Contention Based SCMA for NB-IoT Uplink Communication using Finite Memory Sequential Learning

A Thesis Submitted to the Department of Computer Science and Communication Engineering, the Graduate School of Fundamental Science and Engineering of Waseda University in Partial Fulfillment of the Requirements for the Degree of Master of Engineering

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Abstract

Internet of Things (IoT) is a new paradigm of wireless communication technology, where smart sensors and machines communicate through a combination of many connectivity technologies such as ZigBee, Bluetooth, Radio Frequency Identification (RFID), and licensed cellular bands including future 5G radio access techniques. It is expected that tens of billions IoT devices are connected to the network by 2025, and more beyond then. An important 5G radio requirement is that it should support massive connectivity of large number of devices including many IoT use cases. Sparse Code Multiple Access (SCMA) is a newly emerging non-orthogonal multiple access technique that allows overloading of shared radio resources with multiple users, hence increasing capacity. However, such a massive connectivity comes at the cost of increased signaling overhead and latency.

This research investigated the potential of using Contention-Based SCMA scheme in the newly standardized Narrow Band IoT (NB-IoT) technologies that have diverse application as a low power wide area (LPWA) communication. Since resource allocation is a major challenge in such devices, Finite Memory Sequential Learning (FMSL) is proposed to consider the message diversity and enable the devices learn about the status of other devices to improve the usage of limited resources and delivery of the messages. The contention based SCMA with FMSL system shows that performance in terms probability of successful transmission and the number of IoT devices that will correctly learn about the status of the nearby devices increases with memory size F. Hence, FMSL improves system performance in terms of delivery of critical messages which are assigned certain codes after the learning process converges.

Keywords— Contention Based Access, SCMA, NB- IoT, Finite Memory Sequential Learning

Table of Contents

List of Acronyms

ACK	Acknowledgement
CB	Contention-Based
CHT	Cognitive Hierarchy Theory
CTU	Contention Transmission Unit
DL	Downlink
eMTC	enhanced MTC
eNB	Evolved Node-B/Base Station
FMSL	Finite Memory Sequential Learning
FN	Function Node
GPRS	General Packet Radio System
HTC	Human-Type Communications
IFFT	Inverse Fast Fourier Transform
IMSL	Infinite Memory Sequential Learning
IoT	Internet of Things
LoRa	Long Range Radio
LPWAN	Low Power Wide Area Network
LTE	Long-Term Evolution
LTE-A	Long-Term Evolution Advanced
LTE-M	LTE for Machine Type Communication
MC	Multi-Carrier
MIoT	Massive Internet of Things
ML	Machine Learning
mMTC	Massive Machine Type Communications
MPA	Message Passing Algorithm
MTC	Machine Type Communications
NB-IoT	Narrow Band IoT
NB-SCMA	Narrowband SCMA
NOMA	Non-Orthogonal Multiple Access

NPBCH	Channel narrow-band physical broadcast channel
NPDCCH	Narrow-band Physical Downlink Control Channel
NPDSCH	Narrow-band Physical Downlink Shared
NPRACH	Narrow-band Physical Random-access Channel
NPSS	Narrowband Primary Synchronization Signal
NPUSCH	Narrow-band Physical Uplink shared Channel
NRS	Narrowband Reference Channel
NSSS	Narrowband Secondary Synchronization Signal
OFDMA	Orthogonal Frequency Division Multiple Access
OMA	Orthogonal Multiple Access
PRB	Physical Resource Block
PUCCH	Physical Uplink Control Channel
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
RA	Random Access
RACH	Random Access Channel
RFID	Radio Frequency Identification
RL	Reinforcement Learning
SCMA	Sparse Code Multiple Access
SL	Sequential Learning
SR	Scheduling Request
3GPP	Third-generation Partnership Project
UNB	Ultra-narrow Band
URLL	Ultra-Reliable Low Latency
UL	Uplink
UE	User Equipment
VN	Variable Node

List of Figures

List of tables

CHAPTER 1

INTRODUCTION

1.1.Background

The future 5G network is expected to support massive connectivity of IoT devices used for a variety of applications such as smart metering, smart city, intelligent transportation, security monitoring, smart grid and e-health. The number of such devices is expected to exceed 20 billion in the year 2020 and beyond [1], [2]. The large number of devices at different locations necessitates new technologies and communication standards for massive machine type communications (mMTC) and massive internet of things (MIoT) which in turn need deployment over large area with low device cost and low energy consumption, hence needs longer battery life. For MTC, there are already established techniques of achieving connectivity over short range including Bluetooth, Wi-Fi and Zigbee. But, they cannot meet the demands of large coverage.

To meet the requirement of large coverage with low cost and low power consumption device technologies, the third-generation partnership project (3GPP), in its release 13, has defined two cellular LPWA standards: LTE-M (for machine type communication) and narrowband IoT (for generic IoT application requirements) [3], [4]. NB-IoT technology has been considered as one of the promising technologies to achieve the larger area coverage requirement of massive IoT deployment scenarios such as in smart cities and smart grid applications. Besides, in relation to the massive connectivity there is an increase in the incurred signaling overhead, and contention-based access schemes were considered as one of the possible means to reduce it [5]-[8].

1.2. Problem statement

The massive deployment of IoT devices poses a challenge in terms of requirements of radio resources which are very limited as compared to the existing plethora of devices and applications. Specially for the uplink communication of IoT devices with the base station (eNB) there must be a suitable multiple access scheme. To respond to that there have been many multiple access techniques including the currently emerging non-orthogonal multiple access (NOMA) technique called sparse code multiple access (SCMA). SCMA is a complex codebook based multiple access technique in which the procedures of mapping the incoming bits of each user to Quadrature Amplitude Modulation (QAM) symbol and spreading over the orthogonal frequency division multiple access (OFDM) channels are combined into a single step. This involves direct mapping of bits from each user layers to multidimensional complex codewords selected from a set of codewords that belong to a given codebook. For each user or SCMA layer there is a dedicated codebook that is designed based on the sparsity nature of the codewords. The SCMA signal reception is possible by low complexity message passing algorithm (MPA) and its modified version which make SCMA based systems useful for meeting the massive connectivity demands of the current network.

The need for massive connectivity of IoT devices to the eNB comes with a challenge of increased signaling overhead and latency for the uplink communication. In the conventional Long-Term Evolution (LTE) or LTE-A uplink (UL) data communication, the user is expected to make scheduling request (SR) via periodically occurring UL dedicated resources to the base station which gives a scheduling grant [7], [8]. The periodicity of such dedicated resources is basically every 5 or 10ms. If data arrive at the user equipment (UE) just before the scheduling request, it needs to wait for 7ms from scheduling request to the UL data transmission. The incurred delay could even be longer if the UE needs to transmit in between the SR opportunities or the system has been configured with longer SR periodicity. Hence, it is necessary to reduce the delay incurred in such a scheduling request and grant procedure. For delay sensitive applications it is too long for the machines to wait as they are triggered to transmit very urgent data such as burglar alarm, fire alarm, and temperature reading. Besides, the future network is going to support many ultra-reliable low latency (URLL) applications. Hence, in this work we studied the potential of using non-orthogonal multiple access techniques with contention-based access schemes to meet the requirements of massive connectivity while meeting the need for reduced latency and signaling overheard at the same time.

1.3. Related works

Contention-based (CB) uplink transmission has been used as a technique that enables UEs or IoT devices to attempt the data transmission immediately after its arrival or just after an incident is sensed by an IoT device sensor. The notion of CB uplink transmission is that the UEs do not need to send scheduling request to the base station and wait for scheduling grant [7]-[10]. In CB UL transmission the data is sent directly, and the access delay is greatly reduced. In [7], the merits of CB access and NOMA based multiple access were combined to introduce contention-based

SCMA that will meet the requirements of reduced transmission latency and supporting large number of users to enable massive connectivity. In CB SCMA, the users tend to send data using the nonorthogonal resources known us contention transmission unit (CTU) which are defined as a function of time, frequency, SCMA codebook, and a pilot sequence [7], [11]-[13]. Users try to contend for the CTUs in the uplink transmission.

In the presence of larger number of UEs, the capacity of the CB SCMA system is going to saturate as more users try to simultaneously use the same CTU and finally the effect of collision degrades the performance of the system. To handle the effect of collision, the random back-off procedure was considered in [7]. The UEs set random back-off time which is selected from a back-off window and try to retransmit the data on the original predefined CTU. The mapping of UE-to-CTU is done by a predefined mapping rule which dictates the CTUs allocated for individual UEs. Basically, if the collision is detected, the packets are discarded by the eNB when more than one UEs are selecting the same CTU.

In [11], feedback-based UE-to-CTU mapping was proposed in which the base station gives the feedback information about the previous usage of CTU usage. The scheme is found to improve the system performance as compared to the previous works. ACK feedback-based UE-to-CTU mapping was used in [13], where the users trying to retransmit after the first CTU collision are given special CTU allocation. Here, the selection of CTU after the first collision is based on the exclusive allocation of certain CTUs for users in need of retransmission. The resource allocation problem for massive IoT devices can be handled in many ways including centralized allocation and distributed allocation of the limited resources. This will depend on the scale of the deployment and it is difficult to manually handle the large scale IoT network resource management.

Besides, to consider the heterogeneity of the messages transmitted, the devices used, services given and resources available, there are many researches that consider self-organizing techniques, machine learning algorithms and sequential learning for resource-limited IoT devices [14]-[19]. Since the IoT devices have constraints in terms computational power, memory, and battery life, appropriate learning algorithm should be chosen to optimize the IoT network performance and to meet the preset QoS requirements. The works in [16] and [17], focused on the consideration of the heterogeneity of messages transmitted by IoT devices. The heterogeneity of messages and the resource allocation was managed by finite memory sequential learning techniques which is needs lower computational power as compared to machine learning techniques.

In this paper we propose a contention-based SCMA that relies on FMSL to capture the heterogeneity of the messages and appropriately allocate CTUs after learning the state of the surrounding IoT devices and their CTU usage.

1.4. Thesis Organization

The thesis is organized into 7 chapters as outlined below:

- **Chapter 1 (introduction)** presents the background information, problem statement and review of related works.
- **Chapter 2 (narrow band IoT)** introduces the basics of narrow band IoT, standards, physical layer characteristics and it application areas.
- **Chapter 3 (basics of contention based SCMA)** gives brief explanations for contention-based access, scheduled access, multiple access based on SCMA, SCMA transmission and detection system, and contention based SCMA resource definition.
- **Chapter 4 (sequential learning)** introduces the need for learning techniques in IoT, different learning techniques, finite memory sequential learning and related algorithms.
- **Chapter 5 (contention based SCMA for narrow band IoT using finite memory sequential learning)** gives the descriptions of the system model for this research, the related mathematical analysis for the performance of the system in terms of probability of successful transmission, number of devices that succeed in learning and probability of collision.
- **Chapter 6 (results and discussions)** gives the discussion of the numerical and simulation results obtained in this research.
- **Chapter 7 (conclusions and future directions)** gives the conclusions and future directions of this research.

CHAPTER 2

NARROW BAND IOT

2.1. Introduction

The third-generation partnership project(3GPP), in the release number 13, has introduced the narrowband internet of things (NB-IoT) as one of the promising narrow-band radio access technologies for providing low-power wide-area network connections for massive IoT devices. LPWAN is a newly emerging type of wireless communication network designed to serve long range communications, hence wide area coverage, with relaxed requirements in terms of data rate and latency for information exchange between the core network and many power-constrained IoT devices. In this chapter, we make a brief review and comparison of the leading LPWAN technologies which include the licensed spectrum (NB-IoT and LTE-M), and the unlicensed spectrum proprietary technologies which includes LoRa, and SIGFOX. Although these LPWAN technologies are different in several ways, they still have one common feature of utilizing the narrow-band transmission technique to achieve the fundamental goals of wide coverage, high system capacity or massive connectivity, and long battery life. The fundamental properties of such technologies are summarized in tables given in the coming sections.

2.2. Modes of operation in NB-IoT

As per the standard given by 3GPP, NB-IoT applications can be directly deployed within the existing GSM or LTE spectrum to cut necessary deployment costs and to facilitate easy way of implementing the technology. Particularly, three different modes of operation are designed to support the deployment of NB-IoT [19]-[22]:

- **In-band operation mode: -** In this scenario, NB-IoT is deployed inside the already existing LTE carrier, as shown in fig. 2.1. The narrowband operation consists of one radio resource block with a bandwidth of 180 kHz which is the minimum used for both uplink and downlink communication. In this operation, LTE and NB-IoT share transmit power at the base station.
- **Guard-band operation mode: -** In this mode of operation, the NB-IoT communication channel is placed in a freely available guard band of an LTE/LTE-A channel, as shown in fig. 2.1. In this operation, the NB-IoT downlink communication protocols and data can

share the same power amplifier that is designed for the use of downlink LTE communication channel.

- **Stand-alone operation mode: -** This is a mode of operation in which the NB-IoT application is deployed as a standalone. It operates with at least 180 kHz of the old GSM spectrum, as we can see from fig. 2.1. This is called GSM reframing which enables efficient utilization of radio spectrum. The NB-IoT system can use all transmit power from the base station. Hence, it significantly enhances the network coverage. A NB-IoT device must be aware of the mode of deployment operation as in-band, guard-band, or stand-alone. When it is first turned on, it searches for a NB-IoT carrier. Like the existing LTE systems, the channel raster is 100 kHz in all the above three modes operation.

