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Energy efficient and scalable channel coding and clustering approach for narrowband internet of things (NB-IoT)

Munguakonkwa Emmanuel Migabo

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ÉCOLE DOCTORALE
«Mathématiques, Sciences et Techniques de l'Information et de la Communication»

Thèse de doctorat

Spécialité : Informatique

Munguakonkwa Emmanuel Migabo

*Approches de Codage Canal et de Regroupement Efficace en
Consommation Énergétique et Évolutif en Taille de Réseaux pour
l'Internet des Objets à Bande Étroite (NB-IoT)*

Février 2021

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Declaration

“I hereby declare that the thesis submitted for the degree of Doctor of Philosophy: Computer Science, at the Université Paris-Est (UPE) jointly with the degree of Doctor of Engineering: Electrical at the Tshwane University of Technology(TUT), is my own original work and has not previously been submitted to any other institution of higher education. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references”.

M.E. Migabo

Date



February 17, 2021

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Dedication

This work is firstly dedicated to my beautiful daughter Angelina Mugoli Migabo who has been my main source of motivation and inspiration in completing this work. I hope that I have inspired her to do better than me when she grows up. Secondly, this work is dedicated to my lovely wife Sandrine Neema Bigabwa for her great support throughout this journey. Finally, this work is dedicated to my family; to my dear father Jean Bagula Migabo, to my dear mother Francine Bishikwabo Baliahamwabo, to my beloved siblings and in-laws. I would not have been who I am today without your indescribable love and support. I will forever remain grateful to you and love you all.

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Abstract

The Narrowband-Internet of Things (NB-IoT) is one of the leading licensed Low Power Wide Area Networks (LPWANs) that is expected to play a very important role in connecting the exponentially increasing number of connected devices that make up the Internet of Things (IoT). To enable its network scalability, NB-IoT requires more efficient utilization of its limited energy, channel capacity, and spectrum network resources. These characteristics place various constraints in terms of the design of the physical (PHY) channel coding and spectrum access as well as the network layer protocol for the NB-IoT. A few existing channel coding approaches have been proposed to enhance the NB-IoT's network reliability, and therefore, enable long-distance transmissions. However, most of the existing NB-IoT channel coding approaches are based on repeating transmission data and control signals and do not consider the channel conditions. Although these repetitions ensure network reliability, they are energy expensive and compromise the performance of the data rate of the network. At the same time, the increasing number of devices to be handled by a single Base Station (BS) within a cell increases the probability for interlink interference which compromises the uplink communication reliability, further increases the number of required data transmission repetitions, and therefore, reduces the overall energy efficiency of the network. To mitigate these identified problems, a multi-layer approach is proposed in this study. Firstly, a channel-aware two-dimensional Energy-Efficient Adaptive Channel Coding (EEACC) approach is considered at the PHY layer. The EEACC not only selects an appropriate modulation coding scheme

(MCS) based on the estimated channel conditions (dynamically classified as bad, medium or good based on a periodically assessed BLER performance outcome) but also minimizes the transmission repetition number under a pre-assessed probability of successful transmission. Secondly, at the PHY and network layers, the study considers a two-layers NB-IoT mixed spread spectrum and clustering approach with network coding (N-MANC). At one layer, the approach uses an Adaptive Frequency Hopping Spread Spectrum (AFHSS) technique that uses a lightweight and secure pseudo-random sequence with a varying period T depending on the number of NB-IoT nodes in the considered cell to exploit the channel diversity as a way to mitigate inter-link and cross-technology interference. At the second layer, the mixed approach consists of a cooperative clustering approach based on a defined energy-signal strength gradient used for Cluster Head (CHs) selection, and a network coding (data aggregation) to further boost the overall energy efficiency of the network. A systematic mathematical model of the NB-IoT PHY layer is first developed and modelled. Then, the proposed algorithms are implemented and validated in MATLAB. The obtained simulation results demonstrate that the important QoS metrics such as energy efficiency, network reliability, data rate, transmission latency, network scalability, and lifetime are improved by the proposed algorithms when compared to existing approaches.

Résumé

L'Internet des objets à bande étroite (NB-IoT) est l'un des principaux réseaux étendus à basse consommation énergétique (LPWAN) dans la bande des fréquences sous licence d'utilisation, qui devrait jouer un rôle très important dans la connexion du nombre exponentiellement croissant d'objets connectés qui composent l'Internet des objets (IoT). Pour permettre l'évolutivité de son réseau, la NB-IoT nécessite une utilisation plus efficace de son énergie limitée, de la capacité de ses canaux et des ressources du spectre du réseau. Ces caractéristiques créent ainsi diverses contraintes en termes de conception du codage physique des canaux (PHY) et de l'accès au spectre ainsi que du protocole de la couche réseau pour l'Internet des objets. Quelques approches de codage de canal existantes ont été proposées pour améliorer la fiabilité du réseau de la NB-IoT et permettre ainsi les transmissions à longue distance. Cependant, la plupart des approches de codage de canal existantes de la NB-IoT sont basées sur la répétition des données de transmission et des signaux de contrôle et ne tiennent pas compte des conditions du canal. Bien que ces répétitions assurent la fiabilité du réseau, elles sont coûteuses en énergie et compromettent les performances du réseau en matière de débit de données. En même temps, le nombre croissant de dispositifs devant être traités par une seule station de base (BS) au sein d'une cellule augmente la probabilité d'interférences entre les liaisons, ce qui compromet la fiabilité de la communication sur la liaison montante, augmente encore le nombre requis de répétitions de transmission de données et, par conséquent, réduit l'efficacité énergétique globale du réseau. Pour pallier ces divers problèmes identifiés, une approche multicouche

est proposée dans cette thèse. Tout d’abord, une approche bidimensionnelle de codage de canal adaptatif économe en énergie (EEACC) est proposée au niveau de la couche PHY. L’EEACC ne se contente pas de sélectionner un schéma de codage de modulation (MCS) approprié en fonction des conditions estimées du canal (classé dynamiquement comme mauvais, moyen ou bon sur la base d’un résultat de performance BLER évalué périodiquement), mais il minimise également le nombre de répétitions de transmission en fonction d’une probabilité préévaluée de réussite de la transmission. Deuxièmement, en ce qui concerne les couches PHY et réseau, l’étude développe une approche à deux couches NB-IoT à étalement mixte du spectre et à regroupement avec codage du réseau (N-MANC). Sur une couche, l’approche utilise une technique d’étalement du spectre par saut de fréquence adaptative (AFHSS) qui utilise une séquence pseudo-aléatoire légère et sûre avec une période variable T selon le nombre de nœuds NB-IoT dans la cellule considérée pour exploiter la diversité des canaux comme moyen d’atténuer les interférences entre les liaisons et les technologies croisées. A la deuxième couche, l’approche mixte consiste en une approche de regroupement coopérative basée sur un gradient de force du signal énergétique défini utilisé pour la sélection des têtes de grappe (CHs), et un codage du réseau (agrégation de données) pour stimuler davantage l’efficacité énergétique globale du réseau. Un modèle mathématique systématique de la couche PHY du NB-IoT est d’abord développé et modélisé. Ensuite, les algorithmes proposés sont mis en œuvre et validés utilisant les simulations MATLAB. Les résultats de simulation obtenus montrent que les algorithmes proposés améliorent les paramètres importants de la qualité de service (QoS), tels que l’efficacité énergétique, la fiabilité du réseau, le débit de données, la latence de transmission, l’extensibilité du réseau et la durée de vie, par rapport aux approches existantes.

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Glossary

3GPP	Third Generation Partnership Project
5G	5 th Generation
ARQ	Automatic Repeat Request
AWGN	Additive White Gaussian Noise
BS	Base Station
BLER	Block Error Ratio
CRC	Cyclic Redundancy Check
C-SGN	Cellular Internet of Things Serving Gateway
DL	Downlink
EEACC	Energy-Efficient Adaptive Channel Coding
eNB-IoT	enhance NB-IoT
FEC	Forward Error Correction
FeNB-IoT	further enhanced NB-IoT
HARQ	Hybrid Automatic Repeat Request
HSS	Home Subscriber Server
LoRa	Long Range

LPWAN	Low Power Wide Area Network
LTE	Long Term Evolution
MCS	Modulation Coding Scheme
MIB	Master Information Block
MME	Mobility Management Entity
MNO	Mobile Network Operator
N-AFHSS	Narrowband Internet of Things with Adaptive Frequency Hopping and Spread Spectrum Technique
NB-IoT	Narrowband Internet of Things
NB-IoT node	Device equipped with a processor and an NB-IoT modem such as a sensor node, a smart water meter, etc.
NB-IoTenh3	NB-IoT enhanced version 3
NBLA	Narrowband Internet Link Adaptation
N-LEACH	Narrowband Internet of Things with Low Energy Adaptive Clustering Hierarchy protocol
N-MANC	Narrowband Internet of Things Mixed spread spectrum and clustering Approach with Network Coding
N-MANN:	Narrowband Internet of Things Mixed spread spectrum and clustering Approach No Network Coding
NPBCH	Narrowband Physical Broadcast Channel
NPDCCH	The narrowband physical downlink control channel
NPUSCH	Narrowband Physical Uplink Shared Channel
NPSS	Narrowband Primary Synchronization Signal
NRS	The Narrowband Reference Signal

NSSS	Narrowband Secondary Synchronization Signal
OFDMA	Orthogonal Frequency-Division Multiple-Access
PDN	Packet Data Network
PGW	Packet Data Network (PDN) Gateway
PHY	Physical Layer
PIE	Packet Inspection Entity
PPE	Packet Prediction Entity
PRACH	Physical Random Access Channel
PRB	Physical Resource Block
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RAT	Radio Access Technology
RLF	Radio Link Failure
RSSI	Received Signal Strength Indicator
RU	Resource Unit
SCEF	Service Capabilities Exposure Function
SC-FDMA	Single-Carrier Frequency Division Multiple-Access
SGW	Serving Gateway
SNR	Signal to Noise Ratio
SRB	Signaling Radio Bearer
TBS	Transport Block Size
TDD	Time-Division Duplexing
UE	User Equipment
WSN	Wireless Sensor Network

Chapter 1 Introduction

1.1 Introduction

This chapter provides background for the research study of this thesis. It presents the relevant motivation in support of the needs and benefits of carrying out this research study. The problems identified by this research study are stated and the corresponding sub-problems are determined. The chapter further proposes hypotheses for solving the identified problems within the considered assumptions and specified delimitations of the study. The chapter then highlights the importance and benefits of the study emphasizing the difficulties inherent to NB-IoT and supporting them by means of real-life application scenarios. The chapter finally describes the adopted research methodology, lists the contributions, outputs of the study, and concludes with an outline of the dissertation.

1.2 Background and motivation

A extremely large number of connections is expected to respond to different Internet of things (IoT) use cases such as smart cities, smart wearables, smart homes, etc. ([Salman et al., 2017](#)). Therefore, to cope with such tremendous IoT trends, the Third-Generation Partnership Project (3GPP) introduced the Narrowband Internet of Things (NB-IoT) standard as a pioneer communication technology enabler within the licensed band. In the 3GPP release 13, the NB-IoT was introduced to provide low-power wide-area IoT ([Yu et al., 2017](#)). Current research is considering several techniques that consider the performance enhancement of NB-IoT wireless communication systems. In particular, the authors in ([Xu et al., 2014](#)) presented a systematic review of IoT which includes different definitions, key technologies, open issues, and major challenges. Furthermore, the authors in ([Ericsson, 2016](#)) provided a systematic survey regarding NB-IoT in industry. Extensive research, key enabling technologies, major NB-IoT applications of IoT in industry, and identified research trends, and challenges were reviewed. At a plenary meeting in South Korea, the 3GPP completed the standardization of NB-IoT in which NB-IoT was regarded as an important technology and a large step for 5G IoT evolution. Major telecommunication companies, including Ericsson, Nokia, and Huawei, have shown great interest in NB-IoT as part of 5G systems and have focused significant effort towards standardization.

Recent studies have predicted that there will be around 28 billion connected devices by 2021. According to ([Ericsson, 2016](#)), more than 15 billion of these devices will be

connected Machine-2-Machine (M2M) and consumer electronics devices as illustrated in figure 1.1. The requirement for enhanced NB-IoT performances has never been so stringent in terms of scalability, data rate, energy efficiency and reliability.

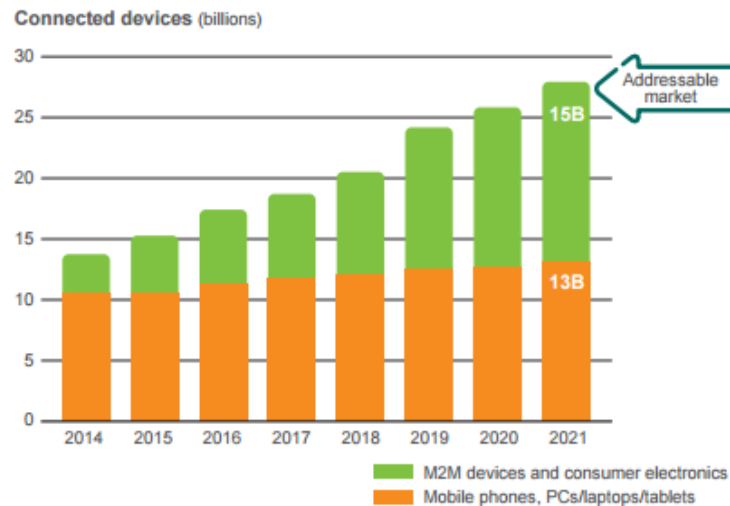


Figure 1.1: Expected growth in number of connected devices (Ericsson, 2016)

Considering the trend in figure 1.1, one of the key design considerations for the NB-IoT is becoming the support for a massive number of devices. Therefore, the NB-IoT infrastructure techniques must be designed to work efficiently with both the increasing number and densities of connected devices. Because there is little development focused on the scalability of NB-IoT in the literature and considering its urgent importance, it is necessary to address the scalability problem.

On the other hand, most current NB-IoT design goals and techniques encountered in the literature have focused on offering a wide-area coverage to low-power devices at the expense of only being capable to achieve low data rates. This is due to

the fact that while there exist IoT applications for short-range transmissions, the objective of most NB-IoT designs consists of maximizing the transmission range while minimizing the transmission power. This is justified by the fact that LPWAN technologies are mainly used for IoT applications that only need to transmit very small amounts of information over a long-range. It is known that a large link budget is needed to achieve a long transmission range in wireless communication. This is why lower modulation rates are used by most NB-IoT designs to achieve more energy per transmitted symbol, and therefore, more resilience to the channel attenuation, better receiver sensitivity, and consequently longer transmission range. At the same time, it is predicted that there will be a wide range of IoT use cases in the future, with the market expanding towards not only Massive IoT deployments but also towards more advanced solutions that may be categorized as Critical IoT as shown in figure [1.2](#).

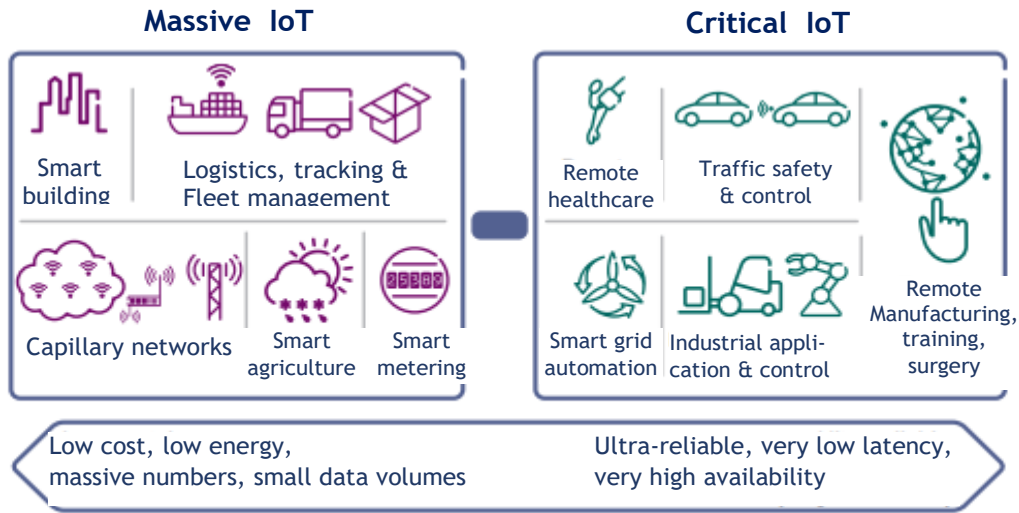


Figure 1.2: Differing requirements for Massive and Critical IoT applications (Ericsson, 2016)

This second category of IoT deployments are mainly real-time applications, and therefore, require higher data rates, very low latency, and reliable communication. It is also true that most NB-IoT research designs as surveyed throughout the literature have not been focused on achieving high data rates. Therefore, this study is considered important as it aims to serve of a precursor for high data rate techniques of NB-IoT with the precaution of preserving acceptable transmission ranges.

Additionally, the NB-IoT is based on cellular network technologies such as the LTE network. An impending decommissioning of these technologies, as announced by some mobile network operators (MNOs), will broaden the technology gap in connecting low-power devices. In general, traditional cellular technologies do not achieve energy efficiency that is high enough to offer the required ten years of battery lifetime

(Huawei, 2015). Therefore, there is a need for much more energy-efficient designs for NB-IoT at both the PHY and Network layers of the NB-IoT system design. This study mainly focuses on efficiently addressing the tradeoff between achieving long-range and reliable communication and lower energy consumption at both the PHY and network layers within a cell of an IoT network.

Raza et al. (2017) have identified the key design challenges and the open research issues of open research for the Low Power Wide Area Network(LPWAN) in general and the NB-IoT in particular. From this well-detailed list of issues, this research work has identified two critical issues that require immediate attention. These consist of efficiently managing the limited network resources (energy, spectrum, etc.) as a mechanism to enable more and more IoT devices to connect to the network.

1.3 Problem Statement

The existing NB-IoT channel coding and modulation coding scheme (MCS) selection techniques have a high energy cost and exhibit low data rate performance. This is because they are primarily designed to ensure a good level of communication reliability. This is not suitable for the growing demand for critical IoT machine-to-machine (M2M) applications. Additionally, due to the exponentially increasing number of IoT devices, the shared NB-IoT radio resources within a cell become limited and causes the degradation of the communication performance. To overcome these challenges, this research work proposes to enhance the energy efficiency, latency, and data rate of the network while improving its network reliability performance as

a mechanism to ensure better network scalability and network lifetime.

1.4 Sub-problems

The above problem can be divided into the following sub-problems:

1.4.1 Sub-problem 1: Channel coding with high energy cost

The first sub-problem considers the proposal of a novel energy-efficient adaptive channel coding approach to ensure that an ultra-low-power operation is achieved. Because the ultra-low-power operation is a key design requirement for most battery-powered IoT/M2M devices, the achievement of a long battery life needs to be considered. Most NB-IoT channel coding and MCS selection techniques are primarily designed based on the repeated transmission to achieve long-range coverage and excellent signal propagation to hard-to-reach indoor places such as basements. According to (Raza et al., 2017), quantitatively, a ± 20 dB gain over legacy cellular systems is normally targeted. The aim of this novel energy-efficient adaptive channel coding technique and MCS selection is to allow the end-devices within a cell to reliably communicate with the base stations at a low energy cost.

1.4.2 Sub-Problem 2: Network scalability

The second sub-problem consists of proposing a novel spread spectrum and clustering approach for efficient spectrum resource allocation among connected devices. The proposed approach needs to ensure that a larger number of devices is connected

without degrading the data rate, reliability, and energy efficiency network performance. A scalability problem related to the network resource allocation complexity is posed because the NB-IoT resources are limited and often shared among the connected devices while the NB-IoT is expected to connect a massive number of devices transmitting data at an unprecedented scale. This scalability issue is characterized by the following,

1. Firstly, the significant density variation across different geographical areas of the network cell requires energy-expensive long-range and energy-expensive transmissions to the BS. Additionally, the BS tends to become overloaded as multiple NB-IoT nodes attempt to individually access it.
2. Secondly, the potential for interlink interference among NB-IoT devices which can severely degrade the network performance.
3. Finally, most NB-IoT technologies use simple ALOHA or CSMA based MAC protocols, which do not scale well with the number of connected devices.

1.4.3 Sub-problem 3: Low modulation data rates

The third sub-problem consists of proposing a suitable adaptive MCS selection approach to enhance the data rate performance of the NB-IoT network. Depending on the quality of the channel, a specific MCS needs to be dynamically selected, and a code assigning method is proposed. This problem mainly affects NB-IoT designs using the Ultra Narrowband (UNB) modulation in the shared Industrial Scientific

and Medical (ISM) bands which, in their current state, offer very low data rates and short payload sizes.

1.5 Hypotheses

To provide a realistic and multi-layers solution to the above-mentioned problems, the following hypotheses have been formulated.

1.5.1 A channel-aware adaptive channel coding approach

The use of channel-aware and adaptive channel coding approach may result in a much more energy-efficient and reliable network performance. It could also reduce the network's latency, and therefore, ensure a longer NB-IoT network lifetime.

1.5.2 An adaptive transmission repetition number selection

A dynamic selection of a minimum transmission repetition number under a pre-assessed probability of successful transmission based on a periodically assessed Block Error Rate (BLER) may enhance the network throughput and therefore, the data rate performance while maintaining acceptable network reliability.

1.5.3 Spread spectrum and clustering approach

The use of a spread spectrum technique may allow the efficient sharing of the spectrum between the IoT devices within an NB-IoT cell. The more IoT devices are

connected within a cell, there will be a higher probability for both self and interlink interference to occur both in the Uplink (UL) and Downlink (DL) communications. The use of a Narrowband spread spectrum with frequency hopping capabilities could help mitigate this interference and allow for more devices to be handled within a cell without considerably affecting the network performance.

The spread spectrum technique coupled with an energy-aware cooperative clustering approach may result in an efficient way to offload the Base Station (BS), and therefore, allows for more IoT objects to be handled at a single cell. A significant amount of potential interference can be mitigated by grouping NB-IoT objects within a cell-based on their geographical location coupled with energy and received signal strength indicator (RSSI) aware mixed gradient for the selection of cluster heads (CHs). Additionally, the overall energy efficiency of the network can be further enhanced by aggregating data packets at the CH before forwarding them to the BS.

1.6 Importance and benefits of the study

The NB-IoT networks will play a very crucial role in connecting the billions of devices which will form part of the next generation of cellular wireless networks. With the increasing number of connected objects, it is becoming more and more critical that the limited network resources such as energy, memory, computation, and channel capacity are used very efficiently.

The network scalability, high data rate, energy efficiency and network reliability are very important requirements for most IoT network in general but very critical for the

NB-IoT network in particular.

- Network scalability: It is unavoidable that as we transition towards the 4th industrial revolution, more and more devices need to be connected to the Internet. For example, a number of countries are now changing the water metering system to smart metering with the ability to independently report their consumption. The benefit of the NB-IoT vis-a-vis the other IoT networks in this regard is that the NB-IoT works in conjunction with cellular networks which are already well deployed. This makes it easier to deploy as it required less infrastructure development. Another reason why network scalability is of ultimate importance to the NB-IoT in particular is that business projections in the IoT sector have demonstrated that the financial viability of the NB-IoT and the profitability from the investments in the sector, solely depends on the connection of as many devices as possible.
- High data rate: The NB-IoT forms part of the 5G network which comes with a specific requirement for high data rates to satisfy the demand of critical IoT applications such as remote healthcare, remote manufacturing etc. It is therefore important for the NB-IoT infrastructure design to cater for enhanced data rate performance to satisfy the demand of these applications.
- Energy-Efficiency: A number of NB-IoT applications such as smart cities, smart water metering to name a few, require the use of battery powered devices. As opposed to other IoT network technologies whose modems already have quite low-current consumption performance, the NB-IoT modems are not

quite power optimized. This is because, they are set to operate within the cellular network infrastructure which is quite power hungry. Therefore, it is critical for any NB-IoT design, at all layers (PHY, MAC, NET) to cater for energy efficiency. This is important to ensure a longer lifetime of the devices and low network maintenance cost.

- Reliability: All NB-IoT applications require a reliable communication as this even defines the relevance, smartness of the applications. For example, a smart water meter with no reliable reporting of its water consumption, water leakage is rendered useless as it is not capable to allow municipal managements to generate accurate water bills or to attempt to a possible serious water leakage causing water wastage.

By developing an energy-efficient adaptive channel coding (EEACC) for the NB-IoT and an NB-IoT mixed adaptive frequency hopping spread spectrum approach with network coding, this study will contribute towards the development of a network infrastructure that is required to enable the massive IoT networks and other critical IoT applications such as vehicular networks, remote health care, smart grid automation, remote manufacturing, training, and surgery.

1.7 Delimitation and assumptions of the study

The present research study assumes the following:

- The IoT objects are static: The modelling work to be conducted in the present research work does not consider the mobility of the connected objects.
- IoT devices are assumed to be battery-powered, and therefore, with limited energy resources.
- The NB-IoT network is assumed to exist within the LTE cellular network.
- The considered channel model is a time-variant slow fading channel with random phase noise following an additive white Gaussian noise (AWGN) distribution. The coherence time of the channel is considered to be large relative to the delay requirement of the application. An urban deployment set-up is considered where multi-path fading is assumed

1.8 Research Methodology

The methodology considered in this research work begins with a set of critical evaluations of the current state of the art of the channel coding, modulation coding scheme selection, spread spectrum, and clustering approaches. Based on the findings of this first step, new algorithms are proposed to enhance data rate, energy efficiency, and scalability performance of the network. These algorithms are theoretically analyzed before their performance is evaluated using a discrete simulator. Given some values

of initial conditions, parameters, and exogenous variables, a simulation is run to represent the behaviour of the algorithm process over time to deduce the significance of the developed algorithms. An overview of the different phases that were considered in carrying out this the study is presented as follows:

Phase 1 - The first phase of this study consists of an intensive literature survey study on the existing LPWA networks Physical and network layer characteristics in general and those related to the NB-IoT in particular. This literature review focuses on studying the existing channel coding and MCS selection approaches for the NB-IoT as well as their advantages and drawbacks in terms of coverage, energy efficiency, data rates, reliability, and scalability.

Phase 2 - The second phase of this study consists of modelling and analyzing the Physical Layer Characteristics of the NB-IoT network.

- Firstly, the NB-IoT link issues such as self and interlinks interference and noise sources are identified and studied. The major channel impairments are identified under typical application scenarios.
- Secondly, energy efficiency, network reliability, and network latency performance are numerically characterized.

Phase 3 - Based on the Physical layer study as conducted in Phase 2, a novel energy-efficient and adaptive channel coding and modulation selection scheme selection approach, is developed to achieve higher data rates while enhancing the energy efficiency and improving network reliability. Additionally, a novel

frequency spreading and clustering approach with network coding is developed with the primary objective to improve the NB-IoT network scalability within a cell while maintaining network reliability.

Phase 4 - This phase mainly consists of the evaluation of the overall performance of the proposed approaches for validation purposes. The performance evaluation is conducted in comparison with some key selected existing methods as studied in Phase 1.

Phase 5 - The last phase of this research work consists of critical analysis and interpretation of obtained results to draw adequate conclusions based on the research objectives. These research objectives include achieving enhancing energy efficiency, data rates, communication reliability while enabling network scalability. This last research phase also formulates recommendations for future related research work.

1.9 Contributions and Outputs of the Study

The major contributions made by this research study can be summarized in terms of the following aspects,

- A comprehensive state of the art study on the resource management performance, challenges, and opportunities as offered by the NB-IoT to meet the 5th Generation

(5G) quality of service (QoS) requirements.

- A comprehensive and systematic mathematical modelling of the NB-IoT PHY layer network performance of the uplink communication in terms of the NB-IoT specific channel considerations by distinguishing them from the ones of the cellular network to which the NB-IoT is attached.
- The development, simulation, and analysis of a novel adaptive channel coding and modulation scheme selection for the NB-IoT that takes into account the channel conditions and dynamically selects an appropriate MCS. This contribution will be of benefit to the diversification and feasibility of the use of the NB-IoT to a wider range of IoT applications while ensuring more energy efficiency and network reliability.
- The development, simulation, and analysis of a novel spread spectrum and clustering with network coding approach which takes into account both the energy levels of the NB-IoT nodes within the cell and their ability to reliably communicate with the BS. The proposed approach constitutes a significant contribution towards enabling the NB-IoT network scalability and is of great significance in terms of how the development of the network infrastructure will cater for the exponentially increasing number of connected devices.
- By comparing the proposed mixed approach with network coding (N-MANC) and without network coding (N-MANNC), this work further elucidates the contribution of data aggregation to the enhancement of the overall energy efficiency of the network. It also discusses and compares the two (N-MANC and N-MANNC) to the traditional

spread spectrum a clustering only approaches in terms of network reliability, energy efficiency, and network scalability.

The list below presents the research outputs in terms of international journal articles publications:

(1). Migabo, M.E., Djouani, K.D. and Kurien, A.M., 2020. The Narrowband Internet of Things (NB-IoT) Resources Management Performance State of Art, Challenges, and Opportunities. *IEEE Access*, 8, pp.97658-97675. doi: <https://doi.org/10.1109/ACCESS.2020.2995938>.

(2). Migabo, M.E., Djouani, K.D. and Kurien, A.M., 2020. An Energy-Efficient and Adaptive Channel Coding Approach for Narrowband Internet of Things (NB-IoT) Systems. *Sensors*, 20(12), pp.3465. doi: <https://doi.org/10.3390/s20123465>.

(3). Migabo, M.E., Djouani, K.D. and Kurien, A.M., 2020. A Novel Spread Spectrum and Clustering Mixed Approach with Network Coding for Enhanced Narrowband IoT (NB-IoT) Scalability, *in Sensors 2020*, 20(18), 5219, 2020. doi: <https://doi.org/10.3390/s20185219>.

The list below presents the research outputs in terms of international and local peer-reviewed conference publications:

(1). Migabo, M.E., Djouani, K.D., Kurien, A.M., and T.O. Olwal. 2017. A Comparative Survey Study on LPWA Networks: LoRa and NB-IoT, *in Proceedings of the Future Technologies Conference (FTC)*, 2017, Vancouver, BC, Canada, November 29-30.

(2). Migabo, M.E., Djouani, K.D. and Kurien, A.M. 2018. A Modelling Approach for the Narrowband IoT (NB-IoT) Physical (PHY) Layer Performance, *in Proceedings of the 44th Annual Conference of the IEEE Industrial Electronics Society (IECON 2018)*, October 21-23, 2018, Washington, DC, pp. 5207-5214. doi: <https://doi.org/10.1109/IECON.2018.8591281>.

(3). Migabo, M.E., Djouani, K.D. and Kurien, A.M. 2019. Data Rate and Energy Balanced Channel Coding Technique for Narrowband Internet of Things (NB-IoT), *in Proceedings of the Southern Africa Telecommunication Networks and Applications Conference (SATNAC)*, September 1-4, 2018, Ballito, Kwazulu Natal, South Africa, pp. 1-6.

The following book chapter has been published as part of the research outputs:

(1). Migabo M.E., Djouani K.D. and Kurien A.M. 2020. Energy Efficient Channel Coding Technique for Narrowband Internet of Things. *In: Arai K., Kapoor S., Bhatia R. (eds) Intelligent Computing. SAI 2020. Advances in Intelligent Systems and Computing, vol 1229. Springer, Cham*, pp. 445-466. Online ISBN: 978-3-030-52246-9, DOI: https://doi.org/10.1007/978-3-030-52246-9_33.

Finally, a research award for best oral presentation in the category Doctoral Degree has been won as part of the Faculty of Engineering and Built Environment at the Tshwane University of Technology, June 12, 2019.

1.10 Thesis Outline

The remainder of the thesis is organised as follows:

- *Chapter 2* describes and discusses the literature relevant to the NB-IoT resources management performance in terms of challenges and opportunities. This chapter analyzes the different existing approaches related to energy-efficient channel coding, throughput enhancement approaches, efficient spectrum resources management, clustering approaches and network scalability enabling.
- *Chapter 3* provides a systematic presentation of a mathematical model of the NB-IoT PHY layer characteristics. This chapter specifically strives to elucidate the impact of the NB-IoT PHY layer characteristics in its different deployment modes on the overall energy efficiency, data rate and latency performance of the NB-IoT system. The chapter describes the three NB-IoT deployment modes, models the energy consumption in each of the three deployment modes, proposes and assesses a predictive processing delay algorithm that models the downlink network latency in each of the three deployment modes.
- *Chapter 4* presents the design, development and performance evaluation of the proposed energy-efficient and adaptive channel coding algorithm (EEACC). In this chapter, some of the selected key existing channel coding approaches for the NB-IoT are discussed, analyzed and compared before the design of proposed EEACC is presented. The performance of the proposed EEACC approach is then evaluated in comparison to the existing approaches in terms of network reliability, energy efficiency and uplink data rate and propagation delay.

