layer optimization between network layers is essential for short-range small-scale networks.
- *Additional Wake-up radio is beneficial to wireless communication:* In general, adding more hardware to the sensor node would increase the over all power consumption. However, in networks like IBSN, in which long idle-mode is required between two communication, additional hardware like a wake-up radio can be beneficial. Specifically in our case, significant amount of power is saved by the additional hardware. One important criteria for such hardware is that it must not increase the overall power-consumption but can provide additional network performance.
- *Context awareness enables adaptability:* In dynamic and heterogeneous wireless networks like IBSN, wireless communication needs to be adaptive in order to save power. For example, a device which has high sampling rate will require more throughput than a device with low sampling rate. Context-aware sensor node can adapt its resource allocation such that the requirements of these devices will be met and no resources will be wasted.
- *On-node processing is more energy-efficient than raw data transmission:* Transmission of the raw data over wireless radio will consume more energy than processing the data locally on the sensor node and transmitting only the context of the data. To ensure energy-efficiency, lightweight signal processing algorithms can be used to pre-process the data. For example a band-pass filter could ensure that only the useful spectrum of the raw data is transmitted over the wireless radio and the not-very useful data can be stored locally for future investigation.
- *Experimental validation is crucial in the design of wireless communication:* The radio frequency spectrum is filled with devices communicating at various sub GHz and GHz frequencies, which cannot be replicated in software simulations. In the case of IBSN, physical channel is itself dynamic between person to person and sometimes within the same person depending on the water content in a human body. The impact of these limitations in the performance of wireless communication protocols cannot be validated without real-world experiments.

- *Machine learning models are only beneficial when used carefully:* In our study we used major machine learning principles such as reinforcement learning, semi-supervised learning, active-learning etc. to optimize wireless communication protocols and seizure prediction frameworks. Accuracy of the machine learning classifier largely depends on the training method, feature-extraction and labelled data. However, direct application of machine learning models without optimizing it for low-power application will result in degradation of the performance. It may even make the existing system unusable for the intended application.
- *Physiological data-set is not easy to obtain:* In our study we used openly available ECoG data set for designing, training and validating the seizure prediction framework. However, any further validation of our algorithm using another data-set was not possible due to the limited availability of similar data-set. One of the main reasons is the difficulty to obtain the data-set from the patient since it requires intra-cranial implantation of electrodes. This problem could be overcome if the research community is open about sharing the data-set. This will significantly help in reproducing the results and improve the collective knowledge and understanding of the subject among the research community.
- *Expert-in-the-loop is safer than fully autonomous closed-loop systems:* One of the important applications of IBSN is closed-loop operation of medical devices such as DBS. From our study it is apparent that brain signals are inherently uncertain, which may also apply to most of other physiological signals, given the dynamic nature of the human body. Although these devices can function autonomously, in real-world scenarios it is possible that one of the devices might fail to function normally. In such cases, an expert must be included in the closed-loop operation to prevent any fatal failures of IBSN systems.

8.3 FUTURE WORK

In this thesis we investigated the energy-efficiency and reliability aspects of wireless communication while being adaptable to the dynamic requirements of IBSN. However, there is still room for improvements in wireless communication for IBSN and our work can be extended in the following ways:

- Given the tremendous advantages of IBSN, more and more health-care centers are starting to use IBSNs to monitor, diagnose and treat different health conditions of large patient groups. In such environment, inter-network interference will significantly affect the network performance when patients are in close proximity with each other. Robust co-existence mechanism must be invented to control and mitigate the effect of these inter-network interference. Clustering the IBSN networks under one global base-station and integration of directional antennas in PHY layer, might be used as co-existence mechanisms.

- We analyzed the context awareness for epileptic use-case, in which the density of the raw data is very high. Different applications such as adaptive pack-maker, on-demand drug-delivery devices could be investigated and wireless communication aspects of those application can be addressed.
- We developed a seizure prediction framework that provide new functionalities for medical devices such as expert-in-the-loop operation, autonomous control of implantable devices, deriving health-consensus from different sensors. Limitations of these functionalities can be studied in clinical trials and design of these functionalities might be improved.
- Wireless communication in IBSN is responsible for the transfer of life-critical data between the nodes and the base-station. Any malicious intent to disrupt the wireless link between the nodes should be avoided. Robust security mechanisms might be included in the MAC layer to prevent any such attacks. Physiological signals can be used for encrypting the data on the node.

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His list of publications are as follows:

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