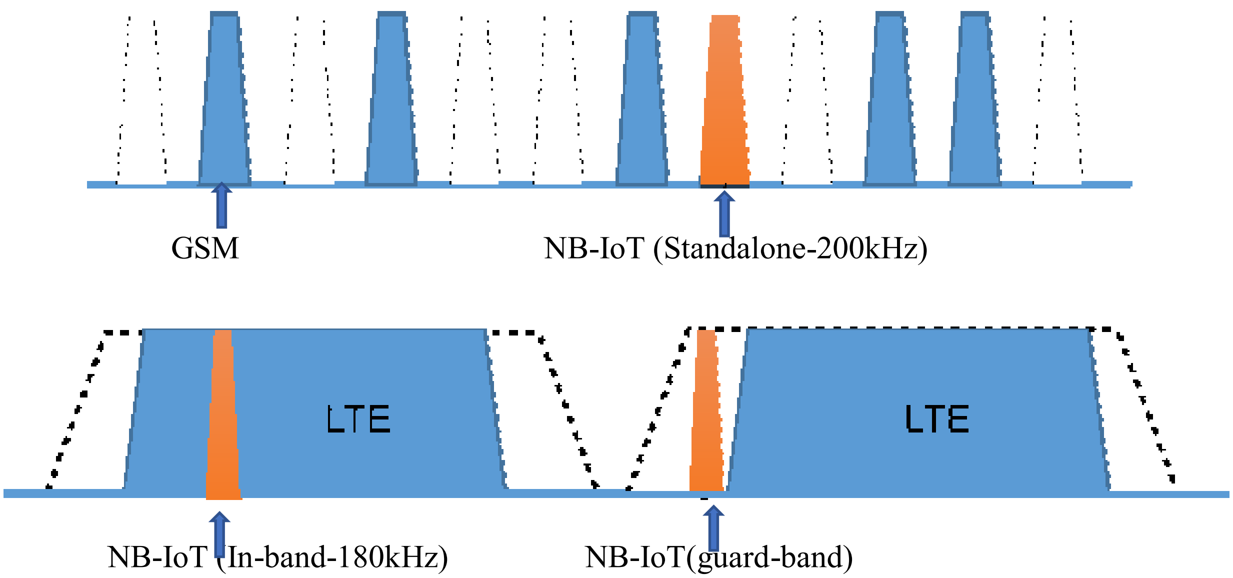

Figure 2.1: Modes of operation in NB-IoT

2.3. Why NB-IoT Standards?

The release 13 of 3GPP has introduced the Narrow-Band Internet of Things (NB-IoT) and its specification [20], [22]. The motivation for standardization of NB-IoT was the need for competitive solution for low data rate and wide area coverage of machine-type communication (MTC) which has a big demand to connect billions of low-cost devices to the network. The objectives of the standard were set as outlined below [20].

- **Improved indoor coverage**: - The NB-IoT technology should support the connectivity for the devices that are deployed in the challenging indoor positions which could be in apartment basements. The standard aims to allow a minimum data rate of 160 bits per second in uplink and in downlink with an extended range of coverage up to 20 dB compared to legacy general packet radio system (GPRS) systems.

- **Support for massive connectivity of low throughput devices:** -There is a need for massive connectivity of a number of IoT devices. However, the devices that occasionally transmit small packets of data which can be supported by small chunks of radio spectrum as discussed in section 2.2. The traffic model in the standard assumes that there are 40 devices per a household and 20 devices per person. It is possible to support 53,000 devices per the 200kHz cell [3].
- **Low delay sensitivity:** The NB-IoT technology is planned for applications that have relaxed delay sensitivity. This is suitable to develop IoT applications for smart metering, smart home and smart city which mostly need to send data at specified intervals
- **low device cost:** NB-IoT devices are supposed to be very cheap so that they can be deployed in large number or even in disposable manner in environments where it is difficult to replace their units.
- **Low power consumption:** It was planned that the battery life of the NB-IoT devices should reach up to 10 years. This was based on assumptions of 5 Watt-hours battery was used and 120 minutes of interval for uplink reporting.
- **Further optimized network architecture:** The network architecture can also be enhanced in various ways for improved security and relaxed packet delay to serve a small data packet transmission.

2.3.1. Characteristics of NB-IoT physical layer

The NB-IoT system supports the possibility of using one of three deployment modes discussed in section 2.2. In the following sub-sections, we will discuss the characteristics of NB-IoT uplink and downlink.

2.3.2. Narrow band-IoT Uplink

The NB-IoT system uses UL transmission bandwidth of 180 kHz. The bandwidth is planned to enable the use of two sub-carrier spacings, namely 3.75 kHz and 15 kHz. From coverage enhancement point of view, the sub-carrier spacing of 3.75- kHz gives higher system capacity than the sub-carrier spacing of 15-kHz. But, regarding compatibility with LTE, particularly for the in-band deployment mode, the sub-carrier spacing of 15-kHz has better performance than sub-carrier spacing of 3.75 kHz. The uplink transmissions of the NB-IoT uses both single sub-carrier and multiple sub-carrier. Besides, for the multiple sub-carrier transmission, the standard has defined a sub-carrier with 15 kHz spacing. However, for single sub-carrier transmission the spacing for sub-carriers can be set to 3.75 kHz or 15 kHz. The IoT devices are required to support both single sub-carrier transmission and multiple sub-carrier transmissions to facilitate the selection by base station which depends on the scenario under consideration.

Single carrier frequency division multiple accesses (SC-FDMA) is adopted for the uplink transmission of both single and multiple sub-carrier spacing. The uplink frame structure of a NB-IoT system that uses the 15-kHz sub-carrier spacing, in terms of frame size or time slot length, is similar to the frame structure for LTE network as can be seen from Fig. 2.2. However, a newly standardized narrow-band time slot of duration 2 ms is selected for the sub-carrier spacing of 3.75-kHz, as shown in Fig. 2.3. There are five narrow-band time slots within one radio frame. Further, each time slot is defined to contain seven symbols and a guard interval is inserted or reserved between each time slot to reduce the interference between the NB-IoT system symbol and LTE system reference signal named sounding reference signal (SRS) [3], [23].

The NB-IoT systems works in such a way that uplink physical channels are changed and re-configured from time to time. The physical channels are narrow-band physical random-access channel (NPRACH) and narrow-band physical uplink shared channel (NPUSCH). However, the physical uplink control channel (PUCCH) is not supported. For the uplink transmission with the sub-carrier spacing of 3.75kHz, the NB-IoT frame structure introduces a retransmission technique in uplink physical channel. This technique enables an enhancement of the uplink coverage. NB-IoT devices are equipped with low-cost crystal oscillators to meet the low-cost requirement as there is a need to deploy massive IoT terminals. If there a long continuous transmission in the uplink, the heat dissipation in the power amplifiers of the devices causes a fluctuation in temperature of transmitter. This in turn leads to the deviation in frequency of the crystal oscillator, hence, seriously affects uplink transmission of terminal and degrades the performance and data transmission efficiency. With the introduction of the uplink transmission interval in the NB-IoT, it is possible to make the device discontinue the uplink transmission and switch to downlink transmission during that period. The signaling information from in terms of NPSS, NSSS, and NRS enables the synchronous tracking and compensation of frequency offset. After the frequency offset is compensated the terminal switches back to uplink transmission [2], [3].

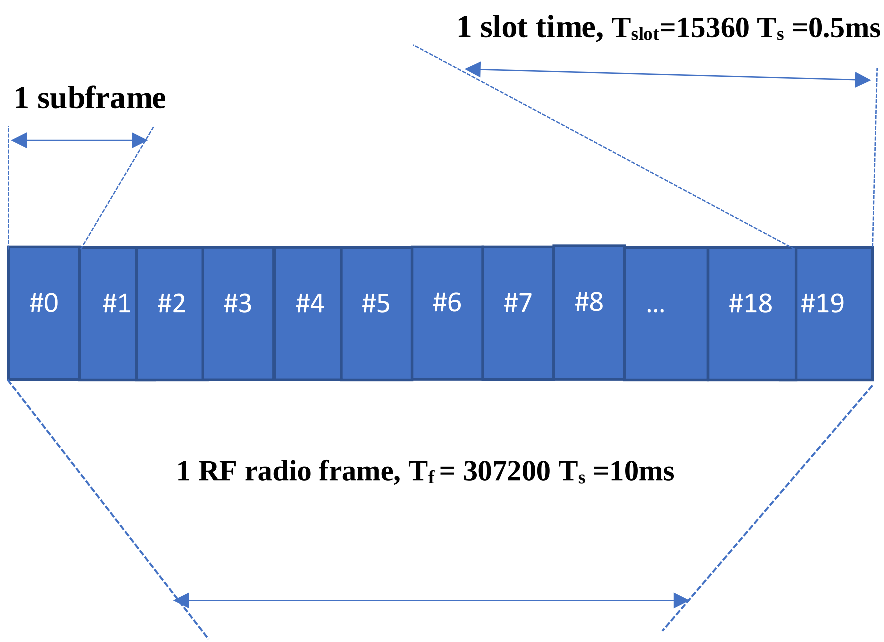

Figure 2.2**:** NB-IoT frame structure for 15kHz sub-carrier spacing of uplink and downlink

2.3.3. Narrow band-IoT Downlink

Like the uplink of NB-IoT system, downlink communication bandwidth of is set to be 180 kHz where sub-carrier spacing of 15-kHz used the same as current LTE. The physical resource block design is similar to the current LTE system where OFDMA based multi-access is used in the downlink. For the frame structure one radio frame constitutes ten 1ms subframes in time domain.

In the frequency domain one sub-frame constitutes 12 continuous sub-carriers. To serve the requirement of coverage extension, with transmission bandwidth of 180kHz, the physical channels of the NB-IoT should be reconfigured for the downlink. The reconfigured physical channels should include the synchronization signals which are defined as narrow-band physical downlink shared channel (NPDSCH), narrow-band physical broadcast channel (NPBCH), narrow-band physical downlink control channel (NPDCCH), narrow-band primary synchronization signal (NPSS) narrow-band secondary synchronization Signal (NSSS). Narrow-band reference signal (NRS) serves as a reference signal. To improve the downlink coverage extension, a retransmission technique is introduced for the downlink physical channel. The technique improves diversity gain which in turn enhances demodulation threshold.

While the coverage is enhanced by this technique, there is a problem of resource blocking which is caused by continuous retransmission in the downlink. This drawback is tackled by allowing the downlink retransmission in a periodic manner where some specified periodic intervals are inserted the periodic downlink transmission interval is introduced. For example, in-band deployment of NB-IoT devices, nearly 1200-1900 ms interval for NPDSCH, and 200-350 ms for NPDCCH retransmission is introduced. This avoids the problem of the blocking packets from other terminals [3], [20], [23].

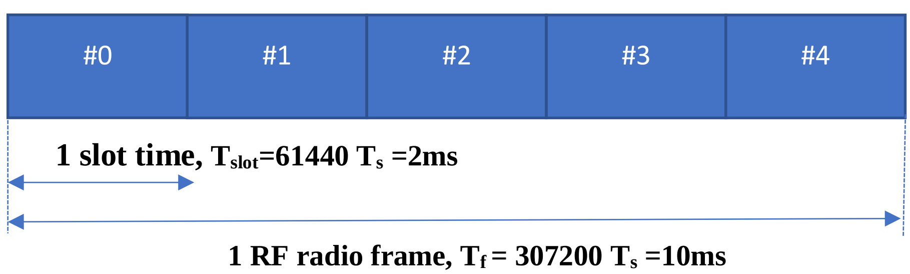

Figure 2.3:NB-IoT frame structure for 3.75kHz sub-carrier spacing in UL

2.4. Other LPWAN technologies

Currently, there are two major LPWAN technologies named SIGFOX and LoRa that are available on the market. They are proprietary technologies developed for LPWAN applications to be deployed within the unlicensed spectrum. The main benefit of using unlicensed spectrum is the fact that it has cost-effectiveness when compared to the applications in the licensed spectrum. In the next sections we will briefly describe and make comparisons of few LPWAN technologies.

2.4.1 LoRa and SIGFOX

Even if these technologies have the benefits of cost-effectiveness they have limitations which includes the reduced system performance. The wide-area deployment of both SIGFOX and LoRa follows a star topology or cellular architecture. In such architecture, the IoT device is connected to a base station which furthers communicates the data to a dedicated network server. LoRa operates in two different modes: device-originated call and network-originated transmission mode [23]. In the device-originated call scenario, maximum battery saving can be achieved as the device only wakes up to transmit data when it is required to do so. On the other hand, in the transmission mode which is named network-originated transmission, the network periodically broadcasts paging signal and the devices wake up periodically to receive paging signal. This is like the conventional LTE network where UE periodically listens for the paging signal.

In the second mode of communication, the dedicated network server or a LoRa gateway facilitates the paging process by transmitting a beacon signal to enable the IoT device get synchronized to the network. Then, the devices look for downlink data transmissions in the dedicated predetermined windows. LoRa network has a capability to dynamically change the communication bandwidth for each IoT device. This is aimed at maximization of network capacity and lifespan of the devices in terms of battery. However, the SIGFOX transmission system relies on fixed bandwidth. From table 2.1., we can get the comparison between the two technologies and the other two narrow band technologies namely, LTE-M and NB-IoT, standardized for LPWAN application. Hence, LoRa has a minimum bandwidth of 125 kHz with a maximum transmission coupling loss of about 157dB.

2.4.2. Ultra-narrowband by SIGFOX

In 2009 SIGFOX standardized a new technology named ultra-narrow band (UNB) for connecting low-power IoT devices within a wide area wireless network. The technology serves as wireless access technology for connecting low-power massive IoT devices such as electricity meters, water meters and washing machines. This enables the centralized monitoring of the devices over a communication network. To meet such a massive connectivity demand, the UNB has the following key features:

- The communications channel bandwidths for UNB system are on the order of 100Hz. The channels can support coupling loss of minimum160dB.
- The transmissions follow an uplink-triggered client-server model
- Multiple base stations jointly receive the signal from an UNB device. This cooperative reception helps to increase the chances for successful receptions of the packets from each IoT device.