- *Chapter 5* presents the design, development and performance evaluation of the proposed two-layers NB-IoT mixed adaptive spread spectrum and clustering approach with network coding (N-MANC). The N-MANC is aimed at efficiently manage the limited narrowband spectrum with a cell and offload the BS to allow for more NB-IoT nodes to join the network without degrading the energy efficiency and reliability performance of the network.
- *Chapter 6* presents a summary of the findings and contributions of the thesis. It also provides recommendations for future studies.

Chapter 2 The Narrowband Internet of Things State of Art, Challenges, and Opportunities

2.1 Introduction

2.1.1 Background and motivation

The Narrowband Internet of Things (NB-IoT) has been introduced in the 3rd Generation Partnership Project (3GPP) Rel-13 to provide low-cost, low-power, wide-area cellular connectivity for the Internet of Things. With the exponentially increasing number of connected wireless devices in the order of 100 billion, it has become crucial that researchers develop efficient resource management techniques to meet the 5th Generation (5G) quality of service (QoS) requirements. Recently, several research challenges including channel coding techniques with a high energy consumption cost, low modulation data rates and the fast-growing number of connected devices have

been identified as some of the main issues encountered in the design and deployment of NB-IoT systems. Besides, several techniques have emerged in the literature to resolve some of these challenges of NB-IoT systems.

However, the research activities towards the enhancement of the NB-IoT resource management are yet to continue in the next five years before high data rates, energy-efficient, and scalable NB-IoT specifications can be released for the standardisation and commercialisation. Considering the limited number of existing surveys of such technical enhancement approaches in a broader perspective (i.e. energy efficiency, data rate performance and scalability) and also the limited comparative surveys in the literature, this chapter seeks to elaborate, describe, and compare the performance of such resource management approaches. Of the multiple NB-IoT resources, the focus of this chapter is on the data rate, energy efficiency, and scalability enhancement schemes that have been proposed for the last three years. The contribution of the chapter lies in the analysis, synthesis, comparison and summarised discussions of some of the major existing schemes towards identifying challenges faced by the NB-IoT development. Finally, this chapter seeks to identify research challenges, open questions, and opportunities that could arise from the existing techniques analysed. In summary, the objective of this work is to provide a survey of existing articles that focus on enhancing one or more of the NB-IoT resources and critically assess their respective performances by comparing them based on energy efficiency, data rates and network scalability. The focus of this study is on existing channel coding approaches, modulation level selection schemes, and network scalability approaches.

2.2 An overview on the LPWANs and the NB-IoT

The Internet today has become ubiquitous. It touches almost every corner of the globe and is affecting human life in its different aspects ([Sethi and Sarangi, 2017](#)). A new class of wireless network technologies is therefore required to support the fast growth and development of the Internet of Things (IoT). This is also due to the specific requirements and characteristics of IoT objects such as low power consumption, long-range, low cost and security. Indeed, the ambitious efficient use of network resources have already triggered considerable research and development interest in terms of the development of novel techniques and approaches at all network layers, that are specific to the IoT.

One of the areas that has received attention recently is Low Power Wide Area Networks (LPWAN). Low Power Wide Area (LPWA) describes a category of wireless communication technologies designed to support the Internet of things (IoT) deployments. LPWA, therefore, represent the group of technologies aimed at enabling energy-efficient and cheap wide area communication that Machine to Machine (M2M) communication can rely on for a much more energy-efficient deployment and operation ([Migabo et. al., 2017](#)). LPWA technologies are expected to serve a diverse range of vertical industries and support a range of applications and deployment scenarios which existing mobile technologies may not currently be best placed to connect. The main aim of the LPWA technologies designs consists of delivering strong coverage over large areas, great power efficiency, massive scale, low-cost communications and low bandwidth ([Vodafone, 2017](#)).

To date, LPWAN has become one of the fastest-growing markets in IoT with many LPWAN technologies being developed both in the licensed and unlicensed spectra. Some of the most popular LPWA technologies being developed can be classified as given in Table 2.1.

Table 2.1: Most common LPWAN technologies

Unlicensed	Licensed
LoRa	NB-IoT
SigFox	LTE-M(LTE Cat-M1)
Symphony Link	NB-Fi (Narrowband Fidelity)
iFrogLab	LTE-MTC
ThingPark Wireless	UNB (Ultra Narrow Band)
Ingenu (Ingenu, 2016)	WEIGHTLESS-P (Weightless, 2017)

From the list of most common LPWAN technologies in Table 2.1, it has been identified that the Long Range (LoRa) as well as the Narrowband Internet of Things (NB-IoT) are the two most popular and emerging technologies within the unlicensed and the licensed bands respectively ([Nolan et. al., 2016](#)).

2.2.1 Comparison of the NB-IoT and other IoT Technologies

The Narrowband Internet of Things (NB-IoT) is a novel narrowband radio technology specifically designed for IoT, which can be directly deployed in Global System for Mobile Communications (GSM) or Long-Term Evolution (LTE) networks to reduce

deployment costs ([Rico-Alvarino et. al., 2016](#)). However, there exist other wireless communication technologies that enable the deployment of the Internet of Things. Fig. 2.1 presents a comparison of different technologies for IoT and the evolution towards 5G.










	NB-IoT  NB-IoT	WIFI 	BLUETOOTH 	SIGFOX 	LoRa 	LTE-M/ (eMTC) (Rel 13)  eMTC	EC-GSM (Rel. 13) 	ZIGBEE Pro 	5G (targets) 
Coverage Area	<15 km 164 dB	17-30+ (meters)	1-10+ (meters)	<12km 160 dB	<10 km 157 dB	<10 km 156 dB	<15 km 164 dB	1-100+ (meters)	<12km 160 dB
Spectrum Bandwidth	Licensed 7-900MHz 200 kHz shared	2.4 GHz 802.11	2.4 GHz 802.15.1	Unlicensed 900MHz 100kHz	Unlicensed 900MHz <500kHz	Licensed 700MHz- 900MHz 1.4 MHz shared	Licensed 800MHz- 900MHz shared	2.4G 802.15.4	Licensed 700MHz- 900MHz shared
Rate	<50 kbps	150Mbps	1Mbps	<100bps	<10 kbps	<1 Mbps	10 kbps	250kbps	<1 Mbps
Terminal cost	4.00\$ (2015) 2-3\$ (2020)	4.00\$ (2016)	4.00\$ (2016)	4.00\$ (2015) 2.64\$ (2020)	4.00\$ (2015) 2.64\$ (2020)	5.00\$ (2015) 3.30\$ (2020)	4.5\$ (2015) 2.97\$ (2020)	3.00\$ (2016)	<2\$
Network Reforming	Small to moderate	None	None	Large	Large	Small	Moderate (LTE reuse)	None	Requires 5G NWs

Figure 2.1: Performance Comparison of some common IoT Technologies ([Ericsson, 2016](#)), ([Vodafone, 2017](#)) and ([Alexiou et. al., 2017](#))

As it can be observed from the comparison table in figure 2.1, the NB-IoT technology maintains a quite wide coverage area (up to 15 km) as compared to the other IoT technologies with the Sigfox, LoRa technologies exhibiting similar performance within the unlicensed category. In terms of the spectrum bandwidth, the NB-IoT has a much smaller shared bandwidth as compared to the LTE-M, eMTC and other 5G IoT technologies within the licensed spectrum. This makes it less prompted to

inter-channels interference, especially when deployed in standalone mode. In terms of the data rate, the NB-IoT, as per its release 13, has quite lower data rate as compared to the other IoT technologies both in the licensed and non-licensed band. This is a disadvantage as it makes it a lesser suitable technology choice for critical IoT applications. The decreasing low terminal cost of the NB-IoT as compared to the other IoT technologies makes it a suitable IoT technology choice for massive machine to machine communications (MTC) applications. Finally, the small to moderate network reforming ability of the NB-IoT network is a disadvantage as compared to other IoT technologies in the unlicensed band such as LoRa and Sigfox but remains an advantage as compared to the other IoT technologies within the licensed band such as the LTE-M, 5G IoT technologies and Zigbee.

At a plenary meeting held in South Korea, the Third Generation Partnership Project (3GPP) completed the standardisation of NB-IoT in which NB-IoT is regarded to be a very important technology and a large step for 5G IoT evolution ([Yu et al., 2017](#)). Major telecommunication companies, including Ericsson, Nokia, and Huawei, have shown great interest in NB-IoT as part of 5G systems, and spent lots of effort in the standardisation of NB-IoT ([Agnes, 2015](#)) which has been widely considered as the main technique for next-generation wireless communications. NB-IoT is expected to provide improved coverage and support a massive number of low-throughput devices, low delay sensitivity, ultra-low device costs, and low device power consumption ([Wang et. al., 2016](#)). The question of how to achieve these benefits, particularly improved coverage, data rates and energy efficiency is a great challenge.

In 3GPP standardisation, repeating transmission data and the associated control

signalling several times has been utilised as a base solution to achieve coverage enhancement for NB-IoT (Yang et al., 2016)(Axmon et al., 2017)(Luo and Zhang, 2016). Other existing works on NB-IoT take into account the new feature of repetition (Yu et al., 2017), (Huusko, 2016). The approach is to consider performing a link adaptation for resource management to enhance energy, data rate, coverage efficiency by considering a two-dimensional space, namely the modulation and coding scheme (MCS) level selection as is considered in traditional LTE systems as well as the determination of the repetition number.

2.2.2 NB-IoT and LoRa PHY layer comparison

This section briefly discusses the key technical differences between the NB-IoT Technology (considered as the leading LPWAN technology in the licensed band) and the Long Range (LoRa) technology (considered as the leading technology in the unlicensed band at the PHY layer).

The LoRa LPWAN technology operates in the non-Licensed band below 1 GHz for long-range communication. It uses Chirp Spread Spectrum (CSS) modulation at the PHY layer which allows it to trade data rate (low) for sensitivity within a fixed channel bandwidth making it quite robust against interference. The CSS modulation is also known for its long-range capabilities mainly due to its robustness against interference. As a result, it finds wide military applications (Wei, Chen and Hwang, 2017).

By using a spread spectrum modulation technique, LoRa not only provides long-range capability but also a great link budget performance. It is important to note

that the spread spectrum provides orthogonal separation between signals. This is done by using a unique spreading factor for individual signals. This approach is advantageous in terms of data rate management. The relationship between the necessary data rate and the chip rate and symbol rate being used for the LoRa network has been modelled in (Semtech, 2015) as:

$$R_b = SF \times \frac{1}{\left[\frac{2^{SF}}{BW}\right]} \text{ bits/sec} \quad (2.1)$$

where SF is the spreading factor and BW is the modulation bandwidth (Hz). As is clearly shown in equation 2.1, the data bit rate is directly proportional to the modulation Bandwidth.

In the modulation of LoRa, the spreading of the spectrum is achieved by generating a chirp signal that continuously varies in frequency. An advantage of this method is that timing and frequency offsets between transmitter and receiver are equivalent which greatly reduces the complexity of the receiver design. LoRa also has other advantages such as adaptive data rate, scalable bandwidth, high-power efficiency, and resistance to multipath.

On the other hand, the NB-IoT can be regarded as a new air interface on its own even though it is integrated into the LTE. This is because NB-IoT removes many features of LTE, including handover, measurements to monitor the channel quality, carrier aggregation, and dual connectivity to satisfy the energy efficiency and low power operation (energy efficiency) NB-IoT design criteria as elaborated in section 2.3.

Unlike LoRa that uses a non-licensed band, NB-IoT uses the same frequency bands as LTE which are licenced frequency bands subdivided into 12 sub-carriers of 15 kHz each in the downlink (DL) using OFDM access method and 3.75 or 15 kHz in the uplink(UL) using the single-carrier FDMA (SC-FDMA) access scheme. It is also important to note that NB-IoT uses a PSK which is the same modulation technique as used in LTE.

NB-IoT occupies a frequency band of 180 kHz bandwidth which corresponds to one resource block in LTE transmission. This results in three possible operational modes depending on where the block is located within the LTE spectrum as illustrated in Fig. 2.2.

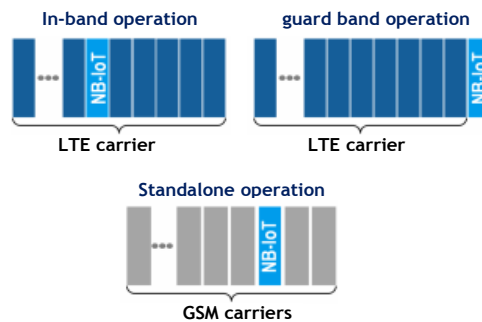


Figure 2.2: NB-IoT band operational modes

The three operational modes include

1. *In-band operation* utilising resource blocks within an LTE carrier.
2. *Guard band operation*, utilising the unused resource blocks within an LTE carrier's guard-band.

3. *Stand alone operation*: A possible scenario is the utilisation of currently used GSM frequencies. With their bandwidth of 200 kHz, there is still a guard interval of 10 kHz remaining on both sides of the spectrum.

Table 2.2 provides a comparative summary of the key differences at the PHY layer between LoRa and NB-IoT.

Table 2.2: Comparative table between PHY features of LoRa and NB-IoT

PHY parameters	LoRa	NB-IoT
Modulation	CSS	QPSK
Link Budget	154dB	150dB
Spectrum Bandwidth	Unlicensed 500 KHz - 125 KHz	Licensed LTE bandwidth 180KHz
Peak Data Rate	290bps-50Kbps (DL/UL)	DL:234.7kbps; UL:204.8kbps
Energy Efficiency	> 10 years battery life of devices	> 10 years battery life of devices
Spectrum Efficiency	Chirp SS CDMA better than FSK	Improved by , Standalone, Inband guard band operation
Power efficiency	Very High	Medium High
Area Traffic Capacity	Depends on gateway type	40 devices per household \approx 55k devices per cell
Interference immunity	Very High	Low
Standardization	De-facto Standard	3GPP Rel.13
Mobility	Better than NB-IoT	No connected mobility (only idle mode re-selection)

The rest of the chapter is organised as follows. Section 2.3 presents and describes the main NB-IoT design objectives. Section 2.4 discusses the most common NB-

IoT applications and their associated resource challenges. Section 2.5 analyses the aspects of NB-IoT as part of 5G cellular IoT while section 2.6 discusses the Software-Defined Network (SDN) and the Network Function Virtualization (NFV) of NB-IoT within 5G systems. Section 2.7 discusses related work on the existing energy-efficient NB-IoT channel coding schemes. Section 2.8 describes and discusses the work related to NB-IoT modulation selection schemes designs for data rate performance enhancement. Section 2.9 discusses link Adaptation Schemes for enhanced NB-IoT scalability. Section 2.10 presents a summary of existing spectrum sharing and clustering techniques for NB-IoT as found in the literature. In Section 2.11, the NB-IoT performance Challenges and open issues are identified and discussed before conclusions are drawn in section 2.12.

2.3 NB-IoT design objectives

NB-IoT mainly aims at offering energy and cost-efficient connectivity to a large number of objects distributed over a wide geographical area (Flore, 2016). Like most IoT technologies, one of the main objectives of the NB-IoT designs is to achieve machine type communication (MTC). Fig. 2.3 depicts the different MTC applications of the NB-IoT together with the corresponding design objectives by clearly classifying them in massive and critical MTC applications.

From the literature, it can be argued that some of the NB-IoT design objectives are conflicting. This section briefly describes the design goals of NB-IoT systems as well as some of the techniques proposed in the literature for achieving them. Some of the

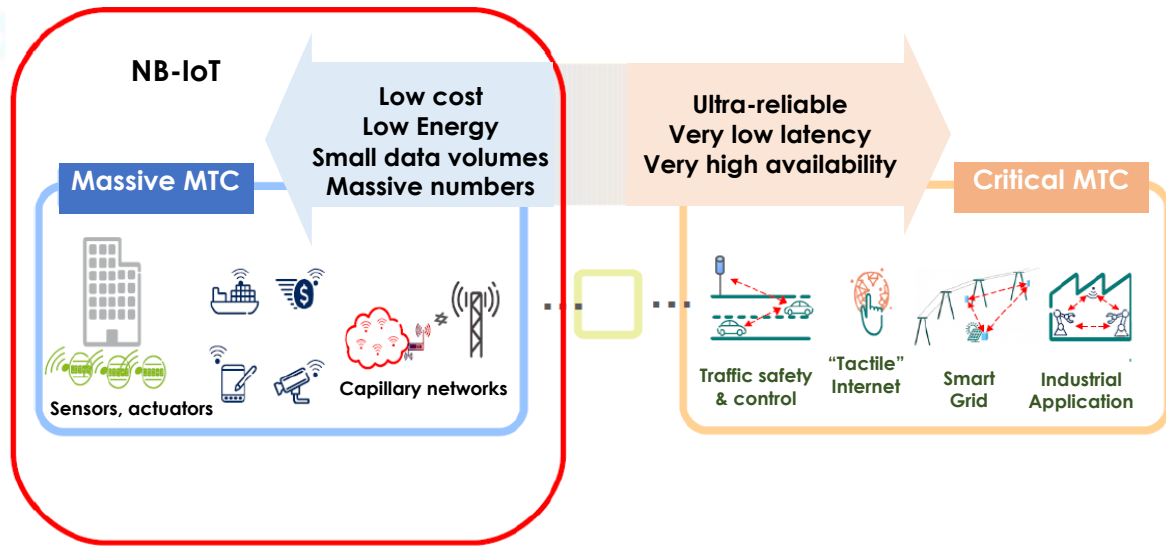


Figure 2.3: NB-IoT Machine Type Communication Applications ([Maldonado et al., 2017](#))

main design objectives in the design of the NB-IoT systems are as follows:

1. Long Range Communication

To achieve wide area coverage, the NB-IoT design is required to produce a high quality of signal propagation and deeper signal penetration capable of reaching basements and deep areas of buildings. According to ([Raza et al., 2017](#)), the design targets signals that are often quantitatively estimated to ± 20 dB gain over average cellular signals. This gain translates into end-to-end device connections over a distance ranging from a few to tens of kilometres and varies depending on the type of deployment environments (rural, urban, etc.). To achieve long-range NB-IoT designs, most of the research work throughout literature has proposed the following (Physical) PHY layer design techniques,

- ***The use of the Sub-GHz band:***

Most NB-IoT designs have proposed the use of the Sub-GHz range to improve the robustness and reliability of communication at lower power costs. The sub-GHz band provides better signal quality at a wider coverage area and longer distance mainly for two main reasons. Firstly, unlike the 2.4 GHz band, the sub-GHz band consists of lower frequencies which therefore experiences lower attenuation and multipath fading caused by obstacles and dense surfaces such as concrete walls as modelled by the Friis formula given by

$$L = 20 \times \log_{10}\left(\frac{4 \times \Pi \times d \times f}{c}\right) \quad (2.2)$$

where L represents the approximation (ideal case: isotropic antennas and free space) attenuation, d represents the distance between the transmitting and receiving antennas, f and c represent the frequency and the speed of light respectively.

Secondly, the sub-GHz band has been proven to be less congested when compared to the 2.4 GHz and 5 GHz bands which are bands used for common wireless technologies such as Wi-Fi, cordless phones, Bluetooth, ZigBee, and other wireless technologies specific to home appliances (Raza et al., 2017). By achieving robust and highly reliable communication, the use of the Sub-GHz band results in longer communication range and lower power consumption.

- ***Optimal selection of modulation scheme:***

To achieve long range communication, some work on efficient NB-IoT designs found in literature such as (Lee and Jaiyong, 2017),(Yu et al., 2017) and (Massam et. al., 2013) have proposed efficient techniques for modulation scheme selection. The common idea behind most proposed approaches consists of a trade-off between high

data rate and higher energy in each transmitted bit (or symbol) at the physical layer (PHY). This design technique allows for a signal that is more immune to noise and interference and that can travel longer transmission distances. Therefore, in general, the identified aim of most designs is to achieve a link budget of 150 ± 10 dB which can translate into a few kilometres and tens of kilometres in urban and rural areas respectively (Yu et al., 2017). Encoding more energy into the bits of a signal (or symbols) results in very high decoding reliability on the receiver side. Typical receiver sensitivities could, therefore, be as low as -130 dBm.

The modulation techniques used for most LPWAN technologies can be classified into two main categories namely narrowband techniques and spread spectrum techniques. Spread spectrum techniques spread a narrowband signal over a wider frequency band but with the same power density. The actual transmission is a noise-like signal that is harder to detect by an eavesdropper, is more resilient to interference, and is robust to jamming attacks (secure) (Raza et al., 2017).

Compared to other LPWAN technologies such as the LTE Cat-M1 which mainly uses spread spectrum modulation techniques, most work on NB-IoT designs found in literature such as (Raza et al., 2017), (Yu et al., 2017) and (Massam et al., 2013), propose the utilization of narrowband modulation techniques. In general, narrowband modulation techniques provide a high link budget which is often less than 25 kHz. They are very efficient at frequency spectrum sharing between multiple links, and they experience a very low noise level within each narrow band. To further reduce the experienced noise, some LPWAN technologies, such as SIGFOX, WEIGHTLESS-N, and TELENESA use ultra narrowband (UNB) with widths as short as 100 Hz

(Massam et. al., 2013). They are therefore able to achieve longer transmission ranges.

One of the major differences between narrowband modulation techniques and spread spectrum techniques is that spread spectrum techniques often require more processing gain on the receiver side to decode the received signal (below the noise floor)(Landstrom et. al., 2016). However, no processing gain through frequency de-spreading is required to decode the signal at the receiver in the case of narrowband modulation techniques. This results in simpler and less expensive transceiver designs. Different variants of spread spectrum techniques such as Chirp Spread Spectrum (CSS) and Direct Sequence Spread Spectrum (DSSS) are used by existing standards LPWA technologies.

Other authors such as (Chafii et. al., 2018) have proposed the use of machine learning techniques as a mechanism to enhance coverage in narrowband-IoT. Instead of employing a random spectrum access procedure, the approach consists of using a dynamic spectrum access technique which results in reducing the number of required repetitions, increasing the network's coverage and reducing the energy consumption. This work proposes the use of a dynamic spectrum access with the ability to detect channel availability and condition in place of the slotted ALOHA approach, currently used to establish connection between NB-IoT nodes and the BS. The spectrum learning process can be modelled as a multi-armed bandit (MAB) framework as proposed in (Jouini et. al., 2010), (Jouini et. al., 2012). Depending on the location of the UE (outdoor, indoor, basements) and the channel conditions (high or low SNR), the quality of the physical channels changes. Therefore, choosing the channel with the

best quality (i.e. coverage level) potentially leads to reliable transmissions, and is less costly in terms of energy consumption.

2. Low Power Operation

To reduce maintenance cost, battery-powered IoT objects should have a lifetime of at least 10 years or more. This is a key design requirement for IoT/M2M designs. According to most work in literature, the battery life is often dependent on several factors which include the network topology, the duty cycle being used and the task distribution between end-devices and Base Stations (BS) ([Shirvanimoghaddam et. al., 2017](#)) ([Nordlof and Lagusson, 2017](#)) ([Pereira, 2018](#)).

- ***Network topology:***

According to ([Oppermann et. al., 2014](#)), when the NB-IoT system is made up of a high number of connected objects over a wide geographical area, mesh network topology not only suffers from high deployment costs, but also it suffers from the “bottleneck problem”. This is because as the traffic is forwarded over multiple hops towards a gateway, some devices become more congested than others depending on their location or network traffic patterns. This results in shortening of their battery lifetime which limits the overall network lifetime to only a few months or years.

Therefore, most NB-IoT systems use the star network topology by connecting end devices directly to base stations obviating the need for the dense and expensive deployments of relays and gateways altogether. This technique results in huge energy savings. Compared to the mesh topology, the devices need not waste precious energy in busy-listening to other devices that want to relay their traffic through them. In

the star topology used by most LPWAN technologies in general and also used by NB-IoT systems in particular, the base station is always kept switched ON to provide convenient and quick access when required by end-devices. It is important to point out that although most LPWA technologies use the star topology, some of them do make use of a tree or mesh topology. However, the later often require considerably complex protocol designs to achieve a similar energy efficiency performance to that of the star network topology (Finnegan and Brown, 2018).

- ***Duty Cycle management:***

Another technique that is often used to achieve power-efficient operation of NB-IoT systems consists of opportunistically turning off M2M/IoT devices of high power consumption such as the radio transceiver circuit. Applying an improved duty cycle on the radio transceiver circuit's power by turning the radio only when data needs to be transmitted or when data is received has shown a considerable reduction in the overall power consumption of the network (Anastasi et. al., 2009).

Several studies in the literature on NB-IoT systems have looked at the impact of other PHY layer aspects on the energy consumption of the system. As a result, the present study proposes to look at the impact and contribution of the modulation scheme selection as well as the channel coding on the overall energy consumption of the NB-IoT system.

3. Low Cost Design

Low-cost design specification remains a key player in the commercial success of NB-IoT designs. This design condition can be better expressed by the following cost

optimisation formulation: “Achieving the connection of a large number of devices (as many devices as possible) while keeping both the hardware cost (e.g. below \$5 (Huawei, 2015)) and the subscription cost per unit device as low as possible (e.g. \$1 (GSMA, 2016))”. Some of the most common techniques, mechanisms and approaches used by NB-IoT technologies for achieving the objective of low-cost design include the following:

- ***The reduction in hardware complexity:*** Significant efforts are made in this area at both the NB-IoT device level as well as on the design of the different hardware platforms involved. These efforts include for example the relaxation of the base-band processing which considerably reduces the computing requirements at the eNB. This automatically translates to cheaper hardware devices that significantly cut on cost (Mwakwata, 2019). Such efforts also include the reduction of the Radio-Frequency (RF) components (RF Design, 2017) on the RF path of the NB-IoT nodes. This is for example achieved by the use of an RF switch integrated circuit capable of switching multiple radios present on the NB-IoT node to the same antenna path using a basic low power output pin of the processor onboard (Zetterblom and Dawji, 2018). This RF hardware minimisation technique has been proven to be cost-efficient but also of minimal local interference between radio activities on the NB-IoT node (Ericsson, 2016).

- ***The simplification of the network infrastructure:*** As a result of the effort of virtualization of NB-IoT network functions (Salva-Garcia et. al., 2018), (Bell, 2017), there has been a significant reduction in memory storage requirements within the various parts in the network architecture such as the SGW (Serving Gateway),

the Mobility Management Entity (MME) and the Cellular Internet of Things Radio Access Network (CIoT RAN) ([Andres-Maldonado et. al., 2016](#)).

2.4 Most Common NB-IoT Applications and Associated Network Resources Challenges

2.4.1 Smart metering

One of the most suitable uses for NB-IoT is smart metering. NB-IoT is commonly used for water, gas and electricity metering ([Adhikary et. al., 2016](#)). The uniqueness of NB-IoT systems as used for water and gas metering as opposed to electricity metering is the limited energy availability for NB-IoT nodes. Most water and gas meters are battery operated. The limited energy availability poses a challenge on their design because the design has to ensure a long network lifetime ([Yeoh et. al., 2018](#)). Due to the energy limitations, water and gas meters are often constrained to using low energy consuming communication technologies, unlike electricity meter designs which can still explore other power-hungry communication technologies such as cellular (LTE, GPRS etc) ([Carlesso et. al., 2015](#)). Battery-powered NB-IoT modules do not need a power connection, deliver deep indoor penetration, and thereby, establish a reliable connection even in areas where mobile reception is poor ([Lauridsen et. al., 2018](#)). The provider can read the meter remotely and the end customer does not have to stay at home to wait for the meter reader to take meter readings at the user's premises ([Pennacchioni et. al., 2017](#)).

Another case scenario is the one of application of the NB-IoT for remote smart energy metering. In the energy sector, the developing of smart metering networks allows operators and companies to improve the production efficiency and to offer an enhanced service to customers ([Kaipainen, 2018](#)).

The authors in ([Pennacchioni et. al., 2017](#)) propose a deployment analysis of the NB-IoT system for several metering systems to assess its coverage and capacity performance. Several case scenarios are set-up ([Pennacchioni et. al., 2017](#)) to assess the performance. This can be summarised as follows:

- Energy metering (Gas metering for example): User equipment is placed in a deep indoor location sometimes in an underground area. This means that they are affected by extra path-loss compared to units in an outdoor situation such as water meters. These devices are static.
- Air quality metering: These type of smart NB-IoT meters are also static (not mobile) and would normally be placed in a household location. Although these devices are placed indoors, they are not often in an area of deep indoor location like the gas meters for example.
- Smart yard water meters: These water consumption counters and loggers are often deployed in an outdoor location. This makes them experience almost no path-losses.

It is important to note that this particular set of application scenarios mostly require very reliable, scalable and energy-efficient performance than it does require the high data rate performance. This is because all the devices in these three case scenarios

are assumed to communicate daily to an NB-IoT Base Station on a periodic interval to send their daily consumption values. This makes their data rate requirement quite low. They are however required to have very reliable uplink communication as very important smart cities management decisions are based on the data from these devices. They are also required to be of very energy-efficient designs across the entire network stack as most of these NB-IoT devices are battery powered. Finally, because these applications are mostly related to smart utilities management, they often involve very large numbers of devices and therefore require the ability to efficiently scale without degrading their energy efficiency and network reliability performance.

2.4.2 Smart Cities

In Smart Cities, NB-IoT systems can be used in street lighting as discussed in (Chen et. al., 2018). Lamp posts fitted with appropriate modules can be switched on and off or dimmed remotely and can trigger an alarm if they malfunction (Abinaya, 2017). If a city connects its parking spaces using NB-IoT, better utilisation is achieved of available parking. Motorists are directed by a smart parking guidance system to the nearest free parking space by the shortest route (Shi et. al., 2017) (Lin et. al., 2017). In waste disposal, garbage cans fitted with NB-IoT modules alert a control centre when they are full. As a consequence, waste disposal companies can optimise vehicle routes and reduce costs (Sinha, 2017).

A typical case scenario for the use of NB-IoT in smart cities applications is described and analysed in (El Soussi et. a., 2018). The scenario consists of NB-IoT devices placed in various parts of a city in heterogeneous environments with different network

coverage conditions. These devices are used for parking management, traffic control, waste management and many other day-to-day city management operations. They primarily serve to log data for predictive and reactive city management planning (El Mahjoubi et. al., 2017). The experience has demonstrated a clear energy performance difference between various types of devices depending on whether they are mobile or static, indoors or outdoors, urban or suburban. Some key challenges related to the deployment of NB-IoT systems in a smart city application have been identified. These include network planning and optimization to ensure reliable and long coverage, network latency and as well as the localisation of nodes

2.4.3 Indoor and Outdoor Localisation Applications

The NB-IoT is suitable for locating pets or valuables both indoor and outdoor scenarios. To not lose sight of a pet or an expensive personal item, an NB-IoT module can be a low-cost alternative to a GSM tracker. NB-IoT presents an entirely new set of opportunities for low power, low-cost localisation of both moveable and fixed assets such as cars, sensor nodes (Song et. al., 2017). As use case scenario is the use of triangulation to establish localisation of NB-IoT nodes between three nearest base stations can be a low energy approach as compared to each nodes having its GPS module. Based on the Signal-to-Noise Ratio (SNR) of the packet received from the three nearby BSs with well-known GPS locations, the NB-IoT node can reasonably be located (Ribeiro et. al., 2018). Many other possible techniques could be used for localization from NB-IoT device-driven communications. These techniques include Observed Time Difference of Arrival (OTDoA) (Hu et. al., 2017) and Received Signal

Strength Indicator (RSSI) ([Sallouha et. al., 2017](#)) for example.