Table 2.1. Comparison of LPWAN technologies

TECHOLOGY	**SIGFOX UNB**	**LoRa**	**3GPP**	
			LTE-M	**NB-IoT**
Receiver sensitivity	–147 dBm	–137 dBm	–132 dBm	–137 dBm
Frequency band	Sub-GHz ISM	Sub-GHz ISM	Licensed	Licensed
Minimum transmission bandwidth	100 Hz, 600 Hz	125 kHz	180 kHz	3.75 kHz
Fully bi-directional	No	Yes	Yes	Yes
Modulation	D-BPSK	LoRa modulation, GFSK	BPSK, QPSK, 16QAM, 64QAM	$\pi/2$ -BPSK, π /4 -QPSK
Medium access control (MAC)	Unslotted ALOHA	Unslotted ALOHA	SC-FDMA	SC-FDMA
Data rate	100 b/s	0.3-38.4 kb/s	Up to 1000 kb/s	Up to 100 kb/s
Over the air upgrade	No	Yes	Yes	Yes
Roaming	Yes	Yes	Yes	Yes
Standard	No	LoRaWAN	LTE (Release 12)	LTE (Release 13)

In the UNB network a centralized scheduling is not required as the network architecture follows a client-server transmission model whereas in the traditional cellular network a device must send an uplink transmission request. This is initiated when there is a need to transmit data. The merit of client-server model is maximization of battery life by removing the periodic wakeup for checking paging signal which is a power-consuming procedure. Hence, only the arrival of uplink application data at an UNB device wakes up it up. Then, the device randomly selects one of the channels for uplink transmission. The channel bandwidth is either 100 Hz or 600 Hz, and a fixed packet size of 96 bits is allowed for transmission. To achieve reliability of successful transmission, the device repeats the transmission three times. After the uplink transmission, a downlink message is received following a time window that is predetermined to be on the order of 10 seconds [23]. In addition to the unlicensed LPWAN technologies considered above, the LTE-M is discussed in the following section as one of the licensed band technologies that serve narrow band applications.

2.4.3. LTE -M

The 3GPP has provided two narrow band technologies which operate on the licensed band. These include NB-IoT and LTE-M. LTE-M was introduced in the Release 12 of 3GPP to support the changing network requirements and further improvements of cellular MTC or enhanced MTC (eMTC). The motivation behind the introduction of LTE-M is meeting the requirements related to massive deployment. The massive deployment comes with the need of reduced cost and power consumption, peak rate, hardware complexity, and the ability to operate in the narrow band of 1.08MHz. However, the LTE-M retains the original LTE design features such as downlink transmission by orthogonal frequency-division multiple-access (OFDMA), and uplink transmission by single-carrier frequency division multiple-access (SC-FDMA). The same channel coding schemes are kept. This includes turbo-coding for data channels and tail-biting convolutional (TBC) coding for control channels. The LTE-M uses bandwidth of 1.08 MHz which is equivalent to six LTE resource blocks. This is because of the fixed and non-configurable bandwidth of existing LTE system for acquisition channel and the random-access channel. The bandwidth is fixed at 1.08MHz. The MTC device uses the same minimum transmission bandwidth of 180 kHz as an LTE UE. This bandwidth is equal to one LTE resource block which is the minimum scheduling unit for legacy LTE network. It will also support backward compatibility. To extend the coverage area of LTE-M for massive deployment of MTC devices, 15 dB coverage extension and a corresponding 155 dB maximum coupling loss is achieved. This enables LTE-M network to reach IoT devices located in areas with high channel fading or losses. The implementation of temporal repetitions helps to achieve the coverage extension at a cost of reduced data rate [2], [23].

2.5. Narrow band IoT Application

The IoT technology in general and the narrow band IoT, in particular, have many application areas or use cases specified by standardization institutions or companies working on the IoT business. There are four major categories of IoT/NB-IoT use cases [2],[24]:

- IoT Public
- IoT industry
- IoT Appliance
- IoT Personal

The target industries for NB-IoT application can be summarized as shown in the fig. 2.3.

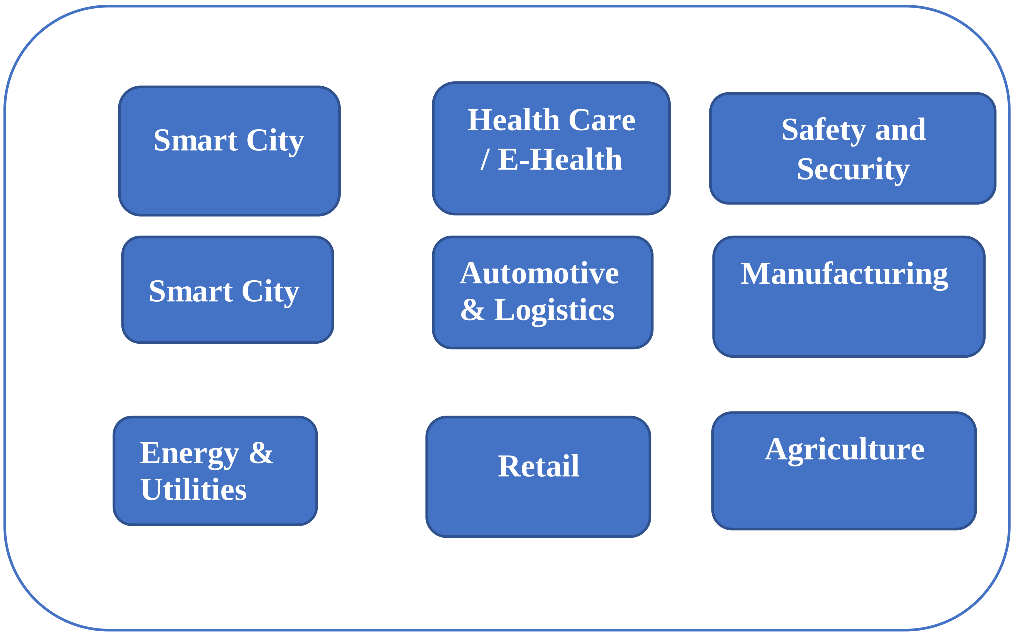

Figure 2.4: The major target industries for NB-IoT application

In general, there are more than fifty uses cases covering the following application areas:

- Smart metering for utility companies: electricity, gas and water
- Smart facility management systems
- Private and commercial security such as intruder alarm and fire alarm monitoring
- Personal and home appliances to monitor health related data, and other wearable devices
- Smart city application such as street lamps monitoring or smart dustbins
- Industrial appliances such as welding machines or air compressors
- Tracking of persons(kids), animals, and assets

CHAPTER 3

BASICS OF CB-SCMA

3.1.Introduction

In the current wireless communication network, specially for the IoT application which has a huge demand for uplink transmission resources, multiple access techniques must be properly selected to support the massive IoT devices. Currently, non-orthogonal multiple access techniques are becoming part of an effort to improve the possible number of connections with the limited radio resources. Besides, the non-orthogonal resource allocation allows the perfect mitigation of interferences with the developed multi-user detection algorithms. In this work, we the sparse code multiple access technique combined with contention-based access to allow both massive connectivity and reduction of signaling overhead in the uplink communication. Contention based access allows the user equipment or IoT devices to directly transmit their data without any uplink scheduling request and grant procedure [25]-[29]. The devices try to contend for the predetermined apply resources. In the coming sections the basics of CB access, the comparison with scheduled access techniques, the basics of SCMA systems, the resource definition for CB-SCMA and the narrow band SCMA techniques will be discussed.

3.2. UL Contention Based Data Transmission

In the current and future IoT networks, the deployment of IoT devices for different use cases comes with some QoS constraints. Besides, the massive connectivity of IoT devices to the eNB brings the need to deal with the signaling information to set up connection and acknowledge the successful transmission of information. Hence, the challenge of increased signaling overhead and latency for the uplink communication motivates the need to devise contention-based techniques that enable the devices to directly transmit their data to the eNB. In the conventional long-term evolution (LTE) and LTE-A uplink (UL) data communication, the user is expected to make scheduling request (SR) via periodically occurring UL dedicated resources to the base station which gives a scheduling grant. There is a predetermined periodicity for such dedicated resources, broadcasted by the base station. The dedicated resources basically arrive at the device every 5 or 10ms. If data arrive at the user equipment (UE) just before the scheduling request, it needs to wait for at least 7ms from scheduling request to the UL data transmission. The incurred delay could even be longer if the UE needs to transmit in between the SR opportunities or the system has been configured with longer periodicity. Hence, it is necessary to reduce the delay incurred in such a scheduling request and grant procedure by employing the appropriate techniques. Contention-based technique could be suitable for applications that require reduced or stringent latency requirements. In the next section, the comparison of contention-based access with scheduled access will be presented.

3.3. CB Access versus Scheduled Access

The massive deployment of NB-IoT devices is followed by the necessity to handle the signaling overhead and reduce latency in certain devices that report urgent messages such as alarm messages for security and environment monitoring, and health status in e-health applications. CB uplink access for IoT was considered as a method to reduce latency compared to the scheduled access scheme in LTE which is suitable for human-type communications (HTC) [8]. In the LTE uplink access, a dedicated UL shared channel, named physical uplink control channel (PUCCH), is used by multiple UEs to transmit their respective scheduling request (SR). The procedure could also employ a random access (RA) procedure. Scheduling request enables several users to be multiplexed together using different cyclic shifts and orthogonal sequences and occupy the dedicated UL resource elements on the physical uplink control channel. In LTE SR procedure, a maximum of 36 UEs can be multiplexed together for SR in a single physical resource block (PRB) on one PUCCH.

To support massive IoT device communication in the uplink, there are two possible ways with respect to scheduling request and its periodicity. On the one hand, a large PUCCH resource should be designed to provide the scheduling request resources for the UL grant request procedure. On the other hand, the periodicity of SR should be configured to be very large. However, this scheduling procedure could result in a delay of several minutes. This prolonged delay is too long for IoT devices that need to be triggered to report some critical data such as burglar alarm, health monitoring, fire alarms, and temperature reading. In LTE, there is a 4-step random access procedure. This is described in the LTE random access channel definition where the UE first sends a random-access preamble. The preamble has with it 1-bit embedded to indicate the required message size for communicating signaling information. Next, in the random-access response, the eNB assigns a UE identification number (ID) for each UE and provides an uplink grant for transmission within a specified time frame. The last two steps involve further signaling exchanges to set up a connection for UL data transmission and to resolve contention if there are more than one users mapped to the same UL grant resource. In [8], it was discussed that the latency for such a 4-step RACH procedure is at least 15ms without the waiting time in the first step. As a result, the system incurred signaling latency and signaling overhead due to the involved handshaking, at least 4 steps, to have a small packet data transmitted to the eNB. However, such procedures are not effective and efficient for the massive number of IoT devices in that need to carry out UL data transmissions.

In the fig.3.1 (a), a scheduling request procedure which is simpler than the LTE RACH based random access procedure is given. In that procedure the UE sends UL scheduling request which also includes the information about the UE (UE ID). The eNB in turn responds by resolving the UL contention in case of many UEs contending for the same resource. Then the UL data transmission follows. The successful reception of the data at the eNB will be confirmed by an ACK/NAK signaling. A simpler UL data procedure is given in the fig.3.1 (b) where UL contention-based procedure can be used as means to directly send a small amount of data. Hence, contention-based procedures reduce signaling overhead and latency.

The contention-based access basically occurs when a group of UEs try to use the same radio resources respectively. In scheduled access, there is no need for the devices to contend over the radio resources as the eNB allocates dedicated units for each device transmitting in the UL via a UE-specific UL grant. In the current and future IoT network, the need for massive connectivity and uplink delay reduction can be supported by the contention-based SCMA system which will be discussed in the coming sections.

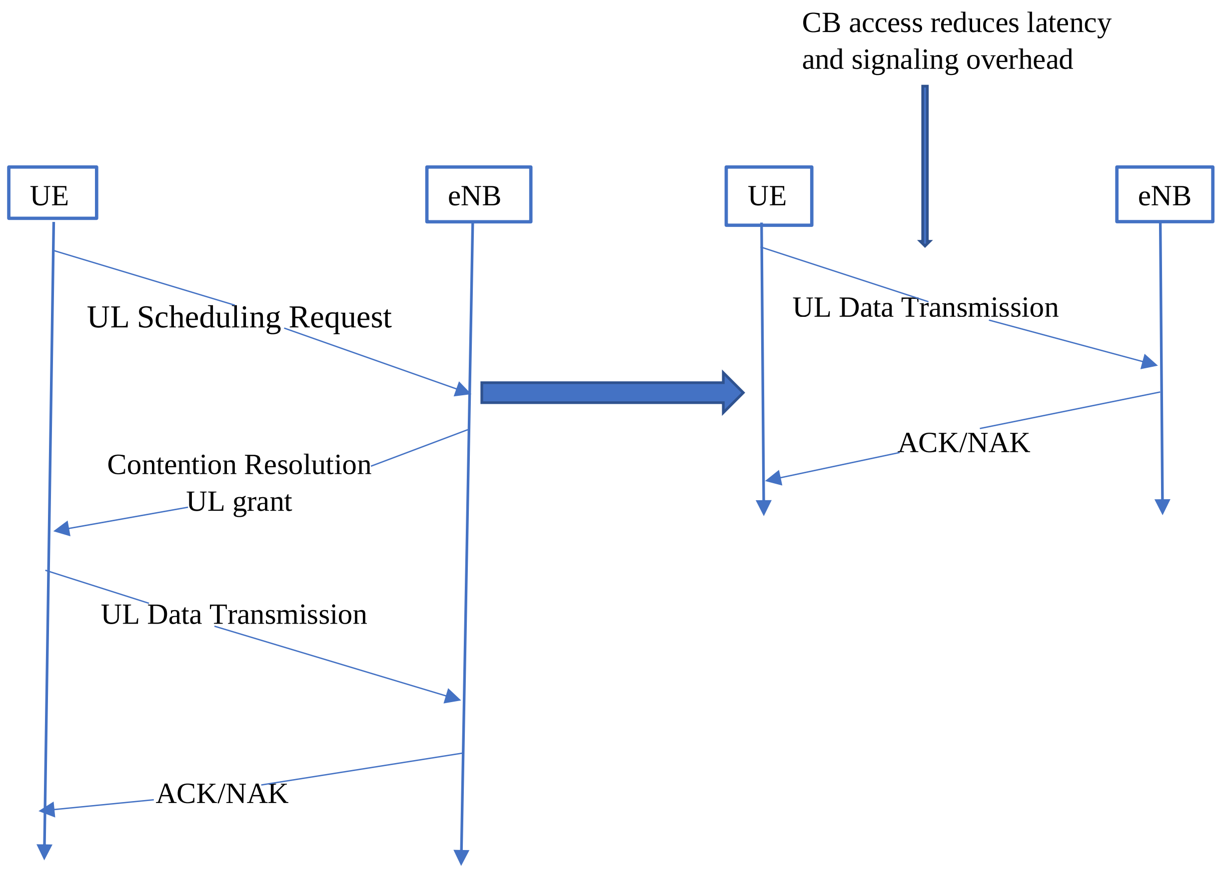

Figure 3.1: Scheduling request versus contention-based UL data transmission procedure