2.4.4 Farming and forestry: Monitoring livestock

NB-IoT technology is also suitable for agricultural use where there is no power supply or where network coverage is poor ([CanLong et. al., 2018](#)). In irrigation of fields or plantations, tank levels, pump pressure, and flow rates are measured. The location and health of livestock can be monitored as well. In forestry, low-cost sensors can be distributed in large numbers to report information such as temperature, smoke development, or wind direction ([Elijah et. al., 2018](#)). With the advent of the NB-IoT technology, the IoT agriculture sensors have become more accessible than ever before, helping farmers maximize yields, conserve resources such as water and fertilizers, reduce waste and enhance productivity ([Digital Matter, 2020](#)). The Internet of Things is allowing agriculture, here specifically arable farming, to become data-driven, leading to more timely and cost-effective production and management of farms, and at the same time reducing their environmental impact. An example is the one of farm management, traceability of produce and forecasting. Forecasting employs NB-IoT sensors as source of data and the collected data can be used for prediction of some of the key farming events through precisely designed analytic methods ([Villa-Henriksen et. al., 2020](#)).

2.4.5 Industry: NB-IoT on pallets and pipelines

In a use case scenario that there is a need to monitor oil and gas pipelines, sensors relay important information about pressure, flow rate, or possible leaks. There is

often no external power source for pipelines in inaccessible areas ([Zhang et. al., 2018](#)). NB-IoT could find appropriate applications since modules have a long service life, require no maintenance, and have a 20 dB wider range than conventional mobile network connections ([Spajic, 2017](#)).

2.5 The NB-IoT as part of 5G cellular IoT

Unlike previous generations of mobile networks, the 5th generation (5G) technology is expected to fundamentally transform the role that telecommunications technology plays in society ([GSMA, 2018](#)). The question many are asking is to know the place of the NB-IoT and other licensed LPWAN technologies such as LTE-M with 5G ([Sinha, 2017](#)). The proposed 5G technology has three main pillars.

- enhanced Mobile Broadband (eMBB)
- Ultra Reliability Low Latency Communication (URLLC)
- massive Machine Type Communication (mMTC)

Figure [2.4](#) briefly describes these three pillars.

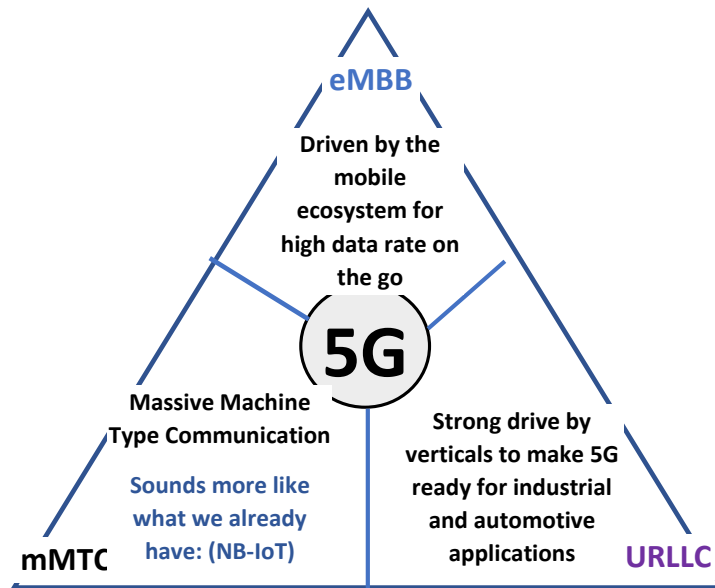


Figure 2.4: 5G three pillars and how NB-IoT fits in

The International Telecommunication union (ITU) has defined several requirements of 5G mMTC to address IoT applications (Kafle et. al., 2016). The key requirements include

- Battery life: 10 years at 200 bytes (UL) and 20 bytes (DL) per day
- Coverage: 164 dB with 160 bit/s
- Density: 1 million devices/ km^2
- Latency: ≤ 10 seconds with 20 bytes application package
- Price: Ultra-low cost device
- Additional features such as positioning, multi-cast, mobility etc.

In order to achieve such requirements, the 3GPP has released three more standard versions as summarized in table 2.3.

Table 2.3: Different NB-IoT releases to cater for ITU requirements (Narayanan et. al., 2018)

Release 14	Release 15	Release 16
Non-anchor carrier		
Release assistance indicator	New PRACH format	
Re-connection with RLF	Small cell support	Improve multi-carrier operation
Maximum Tx power 14 dBm	TDD support	Inter-RAT cell selection
eNB-IoT	FeNB-IoT	NB-IoTenh3
Enhance TBS/HARQ	Enhance cell acquisition	Coexistence with 5G
Positioning	Wake up signal	Group wake up signal
single-cell multicast	Early data Transmission	Early DL/UL transmission

The key issue here has been how to ensure the coexistence of NB-IoT with 5G network different layers (physical and core). In practice, 5G will see initial deployments in urban areas. This is perhaps beneficial from an IoT perspective since most of the key applications of IoT will support Smart Cities, Smart Campuses and Smart Buildings. The NB-IoT being already a licensed band IoT Technology stands a great competitive

advantage in terms of integration with cellular 5G over other IoT Technologies in the unlicensed band such as LoRa, Sigfox etc. One of the key drivers for 5G IoT is the high bandwidth demand which is naturally posed by several applications of the 5G technology. The bandwidth is required to enable enhanced mobile broadband (eMBB)-based 5G services. The integration of the NB-IoT within 5G systems as part of the mMTC is, therefore, a great opportunity towards answering to that huge bandwidth demand as the NB-IoT if well designed, and handle many communication aspects of the network.

However, integrating NB-IoT with 5G systems comes with its issues and challenges. Some of the issues identified include:

- The lack of agreed-upon end-to-end architecture: Standardization at the lower layers (Data Link Control and Physical) can drive the development of a more inclusive multi-layer multi-application architecture.
- Propagation issues: 5G systems are designed to operate at mmWave frequencies to enable high data rates. However, this poses a problem in terms of signal penetration inside buildings ([Lu et. al., 2010](#)). At the same time, indoor solutions are needed for NB-IoT applications. This poses a serious design consideration challenge at the nodal point of view when it comes to NB-IoT networks being used with 5G systems.
- Multiple Access issues: Although in principle it is possible to support multiple access technologies in an IoT sensor (chipset), end-point IoT devices tend to have low complexity to achieve an established target price point and on-board power

(battery) budget. Therefore, several applications will have devices that have a single implemented wireless uplink.

- Energy issues: Because most of the NB-IoT devices are constrained in terms of processing, memory and energy resources, integrating the NB-IoT network with the cellular 5G network poses considerable energy stress on NB-IoT nodes when compared to the non-licensed band IoT networks such as LoRa, Sigfox etc. However, the licensed band comes with the advantage of energy harvesting that can be used to compensate for high energy demand. One of the energy harvesting approaches, as modelled in (Darsena et. al., 2017), considers the ambient backscatter approach. The later consists of taking advantage of the fact that far-field radio frequency (RF) signals in the air carry both information but also energy. If designed properly, the NB-IoT nodes can harvest the energy carried by Electromagnetic Waves (EMs) to sustain their energy levels and, therefore, enhance their lifetime. The work in (Darsena et. al., 2017) considers the transmission of one symbol per Orthogonal frequency-division multiplexing (OFDM) symbol over short distances and demonstrates that this could result in achieving satisfactory data rates while saving and harvesting a good deal of energy.

Despite the different challenges presented by the integration of NB-IoT as part of 5G cellular IoT, NB-IoT remains very competitive over unlicensed technologies, in terms of the selection of the IoT technology that is best suited for 5G systems. This is because, unlike the unlicensed technologies, the NB-IoT does not pose the issue of heterogeneity of the network which would make it more difficult to manage. Some

of the efforts in mitigating the challenges as posed by the integration of the NB-IoT within the 5G systems include the use of SDN and NFV as discussed in section 2.6.

2.6 SDN and NFV for NB-IoT within 5G Systems

Achieving low power consumption and low-cost IoT is among the key design objectives of NB-IoT systems as integrated with the 5G systems (Sinha, 2017). However, the NB-IoT design forming part of a cellular network could become energy and cost expensive to implement. Therefore, the authors in (Beyene et. al., 2017) investigate the use of NB-IoT system implementations to exploit the benefits of another disruptive and emerging technology called the Cloud Radio Network Access (C-RAN). The C-RAN is a concept of centralization and virtualization of the baseband operations of the BS. If properly implemented, the C-RAN can help enhance network performance in various aspects including energy, scalability and reliability. On the other hand, the use of a C-RAN for NB-IoT system design can significantly reduce the high capital expenditures involved in network deployment due to the virtualization of the maximum possible number of network functions by applying NFV and the implementation using robust SDN algorithms (Quek et. al., 2017).

The proposed centralization and virtualization of the NB-IoT network design poses several challenges. For example, in LTE systems, there are challenges for the implementation of C-RAN because of problems related to the fronthaul capacity as well as the difficulty to comply with very stringent latency requirements. This is where 5G systems with their enhanced performance potential become of great value to the

implementation of the NB-IoT functions using a C-RAN approach. Another benefit that can be obtained from the application of the C-RAN to NB-IoT systems is the simplification of the Radio Access Network protocols by removing the functionalities that are not necessary for IoT application. This would not have been possible by using actual hardware-based RAN (Beyene et. al., 2017).

As a result of the virtualization of the C-RAN, a centralized pool of Baseband Units (BBUs) from various BSs can provide statistical multiplexing benefits to the network implementation resulting in higher network performance in terms of lower network latency and lower energy consumption while shifting the transmission burden to the high-speed network infrastructure provided by 5G systems. (Checko et. al., 2015). This centralization of the Base Stations functions allows for a high level of cooperation among them and enables more network scalability (Quek et. al., 2017). This concept has been experimented by (Beyene, Jantti and Ruttik, 2014) in form of a flexible SDR-based C-RAN testbed capable to run most RAN technologies on a commodity server.

Finally, as previously discussed, cognitive ambient backscatter approach as discussed by (Darsena et. al., 2017), is another technique for enhancing the energy efficiency of NB-IoT systems by superimposing information from a secondary device (NB-IoT node in this case) on a primary signal (a 5G User Equipment for example) with no extra power-consuming active component. However, this approach is fully dependant on very accurate channel estimations and sometimes suffers from co-channel direct link interference (DLI) (Liu et. al., 2013). Therefore, (Darsena et al., 2019) proposes the use of a C-RAN architecture in a 5G network whereby the primary and secondary

edge nodes (NB-IoT node and cellular UE for example) would be connected using high-speed links to a cloud SDR. This will avoid the channel estimation errors and the DLI resulting in a more energy-efficient NB-IoT design.

2.7 Energy efficient NB-IoT Channel Coding (CC) schemes

Low-Power Wide-Area Network (LPWAN) technologies both in the licensed and unlicensed bands are striving to become energy efficient over very long distances ([Chen et. al., 2017](#)).

NB-IoT is designed to extend the lifetime of devices and targets a battery life of more than 10 years. To this end, a careful design of smart channel coding schemes has been identified as a potential approach towards enhancing NB-IoT energy efficiency ([Migabo et. al., 2017](#)). Channel coding is one of the most important aspects in digital communication systems which enables error detection and correction possible ([Zarei, 2009](#)).

In its current form, the NB-IoT reuses the LTE design extensively including the numerologies, downlink orthogonal frequency-division multiple-access (OFDMA), up-link single-carrier frequency division multiple-access (SC-FDMA), channel coding, rate matching, interleaving, etc. To the best of my knowledge, the only reason for this extensive reuse of the LTE channel coding was to significantly reduce the time required to develop full NB-IoT specifications ([Spajic, 2017](#)). However, there are issues very specific to the NB-IoT network designs including the issue of limited energy capacity. Researchers ([Tabbane, 2017](#)) and ([Ratasuk et. al., 2016](#)) have, therefore,

identified a very crucial need to develop novel channel coding techniques very specific to the NB-IoT with different design goals. This research work as introduced by this chapter has identified the energy efficiency issue as a potential research problem. However, other researchers have looked into this problem from different perspectives. The different approaches considered by them are concisely reported in the next paragraphs.

2.7.1 Why Is Energy Efficient Channel Coding Important for NB-IoT

One of the most important issues in the design of NB-IoT systems is error correction. If well designed, the channel coding technique for NB-IoT can help save a considerable amount of energy by significantly reducing the number of required retransmissions. This justifies the fact that several research studies have proposed channel coding techniques to achieve energy efficiency. In its current form, the NB-IoT uplink base-band processing can be divided into channel coding and modulation. In the case of the NB-IoT uplink, the channel coding includes Cyclic Redundancy Check (CRC) generation and attachment, turbo or convolutional coding, and rate matching. Reliability is a key performance criterion in any form of wireless communication including the NB-IoT. It is therefore crucial that any NB-IoT design ensures that end-to-end communication occurs reliably between terminals. As in most engineering designs, the effort to enhance one performance often comes with an associated cost in terms of the other. Channel coding is often used in most communication systems to ensure resilience to channel impairments and ensure reliable link transmissions. Therefore, previous research work has proposed various channel coding approaches to ensure

reliability. The main identified approaches have been the traditional repetition approach and the Narrowband Link Adaptation (NBLA) approach (Yu et al., 2017). Despite their attempt to enhance communication reliability, the approaches have been shown to suffer significant energy costs. This issue is what the present research work addresses. It strives to find a balance between ensuring reliable communication on NB-IoT uplinks while maintaining energy efficiency.

2.7.2 Existing NB-IoT Energy-Efficient Channel Coding (CC) approaches

From the survey of the literature, the following approaches were selected based on their relevance to this study and based on their recent works.

1. Automatic Repeat Request (ARQ) Approaches

In ARQ approaches, the receiver requests re-transmission of data packets. If errors are detected, using some error detection mechanism. The authors in (Tabbane, 2017) proposes an open-loop forward error correction technique for NB-IoT networks to optimize the ARQ signalling. In this approach, signalling only needs to indicate the DL data transfer completion and does not have to be specific on which particular Packet Data Units (PDU) are lost during the transmission. This allows to reduce the simplicity of the channel coding approach, and, therefore, allows saving on computational energy consumption. This approach has proven to be efficient in enhancing the data rate performance in the Downlink (DL) of the NB-IoT network. Due to its low complexity, this approach has further proven to also enhance the energy efficiency of the NB-IoT network as it considerably reduces the computational

energy consumption due to data reception on the transceiver of the IoT node. The approach proposed in (Ratasuk et. al., 2016) consists of using a hybrid automatic repeat request (HARQ) process in scenarios where the NB-IoT network can only support half-duplex operations. The HARQ approach has demonstrated the ability to reduce the processing time at the IoT node. The obtained results in (Ratasuk et. al., 2016) can prove that the use of the HARQ approach can lead to savings up to 20% on the overall energy consumption of the network. This energy efficiency performance has also been proven not to be significantly affected by the increase in the scalability of the NB-IoT network when the HARQ approach is used.

The authors in (Inoue and David, 2017) propose a hybrid channel coding approach. It consists of signalling hybrid automatic repeat request (HARQ) acknowledgements for narrowband physical downlink shared channel (NPDSCH) and uses a repetition code for error correction. In this case, the UE can be allocated with 12, 6 or 3 tones. However, only the 6 and 3 tone formats are introduced for NB-IoT devices due to coverage limitations, cannot benefit from the higher device bandwidth allocation which results in higher energy consumption performance.

2. Forward Error Correction (FEC) Approaches

Research ((Wibowo et. al., 2011), (Alexiou et. al., 2011), (Alexiou et. al., 2017)) has investigated the efficiency of different re-transmission and FEC techniques in NB-IoT systems. Several researchers have quantified the effect of several network parameters on the efficiency of error correction techniques (and their associated network costs). However, no effort has yet been made to unify these studies into a systematic approach that could help with the selection of the most effective technique given certain

network conditions.

The authors in ([Cornelius and Helberg, 2013](#)) have proposed an improved error correction algorithm for multicast transmission over the LTE network, and by extension, over the Narrowband IoT network. The model used assumes a random distribution of packet losses and a constant loss rate in each scenario. The model can be expanded to include different error distributions and varying loss conditions during a series of NB-IoT downlink transmissions. The obtained results demonstrate that the use of a hybrid approach (HARQ and FEC combined) outperforms both the HARQ method used alone as well as the FEC approach used alone in terms of energy efficiency.

The authors in ([Havinga, 1999](#)) have proposed the use of open-loop forward error correction technique a mechanism to not only enhance the energy efficiency of the NB-IoT network but also to concurrently achieve efficient downlink data rate performance. The benefit of this approach lies in the fact that it enables extremely reliable firmware downloads which is an important IoT feature in several applications among which sensor network applications.

Another Forward Error Correction channel coding approach for Narrowband IoT proposed in ([Singh and Kumar, 2012](#)) has been specifically designed to reduce the number of retransmission attempts. This is mainly because it has been identified and demonstrated by ([Bouabdallah et. al., 2009](#)), ([Walther, 2006](#)) and ([Migabo et. al., 2015](#)) that most energy consumption in the Internet of Things and Wireless Sensor Networks (WSNs) is consumed through the transmission and the reception phases. Another unique Forward Error Correction approach which is based on algebraic-geometric theory compares the BER performance of algebraic-geometric codes and

Reed-Solomon codes at different modulations schemes over additive white Gaussian noise ([Alzubi et. al., 2014](#)). In this approach, it is found that there is an improvement in terms of BER performance improvement at the cost of high system complexity when algebraic-geometric codes and the Chase-Pyndiah's algorithm ([Chase, 1972](#)) are used in conjunction with each other.

The authors in ([Chronopoulos et. al., 2011](#); [Zakariyya et. al., 2019](#)) propose a new enhanced Parallel Conventional Channel Coding (PCCC) approach which proposes the use of two or more convolutional encoders in parallel using turbo codes, demonstrates the ability to significantly reduce the overall number of received error packets when compared to the typical Serial Conventional Channel Coding (SCCC) as well as the typical PCCC. This channel coding approach can be of benefits in terms of enhancing the overall energy efficiency performance of the NB-IoT systems using the OFDM scheme, provided that its iterative decoding is computationally reliable and implementable on low resources processors of NB-IoT nodes with a restricted number of feedbacks.

On the other hand, the authors in ([Chronopoulos, 2016](#)) propose an enhanced OFDM platform based on Turbo Coding (TC) techniques. This approach considers the presence of a noisy channel (AWGN, Phase noise, Rician noise, ITU PA3) and demonstrates the ability to overcome its impairments to achieve excellent BER performance. Due to the high-reliability performance of the proposed approach as well as its use with the OFDM modulation scheme (used in LTE systems), it can be a suitable channel coding method for NB-IoT systems provided that its energy consumption performance also demonstrates to be efficient for sensor nodes NB-IoT type of ap-

plications ([Iraqi and Al-Dweik, 2020](#)).

One of the most prominent NB-IoT uplink baseband processing designs mainly consists of two main parts, namely the channel coding processing design and the modulation part. According to most work found throughout the literature ([Nokia Networks, 2015](#)), most NB-IoT uplink channel coding approaches includes Cyclic Redundancy Check (CRC) generation and attachment, turbo or convolutional coding, and rate matching in their traditional format as inherited from the LTE network infrastructure.

Unlike most LTE devices, the NB-IoT nodes are mostly battery-powered, and, therefore, energy-constrained. The traditional LTE channel coding approaches, therefore have been identified by certain studies such as ([Lee and Jaiyong, 2017](#)) and ([Whitmore et. al., 2015](#)) as not being as energy-efficient in the context of the Internet of Things (IoT). Therefore, the authors in ([Lee and Jaiyong, 2017](#)) have proposed a prediction-based energy-saving mechanism which mainly consists of reducing the uplink transmission time as a key to ensuring a long lifespan of an IoT device. The mechanism consists of two parts: first, the network architecture predicts the uplink packet occurrence through a deep packet inspection; second, an algorithm predicts the processing delay and pre-assigns radio resources to enhance the scheduling request procedure. In this way, the proposed approach is expected to significantly reduce the number of random accesses and the energy consumed by radio transmission, and therefore, reduce the overall NB-IoT network energy consumption ([Lee and Jaiyong, 2017](#)). The network architecture with the prediction-based energy-saving mechanism as proposed by ([Lee and Jaiyong, 2017](#)) can be further enhanced by

adding a network clustering mechanism on the radio interface between the different NB-IoT nodes and the eNB instead of having multiple individual links between each node and the eNB. This can to further enhance the overall energy efficiency of the network. The proposed energy-enhanced architecture diagram is as shown in Figure 2.5.

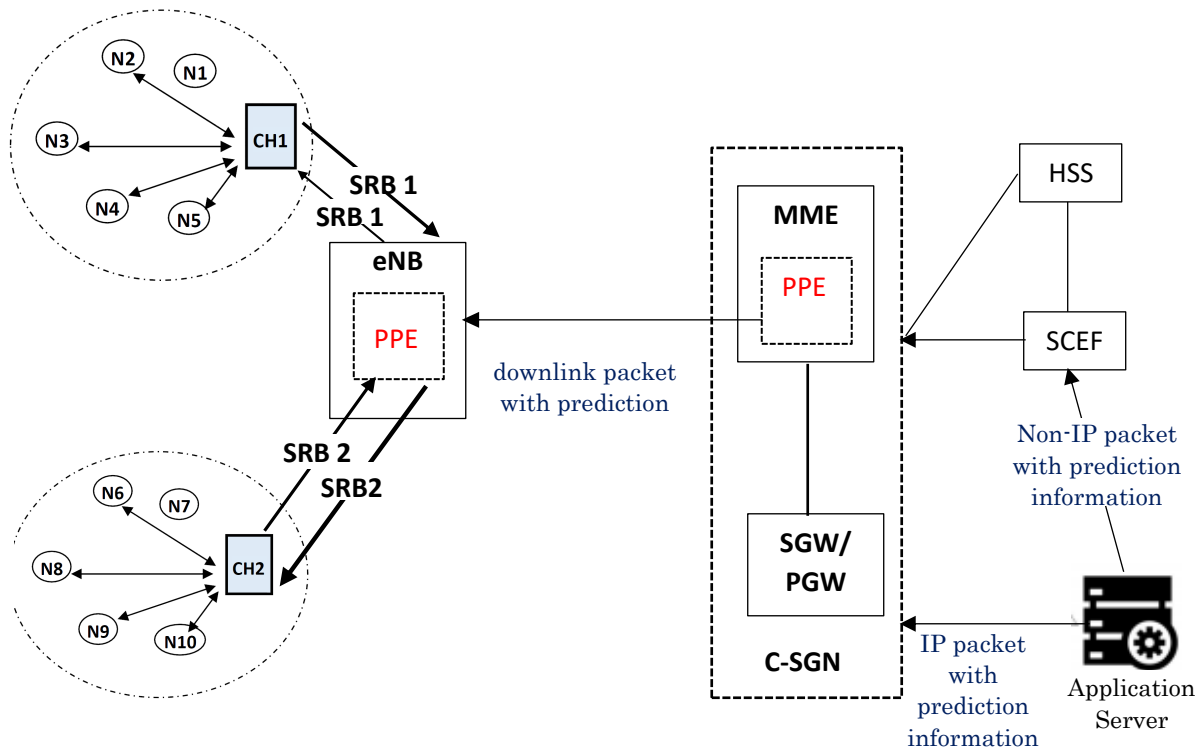


Figure 2.5: Energy-enhanced clustering Network architecture with prediction-based energy-saving mechanism

Figure 2.5 shows the NB-IoT network architecture that includes the proposed mechanism. It is the same as the conventional network architecture and interface structure but considers two new entities namely the packet inspection entity (PIE) and packet

prediction entity (PPE). The PIE, which is logically located on the MME, determines the session type from the packet header inspection, e.g. protocol type, port number, and IP address. The PIE then predicts the occurrence of the up-link response with a designed strategy, aimed at minimising the overall latency.

From an architectural point of view, figure 2.5 complements the idea of (Lee and Jaiyong, 2017) by adding clustering of NB-IoT nodes ($N_1, N_2, N_3, \dots, N_x$) as a technique to further enhance the management of resources within the network. The geographical based clustering of NB-IoT nodes, with one of the nodes playing the role of a Cluster Head (CH, e.g. CH1 and CH2), allows a more decentralized approach in the processing of uplink and downlink packets, and therefore, can be expected to enhance the overall performance of the network in terms of its time (latency), energy and scalability resources.

2.8 Data rate enhanced NB-IoT modulation selection schemes

Most NB-IoT modulation approaches consist of a two-stage modulation scheme where data is modulated with quadrature phase-shift keying (QPSK) scheme. The QPSK is often used in conjunction with the orthogonal frequency-division multiplexing for the base-band modulation part. The QPSK, as used for NB-IoT, encodes all the information into the phase of the transmitted signal. The NB-IoT QPSK modulation takes two input bits and maps them into one complex number $I + jQ$ according to the signal constellations as defined in table 2.4 and visualized in figure 2.6 (3GPP, 2014).

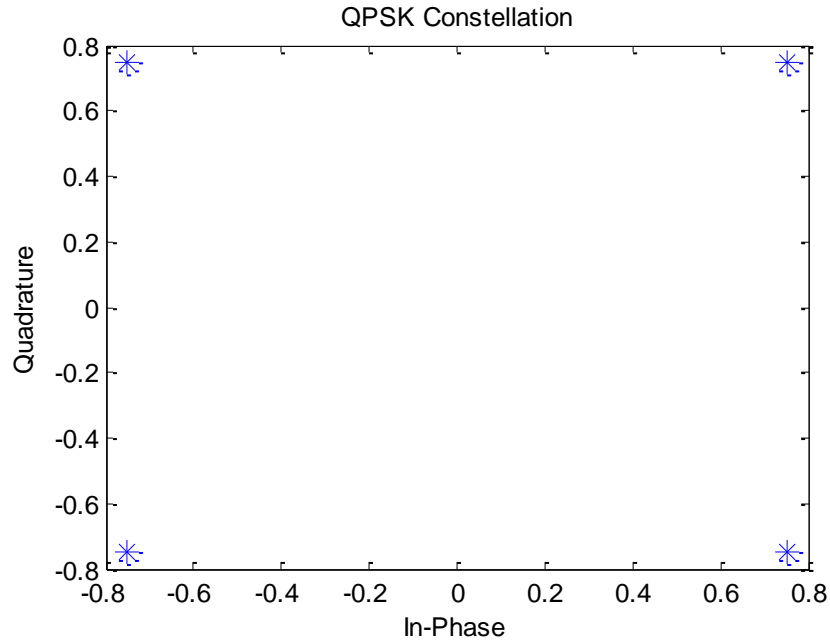


Figure 2.6: The QPSK constellation points used in NB-IoT

Table 2.4: QPSK signal constellation points for NB-IoT where I is the In-phase component and Q is the Quadrature component

b(i), b(i+1)	I	Q
00	$\frac{1}{\sqrt{2}}$	$\frac{1}{\sqrt{2}}$
01	$\frac{1}{\sqrt{2}}$	$-\frac{1}{\sqrt{2}}$
10	$-\frac{1}{\sqrt{2}}$	$\frac{1}{\sqrt{2}}$
11	$-\frac{1}{\sqrt{2}}$	$-\frac{1}{\sqrt{2}}$

Low-Power Wide-Area Network (LPWAN) technologies both in the licensed and in the unlicensed bands are striving to become standardised, and therefore, usable in all

types of IoT applications including high data rate demanding IoT applications. One major approach that a group of researchers are looking into is modulation scheme selection as a way to achieve that emerging goal ([Bor and Roedig, 2017](#)).

LPWAN in general and NB-IoT in particular, demand reliable data communication at high throughput in severe channel conditions like narrowband interference, frequency selective fading due to multipath and attenuation of high frequencies ([Sharifet. al., 2010](#)).

Like any LPWAN devices, NB-IoT nodes typically communicate directly to a sink node (Base station in the case of NB-IoT). This removes the need for constructing and maintaining a complex multihop network. However, to ensure efficient and reliable communication, it is suggested that NB-IoT devices will often provide a large number of transmission parameters ([Chen et. al., 2017](#)). For example, an NB-IoT device can be configured to use different spreading factors, bandwidth settings, coding rates and transmission powers which can result in over 6720 possible settings ([Bor and Roedig, 2017](#)). It is a challenge to determine the setting that minimises transmission energy cost while meeting the required communication performance. This is one of the major issues in current research on LPWAN in general and NB-IoT in particular.

By singling out a particular challenge in this domain, it has been established by ([Bor and Roedig, 2017](#)) that different Modulation Coding schemes (MCS) levels influence the throughput of a system directly. Low MCS and high power are susceptible to improve transmission reliability, and therefore, enhance the NB-IoT network coverage. However, another study by ([Sharifet. al., 2010](#)) has also established that if not performed efficiently, the MCS selection process can contribute to reducing the

NB-IoT system's throughput and, therefore, result in quite low data rates.

Most competitors in the LPWAN arena have been designed to transmit a few bytes per hour and in some cases even per day. This is the case of Long Range (LoRa) and Sigfox which are mainly designed for applications that only require the transmission of up to 52 bytes of data for LoRa and 12 bytes for Sigfox packets at a time. This poses a problem in real-time IoT applications where the application sporadically requires high bandwidth and for which the NB-IoT technology, if well designed, has great potential and advantages.

To enhance the data rate performance of NB-IoT systems, the authors in ([Spajic, 2017](#)) and ([Xu and Darwazeh, 2018](#)) propose the use of an adaptive downlink spreading factor channel coding and modulation scheme selection. This approach consists of enhancing the Transport Block Size (TBS) to 2536 bits. This allows the data rates to go from the standard 250 kb/s and 226.7 kb/s as per Release 13 of the standard ([3GPP, 2014](#)), to higher data rates of about 400 kb/s where it was proposed in ([Spajic, 2017](#)). These data rates can be reached as a result of the ability to support a second Hybrid Automatic Repeat Request (HARQ) process. This second HARQ process is useful for enhancing the reliability of the link for the UEs that experience favourable channel conditions. The implementation of the optional second HARQ process results in throughput gain as it reduces the overhead as a result of NPDCCH scheduling gaps.

In ([Xu and Darwazeh, 2018](#)), the authors present an NB-IoT framework that uses non-orthogonal spectral efficient frequency division multiplexing (SEFDM). SEFDM uses less bandwidth when compared to OFDM. The waveform could improve the

data rate without the need for more bandwidth. At the base station, the minimum Euclidian norm search detector is used for better error correction. The simulation results reveal that the proposed advanced signal waveform could achieve an improvement of 25% on data rate when compared to OFDM. The work also proposed an overlapped sphere decoding (OSD) detector which reduces the computation complexity when compared to the single sphere decoding detector while guaranteeing the needed performance. However, the model does not explain the impact of CFO due to the non-orthogonality of the subcarriers on the received signal.

2.9 Link Adaptation Schemes for enhanced NB-IoT scalability

It has been established in ([Azari et. al., 2018](#)) and the 3GPP Release 13 that repeating transmission data or control signals have been considered as a promising approach to enhance the coverage of NB-IoT systems since the repetition number could enhance the transmission reliability but could cause a loss in spectral efficiency. Thus, ([Malik et. al., 2018](#)) and ([Oh and Shin, 2017](#)) observed that the link adaptation scheme design needs to provide a reasonable trade-off between transmitting reliability and throughput of the system by selecting suitable MCS and repetition.

The authors in ([Zarei, 2009](#)) propose a link adaptation approach that aims at matching the transmission parameters, modulation scheme, and coding rate to the channel conditions to make the efficient use of the channel capacity possible. This proposed link adaptation is based on Adaptive Modulation and Coding (AMC). The AMC

proposed by (Aljburi, 2016) is aimed at adapting the modulation scheme and code rate by considering the following:

- **Modulation scheme:** if the Signal-to-Interference plus Noise Ratio is sufficiently high, higher-order modulation schemes with higher spectral efficiency which would imply higher bit rates such as 64 Quadratic Amplitude Modulation (QAM) are used. In the case of poor SINR, a lower-order modulation scheme such as QPSK (Quadratic Phase Shift Keying), which is more robust against transmission errors but has a lower spectral efficiency is used.
- **Code rate:** for a given modulation scheme, an appropriate code rate can be chosen depending on the channel quality. The better the channel quality, the higher code rate is used, and consequently, the higher the data rate.

In NB-IoT systems, a Turbo encoder with a mother code rate of $1/3$ can be used for data channels (Wang et. al., 2016). This will result in achieving a Rate Matching (RM) module following the Turbo encoder. This configuration has demonstrated that it is possible to obtain other code rates when desired. The authors in (Zakariyya et. al., 2019), as a result, suggest that increasing and decreasing the code rate should be done via puncturing and repetition respectively. Both puncturing and repetition are integrated into the Rate Matching module.

2.10 An overview on the NB-IoT spectrum sharing and clustering

The sharing of network resources remains a very crucial aspect of NB-IoT network designs. It is a key feature for enhancing network scalability and enabling the connection of massive NB-IoT devices to the network. Various approaches have been previously proposed among which tone allocations ([Adhikary et. al., 2016](#)), Physical Resources Blocks (PRBs) allocation techniques ([Xu and Darwazeh, 2018](#)), repetition number techniques ([Ratasuk et. al., 2016](#)), power configurations and control techniques ([Sultabia et. al., 2019](#)), subframes, or time slots management techniques at Medium Access Layer (MAC) level ([Kroll, Korb and Weber, 2017](#)), etc. Therefore, several research works, as discussed in this section, have a special focus on achieving better radio resource management to ensure energy efficiency, high throughput, high spectral capacity, and better coverage. Of these various approaches, this chapter mainly focuses on two aspects, namely efficient spectrum management and clustering techniques.

2.10.1 Spectrum Sharing Techniques in licensed band IoT systems

One of the approaches to deal with the scarcity of available spectrum resources is to consider spectrum sharing for the Internet of Things. In a special manner for IoT, mobile operators are inclined to exploit the existing standards and infrastructures of current cellular networks and deploy licensed IoT such as the NB-IoT within the already congested licensed cellular spectrum ([Palattella et. al., 2016](#)). The reason

why the proposed approach focuses mainly on the NB-IoT among other licensed IoT systems is simply that unlike the other licensed systems such as the eMTC which mainly exploits the LTE spectrum, the NB-IoT standard makes provision not only to exploit the LTE spectrum but all other re-farmed cellular spectra. Compared to other approved IoT systems, this leaves enough room for developing NB-IoT systems. This uniqueness of the NB- IoT spectrum creates space for more efficient use of the spectrum which in turn translates into the ability to provide more connected NB-IoT nodes and better channel capacity utilization. However, this unique benefit requires the use of a well-designed spectrum sharing algorithm capable of mitigating and managing interference while efficiently utilizing the already limited network resources such as energy. One of the main existing approaches for spectrum sharing in the NB-IoT system designs is the orthogonal spectrum allocation technique. This technique consists of centralizing the management of spectrum management. The advantage of this approach is that it allows cellular network operators to avoid cross-technology interference between NB-IoT networks with the current cellular networks (5G, LTE, etc.) on one hand, and on the other hand, the other licensed IoT networks deployed on the same cellular network such as the LTE-Machine Type Communication (LTE-M) that includes the enhance Machine Type Communication network (eMTC). This orthogonal approach is also referred to as overlay spectrum sharing as opposed to the underlay (non-orthogonal Multiple Access (NOMA)) spectrum sharing ([Lin et. al., 2014](#)). In the overlay approach, different users (Cellular User Equipments (UEs), as well as IoT (NB-IoT and LTE-M) nodes, are allocated separate time or frequency resource blocks (RBs) with the same power level, while in the underlay approaches,

different users are allocated different power levels but are serviced using the same time or frequency resource blocks (Abdelmoniem et. al., 2019). The difference between the two approaches is illustrated in figure 2.7.

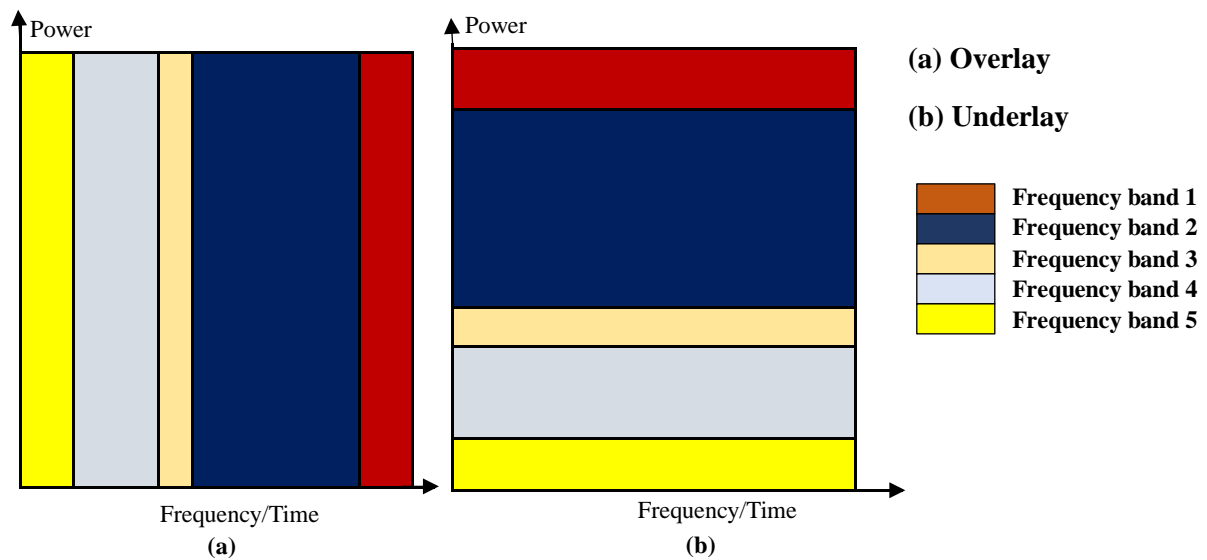


Figure 2.7: Overlay versus underlay spectrum sharing solutions

This study considers the use of a spread spectrum approach as part of the orthogonal frequency sharing techniques because of the nature of the NB-IoT spectrum which does not only comprise of the spectrum as provided by the cellular network to which it is attached but also comprises of other re-farmed cellular spectra. This characteristic provides an opportunity to mitigate interference and therefore, allows to connect more NB-IoT nodes within a cell. This is possible provided that a smart and well-designed frequency selection algorithm is used. This is one of the motivations for the consideration of the approach in this study.

Other spectrum sharing techniques used for NB-IoT systems include spectrum sharing techniques similar to those considered in cognitive radio networks. In most of these cognitive approaches, the licensed IoT networks are considered as secondary cognitive transmitters while the primary transmitters are the UEs of the cellular network to which the IoT network is attached (Song, Hong and Choi, 2013) (Akyildiz et. al., 2008). In the cognitive approaches, the NB-IoT nodes (secondary transmitters) may access the primary spectrum if the primary transmitters are not active or are not susceptible to causing significant interference (Kang, 2009). Most of these algorithms used in cognitive radio are designed in such a way that the secondary transmitters (NB-IoT nodes in this case) are regulated by sensing the activities of primary transmissions and at the same time, impose stringent secondary access constraints on some well-defined network performance objectives such as the probability of collision (Kang, 2009). One of the approaches used to minimize secondary interference is through the use of Multiple Inputs Multiple Output (MIMO) strategies (Hamdi et. al., 2009). However, this approach is not feasible in most contexts of NB-IoT nodes designs because of their limited energy, computational, and memory resources. Other approaches go further by using a dynamical game approach to study the spectrum sharing among a primary user and multiple secondary users (Kalathil and Jain, 2013). Unfortunately, unlike cognitive radios, in the NB-IoT networks, the primary transmitters are normally NB-IoT nodes and BSs. Besides, although the cognitive radio like techniques may work for few connected NB-IoT nodes (10 to 20 nodes per cell), they become non-feasible for massive NB-IoT systems as the probability of interference rises significantly to the extent of almost nullifying their

benefit. Therefore, the question of how Device-to-Device (D2D) networks such as the NB-IoT systems should access the spectrum remains an open problem with its specific challenges as discussed in subsection 2.10.2.

2.10.2 Spread Spectrum challenges in NB-IoT systems

It is expected that the ever-expanding number of connected NB-IoT devices will generate a massive volume of data which has diverse requirements including network lifetime (≥ 10 years (Zayas and Merino, 2017)), latency (< 4 ms (Matz et. al., 2010)), reliability (SNR ≥ -12.6 dB (Mwakwata, 2019)), and throughput (up to 26 kbps in downlink and 66 Kbps in uplink Ratasuk et. al. (2016)). Some of these devices will be dedicated to real-time IoT applications such as remote surgery etc. These specific devices will, therefore, have very low latency requirements which for a given available spectral efficiency accessible to them at a given instant of time, will require a larger bandwidth. These types of applications are the most likely to lose connectivity in a cell as more and more devices join the network. Despite this challenge, it is important to emphasize that the NB-IoT remains the choice of preference for enhanced network scalability Gemalto (2020). This is because unlike the unlicensed IoT technologies (Long Range (LoRa), SigFox etc.), it has the benefit of being able to freely leverage on the cellular spread spectrum technology. Also, when considered against other IoT technologies such as the LTE-M technologies, the NB-IoT is more flexible since it can operate in 2G, 3G, 4G, and 5G bands. This eliminates the need for a gateway which saves costs in the long run. The competitive advantage of NB-IoT technology over the other IoT technologies in terms of achieving network

scalability has been emphasized in the previous paragraph. However, it is important to note that the use of the spread spectrum sharing approaches for NB-IoT systems has challenges of its own. A key issue with the use of spread spectrum techniques is how they afford protection against interfering signals with finite (limited) power [Pickholtz et. al. \(1982\)](#). When more and more NB-IoT devices and cellular UEs attempt to simultaneously access the uplink NB-IoT channel, the probability that their power when spread through the channel will overlap increases and ultimately result in interference. Hence, one key design aspect when it comes to the spread spectrum algorithm lies in the random sequence generation approach. The challenge for the random sequence generation method is to simultaneously achieve repeatability, to pass all statistical randomness checks, to achieve insensitivity to seed values, and finally to ensure that the finite duration during which the sequence repeats itself is much longer than the amount of random number required at a given time as the network grows (as the number of connected NB-IoT devices increases). Therefore, an Adaptive Frequency Hopping Spread Spectrum technique is considered in this chapter that is capable of dynamically adjusting the random sequence number taking into account the amount of remaining energy of the NB-IoT nodes in the network.

2.10.3 Clustering Approaches for energy-efficient NB-IoT

Clustering techniques have proven to be beneficial in terms of enhancing the energy efficiency of the Internet of Things networks. They have also proven to be very effective in balancing the energy consumption of the network. This is because they allow an offload of the Bases Station which, despite the increasing number of nodes,

results in more reliable communications. However, one of the major challenges of clustering has been the fact that the use of fixed cluster heads has proven to shorten the life cycle of the network. This is because, most NB-IoT nodes are energy limited as they run on batteries. Therefore, using selected NB-IoT nodes as relays to a group of others poses a serious energy burden to these relay nodes which eventually die. As the relay nodes die, this results in the inability of some NB-IoT nodes to reach the BS. This problem, also often referred to as a “hotspot problem” has triggered various research interests within the research community. The present section discusses the different clustering approaches that have been considered in the specific case of NB-IoT systems in an attempt to resolve this issue.

Several energy-efficient techniques have been developed for IoT networks in general and NB-IoT networks in particular. Some of the key techniques include but are not limited to the following:

- *Low-Energy Adaptive Clustering Hierarchy (LEACH) and its variants*: LEACH is a hierarchical technique that consists of nodes transmitting data packets to cluster heads which first aggregates the received packets, compresses the aggregated data before forwarding it to the base station (sink). In LEACH, every single node uses a stochastic algorithm at each transmission round to determine if it is its turn to become a cluster head. Nodes that have been cluster heads cannot become cluster heads again for P rounds, where P is the desired percentage of cluster heads. Thereafter, each node has a $1/P$ probability of becoming a cluster head again. At the end of each round, each node that is not a cluster head selects the closest cluster head and joins that cluster. The

cluster head then creates a schedule for each node in its cluster to transmit its data. A major weakness of LEACH when applied to NB-IoT systems is that it is only reliable under the condition that the BS is within the radiation range of each NB-IoT node. Due to their geographical dispersion and mostly randomized locations in some applications, some NB-IoT nodes happen to be at non-communication range to the BS when their radio is operated in low-power (energy saving) modes. Therefore, if the node's firmware is smart enough, it adjusts the radio transmission power to its maximum for the communication round in which a specific node plays the role of cluster head in most cases. Considering the large numbers of data packets from all neighboring nodes and considering that more and more NB-IoT nodes are introduced to the network (massive NB-IoT systems), this particular NB-IoT node would deplete its remaining energy and die. This is despite some sort of network coding technique that is used to save the limited energy resources.

There are other variants of the LEACH protocol that are proposed as a mechanism to enhance its performance. These include the LEACH centralized (LEACH-C) protocol ([Heinzelman et. al., 2002](#)). The LEACH-C scheme is meant to improve the CH allocation in LEACH by using a centralized control algorithm to distribute the CH nodes throughout the system. In LEACH-C, the BS computes the average residual energy of the nodes across the network and only allows the nodes with residual battery powers equivalent to the computed average residual energy to work as CH in each round. The LEACH with fixed clusters (LEACH-F) is another centralized variant of LEACH. In LEACH-F,

the setup phase is not required at all rounds. Only the CH position rotates among the nodes. The data fusion oriented clustered routing protocol based on LEACH (DF-LEACH) is another variant of the LEACH protocol ([Chen and Zhao, 2009](#)). DF-LEACH aims to facilitate both global energy efficiency and reduced energy dissipation at the CHs ([Zhixiang, 2017](#)). In this scheme, data fusion is performed in a hop-by-hop mode among the CHs before transmission to the BS.

- *The Energy-Efficient Hierarchical Clustering (EEHC)*: This clustering approach as proposed by ([Bandyopadhyay and Coyle, 2003](#)) uses Voronoi cells approach to classify (group) nodes into clusters. The cluster head selection is based on residual energy. The nodes with the most residual energy within each cluster is selected as the cluster head. The selected cluster head is then used to allocate time slots to the other nodes within the cell based on a Hidden Markov prediction model. The benefit of the approach is that it has proven to enhance the overall energy efficiency of the NB-IoT network. However, since it does not consider the signal strength parameter in the selection of the cluster heads, some packets do not always get delivered to the BS. This decrease in network communication reliability results in re-transmission attempts that are costly to energy and offset the effect of clustering on the overall energy efficiency of the network.
- *Energy-Efficient Unequal Clustering (EEUC)*: The authors in ([Li et. al., 2005](#)) propose an algorithm that minimizes the number of CHs with full coverage and connectivity. This extra optimization that is performed on the number

of selected CHs is aimed at reducing the energy cost of communication in the network as a way to reduce the overall energy consumption of the network. However, this approach only works under the constraints that the number of CHs still fulfils the requirement that every single node can still relay their packets through one of the selected CHs. The algorithm is based on a spiral sequence generated for arbitrarily deployed nodes. To further minimize the number of CHs, the EEUC proposes the use of some CHs as relay nodes for others under the condition that some CHs run low on their residual energy levels. However, the drawback of the EEUC is that it consumes significant amounts of energy that is incurred by cluster formation overhead and fixed-level clustering.

- *Power-Efficient and Adaptive Clustering Hierarchy (PEACH)*: PEACH is proposed by (Yi, 2007) to solve the issue of energy consumed by cluster formation overheads. PEACH uses overhearing (sniffing) characteristics of the wireless communication channel to form clusters without additional overhead. It also supports adaptive multi-level clustering. Besides, PEACH can be used for both location-unaware and location-aware NB-IoT networks. PEACH has been shown to outperform other hierarchical routing protocols such as LEACH in terms of extending the network lifetime (Mehta, 2018).
- *Hybrid Energy-Efficient Distributed Clustering (HEED)*: The HEED (Hybrid Energy-Efficient Distributed clustering) protocol periodically selects CHs based on a hybrid parameter made of the remaining energy of a node as the primary parameter and a secondary parameter such as the minimum average distance

to a higher number of neighbour nodes. The HEED approach demonstrates a fairly uniform CH distribution across the network and a low computational complexity $O(1)$. However, it suffers from an energy-expensive CH selection process.([Younis and Fahmy, 2004](#)). The HEED approach also has high inter-cluster traffic which results in an imbalance in the energy consumption liable to cause CH nodes to die faster, therefore, shortening the lifetime of the network.

- *Distributed Weight-based Energy-Efficient Hierarchical Clustering (DWEHC)*: The authors ([Ding et. al., 2005](#)) propose an improved version of the HEED approach called the DWEHC. The DWEHC assigns a weight to the primary and secondary CHs selection parameters. The DWEHC approach starts with each node locating its closest neighbours. Based on the received information and its energy parameters, the node works out a hybrid parameter weight value which then serves as decisive in selecting the Cluster Heads. Once more, and like the other approaches, the DWEHC uses a Time Division Multiple Access (TDMA) approach within each cluster as a mechanism for each node within the cluster to send its packet to the CH. However, as the number of nodes increases, the probability of inter-nodes interference increases, network latency deteriorates and so does the network reliability. To minimize the impact of having clusters with congested communication traffic as the NB-IoT network scales, some other approaches such as the Cluster Head Election using Fuzzy logic (CHEF) ([Kim et. al., 2008](#)) have been proposed.
- *Cluster Head Election using Fuzzy logic (CHEF)*: CHEF ([Kim et. al., 2008](#)) proposes the use of a fuzzy logic approach as a mechanism to minimize the

energy consumption of CH selection. It also reduces the inter-cluster communication energy consumption burden on the selected CH by rotating the CH role among nodes for more energy-balanced network performance. The energy level in each node, the concentration (number of nodes present in the vicinity), and the centrality (a value which classifies the nodes based on how central the node is to the cluster) are used as variables in the fuzzy logic rules formulation. However, the model suffers from the following drawbacks:

1. The fact that the BS has to collect information from all the NB-IoT nodes, results in complex and multiple overheads. This results in additional energy consumption which although it is negligible for a few nodes, becomes significant as the number of nodes increases.
2. The approach does not cater for the energy consumption caused by the distance measurement between NB-IoT nodes. This is because the CH selection parameter does not feature any signal strength consideration.

2.10.4 Energy-Efficient Network coding techniques for NB-IoT systems

Several approaches have been previously considered to achieve energy efficiency within an NB-IoT system at various network layers ([Chiti et. al., 2019](#)). One such technique used at the network layer includes minimizing data traffic using data dissemination, data aggregation (network coding) as well as network programming ([Yu et. al., 2010](#)). In a multihop data routing technique, previous studies on existing network coding techniques found in literature can be broadly classified into two main

categories namely the local and the global coding techniques depending on whether the decoding of the aggregated packet is performed at the intermediate NB-IoT nodes or only at the end destination BS. Furthermore, network coding techniques can be classified into intersession and intrasession approaches depending on the fact that the relay node (CH) only encodes packets from different or the same cluster member nodes respectively (Migabo et. al., 2016). While the intrasession network coding approaches are mainly aimed at reducing packets loss, the intersession network coding approaches are mainly focused on reducing the number of packets re-transmissions as a mechanism to reduce the overall network energy consumption (Shrestha, 2015). It is also important to mention that several network coding techniques as found in the literature are also classified as binary(XOR) or random linear(RL) types (Migabo et. al., 2016). Some of the few selected NB-IoT network coding techniques include the following:

- SenseCode: This is a local network coding approach as proposed by (Keller et. al., 2013) that focuses on achieving reliable network performance. SenseCode has demonstrated to significantly reduce the end-to-end packet error rate and is most suitable for highly dynamic environments. However, SenseCode suffers from a high amount of network resources among which energy. The performance evaluation of the SenseCode approach under normal static conditions has proven to reduce the packet error rate by 90% as compared to the routing of packets with no network coding. This performance drops to about 75% under highly dynamic environments as evaluated on TinyOS modules using the TOSSIM simulations.
- CodeDrip: This is a technique proposed by (Ribeiro et. al., 2014) to achieve energy

efficiency and reliability by allowing the recovery of lost packets using a combination of transmitted packets and decoding on the receiving end. CodeDrip is an improved version of the Drip data dissemination method (Tolle and Culler, 2005). The main change from Drip consists of the inclusion of control fields which are necessary for a faster decoding process. However, CodeDrip struggles to cope with high volumes of data packets often encountered in real-time NB-IoT applications.

Given the different identified issues as identified for the various existing approaches described in this section, this chapter proposes a mixed approach strategy that first tackles the inter-cluster communication scalability issues through the use of an adaptive frequency hopping spread spectrum capable to mitigate interlink interference. Secondly, the proposed approach also proposes an energy-signal-strength aware CHs selection method with the intent to reduce and balance the overall energy efficiency of the network while offloading the BS. The detailed explanation of this proposed mixed approach is detailed in the next section.

2.11 The NB-IoT performance Challenges and open issues

Despite, the recent research and developments work on NB-IoT, several technical challenges still remain that require proper modelling and adequate solutions. Some of the key challenges faced by NB-IoT design include network scalability, data rate enhancement as well as energy efficiency, network reliability and latency just to name few.

2.11.1 NB-IoT Energy Efficiency Challenges and opportunities

One basic condition which enables the communication between "things" in the IoT network is the presence of a properly selected wireless connection. For instance, a Wi-Fi connection is sufficient for a small-range home network that connects two computers and a tablet. However, it might be required to communicate with devices located in hard-to-reach places such as building basements. It might also be required to send small portions of data over a long transmission distance. Imagine being able to provide long battery life for water or gas meters, or installing tens of thousands of devices without worrying about interference between them and the bandwidth available to everyone. Well designed NB-IoT could be the answer to these needs and challenges. All these benefits come with associated multiple challenges, primarily amongst which is achieving energy-efficient communications happens which is one of the major challenges. This is mainly because NB-IoT nodes are mostly battery operated. Therefore, their network design poses a research opportunity and challenge which is to enable energy efficiency at all network layers. Some of the key challenges include:

- **Coverage versus energy:** It has been established by experimentation ([Haridas et.al., 2019](#)), that the lifetime of an NB-IoT device depends on the application's reporting rate and the coverage class. This is mainly due to the reliability features (coverage enhancement techniques) in the NB-IoT standard such as high repetitions of sub-frames / resource units and low modulation and coding rates (MCS) used in the physical layer. This constitutes a research opportunity in terms of propos-

ing dynamic and adaptive MCS selection techniques and link adaptation methods more suitable to NB-IoT Technology. The later should still guarantee acceptable communication coverage.

- **The Spatio-temporal variations in available energy the amount that can be harvested:** Various research studies including (Haridas et. al., 2018), (Khan et. al., 2018), (Basharat et. al., 2017), and (Fedele et. al., 2018) have proposed energy harvesting as a solution to the energy deficiency problem in NB-IoT. The authors in (Basharat et. al., 2017) make use of a mixed strategy that jointly combines efforts of non-orthogonal multiple access (NOMA) and energy harvesting from RF signals energy to enhance the energy efficiency of the NB-IoT network. To maximize the amount of energy harvested from the RF signals, the approach formulates an optimization problem that includes user grouping in most suitable resource blocks, power allocation, and time allocation. The authors in (Khan et. al., 2018), on the other hand, propose a technique to harvest energy from the thermal difference between two conductive plates on the NB-IoT device. The approach is shown to produce only tens of $\mu Watts$ for powering the entire sensing/transmitting NB-IoT device.

However, due to the diverse type of environments in which NB-IoT networks could be deployed, considering their wide range of applications, the availability in time and space of energy harvesting resources being so stochastic makes most of the proposed models confined to a well-defined deployment environment, and therefore, not dynamic at all (Sun et al., 2019).

- **Energy efficiency versus communication latency:** NB-IoT, by design, is not meant to offer millisecond latency such as to simplify chip-set and enhance battery autonomy. The latency in NB-IoT depends upon Transport Block Size (TBS), the number of transmission repetitions and even the network deployment mode. NB-IoT can be deployed in in-band, guard-band, and out-of-band modes each having a different link budget. MNOs will configure a different number of repetitions depending upon the deployment mode (link budget).

2.11.2 Data Rates enhancement and network reliability challenges

As NB-IoT networks designs are proposed, some of the key issues raised include how much data can the network handle as well as what is necessary to transfer this data. It is, therefore, necessary for anyone interested in NB-IoT network design to better understand NB-IoT network architecture and deployment/link budget aspects. This opens up a research opportunity for modelling the NB-IoT network at different network layers to comprehend and assess the network behaviours specific to the NB-IoT against the cellular network on which it is attached (LTE, 5G). As critical IoT applications become more and more prominent in multiple IoT applications, the question that comes out is who will win the data rate enhancement war among IoT technologies. NB-IoT being a licensed band technology presents a competitive advantage against non-licensed band technologies such as LoRa and SigFox in this regard. However, achieving data rate enhancement poses a couple of research challenges and introduces the following opportunities,

- **At the PHY layer level:** The current NB-IoT designs mainly propose that the

NB-IoT network adopts the modulation schemes inherited from the cellular network to which it is attached. However, due to specific aspects of the NB-IoT PHY layer, it would be more appropriate to propose NB-IoT specific modulation techniques which will enhance the network's data rate performance without deteriorating its reliability in terms of the probability of successful transmissions from NB-IoT nodes to the Base Station (Uplink) and vice versa (Down-Link).

- **At the Network layer level:** Many NB-IoT design approaches consider single-hop data links within NB-IoT cells. This could result in a lower amount of data being sent to the Base Station during up-link sessions. A research opportunity identified concerning this includes network coding techniques. Technology standards which include network protocols, communication protocols, and data-aggregation standards, are the sum of all activities of handling, processing, and storing the data collected from the NB-IoT nodes. This aggregation increases the value of data by increasing the scale, the scope, and the frequency of data available for analysis.

2.11.3 Network Scalability issues

Connecting a large number of devices will be one of the biggest challenges of the future of NB-IoT. It will defy the very structure of current communication models and the underlying technologies. Presently, the NB-IoT being attached to cellular networks such as the LTE mainly relies on the centralised server/client paradigm to authenticate, authorise, and connect different nodes in a network.

This model is sufficient for current NB-IoT ecosystems, where tens, hundreds or even

thousands of devices are involved. However, when networks grow to join billions and hundreds of billions of devices, the centralised systems will turn into a bottleneck. Such systems will require huge investments and spending in maintaining cloud servers that can handle such large amounts of information exchange. This could lead to going down if the server becomes unavailable.

The future of NB-IoT will very much have to depend on a decentralised approach where clustering approaches based on network topology as well as artificial intelligence techniques will play a big role in enhancing the network scalability. Part of it can become possible by moving some of the tasks to the edge such as using fog computing models where smart devices such as IoT hubs take charge of mission-critical operations and cloud servers take on data gathering and analytical responsibilities.

Other solutions involve the use of peer-to-peer communications where devices identify and authenticate each other directly and exchange information without the involvement of a broker. Networks could be created in meshes with no single point of failure. This model will have its own set of challenges especially from a security perspective, but these challenges can be met with some of the emerging IoT technologies such as Blockchain.

The blockchain technology can be used as a distributed ledger that can record exchanged communication packets between the NB-IoT nodes and the eNB in an efficient manner and in a verifiable and permanent way. Blockchain technology will allow for secure communications as it provides resistance to data modification because each piece of the data being transferred between the two endpoints is linked to its previous block as it contains its cryptographic hash ([Khan and Salah, 2018](#)).

On the other hand, by storing data across its peer-to-peer network, blockchain, as applied in NB-IoT, will eliminate several risks that come with data being held centrally (Chaer et. al., 2019). The decentralized blockchain may use ad hoc message passing and distributed networking. Every NB-IoT node in a decentralized system will in this way have a copy of the blockchain ensuring that Data quality is maintained as well as computational trust. This decentralization effect could help in reducing network latency as well as enhancing the network's energy efficiency among other resources.

The future of the licensed Internet of Things technologies in general, and NB-IoT in particular, will also count on the virtualization of some of its layers to efficiently manage its resources and, therefore, enhance its network performance. This is susceptible to enhance the NB-IoT's network scalability and this way, enable the use of NB-IoT within applications such as Big data analytics required for smart and efficient storage, fog computing as a way to extend the cloud computing platform to the edge of the network.(Mallikarjuna et. al., 2018)

2.12 Conclusion

This chapter has explored, analysed, and discussed comprehensively the different aspects related to network resources efficiency in NB-IoT designs and deployment. This chapter is an important tool for any researcher who intends to embark on the study of the NB-IoT network performance enhancement as it provides a clear and concise overview of the different network resources considerations. The chapter has

paid close attention to issues of energy efficiency, data rate, network reliability, and scalability performance. The chapter has also identified key challenges in terms of the current state of the NB-IoT designs and has identified research opportunities. Based on the identified challenges, the next chapters of the thesis present the modelling of the PHY layer of the NB-IoT network followed by the design and development of an energy-efficient technique for MCS selection, data rate enhancement and the enhancement of network scalability.

Chapter 3 A Modelling Approach of the Narrowband IoT (NB-IoT) PHY Layer Performance

3.1 Introduction

The Narrowband Internet of Things (NB-IoT) is a licensed Internet of Things (IoT) technology directly associated with cellular networks such as the Long-Term Evolution (LTE). However, the NB-IoT remains an independent radio interface technology with its very specific physical (PHY) layer characteristics. This chapter, therefore, provides a mathematical model of the NB-IoT PHY layer characteristics. This chapter specifically strives to elucidate the impact of the NB-IoT PHY layer characteristics on the overall network performance of the NB-IoT system. The chapter starts by formulating the energy efficiency against data rate and network latency performance dilemma. It, then discusses and analyses the different NB-IoT deployment modes and finally, proposes a prediction model for the NB-IoT processing delay to enhance

the data rate performance of the network while maintaining its energy efficiency.

The Internet of Things (IoT) network is a large scale by nature ([Gharbieh and El-Sawy, 2017](#)). As a result of the continuous development in the area of the Internet of Things (IoT), the IoT communication infrastructure has increasingly matured for the past few years ([Wang et. al., 2016](#)). The Narrowband Internet of Things (NB-IoT) is a new cellular technology introduced in the 3rd Generation Partnership Project (3GPP) Release 13 to provide wide-area coverage for the Internet of Things (IoT). The NB-IoT is, therefore, expected to play a very crucial role in connecting the billions of devices that will soon form the IoT. Although the NB-IoT is integrated with the LTE network, its PHY layer remains a separate air interface which is, therefore, not backwards-compatible with the LTE. It is stated by ([Rohde and Schwarz, 2016](#)) that the coexistence of the NB-IoT within the LTE network is realized by clearly specifying the time and frequency resources used from the existing standards, or else, in the area of deployment. As part of Release 13, 3GPP has specified a new radio interface, the Narrowband Internet of Things (NB-IoT). NB-IoT is optimized for machine type data traffic. It is designed to be kept as simple as possible with the goal to minimize device costs and the objective of achieving energy efficiency through the minimization of battery consumption. Besides, one major design objective of the NB-IoT is also to adapt it to work in difficult (harsh) radio conditions. This is mainly because the NB-IoT design normally targets the applications involving Machine Type Communications (MTC) devices and most often, the MTC devices' operational area is of harsh radio conditions.

The main objective of this chapter is to model the NB-IoT PHY layer main char-

acteristics. This chapter, therefore, aims at describing the correlated characteristics of the NB-IoT up-link and downlink within each of the NB-IoT deployment modes. This model also assesses the energy consumption versus the data rate performance enhancement dilemma concerning the network scalability as commonly encountered with the NB-IoT PHY layer design. The other aim of this work is also to propose and assess the performance of a novel predictive processing delay model of the NB-IoT network.

As opposed to the unlicensed and fully autonomous Long Range (LoRa) Low Power Wide Area Network (LPWAN) technology, the NB-IoT reuses the LTE design extensively, including the numerologies, the downlink orthogonal frequency-division multiple-access (OFDMA), the up-link single-carrier frequency division multiple access (SC-FDMA), channel coding, rate matching, interleaving, etc (Wang et. al., 2017). This results in significantly reducing the time required to develop the NB-IoT's full specifications but also comes with an associated cost in terms of non-appropriateness of some of the LTE system's components to the specific type of IoT applications namely the critical IoT applications such as remote health-care, traffic safety and control, smart grid, remote manufacturing and many more. However, it is key to point out that most LTE-Advanced features such as carrier aggregation, dual connectivity, or device-to-device services are not supported by the NB-IoT. The current research and development studies on NB-IoT, including the present one, seek to propose to propose new physical layer signals designs to meet the demanding requirement of extended coverage in rural and deep indoor areas, of high throughput, ultra-low energy consumption and scalability to cater for more connected IoT

devices.

The NB-IoT PHY layer uses a well-defined subset of LTE frequency bands. Table 3.1 provides a comprehensive overview of the selected LTE Uplink and corresponding Downlink frequency bands as specified by the 3GPP Release 13.