3.4. Basics of an SCMA system

SCMA is a kind of NOMA in which each user is configured with a E-dimensional complex codebook of size M. M is the number of codewords used by the SCMA encoder to map from $\log_2 M$ bits to a corresponding codeword. The codewords are E-dimensional sparse vectors with $H < E$ non-zero entries. The E-H entries are zero for all codewords. A codeword corresponding to a user's data is selected from the codebook and transmitted on E subcarriers which could be OFDMA subcarriers, for example. Multiple access is possible by sharing the same time-frequency resources among SCMA layers with multiple UEs. The shared resource at a given time slot is an SCMA block. There is always a possibility that multiple UEs transmit at the same time and collide within a given SCMA block. Let's consider a time slot in which U SCMA layers or UEs transmit through different channels. A UE $u(u = 1,2, \dots, U)$, uses a codeword $\boldsymbol{x}_{\boldsymbol{u}}$ to transmit its data. After synchronous multiplexing of all signals from UEs transmitting in that time slot, the received signal is given by [7]

$$\mathbf{y} = \sum_{u=1}^{U} \sqrt{P_u}\,\mathrm{diag}(\mathbf{h_u})\mathbf{x_u} + \mathbf{i} \tag{3.1}$$

where $\mathbf{y}$ is the $E \times 1$ vector of received signals at the eNB, $\mathbf{x_u} = [x_{1u}, x_{2u}, \dots, x_{Eu}]^T$ is the vector of the codewords of UE u, $\mathbf{h_u} = [h_{1u}, h_{2u}, \dots, h_{Eu}]^T$ is the channel response vector of UE over the SCMA resource block under consideration, diag($\boldsymbol{h_u}$) is a diagonal matrix containing h_{nu} as its n-th diagonal elements, and $\mathbf{i}$ represents white gaussian noise plus total interference from the neighboring devices.

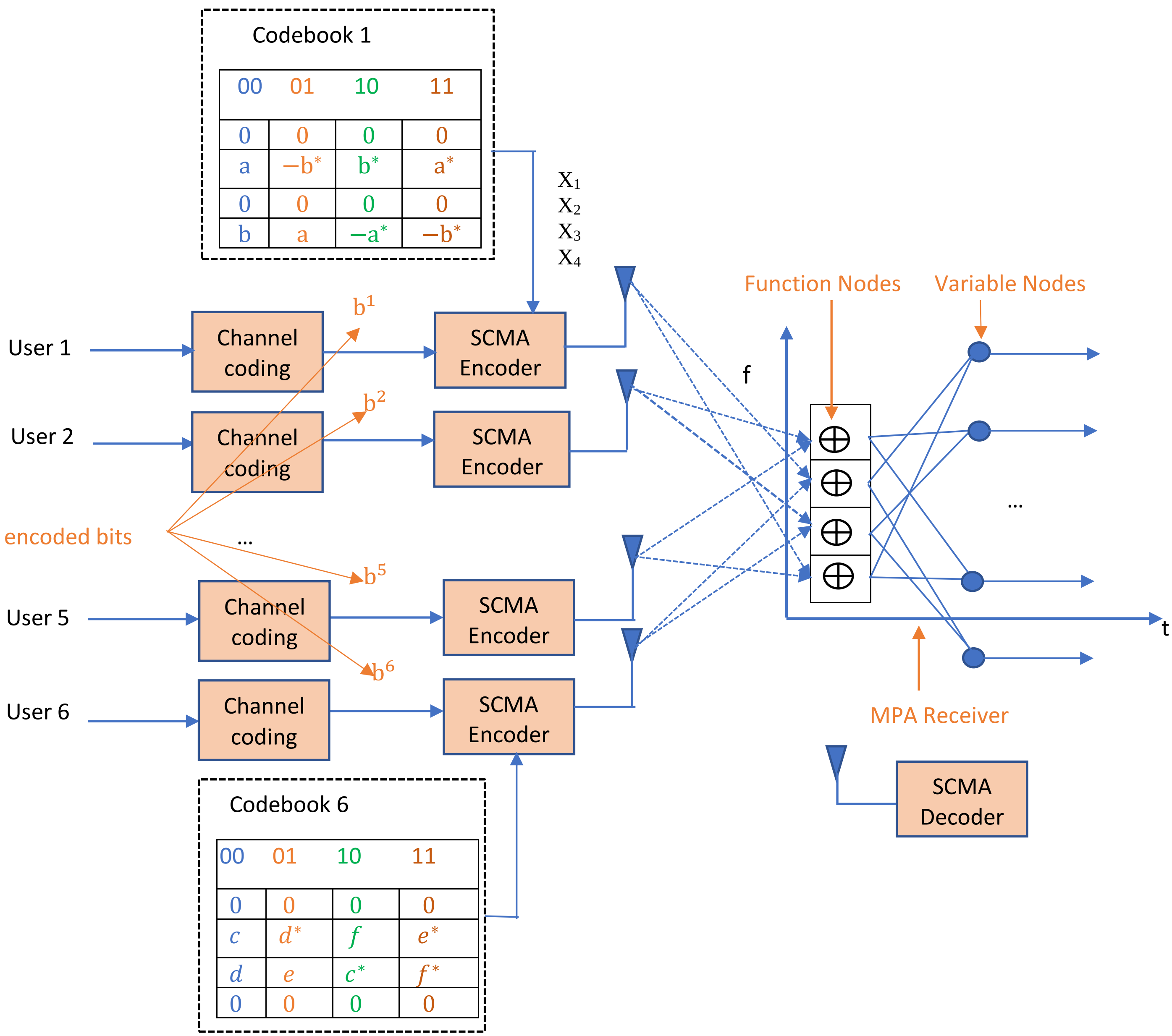

Figure 3.2: A Basic SCMA system

The sparsity of SCMA codewords, where the number of non-zero entries overlapping at a given subcarrier of **y** is smaller than the number of active UE(U), allows the sub-optimal detection by the message passing algorithm (MPA) or its modified form (log-MPA). A basic SCMA system is shown in the fig.3.2. given above.To address the issue of massive connectivity, the number of SCMA codebooks is scalable as a function of E and H. The scalability can be determined from the possible number of arranging the H non-zero entries within a codeword of length E. This is given by a combination function which is described by a binominal coefficient to give a maximum of

$$J = \binom{E}{H} = C_E^H \tag{3.2}$$

codebooks with a user overloading factor of f:

$$f = \frac{J}{E} \tag{3.3}$$

In the figure 3.2. above, we observe that there are H=2 non-zero entries within a codeword of length E=4. Hence, (3.2) provides

$$J = \frac{4!}{(4-2)!\,2!} = 6,$$

codebooks corresponding to 6 users sharing 4 SCMA resource elements. The overloading factor is f=6/4=1.5 or commonly described as 150%. Depending on the SCMA system codebook design parameters the overloading factor could be as large as 200%,300% and so on. The overloading factor is adjusted by changing the parameters E and H. For achieving massive connectivity, it is required to make the overloading factor much greater than 1 or 100%. The possible number of codebooks for an SCMA system can be seen from the figure 3.3. which describes the scalability of SCMA system as a function of H non-zero entries and codeword length E. The maximum number of codebooks could be as large as 70 for E=8 and H=4.

In the fig. 3.2. above, we observe elements known as function nodes and variables. To clearly describe an SCMA system’s resource sharing among multiple users, a factor graph and a corresponding signature matrix can be used. Assuming J=6 codebooks or SCMA layers/users as shown in the fig.3.2., the SCMA can be represented by the following factor graph and a corresponding signature matrix. It is possible to represent the signature of SCMA codebooks by factor graph G(J, H) with J variable nodes (VNs) and H function nodes (FNs). The variable nodes represent data layers that correspond to one or more users whereas the function nodes represent time-frequency resources shared by the SCMA data layers [6], [31].

Fig. 3.4. gives example of an SCMA factor graph that contains 6 variable nodes and 4 function nodes. The described SCMA system has a 6x4 codebook or four-point codebook. The corresponding signature matrix is also shown in the fig. 3.5. The following factor graph shows multiplexing of 6 users' data over 4 radio resources.

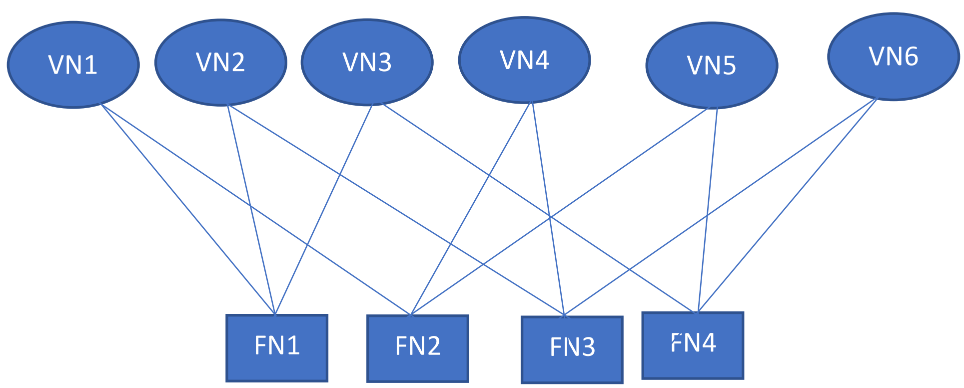

Fig.3.4. A factor graph representation of an SCMA with E=4 and H=2

$$S_{6x4} = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}$$

Fig. 3.5. The signature matrix of the factor graph of a SCMA with E=4 and H=2

The six function nodes describe the SCMA layers or users that are transmitting their data using only two of the four available function nodes that represent time-frequency resources. The signature matrix shows the mapping procedure from the users to the SCMA resource block. The six columns of the signature matrix represent the six SCMA layers and the used resources. For example, the first column represents the VN1 which transmits its data via FN1 and FN2. Hence, the first two entries of the first column are 1 whereas the rest are 0. Likewise, the four rows of the signature matrix represent the four SCMA resources and the entries indicate which FNs are transmitting in that resource. Hence, the first row has the first three entries set to 1s which indicates that VN1, VN2 and VN3 are colliding at the FN1.The sparsity of the SCMA codewords enables the SCMA system to have overlapping of users' data. The signature matrix and a set of mapping matrices determined in the SCMA codebook design specify the number of layers colliding at each resource node which in turn defines the complexity of the multi-user detection algorithm or the MPA. If the design provides sparser codewords, the complexity of the MPA detection will be reduced. The near optimal detection of the 6 SCMA layers can be achieved by iteratively applying the MPA detector over the corresponding factor graph. Sparsity nature of the codewords also helps to limit the complexity of the MPA receiver used in the SCMA system. In the following section, contention-based SCMA will be discussed as an enabler technique of achieving both massive connectivity and reduced signaling overhead and latency.

3.5.Contention-based SCMA system

A contention-based SCMA approach is achieved by defining a contention region in the existing SCMA radio resource block. Fig.3.6. shows the definition of a contention region in the time-frequency plane. The basic transmission unit is called contention transmission unit (CTU) defined as a function of time, frequency, a set of J SCMA codebooks and the assigned pilot sequences L. Hence, the given contention region has the capacity to support LXJ UEs at the same time. In this research we proposed a contention-based SCMA system that achieves both massive connectivity of IoT devices and the reduction of signaling overhead and latency. To achieve the massive connectivity of IoT devices, the merits of SCMA system are adopted whereas contention-based access will enable the system to have a reduced level of signaling overhead and latency. This is because of the absence of the length procedure of setting up connection between the IoT devices and the eNB. The IoT devices can contend for the available resources to transmit their data. As it is outlined above, the contention region can be overloaded with many IoT devices which use unique pilot sequences and codebooks.

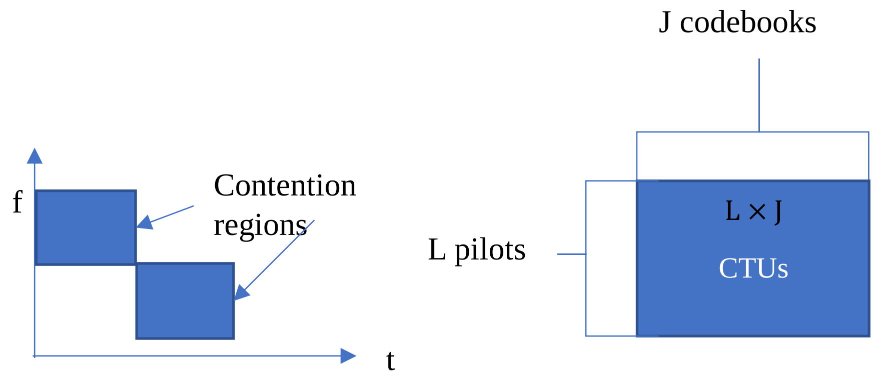

Fig. 3.6. Definition of contention region and CTU

Since there are a large number of IoT devices in the network, the avaible CTUs may not still be enough. There is a probability of user data collision at the receiver. So, it is necessary to devise a means to reduce that collision probability while maintaining the other features of the CB-SCMA system. Hence, in this research we proposed the CTU allocation and UE coordination technique which is based on finite memory sequential learning (FMSL) to allow each IoT device in the network to learn about the nearby devices status on CTU usage and information about critical event near them. The problem of handling massive number of devices and reducing the level of signaling overhead and latency can be addressed by the contention based SCMA which takes the advantage of SCMA layers overloading and nonorthogonality of the resources. The major characteristics of an uplink contention based SCMA system can be summarized as follows [7]:

- Like OFDMA or SC-FDMA radio resource allocation, some of the predefined time-frequency regions are can be reserved for the contention-based SCMA communication applications.
- Contention-based SCMA achieves multiple-access by multiplexing of SCMA layers within the predetermined contention regions. Fig.3.6. shows that a given contention region has the capacity to support LXJ devices at the same time. An SCMA layer is spread over the entire resources of a contention region.
- The SCMA layers represent users or IoT devices in this work. Every SCMA layer has a unique SCMA codebook. To further specify the resources to be used by each device, a specific contention region, SCMA codebook, and pilot sequence is assigned to each device.
- The number of non-zero entries H defines the sparsity of SCMA codewords. Due to the sparsity of the codewords, SCMA systems can rely on a moderate complexity multi-user detection algorithm such as message passing algorithm (MPA). MPA algorithms can

achieve a near-optimal joint user detection and cross-layer interference cancellation for SCMA layers.