Table 3.1: The 3GPP Release 13 Selected UL and DL Frequency bands

Band Number	uplink frequency range(MHz)	Downlink frequency range (MHz)
1	1920 - 1980	2110 - 2170
2	1850 - 1910	1930 - 1990
3	1710 - 1785	1805 - 1880
5	824 - 849	869 - 894
8	880 - 915	925 - 960
12	699 - 716	729 - 746
13	777 - 787	746 - 756
17	704 - 716	734 - 746
18	815 - 830	860 - 875
19	830 - 845	875 - 890
20	832 - 862	791 - 821
26	814 - 849	859 - 894
28	703 - 748	758 - 803
66	1710 - 1780	2110 - 2200

One significant and noteworthy aspect of the bands chosen for use by the NB-IoT is that most of the frequencies selected are in the lower range of existing LTE bands. This is a clear indication of the expectation for a lot of MTC devices to be connected in difficult radio conditions as the lower transmission the frequency, the longer the wavelength, the more robustness and reliability of the communication at low transmission power cost. The lower frequency bands selected provide better signal quality over a broader coverage area and long distances. This is because the lower frequencies experience less attenuation and multipath fading caused by obstacles and dense surfaces such as concrete walls as mathematically modelled by the Friis formula given by

$$L = 20 \times \log_{10}\left(\frac{4 \times \Pi \times d \times f}{c}\right) \quad (3.1)$$

where L represents the approximation (ideal case: isotropic antennas and free space) attenuation, d represents the distance between the transmitting and receiving antennas, f and c represent the frequency and the speed of light respectively.

3.2 NB-IoT Operation Modes

The NB-IoT technology normally occupies a frequency band of 180 kHz bandwidth ([3GPP TS 36.201, 2016](#)), which corresponds to one resource block in LTE transmission. To efficiently utilize the spectrum resource at its disposal, the NB-IoT is designed with three different operation modes namely the standalone, the in-band and the guard-band modes. While each of these operation modes has got its advantages over the other for the specific type of applications and deployment environments,

the Standalone operational mode aims to replace some of the GSM carriers with the NB-IoT carriers, while the In-band operation utilizes resource blocks within a normal LTE carrier and the Guard-band operation uses the LTE carrier's guard-band (Ericsson and Nokia Networks, 2014). The three operating modes are illustrated in Fig. 3.1.

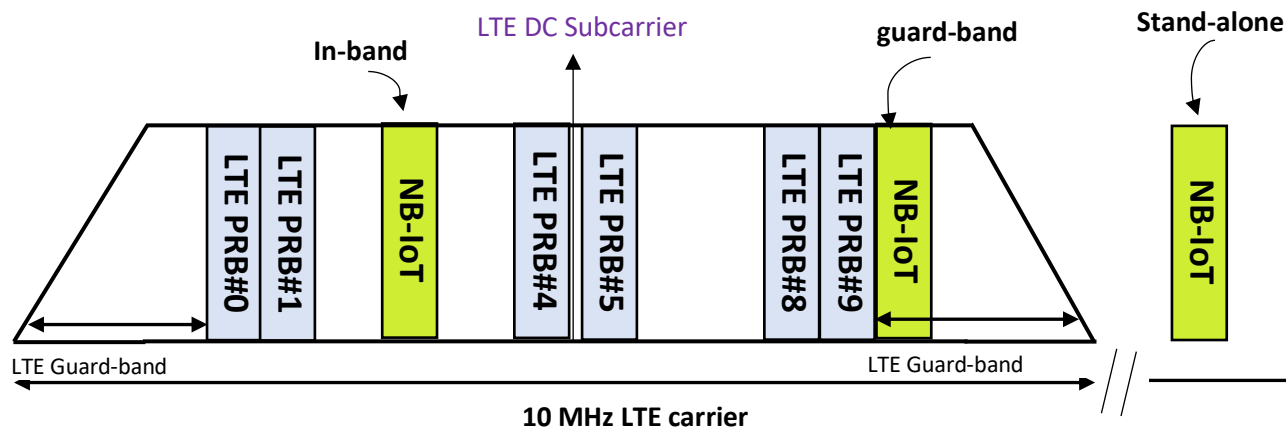


Figure 3.1: NB-IoT operational modes spectrum bands (Wang et. al., 2017)

Fig. 3.1 illustrates an example of the deployment options of NB-IoT with a 10 MHz LTE carrier. The PRB right above the DC sub-carrier, i.e., Physical Resource Block 25 ($PRB\#25$), is centred at 97.5 kHz (i.e. a spacing of 6.5 sub-carriers) above the DC subcarrier. Since the LTE DC sub-carrier is placed on the 100 kHz raster, the centre of $PRB\#25$ is 2.5 kHz from the nearest 100 kHz grid. For an LTE service provider, the in-band option provides the most efficient NB-IoT deployment. For example, if there is no IoT traffic, a PRB which may be available on an NB-IoT carrier may be used instead for other purposes as the NB-IoT is fully integrated within the existing

LTE infrastructure. This allows the base station scheduler to multiplex LTE and NB-IoT traffic in the same spectrum.

1. **In-band operation:** In this operation mode, one or more LTE PRBs are reserved for the NB-IoT. In terms of the network resources allocation, this means that within this reserved PRB region, NB-IoT signals are to be transmitted within their specific time-frequency resources and not within the time-frequency resources reserved for LTE which consists of legacy control region and reference signals (Ratasuk et. al., 2016). This specificity of the NB-IoT time-frequency can mathematically be modeled by comparing and analyzing the difference between the OFDM signal generation of the LTE network with and without the NB-IoT. By considering the number of sub-carriers in resource block (N_{sc}^{RB}), the symbol time (T_s), the number of channel paths in each slot l ($N_{CP,l}$), the resource element in k , the OFDM generated signal in a given path p for the LTE with an in-band NB-IoT can be modeled as follows,

$$S_l^p(t) = \sum_{k=-|N_{sc}^{RB}/2|}^{|N_{sc}^{RB}/2|-1} a_{k^{(-)},l}^p e^{j2\Pi(k+1/2)\Delta f(t-N_{CP,l}T_s)}, \quad (3.2)$$

with $k^{(-)} = k + |N_{sc}^{RB}/2|$.

On the other hand, the LTE OFDM generated signal can be modelled as follows,

$$S_l^p(t) = \sum_{k=-|N_{RB}^{DL}N_{sc}^{RB}/2|}^{-1} a_{k^{(-)},l}^p e^{j2\Pi k\Delta f(t-N_{CP,l}T_s)} + \sum_{k=1}^{-|N_{RB}^{DL}N_{sc}^{RB}/2|} a_{k^{(+)},l}^p e^{j2\Pi k\Delta f(t-N_{CP,l}T_s)} \quad (3.3)$$

with $k^{(-)} = k + |N_{sc}^{RB}N_{sc}^{RB}/2|$, $k^{(+)} = k + |N_{sc}^{RB}N_{sc}^{RB}/2| - 1$

As in the LTE with no NB-IoT, the downlink in LTE with NB-IoT makes use of OFDM waveforms as well. The LTE without in-band NB-IoT OFDM formula can be considered to be much more complex than the LTE with in-band NB-IoT. The modelling of the LTE with no NB-IoT splits the signal into two terms (sections) to remove the center sub-carrier (DC carrier). But in LTE with in-band NB-IoT, there is no DC removal part. As a result, it can represent the whole signal in a single term. In other words, in LTE, k never gets to 0 (the formula is not defined at $k = 0$). However, in LTE-NB, the formula is defined at $k = 0$ as well.

A typical and practical In-band NB-IoT deployment scenario as set by ([Viavi, 2017](#)) is depicted in Fig. 3.2. Fig. 3.2 shows a Non-uniform in-band deployment of the NB-IoT in a typical cellular network with NB-IoT devices located within LTE only cells as well as LTE+NB-IoT cells. The figure shows that if NB-IoT devices and other LTE devices within the cell share at least one common frequency band block within the in-band deployment mode, the same base station will be servicing them. The scenario also shows an IoT device being served by the closest LTE+NB-IoT Base Station which is, therefore, the strongest when compared to the other Base Stations within the network with NB-IoT services.

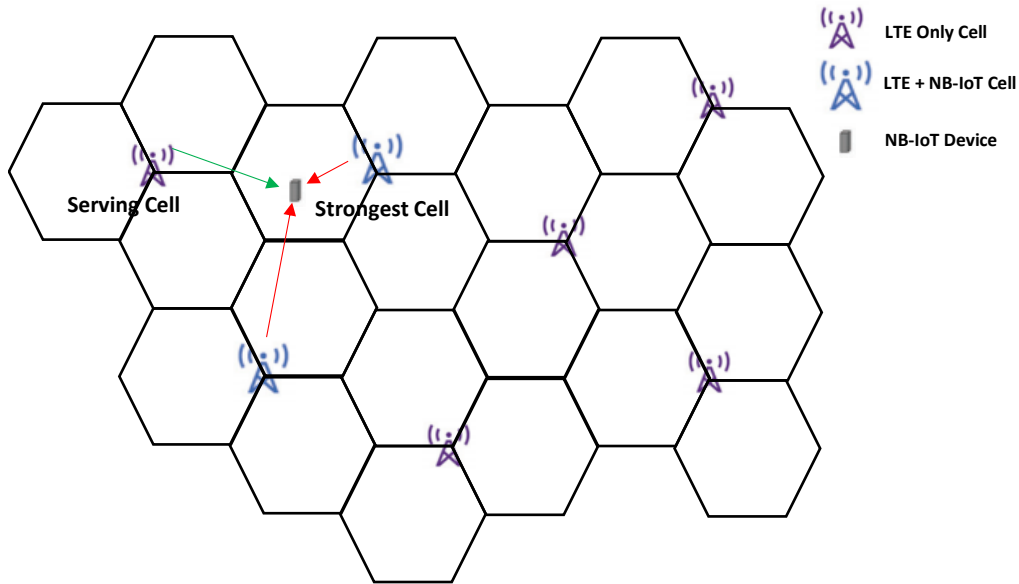


Figure 3.2: Non-uniform in-band deployment for NB-IoT (Viavi, 2017)

2. **Guard band operation:** It utilizes the unused resource blocks within an LTE carrier's guard-band. This allows for a total possible bandwidth of $(100+100)KHz = 200 KHz$ between two consecutive LTE bands since each LTE band has up to 100 kHz in its guard band. Because this operation mode makes use of the guard band, it therefore affects the communication reliability performance within the network as the probability for more channel interference becomes higher.

3. **Stand alone operation:** It uses any available spectrum exceeding 180 kHz. The NB-IoT is used as a replacement of one or more GSM carriers. This allows efficient re-farming of GSM carriers for IoT applications. In this scenario, only 1 transmit antenna is used at the eNB which is the typical deployment scenario for GSM (Ratasuk et. al., 2015).

3.3 The Downlink (DL) interface Model

The modelling of the NB-IoT physical layer considers three types of physical channels and two types of physical signals. The physical channels include

- The narrowband physical broadcast channel (**NPBCH**),
- The narrowband physical downlink control channel (**NPDCCH**) and
- The narrowband physical downlink shared channel (**NPDSCH**).

3.3.1 The narrowband physical broadcast channel (NPBCH)

The NPBCH is a special channel dedicated to carrying the Master Information Block (MIB). It has been identified in this study that the NPBCH channel possesses two main characteristics namely the fact that it uses a Quadrature Phase Shift Keying (QPSK) modulation technique and also the fact that it carries the MIB message which is normally sent from the LTE eNodeB to all potential nodes (broadcast) even when there are no available nodes within the cell ([Troha and Krasowski, 2017](#)). Therefore, the NPBCH channel in its current state can be modeled as a high energy consumption channel. The total energy consumption of the NPBCH channel for a total analysis time T_t can be modeled as

$$E_{Total} = \sum_{j=1}^M (P_{Tx_j} \times T_j) + \sum_{i=1}^N (P_{Rx_i} \times T_i), \quad (3.4)$$

where

1. $M = \frac{T_t}{\Delta T}$: The total number of broadcast times for a broadcast interval ΔT ,
2. N : The average random number of IoT devices serviced by the eNodeB within the cell for the duration of one broadcast interval ΔT ,
3. T_j : The transmission time for the j^{th} broadcast,
4. P_{Tx_j} : The eNodeB average transmission Power within the cell during the j^{th} broadcast,
5. T_i : The signal reception duration of the i^{th} receiving IoT device during a single broadcast interval ΔT and
6. P_{Rx_i} : The i^{th} IoT device's power consumed during reception of the signal.

On the other hand, the overall channel coding process used for the NPBCH channel for the NB-IoT is almost the same as the one of the legacy LTE network. However, there are some key differences in terms of the input/output bit length of each code length for the same code rate. Additionally, the resource element mapping and transmission cycle/subframe drastically differ from one of the legacy LTE networks as clearly modelled through the PHY layer processing diagram presented in Fig. 3.3.

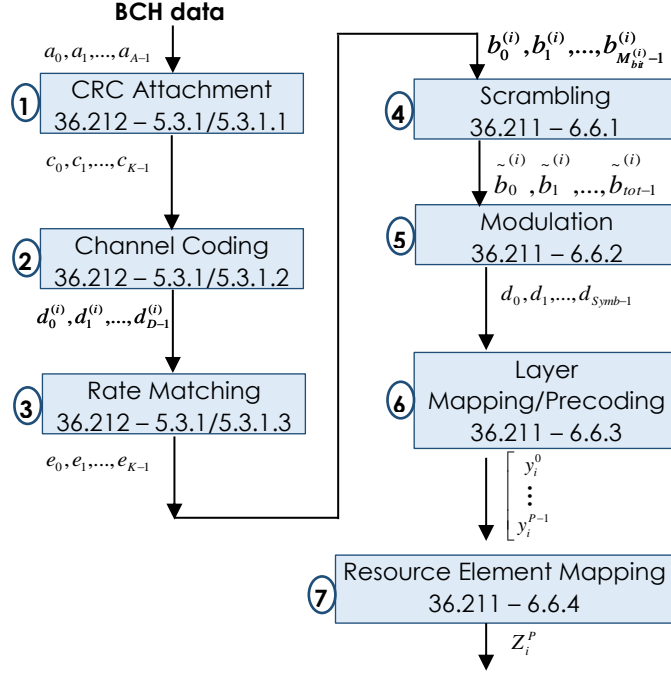


Figure 3.3: NB-IoT PHY layer processing diagram

As it can be seen in Fig. 3.3, a stream of "A" Broadcast Channel (BCH) data bits is first passed to the Cyclic Redundancy Check (CRC) module of a length of $L = K - A$ bits to generate an error detection code of a length of K bits. If A is larger than the maximum code block size $Z = 6144$ as defined in the 3GPP TS 36.212 release 8.1.0 of LTE specifications (3GPP, 2011), the input bitstream is normally divided into segments of an input bit sequence of smaller sizes $A < Z$ and an additional CRC sequence of a maximum of $L = 24$ bits is attached to each segment to form a code block.

3.3.2 The narrowband physical downlink control channel (NPDCCH)

The NPDCCH is the only control channel defined for NB-IoT. This technically means that there is no uplink counterpart like in the LTE without NB-IoT. The NPDCCH on its own handles all the control signals. It carries the DL and UL scheduling grants, acknowledgement information for UL transmissions, paging indication, system information update, and random access response (RAR) (Puschmann et. al., 2017).

3.3.3 The narrowband physical downlink shared channel (NPDSCH)

The NPDSCH channel is the physical sub-channel occupied by the NB-IoT within the LTE Physical Downlink shared channel (LTE-DSCH). One key design consideration of the NB-IoT PHY layer consists of achieving an efficient and reliable NPDSCH performance by overcoming the PHY layer challenges such as the NPDSCH link level to name one (Zhu and Li, 2011).

3.3.4 A Prediction Model for the NB-IoT DL Processing Delay

The NB-IoT by design is not meant to offer millisecond latency to simplify chipset and enhance battery autonomy. The latency in NB-IoT mainly depends upon three main criteria namely the *Transport Block Size*, the *Number of Repetitions* (up to 2048 repetitions in downlink, up to 128 repetitions in uplink at times) and also the *Network Deployment Mode* as discussed in section 3.2 (Afzal, 2017).

The overall DL latency of an IoT device i within an NB-IoT cell can be modelled as follows

$$T_{total}^i = T_{Pck} + T_{Rx} + T_{Queue} + T_{Proc} \quad (3.5)$$

where T_{Pck} represents the time delay consumed at the radio transceiver during the reception of the data packet, T_{Rx} is the time delay consumed on the NB-IoT DL air interface between the BS and the NB-IoT device, T_{Queue} is the delay due to the queuing process of the received data before it is processed and finally T_{Proc} is the DL processing delay of which is of interest in this section.

The processing delay for downlink packets varies according to the protocol category, application type, and device performance. It is therefore stochastic in nature. As a result, the present study proposes a processing delay prediction model that each time makes use of the current and previous processing delay value under the same UE load to estimate the next processing delay value before any downlink transmission activity.

- Assuming that a Packet Prediction Entity (PPE) module manages the prediction metrics for each session and UE, the proposed prediction of the processing delay model introduces a predictive processing delay, T_i for every UE with an ID number i .
- Assuming that the probability for the downloaded data to be successfully received by the IoT device is equal to α , then the probability for the downloaded data not to be received successfully can be modelled as $(1 - \alpha)$.

- Hence, the k_{th} predictive processing delay is defined as $T_i(k)$ and therefore computes the modified predictive processing delay $T'_i(k)$ which applies the probability weights α and $(1 - \alpha)$ to each of the two parts as given below:

$$T'_i(k) = \alpha \times T_i(k) + (1 - \alpha) \times T_{info} \quad (3.6)$$

where T_{info} is the time that takes the received information from the MME to get to the IoT device. The received information normally comes in the form of a positive or negative acknowledgement *ACK* or *NAK* respectively. T_{info} can also be called *reporting* delay.

The proposed model also considers the prediction result and statistics of past predictions. The confirmation that the previous prediction was successful can be confirmed through the decoding result of the preassigned radio resource. The variation of the predictive processing delay follows these criteria: if the previous prediction failed and the current probability, P_k , of successful delay prediction is smaller than the previous probability, P_{k-1} , then the predictive processing delay is increased; if $P_k > P_{(k-1)}$ then the predictive processing delay is reduced. In both cases, this predictive processing delay is either increased or reduced by what is defined as compensation time T_{comp} which can be modelled as

$$T_{comp} = |P_k - P_{(k-1)}| \times T_{step} \quad (3.7)$$

where T_{step} is the compensation step. Otherwise (i.e. if $P_k = P_{(k-1)}$), the predictive processing delay maintains the same value as in the previous case.

Table 3.2: Algorithm: Proposed Prediction Model for processing delay in an NB-IoT network

Algorithm: Proposed Prediction Model for processing delay in an NB-IoT network

1: **Initialization:** $P_0 = 0.9$, $P_1 = 0$, $T_{step} = 0.5$, $\alpha = 0.8$,
 $T_{max} = 30,000$, $T_{min} = 10$ as per the 3GPP Rel. 17 standard

2: **Prediction:**

3: $k = k + 1$

4: $\Delta P = |P_k - P_{(k-1)}|$

5: $T = \alpha \times T(k-1) + (1 - \alpha) \times T_{info}$

6: $T_{comp} = \Delta P \times T_{step}$

7: **if** $P_k < P_{(k-1)}$ and $CRC = 0$ **then**

8: $T(k) = \min\{T \times (1 + T_{comp}), T_{max}\}$

9: **else if** $P_k > P_{(k-1)}$ and $CRC = 1$ **then**

10: $T(k) = \max\{T \times (1 - T_{comp}), T_{min}\}$

11: **else**

12: $T(k) = T(k-1)$

13: **endif**

14: $P_{k+1} = \frac{\sum_{j=0}^k P_j}{k}$

The corresponding criteria, which is detailed in table 3.2, can be modelled as follows,

$$T_i(k) = \begin{cases} \min(1 + T_{comp}) \times T'_i(k-1), T_{max}, \\ \text{if } P_k < P_{(k-1)} \text{ and } Info = NAK \\ \min(1 - T_{comp}) \times T'_i(k-1), T_{min}, \\ \text{if } P_k > P_{(k-1)} \text{ and } Info = ACK \\ T'_i(k-1), \text{ otherwise} \end{cases} \quad (3.8)$$

where T_{max} and T_{min} are the upper and lower boundaries, respectively.

3.3.5 The NB-IoT DL versus the LTE DL: Fundamental differences

One difference with the LTE channels is that the NB-IoT Downlink (DL) interface model does not consider the physical multicast channel PMCH as the LTE infrastructure does not consider any MBMS service for NB-IoT. The physical signals include:

- The Narrowband Reference Signal (NRS)
- The Primary and Secondary Synchronization Signals (NPSS and NSSS)

Unlike the radio network to which the NB-IoT is coupled such as the LTE, 5G etc., the NB-IoT physical channels and signals as described above are primarily multiplexed in time. Fig. 2 illustrates how the NB-IoT subframes are allocated to different physical channels and signals. Each NB-IoT subframe spans over one PRB (i.e. 12 subcarriers) in the frequency domain and 1 ms in the time domain. NPSS and NSSS are used by an NB-IoT UE to perform cell search, which includes time and frequency

synchronization, and cell identity detection. Since the legacy LTE synchronization sequences occupy 6 PRBs, they cannot be reused for NB-IoT and there is, therefore, a need for a new design to be introduced.

3.4 NB-IoT data rate versus energy efficiency mathematical modelling and analysis

Unlike for the LTE PHY layer design where energy efficiency is not critically important, mainly because most LTE network devices operate on high energy capacity power supplies achieving energy efficiency for the NB-IoT is becoming a critical requirement of any physical layer design. This design requirement is often challenged and sometimes even becomes antagonist with the requirement to achieve high data rate transmission as mathematically demonstrated below.

A link budget improvement of about 15/20dB for the existing cellular technologies is targeted to achieve the energy efficiency goal of the NB-IoT PHY layer designs ([Nokia Networks, 2015](#)). To meet this requirement, one of the design techniques to be used at the PHY layer would consist of considerably extending the sensitivity performance of the NB-IoT receiver. The sensitivity of a receiver, on the other hand, is defined as the minimum power required to achieve an arbitrary level of error rate. This can mathematically be modelled as

$$\rho^{dBm} = SNR_{min}^{dB} + 10 \log_{10}(BN_0) \quad (3.9)$$

where B is the bandwidth of the signal (in Hz), SNR_{min} the minimum Signal-to-Noise Ratio (SNR) to reach the level of error rate, and N_0 the spectral density of the noise in mW/Hz . N_0 is thermal noise and is , therefore, temperature dependent. According to a study by (Nokia Networks, 2015), a typical NB-IoT receiver design consideration for N_0 at $20^\circ C$ can be considered as $10 \log_{10}(N_0) \approx -174$ dBm/Hz. The receiver sensitivity ρ is expressed in dBm . The energy efficiency of the NB-IoT physical layer can therefore be estimated from the *energy per bit to noise spectral density ratio*, denoted by E_b/N_0 . The *energy per bit to noise spectral density ratio* metric is an expression of how efficiently the energy is used. This automatically translates to a minimization objective function that can be addressed from different PHY layer design approaches and techniques. The lower the E_b/N_0 required, the more energy-efficient the NB-IoT becomes.

The higher the E_b/N_0 , the higher the Signal to Noise Ratio (SNR) of the NB-IoT network. Therefore, the SNR is directly proportional to E_b/N_0 . The coefficient that defines how the SNR increases to the increase in the E_b/N_0 for the NB-IoT network is the spectral efficiency (η), expressed in $bits/s/Hz$. Therefore, the relationship between the SNR and the E_b/N_0 value can be modelled as

$$SNR = \eta * \frac{E_b}{N_0} \quad (3.10)$$

where the spectral efficiency η which is directly proportional to the downlink or uplink data rate of the NB-IoT network R and inversely proportional to the bandwidth B . Therefore equation 3.10 becomes

$$SNR = \frac{R}{B} * \frac{E_b}{N_0} \quad (3.11)$$

One advantage of the NB-IoT is the narrow (sometimes even ultra-narrow) bandwidth which makes it favorable for higher spectral efficiency. This is provided that the data rate R is significantly improved as in its current form NB-IoT networks mainly achieve low data rates.

By modifying the equation for the receiver's sensitivity, equation 3.9 becomes,

$$\rho^{dBm} = \left(\frac{E_b}{N_0}\right)_{min}^{dB} + 10 * \log_{10}(R) + 10 * \log_{10}(N_0) \quad (3.12)$$

As it can be noticed, the receiver's sensitivity is not dependent on the bandwidth B of the NB-IoT. This explains why the present research work focuses more on data rate performance enhancement than bandwidth minimisation. This is a technique for improving the NB-IoT network's energy efficiency.

However, the improvement in data rate achievable by an NB-IoT network is expected to result in higher receiver's sensitivity requirements according to equation 3.12. This increment in the receiver's sensitivity requirements will reduce the probability to guarantee a good Quality of Service (QoS) performance of the NB-IoT network which will then results in reduced (shorter) achievable communication ranges by the system.

In the context of the NB-IoT, which operates on a narrowband, enhancing the data rate can be done by enhancing the spectral efficiency. Dealing with narrow-band signals involves some technological issues, as it implies a long duration of emitted

signals. However, enhancing the energy efficiency of the NB-IoT depends more on the modulation rather than on the data rate since the required E_b/N_0 is intrinsic to the modulation approach than it is on the data transfer speed.

The possibility for improving energy efficiency through energy-efficient modulation techniques is explorable but also bounded by Shannon's limit of the information theory (Shannon, 1948) which defines the maximum transmission rate with arbitrarily low bit-error probability for a given SNR and bandwidth. A formulation of this limit can be expressed as (Proakis, 1995)

$$\frac{E_b}{N_0} \geq \frac{2^n - 1}{\eta} \quad (3.13)$$

The mathematical analysis leads to the deduction that a minimum value for the E_b/N_0 ratio corresponding to maximum energy efficiency is needed to achieve a reliable NB-IoT communication; increases the spectral efficiency. It is also important to note that while there is a need for increased spectral quality, it is limited to a maximum value of $E_b/N_0 = -1.59 \text{ dB}$ obtained as η tends toward 0. Based on the analysis above, one can deduce that to achieve an NB-IoT system's performance close to this highest limit, it is a requirement that the available energy resource is optimally used for a given spectral efficiency. Therefore, it is clear that to achieve higher data rates while maintaining energy efficiency necessitates decreasing the required E_b/N_0 ratio.

3.5 Performance analysis

To scientifically assess the mathematical model as described in the previous sections, this section presents an assessment of the modelled data rate and energy efficiency of the NB-IoT. This is achieved utilizing computer simulations and computations carried out using the Matrix Laboratory (MATLAB) modelling tool.

The performance evaluation used in this study focuses mainly on five identified critical performance metrics of the NB-IoT. These five main metrics include the data rate performance, the energy consumption of a cell, the spectral efficiency which captures the impact of having a narrow bandwidth on the data rate and energy efficiency and finally the scalability aspect which assesses the impact of increasing the number of NB-IoT devices within a cell on the energy efficiency of the overall NB-IoT system.

3.5.1 Simulation set-up

The NB-IoT network architecture is mainly separated into five parts:

- *The NB-IoT Terminal*, which supports the accessing of IoT devices from various services, and allows them to access to the NB-IoT network by installing the corresponding SIM card.
- *The NB-IoT Access Network*, i.e. the NB-IoT base station, mainly refers to the LTE base stations, i.e. Evolved Node B (eNodeB) which have already been built by operators. From the viewpoint of the deployment type, there three main modes as presented in section 3.2 of this chapter.

- *The Core Network*, which enables the connection between NB-IoT base station and NB-IoT cloud.
- *The NB-IoT Cloud Platform*, wherein various processing can be completed, and results can be forwarded to the vertical industry centre or NB-IoT terminals.
- The Vertical Industry Center, which not only acquires NB-IoT business data from itself but also completes the control of NB-IoT terminals.

It is also important to note that most common NB-IoT applications are mini-packet transmissions, which generally do not support long-term and continuous channel quality change indication. Therefore, NB-IoT does not design a dynamic link adaptation solution, but depends on selecting the Modulation and Coding Scheme (MCS) and re-transmission times of data transmission according to the coverage level. Thus the terminal is adjusted to different coverage levels to realize the semi-static link adaptation (Lu, 2016).

To perform the simulation for the system as modeled in the previous sections, the simulation parameters as described in table 3.3 are considered which describe the NB-IoT environment. The parameter names, values, and ranges have all been selected in conformity with the 3GPP specification as documented in (3GPP Protocol, 2017).

Table 3.3: Simulation parameters table

Parameters	Values
Number of User Equipment (UEs)	300-1800 per cell
Number of eNBs	7 eNBs
Frequency band	DL: 925 MHz, UL: 880 MHz
Number of Resource Blocks (N_{RB})	2 PRBs
Uplink Max traffic period	1 minute
Sectors per cell	Three
Antenna model	Parabolic
Fractional frequency reuse	Hard (FFR)
eNB Max Tx power	46 dBm
UE Max Tx power	20 dBm
Number of IoT devices	100 to 10000
Transmitter	
Max transmit power	43 dBm (Standalone), 35 dBm (In-band)
System bandwidth	200 kHz (Standalone), 10 MHz (In-band)
Thermal Noise Density	-174 dBm/Hz
Receiver	
Noise Figure	5 dB
Sensitivity	-121.4 dBm

3.5.2 Results Obtained

By varying the number of IoT devices per cell from as low as 10 *dpc* (dpc: devices per cell) to as high as 10^6 *dpc*, the average data rate performance of the network yields the results as depicted in Fig. 3.4

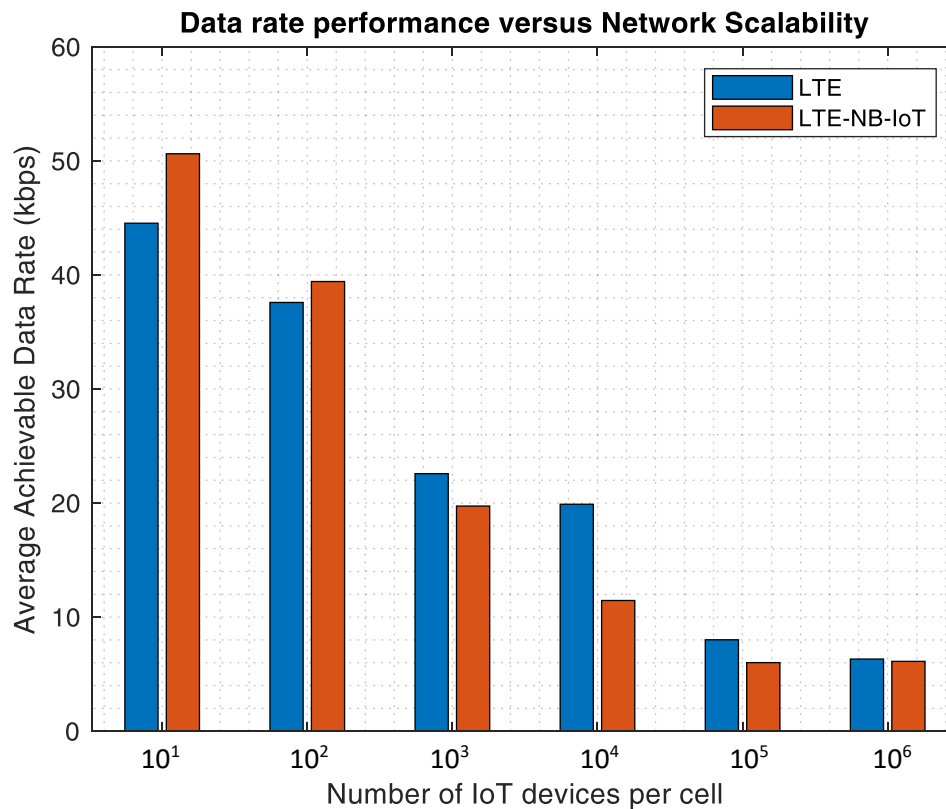


Figure 3.4: LTE-NB-IoT versus Pure LTE Data rate Performance Comparison

It can be seen in Fig. 3.4 that the average data rate performance decreases as the number of NB-IoT devices per cell increases. On the other hand, the analysis shows that with a few IoT devices in the range from 10 to 50 devices, the LTE

network with NB-IoT achieves a better data rate than the LTE without NB-IoT network. However, as the network cell gets congested with the increase of NB-IoT devices the LTE without NB-IoT network exhibits better data rate performance than the one with NB-IoT. As the number of devices significantly increases to a number above 100 000 devices, due to a set of rough uncertainties which become more prominent, the probability of interlink and intra link interferences becomes higher and consequently, the probability of transmission failures increases. This results in the overall data successfully transmitted from end to end to reduce in both the case of the LTE with and without NB-IoT. However, the data rate performance of the LTE without NB-IoT remains higher as compared to the one of the LTE NB-IoT. there is suddenly no significant difference between the data rate achieved by the LTE with or without NB-IoT.