- The SCMA system can be overloaded to support a larger number of users than the available SCMA resources. This is possible by multiplexing the layers which are more than the length of codewords. Due to the sparsity of the codewords, the overloading feature of SCMA enables a massive connectivity of the IoT devices with a limited complexity.

In the fig.3.7. below, a multi-carrier narrowband SCMA(MC-NB-SCMA) system is shown where OFDMA subcarriers are grouped in such a way that the number of subcarriers in each group is equal to the number of the FNs or shared resources in the SCMA. It shows a mapping procedure from a SCMA layer to SCMA resource for a MC-NB-SCMA system. The system has 6VNs overloaded within 4FNs or subcarriers in an OFDMA subcarrier group. The data from an SCMA layer are encoded by the SCMA encoder (as shown in fig.3.8. below) and mapped to the time-frequency resources of the SCMA system. The FNs represent time-frequency resources, which are within one symbol duration and include multiple OFDMA subcarriers.

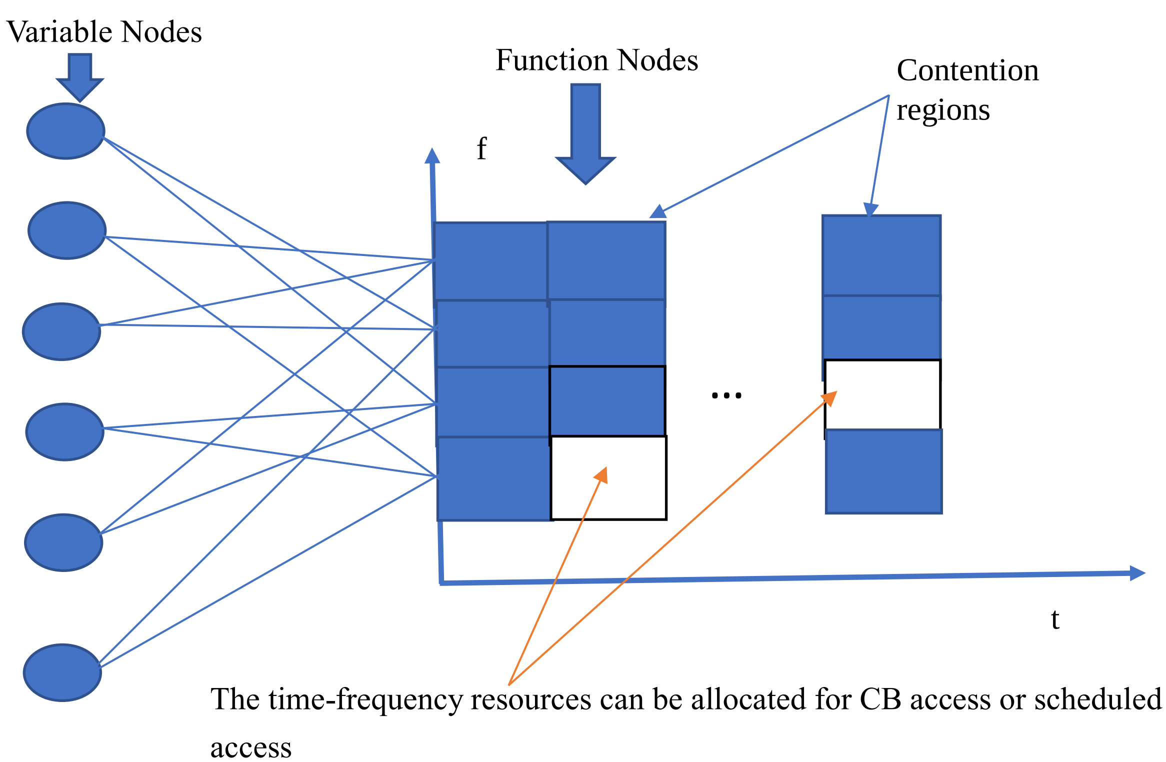

Fig. 3.7. Resource mapping for CB-SCMA with 6X4 codebooks

Hence, it is possible to define the time-frequency resource within one symbol duration and one OFDMA subcarrier as one SCMA resource unit. In MC-NB-SCMA systems shown in the fig.3.7., 4 SCMA resource units in one symbol duration and 4 OFDMA subcarriers are used to define one SCMA resource block and used to send one SCMA codeword. If each SCMA user uses a predetermined codebook for SCMA encoding, it will transmit non-zero data symbols on all its occupied OFDMA subcarriers [4].

3.6. Narrow Band SCMA

NB-IoT has been introduced by 3GPP to meet the demands of competitive solution for ultra-low device cost, low power consumption, deep indoor coverage, low delay sensitivity and suitability for massive deployment by low throughput devices [2]. To meet the wide area coverage requirements of LPWANs, narrow band pulse shaping techniques have been discussed in [4]. Since NB-IoT devices are required to have a minimum hardware complexity, hence low-cost, that is dictated by the standard, they cannot rely on inverse fast Fourier transform (IFFT) for mapping modulated symbols onto multiple sub-carriers. IFFT is used in OFDM systems which have the computational capacity to achieve the required QoS in terms of processing delay limits. In narrow band pulse shaping the principle of frequency localized pulse shaping is used to transmit data symbols over each subcarrier of the SCMA system.

In OFDM, each subcarrier has the same the bandwidth, but in localized pulse shaping different bandwidths are allocated for different users. Hence, localized pulse shaping enables bandwidth assignment to be according to the channel quality and the number of users in the system. If a user has a good channel quality, a user near the BS for example, it can select a broader bandwidth to transmit data to the base station BS compared to those who have severe channel quality. Since OFDM system is very sensitive to frequency offset which causes inter-carrier interference and degrades it performance, the system has a complex and efficient oscillator design to correct the frequency offset. However, OFDM is not suitable for low-cost NB-IoT devices which have relatively cheap oscillator that often leads to frequency offset. But, narrow band pulse shaping is tolerant against the frequency offset, as the subcarriers are localized from each other.

Fig. 3.8. shows a block diagram of UL NB-SCMA systems. The description of the SCMA system is the same as the basic SCMA system depicted in fig.3.2. The channel coded binary information

bits are mapped to an E-dimensional SCMA complex codeword. The mapping to complex SCMA codewords is done by an SCMA encoder.

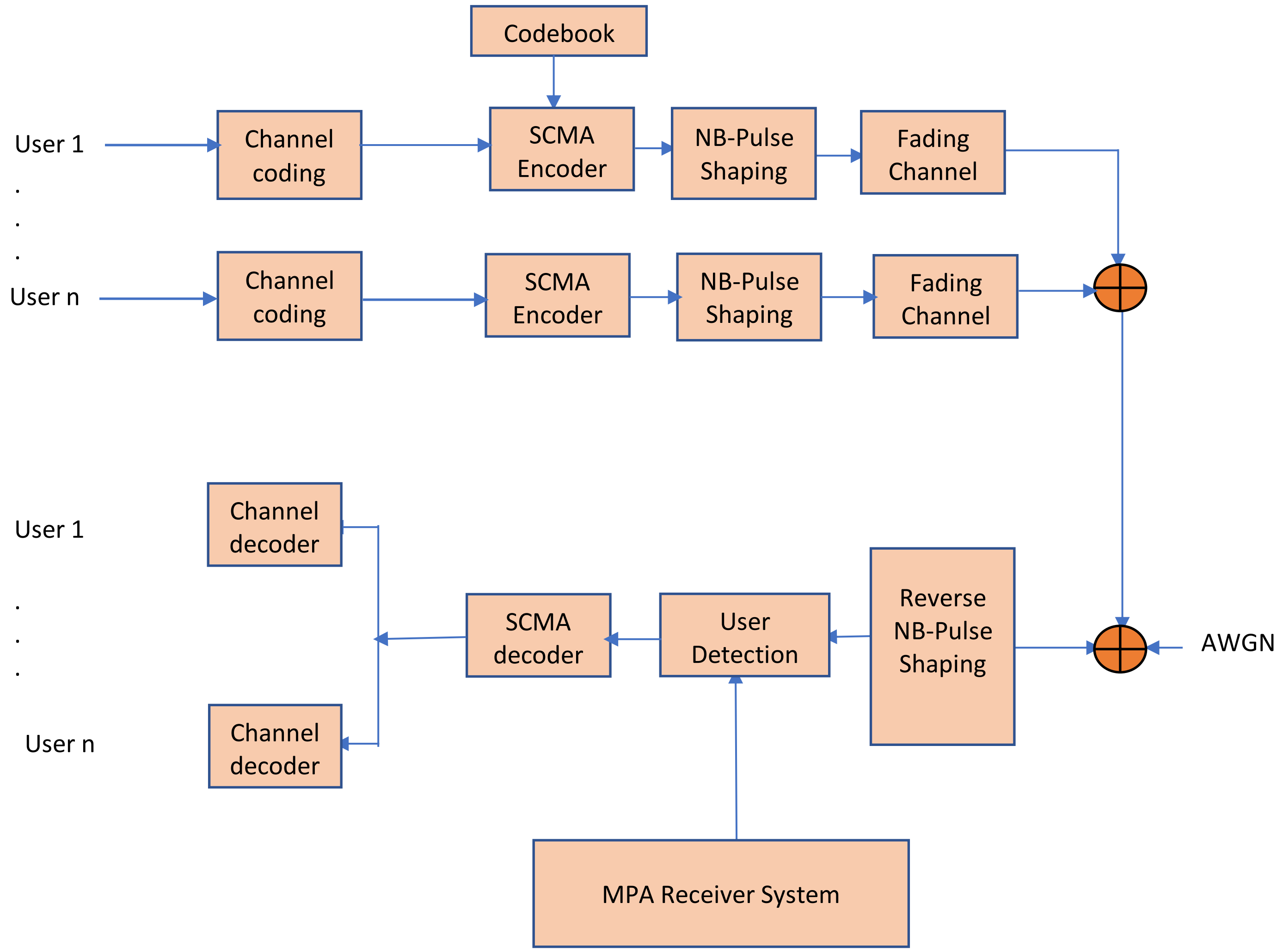

Fig. 3.8. A Narrowband SCMA system

The NB-SCMA different from the conventional SCMA system by the NB-pulse shaping block which follows the SCMA encode block. The NB-pulse shaping is the process of putting the data signal into filters to do up-sampling and achieve a frequency localized signal. Then, the signal is fed to the digital up converter to convert its baseband frequency to passband frequency. At the receiver side, a reverse NB-pulse shaping techniques are used.

CHAPTER 4

SEQUENTIAL LEARNING

4.1. Introduction

The current IoT application scenarios have several challenges such as network resource management, massive data processing, seamless coexistence with existing communication networks, and accuracy of event detection by IoT devices. To address those challenges and enhance effective deployment of massive IoT devices within the existing network, many self-organizing solutions have been studied. The literature related to such solutions is very wide. Hence, we restrict our discussion to only a few learning frameworks which have been used as the most promising solutions in many IoT applications or use-cases. Such learning frameworks have been used to enable the autonomous operation of IoT devices in many dynamic environments. However, to develop learning frameworks for the IoT applications, it is important to consider certain unique characteristics of IoT devices like resource constraints, heterogeneity of messages, and stringent QoS requirements. Machine learning, sequential learning, and reinforcement learning are the most common learning frameworks suitable for IoT applications [14]-[18]. These learning frameworks have their own advantages, disadvantages, and constraints in terms of resources used in the learning process as summarized in the table 4.1. In this research, since we considered the resource constrained and limited memory NB-IoT devices we used sequential learning as a learning framework to allocate resources in the massive uplink communications of the IoT devices. In the coming sections we will discuss different learning frameworks, finite memory sequential learning and the related algorithms.

4.2. Different learning Schemes in IoT

Due to the massive scale of the IoT devices and their applications to different sectors, self-organizing frameworks are inevitable solutions as it is difficult to manage the devices manually. Sometimes the operation of the devices will be in a situation that allows only a minimal human intervention. Besides, the IoT devices could be applied in various environments based on the uses-cases and applications. For example, an application for a smart city involves the deployment of many different IoT devices, fire-sensors deployed across a large area of a forest, devices spread across a large area in a smart agriculture, environmental monitoring sensors such as temperature sensors, and for indoor applications such home automation. The application could involve reporting unpredictable events such as burglar alarms, fire alarms, and medical emergency information. Those events must be reported with low latency and high reliability as they are critical information. The use of learning frameworks enhances performance of the operation in the IoT landscape so that the devices will adapt to their changing environments and effectively manage limited resources. The learning frameworks enable the devices learn about their surroundings, the nearby devices, and their resource allocation patterns. For instance, the IoT devices can learn about peak workload in the network and save energy by adjusting their mode as active-mode or sleep-mode. The learning frameworks can also be employed to facilitate coordination among the IoT devices and HTC devices for using the limited radio resources. If there are critical events triggering urgent uplink transmissions of information, certain portion of the limited radio resources can be allocated based on the adopted learning procedure.

Hence, learning frameworks can be used in various IoT application scenarios to optimize power usage, extend the battery life, to reduce the UL communication bottleneck due to limited radio resources for massive scale of IoT device, to enhance a coexistence of IoT networks with the HTC networks, and employ computationally efficient cloud-based hardware to process the bulky data from IoT systems [14].

4.2.1. Machine Learning

Machine learning and various kind of related algorithms were developed to enable computers and other information processing machines autonomously learn information from predetermined data sets and build appropriate models for making decisions on future actions and inputs. Machine Learning (ML) techniques are typically divided into two categories, namely supervised and unsupervised learning [18]. Their difference lies in the fact that the supervised learning needs a labeled training data set, whereas unsupervised learning, does not need labeled data sets. But, the computational complexity of unsupervised learning is larger than supervised learning. The major limitation of using ML in IoT applications is that the performance of ML depends on the use of extensive data set. The ML framework may need the information about the location of the devices and the measured values. The ML algorithms can effectively process such data sets and enable the IoT devices learn their environment. However, the IoT devices are resource-constrained with limited computation capacity and memory size. Hence, cannot store and process the massive IoT data set. Besides, supervised learning requires a labeled training data set and needs human intervention to give the correct labels. Hence, the use of ML must take such IoT device features and limitations into consideration. Yet, with the cloud-based centralized processing techniques, ML techniques create a great opportunity for processing and analyzing the massive IoT data.

4.2.2. Reinforcement Learning

Reinforcement learning (RL) is one of the learning frameworks used in a wide range of IoT applications. RL is a technique in which several agents learn how to interact with their environment. In RL, the learning framework consists of several agents having a specific set of actions, their corresponding environment with a predetermined set of states, a given initial observation function, a predetermined state transition function, the corresponding and immediate reward function [14]. Starting at each period, the agents observe their environment and take actions to maximize their immediate or future rewards. After the specified period is over, the agents get their immediate rewards. At the same time, there is a change in the state of the environment which is by the state transition function. The agents iteratively continue the learning process and finally converge to a steady state. RL is a computationally simple scheme but it takes a prolonged duration to converge to a steady state. But, there is no need for remarkable interactions between the devices determined over M2M network which is common in SL. Hence, it saves energy to achieve the equilibrium points and avoids the need for the agents be synchronized globally and have the same rate of learning. Besides, RL algorithms are computationally simple for the low-cost and limited capacity IoT devices.

4.2.3. Sequential Learning

Sequential learning (SL) is one of the enabling techniques used for IoT applications as a suitable learning framework [15]. In SL, several autonomous agents or IoT devices will sequentially communicate with each other to learn an underlying binary state in an environment. The underlying binary state represents the status of the IoT device environment where the devices are located. For example, it could represent events of interest such as a medical status in an e-health application, a fire alarm in a smart home, or other environment-triggered critical events in the IoT network. SL enables the agents to learn the underlying state of the environment by following specific sequence. The agents will also observe their environment and the behaviors or observations of previous agents in a sequence. Finally, the agents will converge to a consensus on the true underlying binary state. This is based on repeated hypothesis testing as discussed in [15]. The SL framework is chosen to support the NB-IoT devices learn about their environment and coordinate with other agents or devices for effective resource allocation. In the coming sections, we will discuss SL in detail.

4.2.4. Cognitive Hierarchy Theory

The heterogeneity of the IoT environment requires a learning framework that can efficiently capture the heterogeneity in terms device types, levels of available resources and their computational capacity. In cognitive hierarchy theory (CHT), different levels of resource capabilities and availabilities within the IoT devices are represented by different levels of rationality. Based on their levels of rationality, the IoT devices are mapped to different learning frameworks that will also depend on the available resources [14]. Hence, with CHT, it is possible to integrate different learning techniques at different levels rationality in the IoT landscape. This helps to maximize the overall resource usage using a more realistic model for a heterogeneous IoT environment.

4.3. Sequential Learning for IoT

In addition to observing their environment, the agents in a SL learning framework will also need to know the observation of previous agents and their estimates of the underlying binary state. Hence, based on the number of previous estimates or the number of agents required in a given sequence, there are two categories of SL namely: infinite memory SL(IMSL) and finite memory SL (FMSL) [16], [17]. In the case of infinite memory SL, the involved agents are required observe all the previous agents in their sequence. Thus, IMSL has a memory requirement that grows infinitely with the number of agents involved. For FMSL the number of observations is limited to a fixed number of previous agents, and hence, the required memory for estimates from previous agent is fixed. FMSL approach is suitable for the IoT applications as it can easily converge to the correct underlying state by only observing two of the previous agents as proved in [15]. As shown in the fig 4.1., a SL framework relies the M2M communication between the agents for exchanging their estimate of private signals. Hence, the devices cannot learn if they don’t communicate with other devices.

4.4. Finite Memory Sequential Learning

The major advantage of applying SL for IoT applications is its flexibility with memory requirements. In FMSL, the devices can rely only on a fixed number of previous observations, and the SL can converge [15]. Hence, the IoT devices determine the size of information used for SL based on their available resources. In IMSL, the amount of information required for SL will grow indefinitely as learning progresses in the sequence of agents. As a result, the size of the packets communicated over the M2M networks grows infinitely.

Table 4.1. Summary of different Learning frameworks

Learning frameworks	**Advantages**	**Limitations**	**Applications**
Machine Learning	➢ Various techniques are available with several applications ➢ Used for processing the bulk data collected in IoT to reduce resource consumption ➢ Enabler technique for big data analytics and predictive	➢ Needs centralized implementation ➢ Needs significant amount of computational capacity ➢ Needs extensive data set for training	➢ Data aggregation and compression ➢ Query processing ➢ Big data analytics ➢ IoT security
Sequential Learning	➢ Enables distributed implementation ➢ Enables flexible memory and resource allocation ➢ No need for extensive knowledge of the system ➢ Ability to effective learn unknown parameters	➢ Dependent on M2M for communication ➢ Only for binary state learning ➢ Needs private signal for learning	➢ Event detection ➢ Dynamic resource management under uncertainty ➢ Network operation adaptation
Reinforcement Learning	➢ Enables distributed implementation ➢ Asynchronous operation is possible ➢ Achieves lower computational complexity ➢ Game-theoretic equilibrium solutions can be achieved	➢ Incurs overhead for reaching steady state ➢ Needs complete information about state transition ➢ Computational complexity is higher for incomplete data	➢ Power control ➢ IoT radio resource management ➢ Dynamic scheduling for energy efficiency ➢ Possibility to use drones for enhanced communication

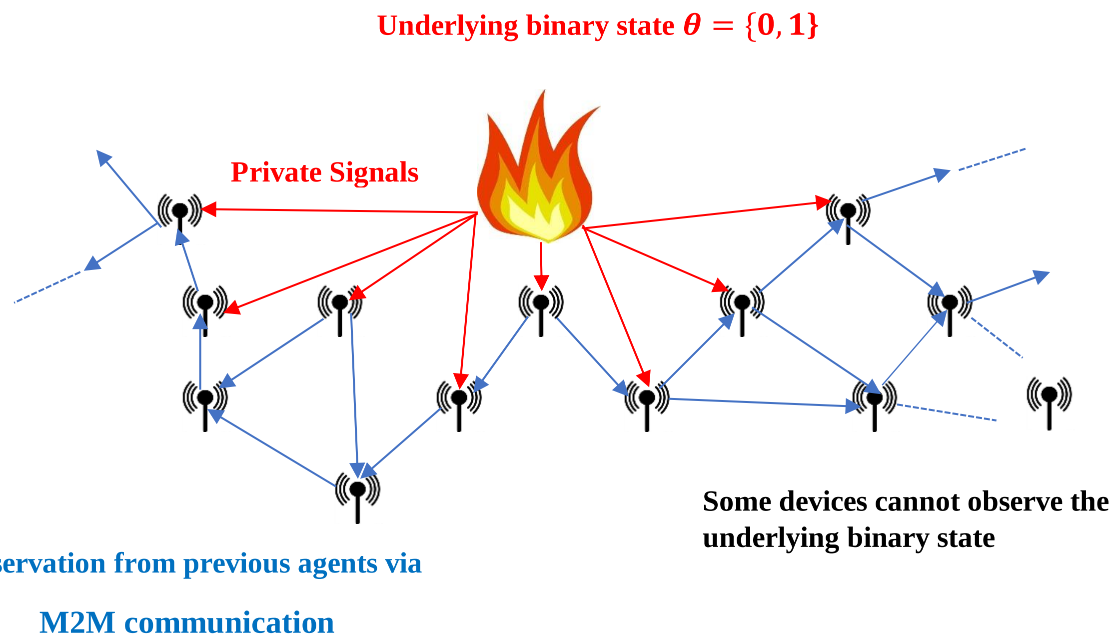

Figure 4.1: An example of sequential learning in IoT

Thus, the IMSL is not suitable for the resource-constrained IoT devices. Therefore, we adopted FMSL for the CB-SCMA so that the IoT device can effectively learn about their underlying binary state and communicate their private signals. Sequential learning is a decision-making process in which certain agents, the IoT devices in this work, sequentially estimate an underlying binary state $\theta = \{0,1\}$ from the observation of their own private signal and the estimated values of private signals of their predecessors. The private signals are modelled as random variables which are independently and identically distributed for different agents.The private signal have some probability of inferring true θ. Here, $\theta = 1$ indicates the occurrence of a critical event such as fire alarm and $\theta = 0$, means there is no alarm message. In the learning process there is no central entity to support the decision process. Hence, the sequential learning is applied to an IoT application scenario to capture the message diversity among the devices that will learn about occurrence of an abnormality near another device and avoid using the resources allocated for the critical messages after reaching a consensus. In this way, enough CTUs are allocated for α critical messages while the rest (C- α) CTUs are allocated for periodic messages whose minimum periodicity depends on [17],

$$\tau_{min} = \left\lceil \frac{\mathrm{U}-\alpha}{\mathrm{C}-\alpha} \right\rceil \tag{4.1}$$

The sequential learning in this work is called finite memory sequential learning in which the agents depend only on a limited number of private signals from previous agents to estimate the undelying binary state.Besides,the IoT devices considered in this work are resource-contrained interms of computational capacity, power and memory. Hence,only F,finite memory size , of the previous agents will be considered for the learning process. Only few steps are enough to effectively estimate the undelying binary state whose convergence is proved in [15].

4.5. Sequential Learning Algorithms

To avoid duplicate code usage and hence,avoid packet drop of critical messages,the FMSL is modeled as given in [17],

$$\left\{x_{j-F+4}, \ldots, x_{j-1}, T_{j-1}, Q_{j-1}, i, C_i\right\} \tag{4.2}$$

where $\left\{x_{j-F+4}, \ldots, x_{j-1}\right\}$ represents (F-4) private signals. Minimum of 4-bits memory are required to capture all the parameters for the learning process which will also include the parameters T_{j-1}, and Q_{j-1} used to track the learning process and update the current estimate of true θ. The parameters i and C_i represent the IoT devices with critical messages and the corresponding CTU allocated to enable others device learn about CTUs used by other devices. In FMSL, as discussed in [16],the devices estimate the maximum likelihood of the true θ based on the previous private signals $\{x_i\}$. An IoT device will determine its private belief b_i based on,

$$b_i = arg\max_{\theta} P_r(x_{i-F+4}, \ldots, x_{i-1}/\theta) \tag{4.3}$$

$$= arg\max_{\theta} \prod_{j=i-F+4}^{i} P_r\,(x_j\,/\Theta), \tag{4.4}$$

$$= arg\max_{\theta} \prod_{j=i-F+4}^{i} p_{1\Theta}^{x_j} p_{0\Theta}^{1-x_j} \tag{4.5}$$

The $p_{1\Theta}$ and $p_{0\Theta}$ represent the conditional probabilities of estimating the true θ given that the event has happened or not,respectively. Based on likelihood ratio test of (4.5) and assumptions that p_{10} , the probability of observing a critical alarm while there is no such an alarm ,is negligible compared to p_{11} ,the probability of observing alarm while a user has a critical message,the private belief of an IoT device will i be:

$$b_i = \begin{cases} 1 & if \left(\sum_{j=i-F+4}^{i} x_j\right) \geq 1 \\ 0 & otherwise \end{cases} \tag{4.6}$$

The private belief of the IoT devices that don't readly know p_{10} and p_{11} will be 1 if any of the private signals is 1. The probability of b_i reflecting true θ is dependent on the memory size F and will be more informative about true θ than the private signals x_i as can be shown in,

$$P_r(b_i = 1/\theta = 1) = 1 - p_{01}^{F-1} = 1 - (1 - p_{11})^{F-1} \tag{4.7}$$

CHAPTER 5

CB-SCMA FOR NB IOT WITH FMSL

5.1. System model

In this work we consider an uplink communication of U narrowband IoT devices with a base station located in the center of a given geographical area A. We assume an uplink communication of the IoT devices that will rely on CB SCMA wherein the CTUs are allocated based on finite memory sequential learning algorithms. We will consider a total of C CTUs in a given contention region (as shown in fig.1) which is defined at a given time slot. There are far larger number of devices than the number of CTUs. Hence, the preconfigured or designed SCMA codebooks that are already known can be used in all subsequent contention regions or time slots. The IoT devices that are distributed in the give area are assumed to have heterogeneous message types. There are critical messages that require urgent transmission using the available CTUs. Since the critical messages are delay sensitive, such as forest-fire alarm and other security alerts, the devices learn about the status of their neighboring devices will not use the CTUs allocated for critical messages. The periodic messages which are delay tolerant can rely on the remaining CTUs. The communication between the devices for sequentially passing the previous private signals of other devices for learning process is assumed to be carried out via the control plane signaling channel or M2M communication.