The second performance evaluation consists of assessing the expected energy consumption as per the mathematical model developed in this study. For a total simulation time of about 140 000 *ms* with an average active radio time of 13 860 *ms*, which corresponds to approximately 10% of the total time, the average energy consumption in each of the three NB-IoT deployment modes (In-band, Guard band & Standalone) varies with the number of IoT devices per cell as show in figure 3.5.

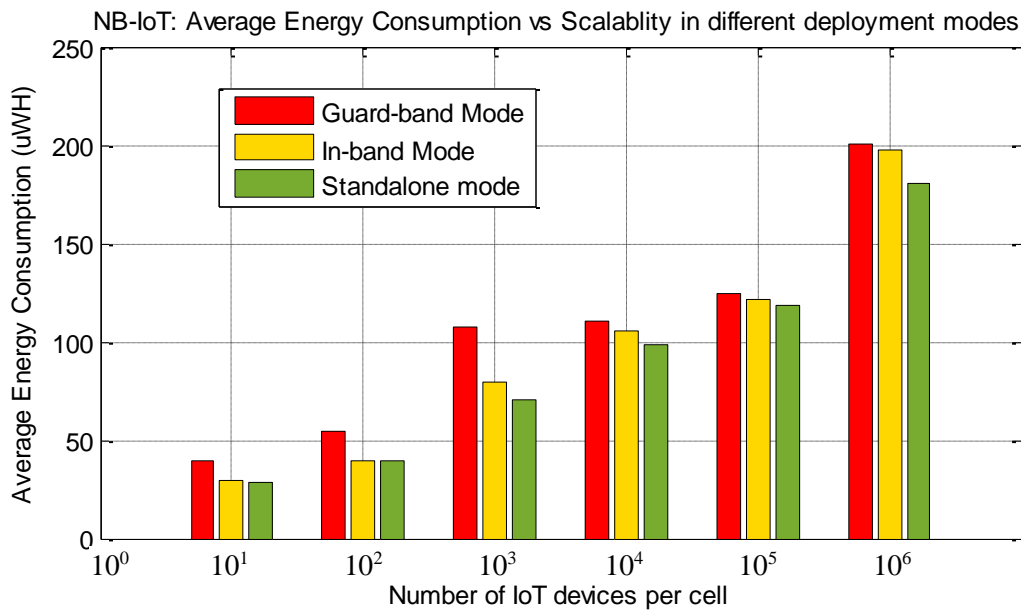


Figure 3.5: Effect of Network scalability on the NB-IoT Average Energy Consumption

The following set of application scenarios can be used for the 6 selected numbers of IoT devices per cell:

- 10 devices per cell: This is a typical application scenario of network of irrigation controlling devices within a lower density rural area. This scenario considers a few number of large farms each with a central irrigation NB-IoT controller all being serviced by a single Base station.
- 100 to 1000 devices per cell: This is a typical application scenario of a set of

NB-IoT sensors and actuators in a small size manufacturing plant. In such a plant with roughly 100 devices and a mini base station forming a femtocell.

- 10000 to 1000000 devices per cell: These are typical urban case scenarios from low density, medium to high density cities where we have a variety of devices ranging from smart water, electricity meters, street lights, traffic lights, speed detection sensors, smart TVs, smart fridges etc.

As can be noted in Fig. 3.5, the greater the number of NB-IoT devices, the less energy efficient the network becomes. The NB-IoT network consumes more energy when deployed in the Guardband mode than it does when deployed in the in-band mode and much more than it does when deployed in the standalone mode. This can be justified by the extra energy consumption due to the data transmission, as the probability of interference of the NB-IoT in the Guardband mode is expected to be higher than in the In-band mode and even much higher in than in the standalone mode.

The other modelling assessment that was performed by computer simulation is one of the predictive processing latency of the NB-IoT Downlink time. With a total of 10^4 deployed NB-IoT devices, for a total simulation time of about 140 000 *ms* for each of the three NB-IoT deployment modes, the average predictive processing latency per NB-IoT that was obtained is illustrated in figure 3.6.

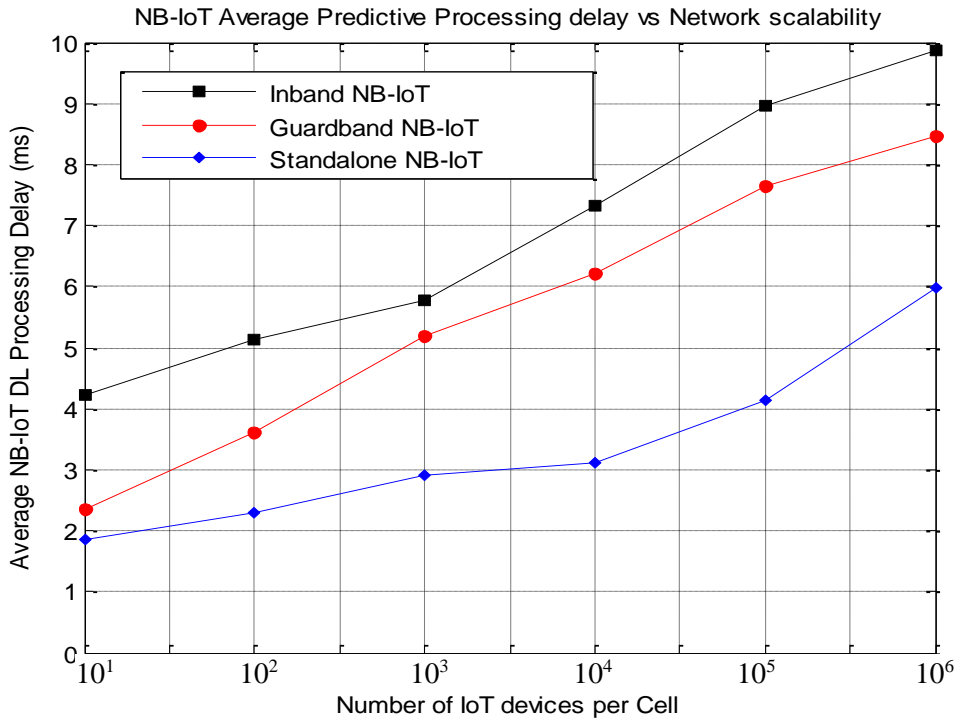


Figure 3.6: NB-IoT Average Predictive Processing delay vs Network scalability

Fig. 3.6 depicts that there is more expected processing delay as the NB-IoT network scales up independently of which mode it is deployed in. However, the results obtained also show that, when the NB-IoT network is deployed in standalone mode, there is an estimate of a much less processing delay than when deployed in either the inband or the guardband modes. For example, for a total of 10 000 NB-IoT devices per cell, the NB-IoT network, as deployed in standalone mode, is predicted to have a processing delay of 29.61% and 49.24% less than when it is deployed in guardband and inband modes respectively.

3.6 Conclusion

This chapter summarizes the PHY layer characteristics of the NB-IoT within its three deployment modes. The chapter then discusses the downlink interface model in terms of the types of physical channels and signals before analyzing the NB-IoT data rate and energy efficiency dilemma. The finally chapter proposes a delay processing prediction model and assesses its performance in terms of maximum achievable data rate, energy efficiency and latency. The obtained results are analysed and discussed.

Chapter 4 An Energy-Efficient and Adaptive Channel Coding Approach for Narrowband Internet of Things (NB-IoT) Systems

4.1 Introduction

Most of the current research work on the Narrowband Internet of Things (NB-IoT) focuses on enhancing its network coverage. Most of the existing NB-IoT channel coding techniques are based on repeating transmission data and control signals as a way of enhancing the network's reliability and therefore, enabling long-distance transmissions. Although most of these efforts are considered at the expense of reducing the energy consumption of the NB-IoT network, they do not always consider the channel conditions. Therefore, this chapter proposes a novel NB-IoT Energy-Efficient Adaptive Channel Coding (EEACC) scheme.

The EEACC approach is a two-dimensional (2D) approach which not only selects an appropriate channel coding scheme based on the estimated channel conditions (dynamically classified as bad, medium or good from initial based on a periodically assessed BLER performance outcome) but also minimizes the transmission repetition number under a pre-assessed probability of successful transmission (based on the ratio of previous successful transmissions over the total number of transmissions). This results in creating a single mixed gradient based on which a higher or lower Modulating Coding Scheme (MCS) is selected on each transmission. It is aimed at enhancing the overall energy efficiency of the network by dynamically selecting the appropriate Modulation Coding Scheme (MCS) number and efficiently minimizing the transmission repetition number. Link-level simulations are performed under different channel conditions (good, medium, or bad) considerations to assess the performance of the proposed approach.

4.2 Background and Motivation

The Low Power Area Networks (LPWAN) is a promising technology of the Internet of Things (IoT) for future wireless communications. In the last decade, LPWANs have rapidly developed and have been attaining significant attention from many researchers around the globe. The authors in ([Miao, Li and Tian, 2018](#)) identified the Narrowband Internet of Things (NB-IoT) as well as the Long Range (LoRa) as the two leading LPWAN technologies towards enabling the future of the Internet of Things within the licensed and the unlicensed bands respectively. However, more

and more network performance issues have been observed as the number of connected IoT devices has grown rapidly in the past few years. One of such issues is the energy consumption of the network which is directly related to the network's lifetime as identified in (Li, Xu and Zhao, 2015).

The NB-IoT is a new narrowband radio technology that was introduced in the Third Generation Partnership Project release 13 for providing low-power wide-area IoT (Yu et al., 2017). Several techniques that consider the performance enhancement of NB-IoT wireless communication systems are being studied in current research. Specifically, the authors in (Xu et al., 2014) presented a systematic review of IoT which includes different definitions, key technologies, open issues and major challenges. Furthermore, the authors in (Ericsson, Nokia & ZTE, 2016) provided a systematic survey regarding NB-IoT in industry. Extensive research, key enabling technologies, major NB-IoT applications of IoT in industry, and identified research trends and challenges were reviewed. At a plenary meeting in South Korea, the Third Generation Partnership Project (3GPP) completed the standardization of NB-IoT in which NB-IoT was regarded as an important technology and a large step for 5G IoT evolution. Major telecommunication companies, including Ericsson, Nokia, and Huawei, have shown great interest in NB-IoT as part of 5G systems and have focused significant effort towards standardization.

In 3GPP standardization, repeating transmission data and the associated control signalling several times has been utilized at the base station to achieve coverage enhancement for NB-IoT (Atzori et. al., 2010). However, repeated transmissions come with a multiplicative energy cost as it has been demonstrated by several wireless

networks energy consumption modelling studies such as (Sharifet. al., 2010; Migabo et. al., 2015) which showed that the major contributors to the overall average energy consumption of a wireless network are the energy consumed during transmission as well as the energy consumed during packet reception. This can be represented as

$$E_{Trans} = \frac{(P_{Tx} + P_{Rx}) \times M}{B \times P_{st}} \quad (4.1)$$

where

- E_{trans} is the energy consumed by the transceiver circuit on single wireless link,
- P_{Tx} is the transmission power,
- P_{Rx} is the reception power,
- M is the uplink packet size in bits,
- B is the transmission bit rate, and
- P_{st} is the probability of successful transmission.

Other related research works such as (Mwakwata, 2019) have highlighted that the use of the NB-IoT link adaptation technique with adaptive modulation and coding schemes as well as adaptive power in the context of the Long Term Evolution (LTE) would be beneficial to reduce the overall power consumption of the network. This approach, however, is limited to the context of using the QPSK modulation scheme to ensure low complexity. Other approaches such as (Boisguene et. al., 2017; Hsieh et. al., 2018) propose the use of a scheduler for the NB-IoT system as a mechanism

to enhance its overall average delay, to ensure the efficiency of energy consumption and other resources and to reduce nodes' processing time. Finally, the authors in ([Andres-Maldonado et. al., 2018](#)) propose a repeated transmission approach coupled with efficient bandwidth allocation as a mechanism to achieve energy efficiency.

The proposed approach seeks to mitigate the high energy consumption by proposing an adaptive energy-efficient channel coding approach. It is also important to note that the choice of different Modulation Coding Scheme (MCS) levels considerably influences the overall network performance of the NB-IoT system in terms of its reliability, its energy efficiency, its scalability, and latency. This is because of the higher the modulation coding scheme, the higher the transmission power per modulated bit of information (lower energy efficiency). However, the transmitted packet is more resilient to noise and other channel impairments (more transmission reliability). The use of low MCS coupled with high transmitting power has been demonstrated to improve the transmission reliability and therefore, enhance the network coverage in terms of longer transmission distance and immunity to noise ([Mostafa, 2017](#)). However, this results in the reduction of the network's throughput and causes the overall energy consumption of the network to be significantly high. Although the number of repeated re-transmissions is significantly cut-down, the transceiver's energy consumption as modelled by Equation (4.2) remains very high. This model is based on the fact that the NB-IoT receiving node has three operational states. It is either in synchronization mode or in the active mode (handling of the received packets) or otherwise in Idle mode. Most of the energy consumption normally occurs in its active state. A medium amount of energy consumption then occurs in its synchronization

state, and a lower amount is consumed during its Idle state (El Soussi et. a., 2018).

The transceiver's energy consumption during reception E_{Rx} can be represented as

$$E_{Rx} = KP_{Rx}t_{synch} + \sum_{k=1}^K P_{sleep}t_{sleep}^k + P_{Idle}t_{active}^K \quad (4.2)$$

where

- t_{synch} is the synchronization time,
- K is the number of cycles or iterations involved in the synchronization process for connection to be effectively established,
- t_{sleep}^k is the time spent in the sleep state in a reception cycle k ,
- t_{active}^K is the total active time during all the K cycles, and
- P_{Rx} , P_{sleep} and P_{Idle} are the power value for the receiving, sleeping and idle states, respectively.

While the repeating of transmission data or control signals has been selected as a promising approach to enhance coverage of NB-IoT systems according to the 3GPP release 13 because a larger repetition number would enhance the transmission reliability. However, it results in a significant spectral efficiency loss (Chakrapani, 2017).

To overcome this, the approach considered in this study proposes a 2-dimensional channel coding and link adaptation scheme capable of providing a trade-off between the transmit reliability and the throughput of the system by selecting a suitable MCS

on one hand and an appropriate transmission repetition number on the other hand. This is proposed based on the fact that it has been identified that most existing link adaptation schemes found in the literature are solely focused on the selection of a suitable MCS value without consideration of the repetition number which as demonstrated in the paragraphs above is has demonstrated potential benefits towards addressing the energy efficiency of the NB-IoT network.

4.3 Methods and Experimental Approach

In the proposed approach considered in this study, key technologies in uplink scheduling and the design of an uplink link adaptation scheme for NB-IoT systems are focused on. The remainder of the chapter is organized as follows: First, in Section 4.4, a comprehensive literature survey that concisely and critically discusses the different existing channel coding and MCS selection approaches found in literature is provided. Section 4.5, then presents and discusses the proposed algorithm as well as the modelling. This is then followed by a detailed description of the methods used for the validation of the proposed approach in Section 4.6. In this section, a comprehensive table of key simulation parameters is provided, and the different design considerations and assumptions are presented and justified. A step-by-step description of the research design using a simulation script written in the R2019b version of MATLAB and its LTE toolbox is presented in Section 4.6.2 before the obtained results are presented in Section 4.6.3 and critically analyzed and discussed. The existing approaches are compared under the same setting to show the strength

of the proposed EEACC scheme compared to the traditional repetition-based as well as Narrowband Link Adaptation (NBLA) schemes. Finally, conclusions are drawn in Section 4.7 based on the research objectives.

4.3.1 Power Consumption Model

The stochastic energy consumption model developed for the NB-IoT network at an NB-IoT node can be represented as follows. Traditionally, energy consumption in NB-IoT is often analyzed in terms of its average value (Alcalà et. al., 2013). The energy in an NB-IoT is consumed at different levels and through different processes describing the network operation. For every communication in an NB-IoT, part of the energy is consumed by the electronic circuitry of the transmitting node while another important part is consumed in the transmission process at the sender NB-IoT node in the case of an upload operation. Finally, energy is consumed in the reception process at the receiving node in the case of a download operation.

4.3.1.1 The Processing Energy Consumption

During the execution of its task, the processor operates in either in the active, sleep or idle state, and dissipates different amounts of energy in each of them. Its energy dissipation can be modelled at two levels namely:

- (a) During a specific operational state: data processing state (active), idle mode and even sleep mode.
- (b) During state transition time.

Determining the energy consumption at the processor's level is not a deterministic experiment but a stochastic one. The process depends on multiple aspects especially the randomness of the duration quantity which itself is due to the random nature of the type of physical phenomena and events for which the NB-IoT is deployed. A typical example is a scenario in which the NB-IoT nodes are deployed within a water distribution system for leakage detection as in (Burger, 2018). In such a scenario, there is no certainty on when and where exactly a water leakage occurs.

Part of the major sources of uncertainty of the energy consumption of IoT networks includes the uncertainty of time duration in each of its three power modes and the uncertainty of the number of transitions between the different power modes. During its operation, the Central Processing Unit (CPU) of the NB-IoT node goes through different power mode states. The total energy consumption (E_{DS}) of the NB-IoT node's CPU during n active, m sleep and l idle states can be modeled as

$$E_{DS} = \sum_{k=1}^n P_A T_A(k) + \sum_{k=1}^m P_S T_S(k) + \sum_{k=1}^l P_I T_I(k) \quad (4.3)$$

where P_A , P_S and P_I are the energy consumption of the CPU in each of the three modes (Active, Sleep and Idle) respectively and $T_A(k)$, $T_S(k)$ and $T_I(k)$ are the randomly varying times of the CPU for each of the different power modes. The power values are computed from the current consumption of each mode and the nominal operating battery voltage.

In general, the processor's operation in a NB-IoT node goes through five possible state transitions which include the transitions from *Active to Idle*, *Idle to Active*, *Active to Sleep*, *Sleep to Active* and *Idle to Sleep*. In addition to the total energy

consumption E_{DS} during the operation of the CPU in the different states, the energy consumed during the above mentioned five possible transition states, referred to as E_{ST} , can be modelled as

$$E_{ST} = \sum_{k=1}^n F_{TR}(k) T_{TR}(k) \frac{(P_{IS}(k) + P_{FS}(k))}{2} \quad (4.4)$$

where $F_{TR}(k)$ is the frequency of occurrence of a power state transition as computed for the different operations (initialization, transmission, information relay, reception, etc.) of the NB-IoT node, $T_{TR}(k)$ is the duration of a state transition k , and $P_{IS}(k)$ and $P_{FS}(k)$ are the power consumption in the initial and final states respectively. Equation (4.4) describes the total energy consumed by an NB-IoT node CPU during its multiple transitions (n transitions) from one of its five operating states (e.g., Active state) to another state (e.g., sleep state). The energy consumed during state transitions is modelled as the sum of all individual energy consumption if all n state transitions that are undergone by the node during its operation period. Each of these n energy consumptions is modelled to be directly proportional to the frequency of occurrence of that particular state transition within the operation duration of the node ($F_{TR}(k)$). It is also directly proportional to the duration of the particular state transition under consideration ($T_{TR}(k)$). The product of $F_{TR}(k)$ and $T_{TR}(k)$ brings in the time aspect of the electrical energy formula. As it is known, electrical energy is the product of power and duration the second part of the formula is the average power consumed by the state transition and is calculated as the numerical average of power consumption during the initial state ($P_{IS}(k)$) and the final state to which transmission occurs ($P_{FS}(k)$).

The resultant power used in this case is the average (expected) power of the random

change of state process. Equations (4.3) and (4.4) are used to compute the CPU's energy (E_{PR}) consumption which may be expressed as

$$E_{PR} = E_{DS} + E_{ST} \quad (4.5)$$

There are existing statistical approaches for quantitatively estimating the relationship between the state transitions of a processor and the corresponding power consumption. Some of the well-known approaches include the Performance Monitoring Counters (hardware Monitoring Counters) and the complementary approach. The latter has been proposed by (Waltanegus, 2015) and simply employs the CPU's utilization data to perform the estimation. The complementary approach, in addition to the instantaneous power consumption, estimates the statistics Cumulative Density Functions (CDF) and Probability Density Functions (PDF) of the power consumed by a processor and relates it to the statistics of its state transitions.

4.3.1.2 A Stochastic Energy Consumption Model of the Processor Unit Using a Markov Model

Consider a processor operation process as illustrated in Figure 4.1. The processor operates within three states in which it consumes different levels of power. As it operates in sleep mode, it consumes the least amount of energy. When it operates in idle mode, it consumes a medium level of energy. It consumes the most amount of energy when it operates in active mode. Although the aim is to spend the least of time in the Active mode, the amount of time spent in each mode is unpredictable. The proposed Markov model depicts the various increasing states through which the

processor passes during its most energy-consuming state (active). Let these states be named pa1, pa2, pa3, etc.

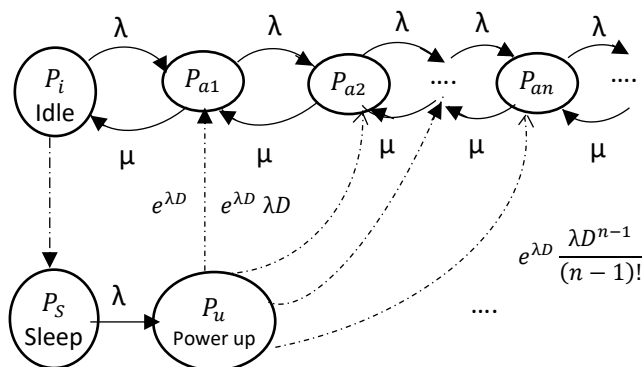


Figure 4.1: Birth and death process of processor's tasks.

Given a job arrival rate λ at which the different tasks are given to the processor, it services these tasks at a rate μ while strives to move back to the lowest power mode (Sleep mode) or eventually to the idle mode. Statistically, it is proven that most NB-IoT nodes' processors are designed to spend almost 98% of their time in the sleep mode while they spend roughly 1.5% in the idle state and only 0.5% of their operational time in active mode. Therefore, although all the three operational modes' times are purely stochastic, the proposed model focuses on modelling the time spent in the active mode. It however also assesses the probability of operational failure which therefore guides the entry into the idle state.

In the proposed model, it is considered that the processor remains in the idle state for a time interval greater than a threshold. The processor then moves back to the sleep mode. The proposed model in this study makes the following assumptions

- The request arrivals follow a Poisson process with a mean rate of λ .
- The service time is exponentially distributed with a mean of $1/\lambda$.
- The CPU enters sleep mode if there are no more tasks to be executed for a time interval longer than an energy-aware defined threshold T that the network designer heuristically defines depending on the energy consumption objective of the design under consideration versus the network reliability objective.
- The power-up processor of the processor takes a constant time D which depends on the type of processor being used.

The operation process of the processor cannot naturally be modelled using the Markov model. Therefore, the method of supplementary variables as proposed in (Cox, 1955) is used to derive an alternative set of state equations to approximate the transitions for stationary analysis. The different mode transitions as highlighted in Figure 4.1 follow either of the two probabilistic distributions. As the processor transitions from the sleep state to the active mode, the processor goes through a power-up fixed duration D which then makes the probability for the processor to stay in each of the active states P_{a0} to P_{an} to exponentially decay by $e^{-\lambda D}$. It is also directly proportional to the parameter $\frac{\lambda D^{n-1}}{(n-1)!}$ for each active state n . This implies that the more active states that the processor's operational process is involved in, the longer the duration it is in the active mode. On the other hand, the duration within the idle mode is any value from a few processor's machine cycles to a maximum threshold duration of T . The duration of the transition from the active mode to the idle mode is directly proportional to the rate of arrival of tasks λ but inversely

proportional to the rate at which tasks get services μ . This transition duration can be modelled as

$$T_{ai} = \frac{\lambda \times e^{\lambda T}}{\mu} \quad (4.6)$$

Considering that the NB-IoT nodes do not stay in any of the states permanently but rather move from one mode to the other, the sum of probability of staying in either mode is equal to unity (certainty). This important constraint is modelled using the following equation

$$\sum_{k=1}^n P_{ak} + P_i + P_s + P_u = 1 \quad (4.7)$$

4.3.1.3 The Transceiver Energy Consumption Model

Several research works have confirmed that radio communication dominates the power consumption in NB-IoT above all other functions (Kroll, Korb and Weber, 2017; Lee and Jaiyong, 2017; Mekki et. al., 2018). The energy consumption model of the transceiver module follows the same analogy as one of the processors modelled in the previous sub-section. Like the processor, the transceiver also has different operation states. These operational states include the transmission, the reception, the idle, and the sleep states in general. The latter consume different levels of energy. The operation of the transceiver consequently also involves state transitions. By taking into account both the different operational states as well as the states transitions, the total energy consumption of a transceiver can be modelled as

$$E_{Transceiver} = (E_{TX} + E_{RX} + E_{Idle} + E_{Sleep}) + E_{Trans}, \quad (4.8)$$

where E_{TX} , E_{RX} , E_{Idle} and E_{Sleep} represent the energy consumed during the transmission, the reception, the idle as well as the sleep states respectively and E_{Trans} is the total energy consumed during the transitions between the states.

In most cases, there are nine possible state transitions from the four power mode states. These include a transition from the transmission to the idle state, and vice versa, the reception to the idle state and vice versa, the transmission state to the sleep mode and vice versa, the reception state to the sleep mode and vice versa, and the single transition from idle to sleep mode. Taking into account all the nine-state transitions mentioned above the energy consumption E_{Trans} for the probabilistic n possible transitions that can occur during a network operation are modelled as

$$E_{Transitions} = \sum_{i=1}^n N_{st}(j) E_{st}(j) \quad (4.9)$$

where $N_{st}(j)$ is the frequency of a state transition j to occur. The value of this frequency varies with the type of operation that the NB-IoT node is carrying out (relaying information, transmitting or receiving) and $E_{st}(j)$ is the energy consumed by every state transition j . It is also important to point out that the number of possible transitions between power modes is stochastic and can be modelled as given below. Given that

- The state in which the processor of NB-IoT nodes normally remains in is mostly the sleep mode. This is the state in which it consumes the least of energy possible with most of its internal modules and clocks disabled. However, on event-driven instants, either time events or sensing events, the processor of the NB-IoT nodes will

normally wake up and go from sleep mode to active mode to perform transmission or a reception handling activity.

- Upon completion of the activity, it might go to another activity. If all activities are completed successfully, then it would normally go back directly to sleep mode or would momentarily go to the idle mode for a threshold amount of time and only later to sleep mode. This would mean that there would be 3 transitions on successful executions of a single activity and 4 transitions on failed execution of an activity (task) by the processor.

- The number of possible transitions n between modes is therefore uncertain and can be modelled as follows

Given a set of k activities to be carried out by the NB-IoT processor and given P_s the probability of successful execution of each activity, then the probability of failure of execution of an activity is $1 - P_s$, and thus

$$n = 3 \times k \times P_s + 4 \times k \times (1 - P_s) = 3 \times k \times P_s + 4 \times k - 4 \times k \times P_s = k \times (4 - P_s) \quad (4.10)$$

Based on the above analysis, Equation (4.8) can be re-written in terms of power consumption as

$$E_{Transceiver} = (P_{TX} + P_{RX}) \times T_d + E_{Idle} + E_{Sleep} + E_{Trans}, \quad (4.11)$$

where P_{TX} and P_{RX} represent the transmit and the receive powers respectively, and T_d is the transmission time duration on a single hop which is a probabilistic measure.

The transmission time T_d is a random variable which models the time duration for successful transmission on a single link. T_d is random due to the unpredictable

nature of the wireless channel. However T_d remains a function of a few calculated parameters. Some of the main parameters include data size, data rate, and packet collision.

- *Data size*(M): represents the size of the data being transmitted over the link. This size is a variable that depends on the type of message being transmitted which could be the interest message, data message, or a control message such as acknowledgement messages (ACK). This quantity is usually measured in bits.
- *Data rate*(B): This quantity represents the bit rate and is usually measured in bits per second.

Considering an ideal channel condition the transmission time duration can be modelled as

$$T_d = \frac{M}{B} \tag{4.12}$$

However, in a practical situation, the time duration could vary from its ideal value as modelled in Equation (4.12). One of the main random parameters is ***packet collision*** which can be described as follows: In a MAC protocol that makes use of a carrier sense multiple access, after a successful carrier sense has taken place, a collision could occur if another node transmits during the vulnerable period (τ). In a network with a total generated traffic λ , the probability of collision can, therefore, be modeled in terms of Poisson's distribution with λ being the rate of successful transmission. It can be represented as

$$P_{Coll} = 1 - e^{-\lambda\tau} . \tag{4.13}$$

At the network layer, the causes of the difference between the ideal transmission time (minimum transmission time) and the random transmission time duration can be looked at as being caused by re-transmission attempts. In a very broad sense and with some level of abstraction, a random parameter defined as P_{st} (probability of successful transmission) can be defined as

$$T_d = \frac{M}{B \times (P_{st})} \quad (4.14)$$

The probability of successful transmission is inversely proportional to the transmission time duration because the higher ($P_{st} \approx 1$), the closer it is to the ideal transmission time duration. In the approach as proposed in this study, this probability value is statistically modelled as given below.

Due to the stochastic nature of the wireless propagation channel, the probability of successful transmission is uncertain and therefore can be considered to be stochastic. However, in the algorithm, as proposed in this study, it is computed dynamically and statistically based on the previous transmission success rate. The assumption is that all the uplink transmissions are followed by a downlink packet (either an ACK or NACK downlink packets for the successful and not successful transmission of the packet). The cumulative accounting of ACK and NACK packets on previous transmissions is used to categorize the state of the channel as either bad, medium or good conditions as well as to define the probability of successful transmission P_{st} which is given as follows

$$P_{st}(m) = \frac{\sum_1^{m-1} (ACKs)}{\sum_1^{m-1} (ACKs + NACKs)} \quad (4.15)$$

The energy consumption on a single link can, therefore, be modelled as

$$E_{Transceiver} = \frac{(P_{TX} + P_{RX}) \times M}{B \times P_{st}}. \quad (4.16)$$

The energy consumption in the sleep mode (E_{Sleep}) and the energy consumption in the idle mode (E_{Idle}) can also be modelled in terms of power consumed in each of the two modes multiplied by the duration that the transceiver spends in each of them respectively. The duration of the NB-IoT node in sleep mode is a random variable that can be considered to be exponentially distributed with a mean value of β . The energy consumption during the sleep period can be modelled as

$$E_{Sleep} = P_{Sleep} \text{Expected}[T_{sleep}] \quad (4.17)$$

where P_{Sleep} is the transceiver's power consumption during sleep mode which can be computed from the current consumption obtained from the transceiver's manual, and the nominal battery voltage and $\text{Expected}[T_{sleep}]$ is the expected (mean) sleep time duration which can be modelled as

$$\text{Expected}[T_{sleep}] = \int_{-\infty}^{+\infty} T_{sleep} \text{pdf}(T_{sleep}) d(T_{sleep}) \quad (4.18)$$

where $\text{pdf}(T_{sleep})$ is the probability density function of the sleep time which can be modelled as

$$\text{pdf}(T_{sleep}, \beta) = \beta e^{-(\beta \times T_{sleep})} u(T_{sleep}) \quad (4.19)$$

It is also important to highlight that a significant quantity of energy is consumed in the idle state of the NB-IoT node's radio operation. This energy cost for a node in idle mode is modelled as approximately equivalent to the energy cost in the receive

mode. Therefore, protocols that assume that the receiving and idle power are of little consequence are not efficient for NB-IoT networks. The energy cost during idle listening due to the time spent waiting to receive packets is significant. During the idle state, the transceiver can be considered to be just listening to the channel noise (no actual information being received or transmitted), and therefore, consumes P_{Idle} amount of power for a normally distributed random time when there is no significant activity of the radio T_{Idle} . The energy consumption of the transceiver during idle state can then be modelled as

$$E_{Idle} = P_{Idle} \times T_{Idle} . \quad (4.20)$$

4.3.1.4 Electronic Circuitry Energy Consumption

Though it is negligible in many cases, energy is also consumed by the NB-IoT node's electronic circuitry. In general, the NB-IoT circuit is made of sensors and signal converters such as ADCs. Most NB-IoT nodes' circuitry operates either in *burst* or *periodic* mode. For periodic sensing mode, the NB-IoT node's energy consumption is almost equal to the sensing energy consumption (meaning when the sensing circuit is "ON") added with the energy consumed during the "ON" to "OFF" as well as the "OFF" to "ON" state transitions. The electronic circuitry energy consumption can, therefore, be expressed as

$$E_{Circuit} = E_{on-off} + E_{off-on} + E_{Sensing} . \quad (4.21)$$

4.4 An Overview of Existing Energy Efficiency Techniques for NB-IoT Systems

Low-Power Wide-Area Network (LPWAN) technologies both in the licensed and in the unlicensed bands such as the NB-IoT, Long Range (LoRa), and many others are striving to become energy efficient over very long distances (Chen et. al., 2017). NB-IoT is designed for long-life devices and targets a battery life of more than 10 years. To this end, the careful design of smart channel coding schemes has been identified as a potential approach towards enhancing energy-efficiency in NB-IoT (Migabo et. al., 2017). Channel coding is one of the most important aspects of digital communication systems, which can be considered as the main difference between analogue and digital systems making error detection and correction possible (Zarei, 2009).