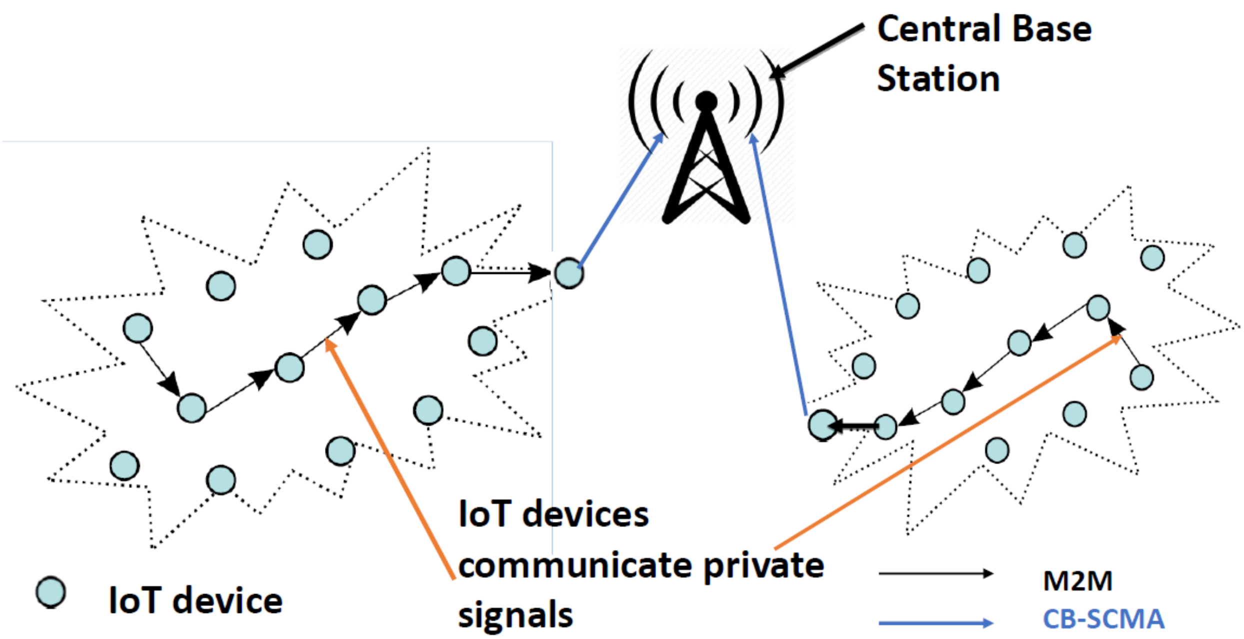

Fig 5.1. System Model for CB-SCMA with FMSL

5.2. Analysis of SL model

In the FMSL that is used in this work we assume that the learning process is initiated by one of the IoT devices that has already learned the true θ. It will initiate the neighboring devices within the communication range r_c. There should be at least one device within range r_c so that the learning process starts. The performance of FMSL depends on the geographical location of the points where critical messages are generated. Hence, we define r_d to represent a distance from a critical event within which a device can observe the event with high a probability. But, the devices located at a point further than r_d may not correctly observe the event and their private signal is less informative. The effective observation radius r_d^{eff} for a critical event is dependent on the number of agents involved in the learning which is determined by the size of F-bits of memory. Hence,

$$r_d^{eff} = r_d + (F - 4)\, r_c \tag{5.1}$$

This is because there are $(F - 4)$ bits of previous private signals and the number of private signals that are from the devices within the observation range will be zero as the learning progresses

$(F-4)$times. So, there is a device with an informative located as far as $(F-4)\ r_c$ from r_d .It is important to consider the time dependence of r_d^{eff} as $r_t^{eff} = \min(r_c\,t, r_d^{eff})$ by noting that the devices will learn the true θ after t of the occurrence of the critical event. Hence, the random variable that represents the number of devices that will correctly learn the true θ and change the usage of CTU is [17],

$$\frac{U\pi {r_t}^2}{4A} \leq E[N_t] \leq \frac{U\pi {r_t}^2}{A} \tag{5.2}$$

$$\frac{U\pi {r_t}^2}{4A.C.\tau_{min}} \leq E[P_t] \leq \frac{U\pi {r_t}^2}{A.C.\tau_{min}} \tag{5.3}$$

Since, in (5.2) we consider a rectangular area of A, the upper bound and the lower bound of the expected number of devices is expected to occur at the center and edge of the geographical area, respectively. The devices A the center of the area, there are more devices in the observation range and more devices will quickly learn about the occurrence of a critical event that when the event happens at the edge of the area where there may be few devices for the learning to progress. After the learning process converges, the devices with periodic messages periodicity of τ_{min} learn to change the codes allocated for critical messages. Hence, the probability of successful transmission is given by (5.3).

5.3. Number of Connections in CB-SCMA

Compared to OFDMA, contention-based SCMA supports more number of UEs. This is due to the overloading factor which can be chosen to be greater than 1(1.5,3 or more). In CB-SCMA transmission scenario there are E orthogonal resources in a certain time-frequency region (contention region). Due to sparsity of codewords only H out of E resources are occupied in SCMA. However, All E resources are used for OFDMA.

Hence, the number of UEs that can be supported in uplink SCMA will be:

$$N_{SCMA} = C_E^H \mathrm{xLx} m_1 \tag{5.4}$$

where m_1 UEs share the same CTU on average

For OFDMA, the number of UEs in the uplink will be:

$$N_{OFDMA} = \mathrm{Ex} m_2 \tag{5.5}$$

where m_2 UEs share a CTU on average

Capacity gain of SCMA over OFDMA will be:

$$\text{Gain}=\frac{C_E^H \text{xLx} m_1}{\text{Ex} m_2} \tag{5.6}$$

For $H \geq 2, 2 \leq H \leq \text{E}$, $L \geq 2$ and assuming $m_1 = m_2$ the next figure shows the connection gain of CB-SCMA over OFDMA.

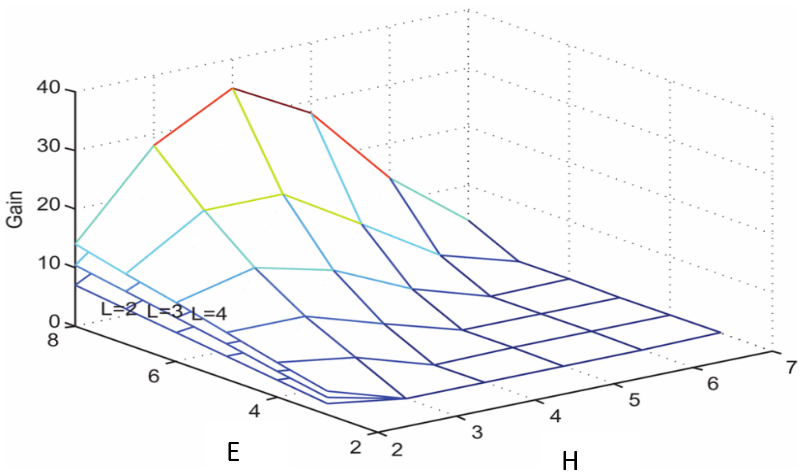

Fig 5.2. Connection gain of CB-SCMA over OFDMA

The packet drop rate for a CB-SCMA system can be defined as the probability of its first transmission failing. Fig.5.3 shows that the effect of packet collision is higher when there are more users that share same CTU. Hence, Finite memory sequential learning (FMSL) is proposed for the above systems.

A packet drop rate is:

$$r_{lost=1-(1-\alpha)^{m-1}} \tag{5.7}$$

where α is probability that each user sends packet at anytime.

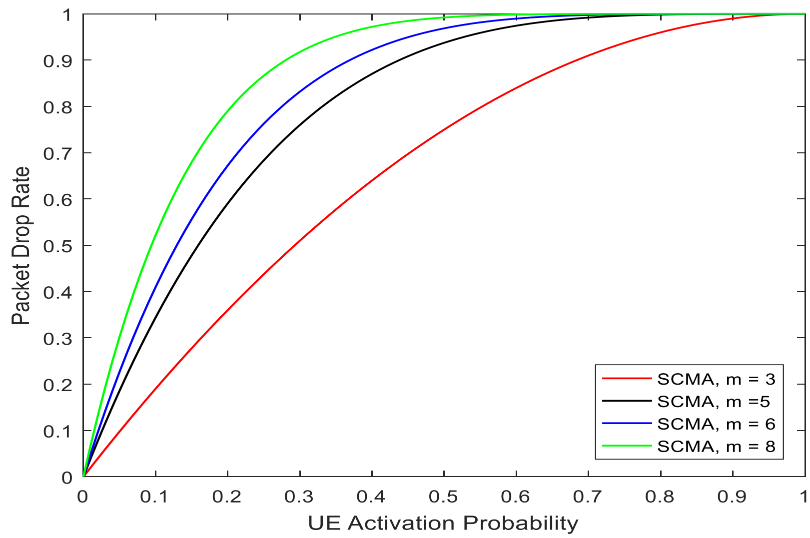

Fig 5.3. Packet drop rate of CB-SCMA

5.4. Analysis of Probability of collision

In this work, we analyze the collision probability within the CTU, where the number of IoT devices assigned within one CTU is not large enough. Hence, the binomial distribution is used here. The probability that *m* UEs send data simultaneously follows the binomial distribution, which can be written as

$$P_{conv}=\frac{C\sum_{m=2}^{n} p_{n.m.p} m \sum_{m=1}^{n-1} p_{n-1.m.p}(m+1)+C(1-\sum_{m=2}^{n} p_{n.m.p} \sum_{m=2}^{n} p_{n.m.p} m)}{Cnp} \quad (5.8)$$

In sequential learning for the devices that successful learn about the other devices and avoid using their CTU, the collision probability, based on analysis in [7], will be:

$$P_{SL}=\frac{((m+1)(1-na)-n(1-a)(np)\left(1-q^{n-1}\right)+ \left(n(1-a)-m(1-na)((n+1)p)\left(1-q^{n-1}\right)\right))}{np} \quad (5.9)$$

$$a=\sum_{m=2}^{n} p_{n.m.p}=\sum_{m=2}^{n}\binom{n}{p} p^{m} q^{n-m} \quad (5.10)$$

Where n is the average number of devices assigned to a CTU.

CHAPTER 6

RESULTS AND DISCUSSIONS

Numerical Results and Analysis

In the numerical analysis we considered a contention based SCMA system $U = 1500$ devices are deployed in a geographical area with square shape, and side, $S = 50m$. Hence, the area is $A = 2500m^2$. To capture the nature of the user density in the area we assumed the poisson point process with parameter λ. Hence the effective number devices will be $A\lambda$. The number of CTUs available for the devices is chosen based on works in [7], $C = 28$ which belongs to $J = 7$ and $L = 4$ and and $C = 280$ belongs to $J = 70$ and $L = 4$. The observation range r_d of 10m and r_c of 2m for the inter-device communication range to achieve learning is considered. Since, the IoT devices are communicating very short messages, the unit for time slot in which a contention happens is considered as 1 second.

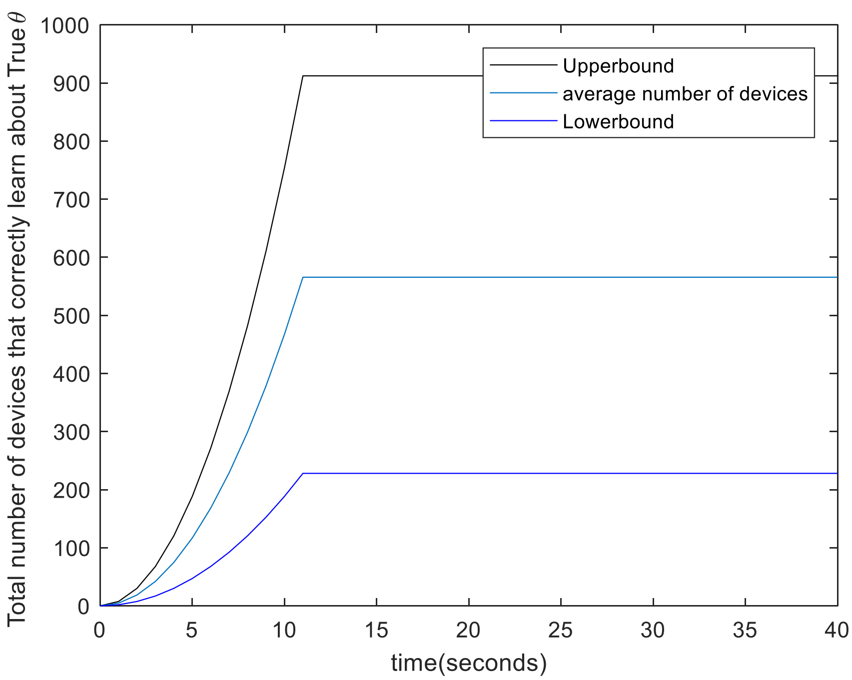

Fig. 6.1. Lowebound,average and upperbound on the number of devices that will correcly learn about the status of their neighbouring devices.

In the fig.6.1, Lowebound,average and upperbound on the number of devices that will correcly learn about the status of their neighbouring devices is shown. The number of devices that correctly learn the true value of the binary state θ and change their allocated CTUs increases with time as more devices are reached as the learning progresses. The rate of increase of the number of devices is higher, at the beginning when the learning is initiated, for the upper bound than the lowe bound. This is due to the fact that the upper bound captures the effect of learning in the center of the area where more devices are likely to have neighbouring devices within their communication range. Hence, the learning progresses fast and finally reaches a saturation point where the learning ceases due to the Finite memory nature of the system.