In its current form, NB-IoT reuses the LTE design extensively including the numerologies, downlink orthogonal frequency-division multiple-access (OFDMA), uplink single-carrier frequency division multiple-access (SC-FDMA), channel coding, rate matching, interleaving, etc. One of the factors for this extensive reuse of the LTE channel coding is to significantly reduce the time required to develop full NB-IoT specifications (Spajic, 2017). However, some issues are very specific to the NB-IoT network designs among which is the limited energy capacity issue. Therefore, researchers (Tabbane, 2017; Ratasuk et. al., 2016) have identified a crucial need to develop novel channel coding techniques that are specific to the NB-IoT with different design goals. In this research work, the energy efficiency issue has been identified as a potential research problem. However, other researchers have looked into this prob-

lem from different perspectives. The different approaches that have been considered are concisely reported in the next paragraphs.

4.4.1 Existing NB-IoT Energy-Efficient Channel Coding (CC) Approaches

Two main channel coding and uplink link adaptation schemes can be found in the literature. The first one is termed as an MCS-dominated approach, in which the MCS level is first adjusted based on feedback signals after which the repetition number is adjusted. The second one is the repetition-dominated approach in which the focus is first on determining the appropriate repetition number based on the predefined NB-IoT network design criteria and then focusing on selecting the MCS level using the currently determined repetition number as part of the decision criteria. Apart from these two dominating approaches, there exist other approaches in literature such as the cooperative approaches ([Li et. al., 2013](#)) in which the impact of uplink interference on resources (energy, spectral efficiency, etc.) utilization efficiency is investigated each time before making transmission decisions by exploiting the cooperation among base stations which needs to be already designed.

4.4.2 Efficient Selection of Modulation Coding Scheme (MCS)

The design of an energy-efficient channel coding scheme for NB-IoT is directly linked to the selection of an appropriate modulation coding scheme (MCS). To achieve long-range communication, some work on efficient NB-IoT designs found in literature ([Lee and Jaiyong, 2017](#); [Yu et al., 2017](#); [Massam et. al., 2013](#); [Maldonado et. al., 2017](#))

have proposed efficient techniques for modulation scheme selection. The common idea behind most proposed approaches consists of trading off high data rates for higher energy in each transmitted bit (or symbol) at the physical layer (PHY). This design technique allows for a signal that is more immune and that can travel longer transmission distances. Therefore, in general, the identified aim of most designs is to achieve a link budget of 150 ± 10 dB which can translate into a few kilometres and tens of kilometres in urban and rural areas respectively (Yu et al., 2017). The reason why a value of 150 dB is used is because it represents the lowest possible detectable radio signal power by the most sensitive possible radio receivers with noise sensitivity levels as low as -150 dBm which translates to 10^{-6} pico-watt reception power as per the following mathematical deduction,

$$\begin{cases} -150 = 10 \times \log\left(\frac{P_{Rx}}{1 \text{ mW}}\right) \\ \frac{P_{Rx}}{10^{-3}} = 10^{-15} \\ P_{Rx} = 10^{-18} \text{ Watts} = 10^{-6} \text{ pW} \end{cases} \quad (4.22)$$

These types of radio receivers are often used in the most sophisticated applications such as telemetry applications for example (Johnson, 1961).

Encoding more energy into signal's bits (or symbols) results in very high decoding reliability on the receiver side. Typical receiver sensitivities could, therefore, be as low as -130 dBm. Modulation techniques used for most LPWAN technologies can be classified into two main categories namely narrowband techniques and spread spectrum techniques. Spread spectrum techniques spread a narrowband signal over a wider frequency band but with the same power density. The actual transmission

is a noise-like signal that is harder to detect by an eavesdropper, more resilient to interference, and robust to jamming attacks (secure) (Raza et al., 2017).

As opposed to other LPWAN technologies such as the LTE Cat-M1, which mainly uses spread spectrum modulation techniques, most work on NB-IoT designs found in literature (Raza et al., 2017; Yu et al., 2017; Massam et. al., 2013), propose the use of narrowband modulation techniques. In general, narrowband modulation techniques provide a high link budget which is often less than 25 kHz. They are very efficient at frequency spectrum sharing between multiple links and they experience very low noise levels within each narrow band. To further reduce the noise, some LPWAN technologies such as SIGFOX, WEIGHTLESS-N, and TELENSA use ultra narrowband (UNB) of widths as short as 100 Hz (Massam et. al., 2013). They are therefore susceptible to achieving longer transmission ranges.

One of the major differences between narrowband modulation techniques and spread spectrum techniques remains that spread spectrum techniques often require greater processing gain on the receiver side to decode the received signal (below the noise floor) while no processing gain is required to decode the signal at the receiver through frequency de-spreading for the case of narrowband modulation techniques. This results in simpler and less expensive transceiver designs. Different variants of spread spectrum techniques are used by existing standard LPWAN technologies such as Chirp Spread Spectrum (CSS) and Direct Sequence Spread Spectrum (DSSS).

4.4.3 Repetition-Dominated Channel Coding Approaches

In the repetition-dominated method, the repetition number is first adjusted based on the feedback ACK/NACKs, and then the MCS level is updated. Repetition is the key solution adopted by most NB-IoT designs to achieve enhanced coverage with low complexity. On the other hand, for one complete transmission, the repetition of the transmission is required to be applied to both data transmission and the associated control signalling transmission. Therefore, in most NB-IoT systems, before each NPUSCH transmission, the corresponding control signal data must be sent via the Narrowband Physical Downlink Control Channel (NPDCCH) which includes the Resource Unit (RU) number, the chosen MCS and repetition numbers (Yu et al., 2017). The sequence of transmission with repetition during a single transmission is illustrated in figure 4.2.

Figure 4.2 illustrates the concept of repeated transmission in NB-IoT where both the NPDCCH and the NPUSCH transmission blocks with the same content highlighted using the same colour are repeated four times in the duration of a single transmission. It is also important to highlight that according to the 3GPP TS 36.211 standard (3GPP, 2016), the repetition number for the same block for NB-IoT can only be selected from 1, 2, 4, 8, 16, 32, 64 or 128.

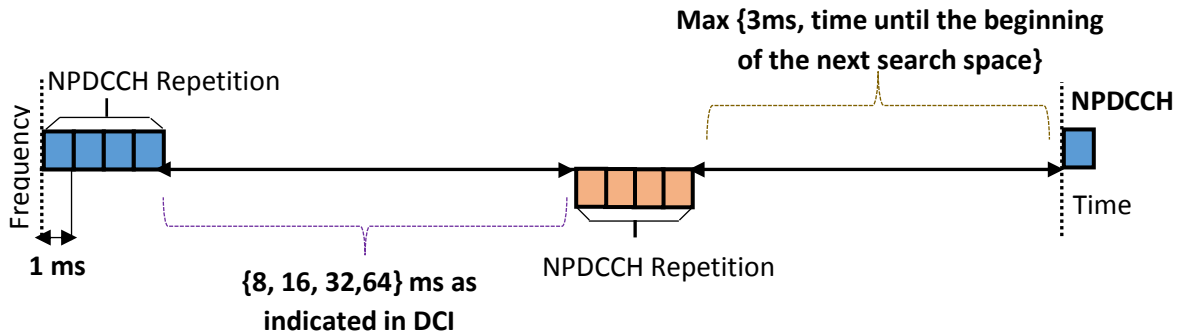


Figure 4.2: Illustration of data repetition during a single transmission.

Selecting a repeat number from the collection of 2^n with n from 0 to 7, the process follows a standard network automatic repeat request (ARQ) as specified in (Ericsson, Nokia & ZTE, 2016) by the 3GPP Release 13. On the first successfully decoded uplink packet reception, the BS assesses the perceived radio quality in terms of received signal power. The received power parameter is also used as an input to the scheduler to decide which of the available 8 repetition numbers to use and it is reported back to the NB-IoT node which uses that repetition number till the next time, it experiences a failed transmission. At that moment, another repeat request packet is issued to define a new transmission repetition number. It can be noticed that the traditional repetition approach, the repetition number is not only selected from a limited set of numbers and also does not reduce should channel conditions improve. This is one of the drawbacks that the proposed EEACC approach has identified and attempts to mitigate.

4.4.4 The NBLA and Its Open-Loop Power Control Approaches

The NB-IoT link Adaptation (NBLA) approach is mainly focused on an inner loop link adaptation aspect that is mainly focused on addressing the issue of rapid changes that are often observed with the transmission BLER in NB-IoT systems. The NBLA approach as proposed in (Yu et al., 2017) works as follows.

- During the duration of a single period of T , all transmission ACK/NACKs are computed to work out an estimated value of the BLER,
- Based on the obtained BLER value, the transmission repetition number is adjusted accordingly to cope with the variation in the channel's condition and to ensure that there is less probability of failed transmission.
- This is a way to save on energy consumption of the NB-IoT network.

The main challenge faced by the NBLA approach resides in the fact that despite its effort in estimating the channel condition based on the computed BLER value due to the reduced (narrow) bandwidth and considerably unstable channel conditions of the NB-IoT systems, the NBLA power control strategy often fails to ensure reliable uplink transmissions. This results in significant energy wastage due to repeated unsuccessful transmissions. The development of a new and more energy efficient approach that is capable of adaptively addressing the variations of channel conditions by looking at more than one-dimensional aspect of previous BLER performance but also considering the MCS level in selecting an appropriate repetition number is

needed. This is expected to contribute towards adequate energy management within NB-IoT systems.

4.4.5 NBLA Open-Loop Power Control

In the uplink scenario, the NB-IoT network normally only supports an open-link power control as stated in (3GPP, 2016). The reason for this open-loop power control exclusivity is mainly motivated by limited energy and processing capacity of most NB-IoT nodes such as sensor nodes which run on batteries most of the time. The way in which open loop power control is implemented within the NB-IoT nodes is based on the MCS and RU information alone. The NB-IoT node works out an estimate of the required power necessary to achieve an uplink transmission. This means that the Base Station (BS) (eNB in the case of LTE) does not send any form of power control command (information) to the NB-IoT before the uplink transmission.

According to the authors in (3GPP, 2016, 2011), the transmit power ($P_{NPUSCH,c}(i)$) required by a NB-IoT node within a Narrowband Physical Uplink Shared channel (NPUSCH) during an uplink session within a given uplink slot i for serving a cell c given that the number of repetitions of the allocated NPUSCH RUs is less than 2 and can be modelled as

$$P_{NPUSCH,c}(i) = \min\{P_{CMAX,c}(i), 10 \times \log_{10} \times (M_{NPUSCH,c}(i)) + P_{O,NPUSCH,c}(j) + \alpha_c(j) PL_c\} \quad (4.23)$$

where

- $P_{CMAX,c}(i)$ is the configured NB-IoT node uplink transmit power in slot i for serving cell c ,
- The possible values for $M_{NPUSCH,c}(i)$ are $\{\frac{1}{4}, 1, 3, 6 \text{ or } 12\}$ as defined in (3GPP, 2011),
- $P_{O_NPUSCH,c}(j)$ is a parameter composed of the sum of two components from the higher layers within the NPUSCH data re-transmission channel model,
- PL_c is the downlink path loss estimate calculated in the UE for serving cell c , and
- $\alpha_c(j)$ is a coefficient configured by higher layers based on the estimated total loss over the link

Should the number of repetitions of the allocated NPUSCH RUs be higher or equal to 2, then, the $P_{NPUSCH,c}(i)$ can be modelled as

$$P_{NPUSCH,c}(i) = P_{CMAX,c}(i) \quad (4.24)$$

In summary, it is important to note that none of the existing approaches (neither traditional repetition schemes nor the NBLA) consider the channel conditions in the selection of the repetition number for the traditional repetition schemes as well as dynamically minimizing this value based on the improvement of the channel conditions. At the same time, the existing NBLA scheme does not dynamically vary the Modulation Coding Scheme number based on the channel conditions. This constitutes the key contribution of the proposed approach in this study.

4.5 The Proposed Adaptive Channel Coding Technique

The objective of the EEACC approach is to design an appropriate link adaptation scheme integrated with a proper selection mechanism of repetition number and MCS for the NB-IoT systems solely based on the aim of achieving greater energy efficiency, transmission distance, and high throughput while maintaining high transmission reliability.

The channel coding approach proposed in this study is a 2-dimensional (2D) link adaptation approach which translates to a dual-objective optimization problem that aims at enhancing the NB-IoT network coverage without compromising on its energy efficiency performance. The proposed adaptive channel coding technique is twofold. It is composed of an inner loop and an outer loop adaptation scheme both aimed at enhancing the energy efficiency as well as the throughput of the network. In particular, the inner loop adaptation scheme is designed based on the channel conditions to guarantee transmission reliability and consequently, enhance the data rate of the network. On the other hand, the outer loop scheme is designed based on the Modulation Coding Scheme (MCS) number and the transmission repetition number. Because the channel conditions of NB-IoT systems are known to be quite unstable ([Pollet et. al., 1995](#)) as their transmission block error ratio (BLER) rapidly changes, the present approach introduces an inner loop link adaptation procedure which focuses on dynamically varying the transmission repetition number based on a periodically sampled and estimated channel condition that is quantified based on the BLER performance. The current BLER performance is used to predict the chan-

nel conditions each time on the next transmission based on the Sequential Channel Estimation in the Presence of Random Phase Noise in NB-IoT Systems as proposed by (Rusek and Hu, 2017). The key factor in this channel estimation model is that the fading channel’s coherent time is expected to be relatively long due to the presumed low mobility of NB-IoT user-equipment (UEs). Therefore, phase noises are considered before combining the channel estimates over repetition as a mechanism to improve the accuracy of the approach.

With phase noise $\phi_l[n]$ caused by oscillator fluctuations and a residual FO f_e normalized by the sub-carrier frequency, the time-domain baseband received signal at the n^{th} sampling time of the l^{th} orthogonal-frequency-division-multiplexing (OFDM) symbol can be expressed as

$$s_{l(Estimated)}[n] = e^{j\phi_l[n]} \left(\frac{1}{\text{sqr}tN} \sum_{k=-N/2}^{(N/2)-1} S_l[k] e^{j2\pi n(f_e+kN)} \right) * h_l[n] + w(n) \quad (4.25)$$

where ‘*’ denotes the linear convolution, $S_l[k]$ is the transmit symbol on the l^{th} OFDM symbol and the k^{th} sub-carrier, $h_l[n]$ is discrete fading channel taps, $w(n)$ is additive-white Gaussian-noise (AWGN), and N is the Fast-Fourier-Transform (FFT) size.

The purpose of the inner loop link adaptation is to guarantee the transmission BLER to the target. Accordingly, the former is referred to as outer loop link adaptation that is inclusive of MCS level selection and repetition number determination. The proposed link-adaptation method is presented as follows.

4.5.1 The Inner Loop Approach

As discussed in a previous section, the inner loop link adaptation approach is designed to handle the rapid transmission of BLER fluctuations. This proposed inner loop approach works as described below:

- In a single period T , all transmissions of both positive and negative acknowledgements (ACK and NACKs) respectively are computed to work out the average BLER for the period which is then recorded for the specific period. Specifically, the appropriate evaluation period T for LTE systems is chosen to be in the order of tens of milliseconds while hundreds of milliseconds are used for the NB-IoT systems. This selection is mainly motivated by the realistic expected traffic rate on the LTE systems being normally higher than the NB-IoT counterpart.
- At the end of the considered period, the obtained BLER value is passed to the outer loop and used as a parameter in the selection of the appropriate transmission repetition number as clearly labelled in the description of the algorithm as presented in Table 4.1,
- If the current BLER (the one of the present period) is found to be less than a defined *BLER lower threshold value*, the repetition number for the next transmission should be decreased because it means that the channel conditions are good, and therefore, the probability of successful transmission is high since there are fewer channel impairments.
- On the other hand, if the BLER is found to be between *the defined BLER lower*

and upper threshold values, the channel is considered to be in a medium condition state. The proposed link adaptation approach considers that the repetition number should be maintained during the next period.

- Finally, if the current BLER is greater than *the defined higher threshold BLER value*, the channel is considered to be in a bad conditions, and therefore, the probability of successful transmission is reduced. This requires that the number of transmission repetitions must therefore be increased to guaranty a certain level of transmission reliability.
- A lower BLER threshold value of 7% and a higher BLER threshold value of 13% are typical values used for specifying the channel state in an NB-IoT system to be good, medium, or bad. This choice is directly linked to the objective of maintaining the $\pm 3\%$ margin around the targeted 10% BLER as per the 3GPP standard specifications ([3GPP, 2016](#)).

4.5.2 The Outer Loop Link Adaptation Approach

The outer loop link adaptation approach consists of the MCS level selection which is performed as described below:

- If a certain number of ACKs are successively successfully decoded at the NB-IoT receiver, then the MCS level is increased.
- On the other hand, when a certain number of NACKs are successively decoded at the NB-IoT receiver, then the MCS level is decreased.

In general, the number of ACKs is greater than that of NACKs to ensure a slow increase of the MCS level with ACK feedback and a quick decrease of the MCS level with NACK feedback. Due to the narrowband and low data rate for NB-IoT systems, the settings for LTE systems may not be applicable. Therefore, two aperiodic and event-based actions are defined for the EEACC approach namely the fast upgrade (FUG) and the emergency downgrade (EDG). In the event of FUG, the MCS is increased by one while in the event of an EDG it is decreased by one. Thus, the EEACC approach introduces a compensation factor $\Delta C(t)$ which can be modelled as

$$\Delta C(t) = \begin{cases} \min \{ \Delta C(t-1) + C_{stepup}, \Delta C_{max} \}, \\ \quad \text{if HARQ feedback} = ACK; \\ \max \{ \Delta C(t-1) - C_{stepdown}, \Delta C_{min} \} \\ \quad \text{if HARQ feedback} = NACK; \\ \Delta C(t-1), \\ \quad \text{if HARQ feedback} = N/A; \end{cases} \quad (4.26)$$

where

- ΔC_{max} and ΔC_{min} are the upper and lower limits of the compensation factor $\Delta C(t)$,
- C_{stepup} and $C_{stepdown}$ are the incremental compensation step sizes which is modelled as,

$$C_{stepdown} = C_{stepup} \times \frac{1 - BLER_{target}}{BLER_{target}} \quad (4.27)$$

- N/A implies discontinuous transmission (DTX) which happens when the eNB does not detect any NPUSCH signal.

Various values for the simulation parameters are selected for the simulation of the proposed algorithm. The choice of these parameter values is motivated with the objective of making the simulation process as realistic as possible. These parameter values include

- A targeted Block Error Rate (BLER) value of 10%: The choice of this targeted BLER value is guided by the 3GPP standard Release 13 ([3GPP, 2016](#)). This targeted BLER value is considered to be the normal out-of-sync error rate condition for LTE/4G technology during Radio Link Monitoring (RLM) ([Helmersson, 2005](#)).
- The C_{stepup} and $C_{stepdown}$ values are the incremental compensation step sizes. As in any iterative process, there is a need to choose a reasonable initial step size. The authors have chosen an initial C_{stepup} value and not a $C_{stepdown}$ one since the $C_{stepdown}$ value is modelled first as dependent on being C_{stepup} .
- The initial value of 0.2 for the C_{stepup} parameter is used to ensure that the MCS level is stepped down when it experiences an initial 20% probability of communication error. This is because 20% is the maximum 3GPP standard value for BLER when using LTE/4G Technology.

The proposed algorithm can be summarized as given in Table [4.1](#).

The inner loop part is described between lines 2 \rightarrow 8 of the pseudo-code as presented in Table [4.1](#). In this section, the Block Error rate (BLER) for each encoded block is

checked every predefined T period time against the threshold values of 7% and 13% for good, medium, and bad channel states. Depending on the observed type channel condition (good, medium or bad), the channel repetition number N is either reduced to half, progressively increased by one, or doubled respectively.

The pseudo-code for the outer loop section is described in lines 3 \rightarrow 52. The outer loop consists of three scenarios namely:

- When the Modulation Coding Scheme (MCS) value is between the two predefined threshold values ($L_{min} < L < L_{max}$). In this situation, the compensation value ΔC is updated to the lowest or highest value based on whether the transmitter receives positive feedback (*ACK*) or negative feedback (*NACK*). The MCS level is increased by one or reduced by one accordingly.
- When the MCS reaches the minimum value (L_{min}), then based on the type of feedback received by the transmitter (*ACK* or *NACK*) and the position of current repetition number N to the minimum predefined value N_{min} and N_{Max} , a new MCS level is defined with an increase of 1 or maintained. The transmission repetition number N is reduced by half or doubled accordingly.
- Similarly, when the MCS value reaches the maximum value L_{Max} , then based on the type of feedback received by the transmitter (*ACK* or *NACK*) and the position of current repetition number N to the minimum predefined value N^{min} , a new MCS level is defined by either reducing 1 to the current value if an *ACK* is received or maintaining the current value if a *NACK* is received.

It is important to note that the validity of the proposed EEACC approach is based on the accuracy of the channel conditions assessment. Some key characteristics of this channel condition assessment have been empirically defined and standardized under the 3GPP standard release 13. The parameter $\Delta C(t)$ as used within the proposed approach plays the role of a channel characteristic compensation value. This approach is used to determine what level of channel noise and interference need to be suppressed from the current assessed channel conditions to move either to the classification as bad, medium, or good condition as defined in the standard. The $C_{stepdown}$ and C_{stepup} parameters therefore represent the exact channel coding scheme reduction or increase needed to achieve the $\Delta C(t)$ channel compensation.

The choice of $N/2$ (half of the current repetition value) is a starting value for the algorithm to run from. This is done to represent a scenario in which the error rate has reduced (channel conditions have improved). The repetition number is reduced by half as a way to reduce re-transmission attempts and improve energy efficiency. If the reduction is found to be too large, the algorithm will self-adjust the value back to a higher value than $N/2$. Similarly, in the medium channel condition, the repetition number is increased by 1 as a starting point. Naturally, the algorithm will swing between the repetition numbers in one of the two other cases. Similarly, in a severe event, when the channel condition is considered to have deteriorated, the number of repetitions as a starting point is doubled. If the doubled value is found to be too high, the next transmissions will naturally undergo self-readjustment.

Algorithm 1: The proposed EEACC pseudo-code

```
1: Initialization:  $BLER_{target} = 10\%$ ,  $C_{stepup} = 0.2$ ,  
 $C_{stepdown} = C_{stepup} \frac{1-BLER_{target}}{BLER_{target}}$ ,  $\Delta C=0$ ,  
 $\Delta C_{max} = +5$ ,  $\Delta C_{min} = -5$ , MCS level  $L$  and its bounds  $L^{max}$ ,  
 $L^{min}$ , repetition number  $N$  and its bounds  $N^{max}$ ,  $N^{min}$ .  
The MCS level and repetition number are empirically  
initialized based on the channel condition.  
2: if period T expired out then  
3:   if  $BLER < 7\%$  then  
4:      $N = N/2$   
5:   else if  $7\% < BLER < 13\%$  then  
6:      $N = N + 1$   
7:   else if  $BLER > 13\%$  then  
8:      $N = 2N$   
9:   end if  
10: end if  
11: if  $L > L^{min} \& L < L^{max}$  then  
12:   if HARQ feedback=ACK then  
13:      $\Delta C = \min \Delta C + C_{stepup}$ ,  $\Delta C_{max}$   
14:   else if HARQ feedback=NACK then  
15:      $\Delta C = \max \Delta C - C_{stepdown}$ ,  $\Delta C_{min}$   
16:   end if  
17:   if  $\Delta C = \Delta C_{max}$  then  
18:      $L = L + 1$   
19:   if  $\Delta C = \Delta C_{min}$  then  
20:      $L = L - 1$   
21:   end if  
22: else if  $L = L^{min}$  then  
23:   if HARQ feedback=ACK then  
24:     if  $N = N^{min}$  then  
25:        $\Delta C = \min \Delta C + C_{stepup}$ ,  $\Delta C_{max}$   
26:       if  $\Delta C = \Delta C_{max}$  then  
27:          $L = L + 1$   
28:       end if  
29:       if  $N > N^{min}$  then  
30:          $N = N/2$   
31:       end if  
32:     else if HARQ feedback=NACK then  
33:       if  $N = N^{max}$  then  
34:         the current channel condition is very bad  
35:       else if  $N < N^{max}$  then  
36:          $N = 2N$   
37:       end if  
38:     end if  
39: else if  $L = L^{max}$   
40:   if HARQ feedback=ACK then  
41:     if  $N = N^{min}$  then  
42:       the current channel condition is very good.  
43:     else if  $N > N^{min}$  then  
44:        $N = N/2$   
45:     end if  
46:   else if HARQ feedback=NACK then  
47:      $\Delta C = \max \Delta C - C_{stepdown}$ ,  $\Delta C_{min}$   
48:     if  $\Delta C = \Delta C_{min}$  then  
49:        $L = L - 1$   
50:     end if  
51:   end if  
52: end if
```

It is also quite critical to mention that, although small, the execution latency of the proposed algorithm has been assessed to form part of the overall up-link communication. This execution duration could be assumed to be quite negligible simply because of the substantial progress that can now be observed in the processing speed of microcontrollers today. With the capability to be interfaced with clock frequencies of few dozens of MHz, microcontrollers today that form the processor of the NB-IoT nodes, could have sampling speed of up to 70 MHz implying sampling times of about 14.3 ns (Meijer et. al., 2018). However, for the proposed research in this study, the computational latency has been assessed as follows,

- Assume that the CPU of the NB-IoT node's processor is running at a clock frequency of f_{clk} .
- Assume that the CPU has a machine cycle equal to m clock pulses (periods).
- The duration of a single machine cycle can be computed as $T_{mc} = \frac{m}{f_{clk}}$.
- Based on the principle for a multi-cycle microprocessor without Interlocked Pipelined Stages (MIPS) considers the following five types of instructions with the following respective number of machine cycles:
 1. Load (5 cycles)
 2. Store (4 cycles)
 3. R-type (4 cycles)
 4. Branch (3 cycles)
 5. Jump (3 cycles)

- Using the MATLAB R2019b Instruction Classification Learner application (Table 4.1), it was assessed that the algorithm implementing the EEACC algorithm has an average total instruction count of $n = 15$ and the following percentages of instructions per type.

Table 4.1: MATLAB instructions classification application results.

Instruction Type	Percentage
Load	52%
Store	23%
R-type	14%
Branch	9%
Jump	2%

This leads to an average of Cycles per instructions (CPI) of

$$CPI = \frac{5 \times 52 + 23 \times 4 + 14 \times 4 + 9 \times 3 + 2 \times 3}{100} = 4.41$$

The execution time of the algorithm can be computed as:

$$T_{Ex} = CPI \times n \times T_{mc} = 4.41 \times 15 \times \frac{m}{f_{clk}} \quad (4.28)$$

This means that for the implementation on a typical NB-IoT node with a basic cheap microcontroller such as the PIC16F627A running on an external crystal oscillator with a clock frequency $f_{clk} = 16 \text{ MHz}$ with $m = 4$ clock cycles per machine cycle, the execution time of the EEACC algorithm can be computed as

$$T_{Ex} = 4.41 \times 15 \times \frac{4}{16 \times 10^6} = 16.5375 \text{ us} \quad (4.29)$$

This processing duration significantly reduces with faster modern microcontrollers. Depending on the type of applications for which the NB-IoT system is deployed as well as the cost constraints, ultra low power and faster microcontrollers such as the Silicon Laboratories EFM32 microcontrollers can be used to implement the EEACC algorithm along with full LTE protocol stacks for complex applications such as the control of unmanned aerial vehicles (UAVs) ([Lin, 2018](#)).

4.6 Performance Evaluation

4.6.1 Evaluation Setup

In order to assess and validate the performance of the proposed EEACC approach, various simulations were carried out under the NB-IoT network conditions summarized in [Table 4.2](#).

Table 4.2: Key Simulation parameters.

System bandwidth	200 kHz
Carrier frequency	900 MHz
Subcarrier spacing	15 kHz
Chanel estimation for NPDCCH	Sequential Channel Estimation in the Presence of Random Phase Noise (Rusek and Hu, 2017)
Interference Rejection Combiner	MRC
Number of Tx antennas	1
Number of receive antennas	2
Frequency offset	200 Hz
L_{min}	4
L_{max}	12
N_{min}	2
N_{max}	10
Time offset period	2.5 μ s
Network deployment Model	Mesh Network (Meshnet)
Channel Model	Time-invariant slow fading with random phase noise following an Additive White Gaussian Noise (AWGN) like distribution
slow or almost no nodes mobility considered	Static nodes No fading channel consideration.
LTE Modulation Scheme	Quadrature Phase Shift Keying (QPSK)

Furthermore, it should be noted that a 4 : 1 Multiple Input Multiple Output (MIMO) with Alamouti decoding technique is considered as the eNB antenna design in these

simulations. This is in conformity with the LTE network design considerations.

As the study was carried out in the context of a Narrowband Internet of Things (NB-IoT) network deployed in an LTE cellular network, the Quadrature Phase Shift Keying (QPSK) LTE modulation scheme is considered. The eNodeBs in an LTE network is usually built to support QPSK, 16 QAM, and 64QAM modulation techniques for the Down Link direction. But considering that the end nodes (NB-IoT motes) are often computationally limited devices that are microcontroller based in many cases (sensor nodes, smart water meters, etc.), the choice of the modulation scheme is often oriented towards QPSK ([Schlienz and Raddino, 2016](#)).

4.6.2 EEACC MATLAB Simulation

The proposed EEACC MATLAB simulation consists of the following steps:

- First, a random NB-IoT network of nodes is generated on a planar using the uniform distribution functions of MATLAB.
- The Base Station (BS) is then positioned using the geometry middle point as the root to generate a tree topology using the Dijkstra's algorithm.
- A meshnet topology is formed as NB-IoT nodes are progressively deployed. Upon deployment, every node broadcasts a small interest message to identify its neighbours and path to the BS as guided by the Friis transmission equation. It is also important to mention that the meshnet is the most preferred deployment approach for the NB-IoT networks ([Ar-Reyouchi et. al., 2020](#); [Wan, Zhang and Wang, 2016](#)). This is due

to the self-forming and self-healing nature of meshnets which presents the following advantages when used for NB-IoT systems:

1. Better efficiency: With its ability to quickly create robust ad-hoc networks, mesh technology is proven to be a high-performance data transfer solution which happens to be the core of most NB-IoT applications (example of Wireless Sensor smart metering NB-IoT networks and many more).
2. Easier maintainability: Built-in diagnostics and fault reporting ensure you can respond to maintenance issues quickly and ensure continuity of service.
3. Easy installation: The network builds as the NB-IoT system is deployed. This is very important for Internet of Things networks in general because one of the major challenges of IoT network deployment is its financial remuneration aspect as it takes millions of devices to be deployed for a network to start to become profitable. It is also important to mention that, the deployment of IoT networks follows a more contagious approach as more nodes connect to the network because of the demonstrated benefits of existing nodes. Therefore, the deployment of NB-IoT networks must follow a meshnet approach so that on a new installation of a new node, it can self-configure by identifying first its neighbouring nodes for relay purposes and secondly its associated Base Station.