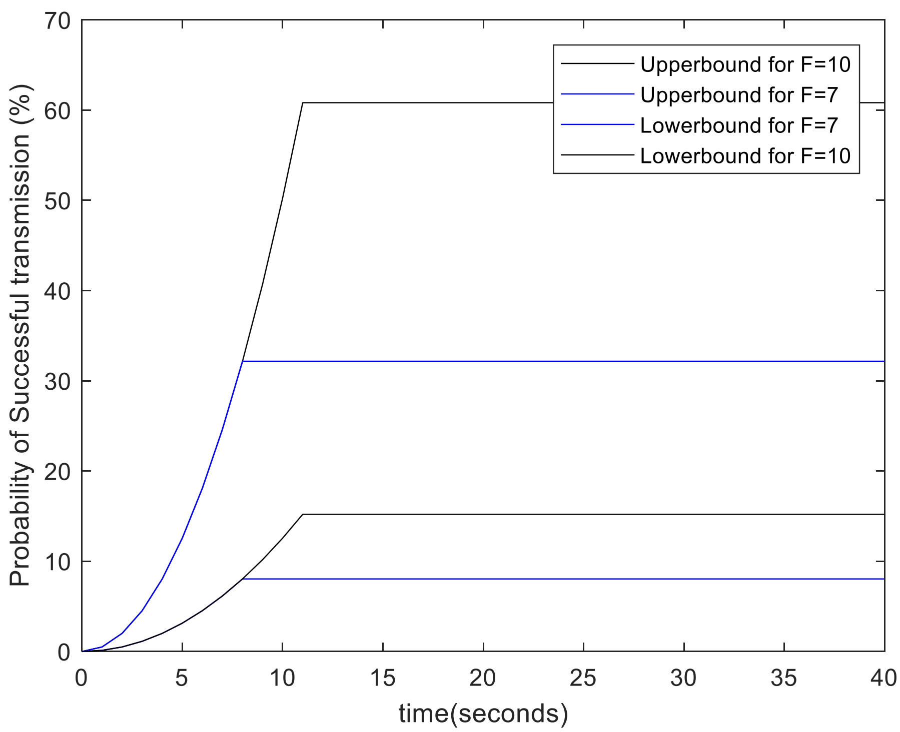

Fig 6.2. Probability of successful transmission at different values of F

The Probability of successful transmission at different values of K has been shown in the fig 6.2. As a main feature of FMSL, the upper and lower bounds for the probabilities of successful transmission indicate the possible region in which the learning is successful as the it progresses to the nearby devices with time. The probability of successfully learning about the underlying binary state is increasing with time as more devices are reached once the learning process is initiated. The memory size can be chosen based on the type of application or the capacity of the devices involved in the learning procedure.

Even though the larger values of F have better convergence and achieve higher probability of successful transmission and hence, more reliable the are chosen at the cost of increased communication overhead due to the M2M communication involved for exchange of the learning parameters.

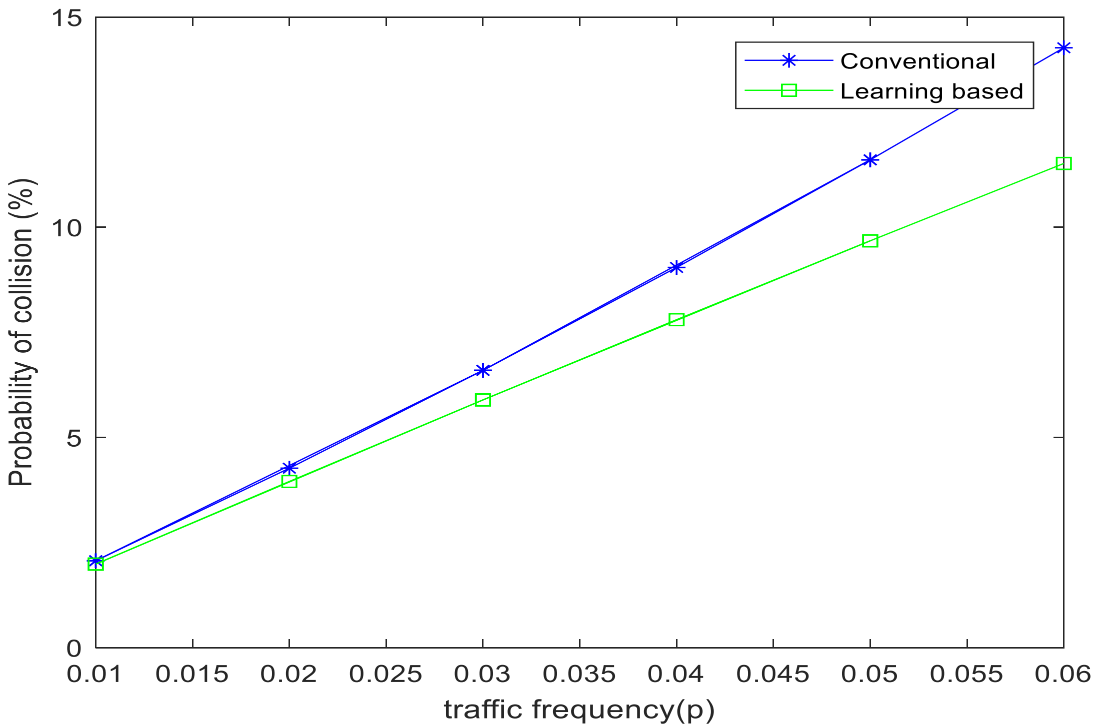

Fig 6.3. Probability collision for the proposed learning scheme and a conventional scheme

In the fig.6.3 we observed that the learning based scheme proposed for the CB-SCMA has lower probability of collision as the traffic frequency increases. This is due to the fact that more devices will learn about the resources used by the other devices in the network and hence, a reduction in packet collision over a given CTU.

CHAPTER 7

CONCLUSIONS AND FUTURE DIRECTIONS

7.1. Conclusions

In this research we investigated the potential of using Contention-Based SCMA scheme in the newly standardized Narrow Band IoT (NB-IoT) technologies that have diverse application as a low power wide area (LPWA) communication. Since resource allocation is a major challenge in such devices, Finite Memory Sequential Learning (FMSL) was proposed to consider the message diversity and enable the devices learn about the status of other devices to improve the usage of limited resources and delivery of the messages. The contention based SCMA with FMSL system was studied in terms probability of successful transmission and the number of IoT devices that will correctly learn about the status of the nearby devices which depends on with memory size F. Finally, we conclude that, the contention based SCMA with FMSL system shows improved performance in terms probability of successful transmission and the number of IoT devices that will correctly learn about the status of the nearby devices which increases with memory size F. Hence, FMSL improves system performance in terms of delivery of critical messages which are assigned certain codes after the learning process converges. When the devices are assigned certain codes after the learning process converges, the probability of collision decreases as compared to conventional systems.

7.2. Future Directions

In the next part of this work an elaborate study will be carried out to consider the effect of the learning process on the delay of the critical messages, the probability of collision when certain devices near the edge of the area are not involved in the effective observation area for learning, the tradeoff between increasing memory size F and the reduction of system throughput due to the M2M communication for learning procedure. There are still many open issues that can be studied in relation to CB-SCMA in NB-IoT scenario. Two major issues are the consideration of the heterogenous NB-IoT devices, and the energy management in the devices. For example, energy harvesting, conservation and consumption, in NB-IoT systems can be considered.

REFERENCES

[1] 5G Americas White Paper on Cellular Progress Toward IoT,December,2017.

[2] O.Liberg, M.Sundberg, E.Wang, J.Bergman and J. Sachs, Cellular Internet of Things: Technologies,Standards and Performances, 1st ed.,London,UK: Elsevier,2018.

[3] Y. Miao, W. Li, D. Tian, M. S. Hossain and M. F. Alhamid, "Narrow Band Internet of Things: Simulation and Modelling," in *IEEE Internet of Things Journal*.

[4] J. Wang, C. Zhang, R. Li, G. Wang and J. Wang, Narrow-Band SCMA: A New Solution for 5G IoT Uplink Communications," *2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)*, Montreal, QC, 2016, pp. 1-5.

[5] M. Taherzadeh, H. Nikopour, A. Bayesteh, and H. Baligh, “SCMA codebook design,” in IEEE 80th Vehicular Technology Conference (VTC Fall), 2014, pp. 1–5.

[6] H. Nikopour and H. Baligh, “Sparse Code Multiple Access,” *Proc. IEEE PIMRC*, London, UK, Sept. 2013.

[7] K. Au *et al*., "Uplink contention based SCMA for 5G radio access," *2014 IEEE Globecom Workshops (GC Wkshps)*, Austin, TX, 2014, pp. 900-905.

[8] D. Lin, G. Charbit and I. K. Fu, "Uplink Contention Based Multiple Access for 5G Cellular IoT," *2015 IEEE 82nd Vehicular Technology Conference (VTC2015-Fall)*, Boston, MA, 2015, pp. 1-5.

[9] A. Li, X. Chen and H. Jiang, "Contention Based Uplink Transmission with NOMA for Latency Reduction," *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*, Sydney, NSW, 2017, pp. 1-6.

[10] N. Lee and Y. Choi, "A contention based uplink scheduling request method in LTE-A," *2015 International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju, 2015, pp. 1022-1024.

[11] S. Han, X. Tai, W. Meng and C. Li, "A resource scheduling scheme based on feed-back for SCMA grant-free uplink transmission," *2017 IEEE International Conference on Communications (ICC)*, Paris, 2017, pp. 1-6.

[12] C. Wang, Y. Chen, Y. Wu and L. Zhang, "Performance Evaluation of Grant-Free Transmission for Uplink URLLC Services," *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*, Sydney, NSW, 2017, pp. 1-6.

[13] J. Shen, W. Chen, F. Wei and Y. Wu, "ACK feedback based UE-to-CTU mapping rule for SCMA uplink grant-free transmission," *2017 9th International Conference on Wireless Communications and Signal Processing (WCSP)*, Nanjing, 2017, pp. 1-6.

[14] T. Park, N. Abuzainab and W. Saad, "Learning How to Communicate in the Internet of Things: Finite Resources and Heterogeneity," in *IEEE Access*, vol. 4, pp. 7063-7073, 2016.

[15] K. Drakopoulos, A. Ozdaglar, J. N. Tsitsiklis, "On learning with finite memory", *IEEE Trans. Inf. Theory*, vol. 59, no. 10, pp. 6859-6872, Oct. 2013.

[16] T. Park and W. Saad, "Learning with finite memory for machine type communication," *2016 Annual Conference on Information Science and Systems (CISS)*, Princeton, NJ, 2016, pp. 608-613.

[17] T. Park and W. Saad, "Resource Allocation and Coordination for Critical Messages Using Finite Memory Learning," *2016 IEEE Globecom Workshops (GC Wkshps)*, Washington, DC, 2016, pp. 1-6.

[18] M. Chafii, F. Bader and J. Palicot, "Enhancing coverage in narrow band-IoT using machine learning," *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, Barcelona, Spain, 2018, pp. 1-6.

[19] Z. Li, T. Braun, X. Zhao, Z. Zhao, F. Hu and H. Liang, "A Narrow-Band Indoor Positioning System by Fusing Time and Received Signal Strength via Ensemble Learning," in *IEEE Access*, vol. 6, pp. 9936-9950, 2018.

[20] Y. D. Beyene, R. Jantti, K. Ruttik and S. Iraji, "On the Performance of Narrow-Band Internet of Things (NB-IoT)," *2017 IEEE Wireless Communications and Networking Conference (WCNC)*, San Francisco, CA, 2017, pp. 1-6.

[21] C. Yu, L. Yu, Y. Wu, Y. He and Q. Lu, "Uplink Scheduling and Link Adaptation for Narrowband Internet of Things Systems," in *IEEE Access*, vol. 5, pp. 1724-1734, 2017.

[22] S. M. Oh and J. Shin, "An Efficient Small Data Transmission Scheme in the 3GPP NB-IoT System," in *IEEE Communications Letters*, vol. 21, no. 3, pp. 660-663, March 2017.

[23] W. Yang *et al*., "Narrowband Wireless Access for Low-Power Massive Internet of Things: A Bandwidth Perspective," in *IEEE Wireless Communications*, vol. 24, no. 3, pp. 138-145, June 2017.

[24] https://www.huawei.com/minisite/iot/img/nb_iot_whitepaper_en.pdf

[25] J. Zhang *et al*., "5G PoC of SCMA-Based Uplink Grant-Free Transmission in UCNC Framework," *2017 IEEE 85th Vehicular Technology Conference (VTC Spring),* Sydney, NSW, 2017, pp. 1-5.

[26] B. Singh, O. Tirkkonen, Z. Li and M. A. Uusitalo, "Contention-Based Access for Ultra-Reliable Low Latency Uplink Transmissions," in *IEEE Wireless Communications Letters*, vol. 7, no. 2, pp. 182-185, April 2018.

[27] Z. Zhao, D. Miao, Y. Zhang, J. Sun, H. Li and K. Pedersen, "Uplink Contention Based Transmission with Non-Orthogonal Spreading," *2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)*, Montreal, QC, 2016, pp. 1-6.

[28] A. Bayesteh, E. Yi, H. Nikopour and H. Baligh, "Blind detection of SCMA for uplink grant-free multiple-access," *2014 11th International Symposium on Wireless Communications Systems (ISWCS)*, Barcelona, 2014, pp. 853-857.

[29] C. Wang, Y. Chen, Y. Wu and L. Zhang, "Performance Evaluation of Grant-Free Transmission for Uplink URLLC Services," *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*, Sydney, NSW, 2017, pp. 1-6.

[30] S. Zhang, X. Xu, L. Lu, Y. Wu, G. He and Y. Chen, "Sparse code multiple access: An energy efficient uplink approach for 5G wireless systems," *2014 IEEE Global Communications Conference*, Austin, TX, 2014, pp. 4782-4787.

[31] Z. Bai, B. Li, M. Yang, Z. Yan, X. Zuo and Y. Zhang, "FH-SCMA: Frequency-Hopping Based Sparse Code Multiple Access for Next Generation Internet of Things," *2017 IEEE Wireless Communications and Networking Conference (WCNC)*, San Francisco, CA, 2017, pp. 1-6.

Research Achievements

Bayisa Taye Mulatu, Zhenni Pan, Jiang Liu, Shigeru Shimamoto, "Contention-Based SCMA for Narrow-Band Internet of Things using Sequential Learning", in a proceeding of the 37th JSST Annual International Conference on Simulation Technology, Muroran Institute of Technology, Muroran City, Hokkaido, Japan, September 18-20, 2018.