A typical meshnet planar deployment scenario is represented in Figure 4.3.

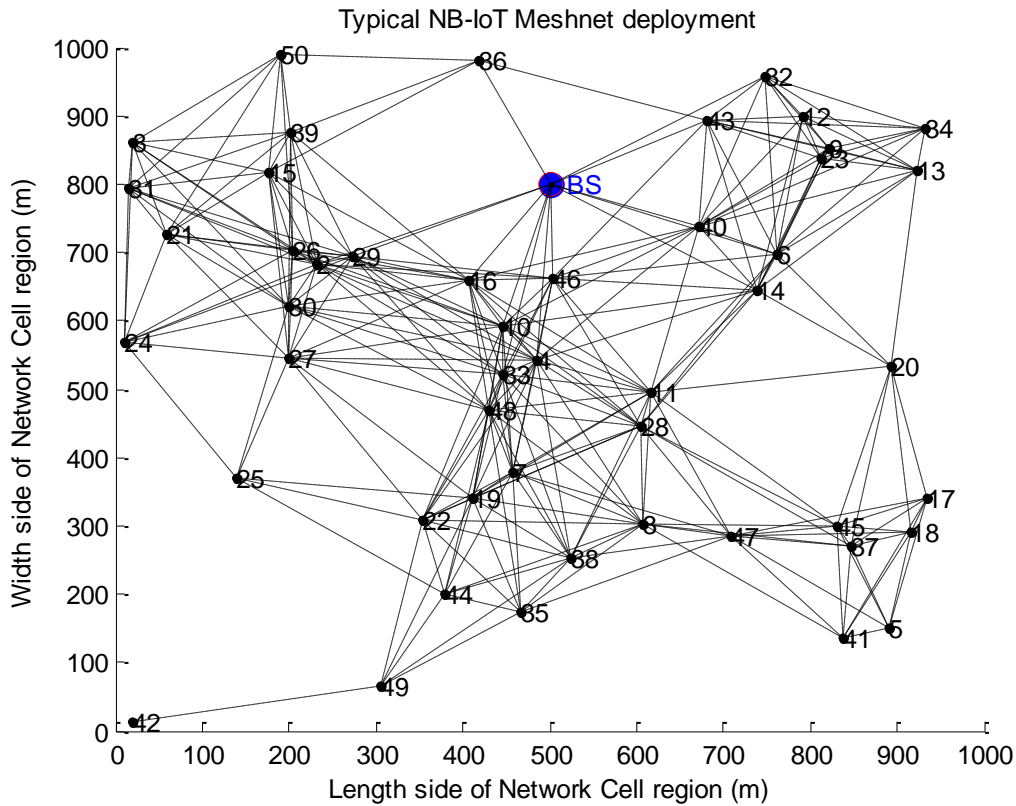


Figure 4.3: A typical meshnet NB-IoT cell deployment.

- The various simulation parameters used in this study are summarized in Table 4.2.
- Each NB-IoT node is assumed to be running from a 4.5 V battery pack of 3 Lithium-Ion battery cells each of 1.5 V.
- Each NB-IoT node is assumed for most of its operation lifetime, to run its micro-controller chip in the sleep mode with only its time clock and NB-IoT radio interface external interrupt active to allow for the detection of possible activities on the radio in order not to miss the handling of any incoming downlink data packets.

- A MATLAB timer class with an instantiated object for each NB-IoT node based on the simulation computer's clock is used to keep track of the timing function at each node.
- Based on a random uniform process, each NB-IoT node is expected to send a single data packet at a predefined rate (could be hourly, daily, etc depending on the application at hand). For every single transmission, every single NB-IoT node described as an object of a defined class (mote), implements the EEACC algorithm as presented in Table 4.1 for transmission of data packets.
- During the running of the simulation, every node maintains a history of its parameter values in the form of a table including its residual energy value.
- At the end of the predefined simulation time, all the data from the different nodes are computed and compared for each of the three algorithms (traditional repetition algorithm, the NBLA as well as the proposed EEACC).

4.6.3 Obtained Results and Discussion

This section critically discusses and interprets the obtained results in light of the research objectives and goals of the research. It is important to note that the sequential channel estimation considered in the proposed approach as proposed in (Rusek and Hu, 2017) takes into account the presence of random phase noises present in the signal. The AWGN channel models the random phase noises in this study. The channel model used in the simulations considers a slow fading channel model where the coherence time of the channel is large relative to the delay requirement of the

application. This is because real-time NB-IoT applications were not considered in this study which would require extremely small latencies. This is a drawback as it poses an extra constraints to the design. Although latency performance is part of what the study assesses, it is not the main design consideration. On the other hand, it is assumed that the nodes are not mobile which makes the proposed model time-invariant. An urban deployment set-up is considered where multi-path fading is assumed. The AWGN simply models the random phase noise which forms part of the slow fading channel model that is used for the simulations in this study. For a fair evaluation of performance and comparison between the three considered schemes namely the NBLA, the traditional repetition approach as well as the proposed EEACC approach, all three systems make use of the same block size. As per the 3GPP TS36.213 standard ([3GPP, 2016](#)), an NB-IoT device can select a downlink transport block size (TBS) on the MAC layer from a size of 2 bytes (16 bits) up to a size of 85 bytes (680 bits). In the case of the simulation, an average block size of 44 bytes is considered in this study.

First, the performance in terms of transmission reliability of the proposed approach is assessed in comparison to the traditional repetition approach as well as the NBLA approach. This assessment is performed by varying the transmission power of the different NB-IoT nodes and for the same number of transmissions, the average BLER value is computed for each of the three approaches.

The obtained results as illustrated in [Figure 4.4](#) demonstrate that the Block Error rate (BLER) of the traditional repetition approach, the NBLA approach as well as proposed EEACC approach are all seen to reduce as the Signal-to-Noise Ratio

(SNR) increases. This is as expected which confirms the hypothesis that the higher the transmission power, the higher the amount of energy as encoded in a bit through modulation and channel coding and the higher the resilience to noise and other channel impairments. However, the focus is on observing the performance of the proposed approach in comparison to the other two approaches in terms of the extra contribution in terms of network reliability. In terms of further analysis, it can be observed that the slope of the EEACC decreases much faster than that of the others after an SNR of -14 dB. This is justified by the contribution of the repeated transmission capability of the EEACC coupled with its channel-aware MCS selection which demonstrates fewer transmission failures, and therefore, further enhances the overall reliability performance of the network. These previous two justification factors are further emphasized by the increase in transmission power P_{Tx} which enhances the SNR within a single transmission period T where the channel conditions remain more or less the same. The increase in the transmission power for the same noise floor level translates in a higher Signal-to-Noise Ratio (SNR). This is because the increase in SNR is directly proportional to the increase in the transmission power in terms of the SNR ratio value definition which translates to an additional dB offset value. It is also important to observe that for SNR values that range from -18 dB to -14 dB, all the BLER values are the same for the three approaches. Overall, the BLER values of the NBLA, as well as the traditional repetition approaches are higher when compared to the proposed EEACC approach for the various SNR values. This means that the EEACC exhibits better network reliability performance as compared to the NBLA and the traditional repetition approaches. Finally, it can be noticed that the BLER

performance of the NBLA as well as the one of the traditional repetition approach remains closer to each other as the transmission power is increased. Considering the EEACC approach, the BLER performance significantly drops faster as low as 0.18% for an SNR of -4 dB.

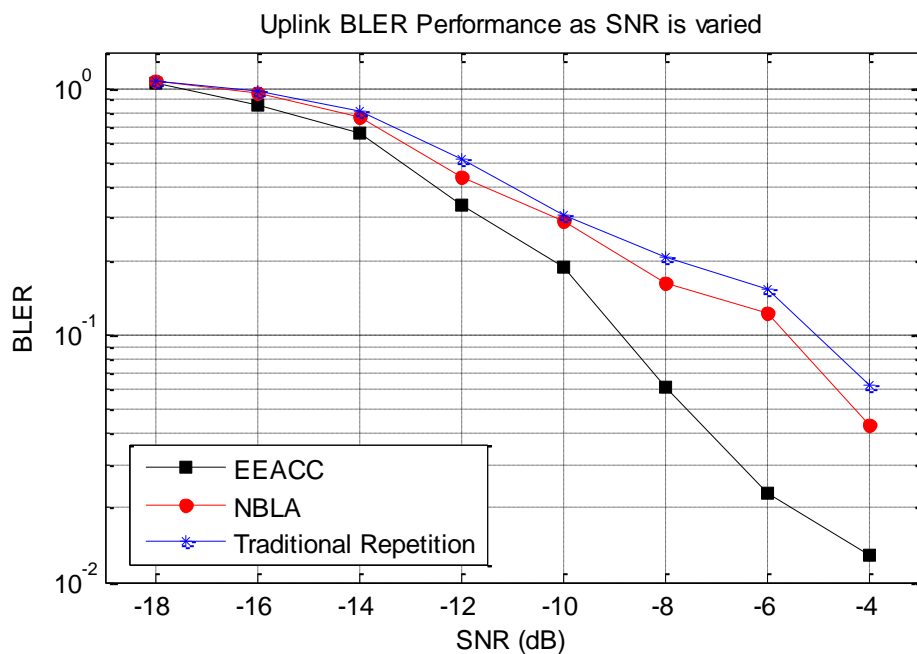


Figure 4.4: Uplink BLER Performance Comparison as Power is varied.

Secondly, the average energy consumption of the NB-IoT network was also computed as the number of NB-IoT nodes is varied with each of the three approaches, namely the traditional repetition, the NBLA as well as the proposed EEACC approach. The obtained results are depicted in Figure 4.5. Various simulations were conducted with various NB-IoT nodes as a mechanism to assess the impact of the network’s scalability on its energy efficiency performance for the different approaches. This is

important as it assesses the compatibility of the proposed EEACC approach with the massive IoT deployments today in terms of maintaining an acceptable level of network performance.

It can be observed from Figure 4.5 that the EEACC approach is more energy-efficient than the NBLA and the traditional repetition approaches. Also, the average energy consumption of all three approaches increases as the number of NB-IoT nodes is increased in the network. For example, given a total of 800 NB-IoT nodes considered within a cell, the proposed EEACC approach consumes 44.01% less energy compared to the NBLA approach and a 49.51% even less energy compared to the traditional repetition approach.

Additionally, the behaviour of the BLER performance is considered as the number of repeated transmissions was increased. This performance evaluation was aimed at assessing the impact of increasing the transmission repetition on the transmission reliability of the NB-IoT network. Therefore, the transmission power was kept constant at 0.1 W which translates to a constant $SNR = -10\text{ dB}$ assuming that the channel conditions did not change significantly during a particular simulation period. The obtained results are given in Figure 4.6.

As seen in Figure 4.6, the BLER is almost half of what it was for an SNR of -10 dB as depicted in Figure 4.4 as the transmission repetition number is doubled ($N = 2$). This translates to the fact that doubling the number of transmission repetitions, the probability of failed block transmission is almost reduced by half. It can also be noticed that as the number of transmission repetitions increases, the BLER is reduced for all three approaches. It is important to notice that the BLER of the

traditional repetition approach, as well as the one of the NBLA approach, remains close to each other as the number of transmission repetitions is increased. On the other hand, it is observed that in the case of the EEACC approach, it significantly reduces to as low as 0.18% as the repetition number N reaches the preset maximum value $N_{Max} = 10$.

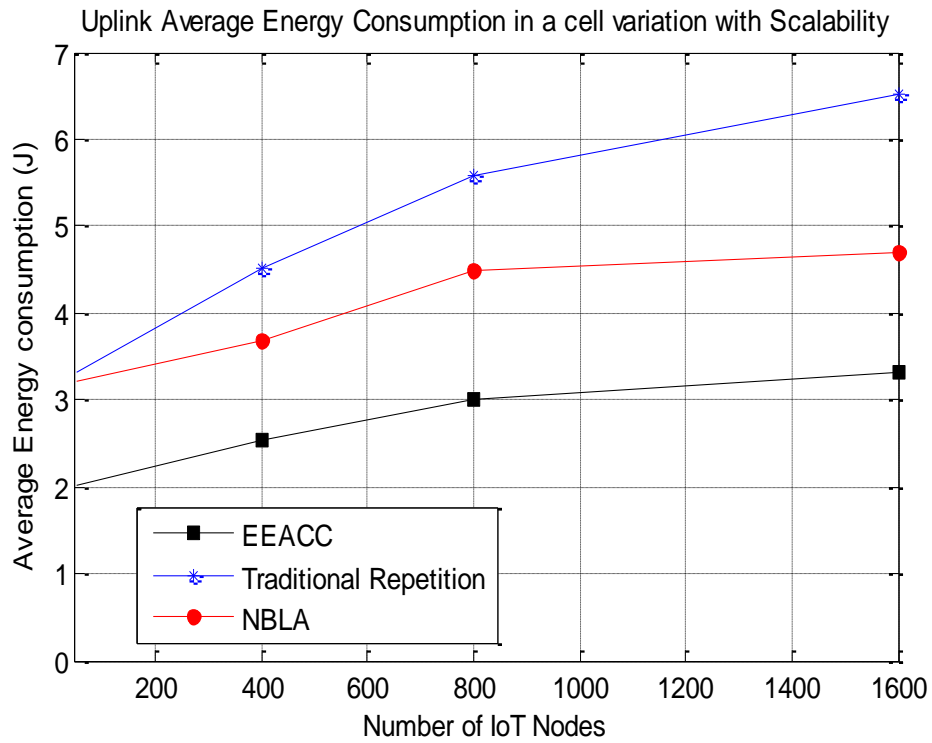


Figure 4.5: Uplink Average Energy consumption variation with increased scalability.

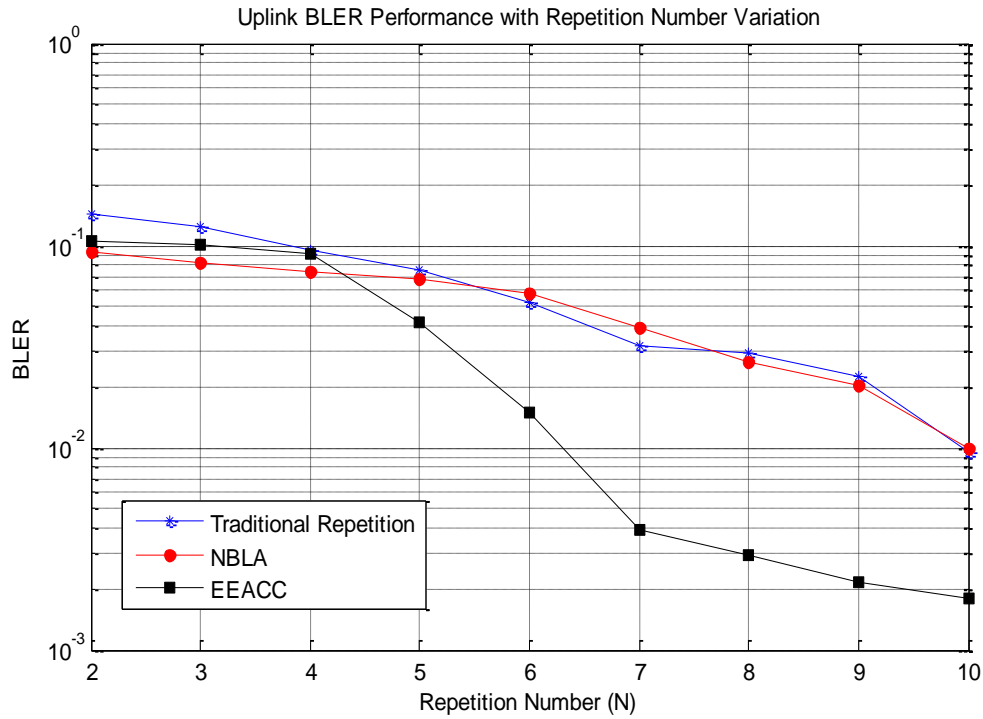


Figure 4.6: Uplink BLER Performance Behaviour with increased transmission repetition number.

Finally, the average transmission delay on a link basis was also evaluated as the number of NB-IoT nodes was scaled up within a cell. This was to assess the impact of network scalability on the latency performance of the NB-IoT network for the proposed EEACC approach as a mechanism to evaluate the applicability of the proposed EEACC method in real-time IoT applications where low latency performance is critical. The obtained results are shown in figure 4.7.

As can be noticed in Figure 4.7, despite its increased computational activities, when compared to the NBLA and the traditional repetition approaches, the EEACC still

achieves lower latency on a link basis. This is mainly due to the advancement of fast and low power processors today. Once again, as can be noticed that the latency performance of the NBLA and the traditional repetition approaches are close to each other despite the fact the NBLA still performs with less latency when compared to the traditional repetition approach.

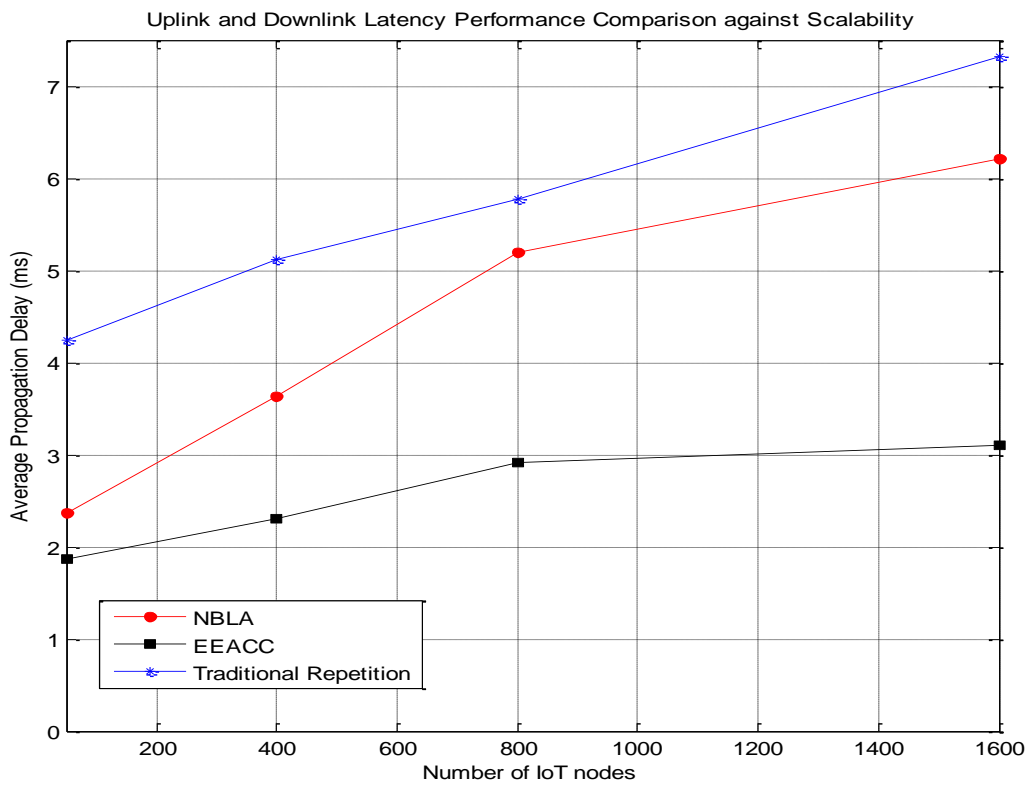


Figure 4.7: Uplink and Downlink Average full transmission delay with increased scalability.

4.7 Conclusion

This chapter presents a new 2-D adaptive channel coding and link adaptation technique which is relevant to reducing the energy consumption of NB-IoT systems in lights with the current massive, time-critical, and industry ultra-reliable requirements of IoT applications. As a typical application scenario to smart water metering, the obtained results would mean that with smart water meters would require lower transmission power and lesser repetition, to ensure reliable uploading of their daily consumption packets. At the same time, more smart meters in a densely populated area would be handled by a single base station without compromising on the overall reliability and energy efficiency of the network. Part of this work has been accomplished through extensive review of literature on the NB-IoT channel coding and link adaptation schemes with a brief analysis of the advantages and disadvantages of each. The development of the proposed EEACC approach was then presented step-by-step. The obtained results and their discussion highlights the major contributions of the proposed approach as at the results demonstrate much more resilience of the proposed approach to channel impairments resulting in the enhancement of the reliability of transmission. The proposed novel 2-D adaptive channel coding and link adaptation technique was shown to minimize the overall energy consumption of the NB-IoT system and demonstrates its ability to sustain network scalability without significant increases to network latency. The observed performance of the proposed EEACC in terms of network scalability, latency, energy efficiency, and reliability metrics, when compared to the existing traditional repetition approach as well as the NBLA approach is a key contribution of the proposed EEACC technique.

Chapter 5 A Novel Spread Spectrum and Clustering Mixed Approach with Network Coding for Enhanced Narrowband IoT (NB-IoT) Scalability

5.1 Introduction

As highlighted previously, the Narrowband Internet of Things (NB-IoT) is a very promising licensed Internet of things (IoT) technology that has the potential to accommodate massive device connections in 5G and beyond. To enable network scalability, this chapter proposes a mixed approach that aims to not only create an efficient spectrum sharing approach among the many NB-IoT devices but also provides an energy-efficient network. The proposal of this approach is mainly moti-

vated by the proven scarcity of available spectrum resources as well as the need to offload the base stations (BSs) within the network. Therefore, this chapter proposes a two-layers novel mixed strategy. At one layer, the approach utilizes an Adaptive Frequency Hopping Spread Spectrum (AFHSS) technique that makes use of a lightweight and secure pseudo-random sequence with a varying period T depending on the number of NB-IoT nodes in the considered cell; to exploit the channel diversity as a way to mitigate inter-link and cross-technology interference. At the second layer, the mixed approach consists of a cooperative clustering approach based on a well-defined energy-signal strength gradient used for Cluster Head (CHs) selection, and a network coding (data aggregation) to further boost the overall energy efficiency of the network. This second layer contributes to the offloading of the BS, allows for energy-efficient network scalability, helps balance the energy consumption of the network, and enhances the overall network lifetime.

The Internet of Things (IoT) has changed the way we view and use technology. Consumers today have come to expect connectivity and access to information wherever they go. According to the Information Handling Services (IHS) technology forecast, the Internet of Things (IoT) market is expected to grow to billions of devices by 2020 ([Lucero, 2019](#)). Massive connections are expected to respond to different IoT use cases such as smart cities, smart wearables, smart homes, etc. ([Salman et al., 2017](#)). For these applications, latency-insensitive devices can be positioned in hard-to-reach areas and do not require high throughput or frequent reporting. Therefore, to cope with such tremendous IoT trends, the Third-Generation Partnership Project (3GPP) introduced the Narrowband Internet of Things (NB-IoT) standard as a pi-

oneer communication technology enabler within the licensed band. However, it is still acknowledged that in its current shape and form, the NB-IoT is still faced with multiple challenges and design issues some of which this research work proposes to address. The spectrum resource limitation remains a key aspect in enabling massive IoT. It is not only important to ensure efficient spectrum sharing to enable network scalability, but also to ensure energy efficiency.

The NB-IoT is categorized as one of the licensed Low-Power Wide-Area Networks (LPWAN) cellular technologies based on cellular Technologies such as the Long-Term Evolution (LTE) and the 5th generation technology (5G) with long-range and low cost. In the LPWAN category, exists other licensed technologies, i.e., Long-Term Evolution Category M1 (LTE-M), and unlicensed technologies, i.e., Long Range (LoRa), SigFox, Ingenu, etc. ([Bardyn, 2016](#)), ([Devalal and Karthikeyan, 2018](#)), ([Mekki et. al., 2018](#)), ([Lauridsen et. al., 2017](#)), ([Sinha, 2017](#)). However, they are not the focus of the current work since they are not based on cellular technology. The term Narrowband refers to NB-IoT's bandwidth of maximum 200 kHz due to to which it can coexist either in the Global System for Mobile Communications (GSM) spectrum or by occupying one of the legacy LTE Physical Resource Blocks (PRBs) as in-band or as guard-band ([Mekki et. al., 2018](#); [Lauridsen et. al., 2016](#)). Since it coexists in the LTE spectrum, NB-IoT follows the legacy LTE numerologies as it uses Orthogonal Frequency Division Multiplexing (OFDM) and Single-Carrier Frequency Division Multiple Access (SC-FDMA) in the downlink and uplink transmission schemes, respectively ([Gozalvez, 2016](#); [Adhikary et. al., 2016](#)). Some modifications in the physical (PHY) and medium access control (MAC) layers are

implemented to support the long-range massive machine-type (mMTC) connections with low power, low data rates, low complexity, and hence low cost. However, despite its low complexity, this new radio access technology (RAT) delivers better performance in terms of the supported number of devices, and coverage enhancements for latency-insensitive applications with maximum coupling loss (MCL) of about 20 dB higher than LTE (i.e., 164 dB) (Bardyn, 2016; Devalal and Karthikeyan, 2018; Rico-Alvarino et. al., 2016).

5.2 Background, Motivation and Objectives

The NB-IoT is one of the most prominent IoT technology within the licensed band. Despite all the challenges faced by NB-IoT such as the challenges of energy efficiency due to NB-IoT nodes that run on batteries, challenges with range and coverage, the reliability of Uplink (UL) and Downlink (DL) communications, etc, more and more devices are being added to the network as the range of applications and needs keeps increasing. This poses a serious challenge when it comes to the NB-IoT network design considerations in terms of its different layers. This work focuses on proposing a novel spread spectrum and clustering combination approach as a mechanism to enhance network scalability of the NB-IoT. However, the task remains to ensure that with the use of the proposed mixed solution, the NB-IoT network still retains a reasonable level of energy efficiency, network stability and data rate. Several clustering techniques for wireless IoT exist. However, to the best of our knowledge, the existing approaches do not simultaneously consider signal strength and remaining

energy of nodes as a combined parameter for cluster head selection.

The Frequency Hopping Spread Spectrum remains one of the most reliable and ruggedized options for modern Internet of Things communications. Therefore, despite the rapidly changing technology landscape, the FHSS remains a good choice for long-range communication and has the potential to accommodate the growing number of devices in the field due to its ability to efficiently and dynamically share network spectral capacity among devices. Therefore, a new FHSS based spread spectrum approach is proposed in this study which is adapted to the NB-IoT PHY characteristics which when coupled with a novel clustering approach aims at enhancing the NB-IoT network scalability while preserving its energy efficiency and network reliability.

Due to the limited available spectrum (roughly 200 kHz), as allocated to the NB-IoT within its three deployment modes (in-band, standalone, and guard band), one of the key issues is to determine how to efficiently use these resources to support massive IoT devices. Since the NB-IoT technology is also considered to be of a higher standard base station's computational complexity relative to its unlicensed band rivals such as LoRa and Sigfox; previous studies such as ([Ratasuk et. al., 2016](#)) and ([Ericsson, 2015](#)) have suggested concepts of time-offset as well as transmission repetition. Finally, there is also the fact that frequency band allocation within the cellular network's band (in-band deployment) or as standalone does often causes non-synchronization among different cells which results in inter-cell interference from the neighbour cells' LTE users or NB-IoT users.

The above three reasons coupled with the fact that most NB-IoT technology designs,

as currently proposed, mainly use simple ALOHA or CSMA based MAC protocols which do not scale well with a large number of connected devices. There have been considered in this study as the motivation for a need for a novel spread spectrum and clustering approach for the NB-IoT. Therefore, this study proposes a mixed-strategy of frequency hopping spread spectrum and clustering approach to mitigate the inter-cell interference and reduce computational complexity at the BS. This is expected to enhance NB-IoT system designs as a way to enable network scalability, data rate enhancement, and also maintain energy efficiency and network reliability.

The rest of this chapter is organized as follows. Section 5.3 presents a detailed development of the proposed mixed spread spectrum and clustering algorithm. Section 5.4. presents the performance evaluation of the proposed followed by the analysis and discussion of the obtained results. Section 5.5 concludes the chapter.

5.3 The proposed Intelligent Mixed Approach

5.3.1 Hypothesis of the proposed approach

The proposed approach is based on the hypothesis that the proposed smart mixed approach is capable of switching a common carrier signal among many frequency channels, using a lightweight and secure pseudo-random sequence of a finite period T which varies depending on the number of NB-IoT nodes deployed in the cell. The random sequence is made known to other NB-IoT nodes as well as to the Base Station (BS) through an initial broadcast of interest packets. Assuming that only static NB-IoT nodes are considered, this broadcast of interest messages is performed

during the initial network deployment. Also, because of the adaptive nature of the proposed cluster head selection algorithm and the need therefore to swap CHs, the broadcasting of interest messages also happens periodically intending to reconfigure the network by selecting new CHs based on a residual energy and signal strength mixed gradient.

The random sequence at a node must be known by neighbouring nodes because of the multi-hop cooperative clustering aspect of the proposed method which dictates that some NB-IoT devices within the same cluster are selected to play a relay role to offload the BS. This is expected to reduce the transmission traffic, enhance the Up-link throughput, and consequently, the up-link data rate mitigating the inter-cell interference, reducing the number of re-transmission attempts and thereby, enhancing network reliability and energy efficiency.

It is also very important that the pseudo-random sequence generator algorithm is lightweight because of the limited computational, memory but also energy resources of the NB-IoT nodes ([Peinado, 2014](#)). Usually, this random number generator algorithm should be implemented on a simple 8-bit microcontroller, and its hardware complexity in terms of Gate Equivalence (GE) should prove its low complexity. This is a way to ensure that the algorithm is implementable on a small chip area as a single GE in this context is defined to be the silicon area occupied by a single NAND gate.

In summary, the proposed approach is based on the hypothesis that the adaptive frequency hopping spread spectrum technique using a lightweight pseudo-random sequence generator, coupled with a cooperative adaptive clustering approach can

result in an efficient way to offload the Base Station (BS), and therefore, allows for more NB-IoT nodes to be handled within a single cell. With an efficient way of grouping NB-IoT nodes within a cell and an appropriate cluster head selection based on a composite residual-energy aware and signal strength gradient, in smaller clusters, there is the possibility that noise and interference mitigation will be handled better within the cell. The hypothesis is that the proposed approach could enhance network scalability of the NB-IoT network without degrading energy-efficiency performance.

5.3.2 The Mixed Frequency Hopping Spread Spectrum and Clustering Algorithm

5.3.2.1 The proposed Frequency Hopping Spread Spectrum approach

As the first j NB-IoT nodes join the network, they send interest messages to the BS. The BS records the Received Signal Strength Indicators (RSSI) of all the j nodes and sorts them in ascending order. The lowest RSSI value which represents the NB-IoT node with the lowest level of access to the BS while the NB-IoT node with the highest RSSI represents the node with the highest access to the BS. The RSSIs of the j first deployed nodes in their order of arrival form the initial seed of a lagged Fibonacci generator (LFG) series that is used to generate the pseudo-random number sequence. The generated sequence is then used for frequency channel hopping access.

Given several T of all nodes within the network, the number of elements of the initial seed j is selected as per the following considerations:

- A random number generator's period is the number of new random values that it generates before returning to the start of the sequence.
- The period of the pseudo-random number generated is equal to the number of NB-IoT nodes T .
- Maximizing the period ensures that the random numbers generated for each node are from a different period of the LFG.
- The value j is selected to provide an optimal balance between the random number generation period and the amount of memory used. This is because the higher the period T the higher the consumption of the already constrained memory space of the NB-IoT nodes.

The proposed algorithm uses a multiplicative LFG (MLFG). For an NB-IoT node with m -bits word-length processor, an MLFG is defined as follows

$$MLFG[j, k, N; \{x_0, x_1, \dots, x_{j-1}\}], \quad (5.1)$$

where

- $N = 2^m$,
- j and k are the lag offsets of the past samples in such a way that $j > k > 0$,
- $\{x_0, x_1, \dots, x_{j-1}\}$ is the initial seed, and
- the trinomial $x^j + x^k + 1$ is irreducible and primitive over the Galois Field $GF(2)$.

For a number of NB-IoT nodes T , an initial seed size of j is chosen such as $T = (2^j - 1) \times 2^{m-3}$. This will ensure that the maximum period of the MLFG is equal to the number of NB-IoT nodes T . The MLFG pseudo-random values x_n are computed by the different nodes as

$$x_n = (x_{n-k} \times x_{n-j}) \text{ Mod } N \quad (5.2)$$

The j seed elements, on the other hand, are selected by the BS upon reception of the interest messages from all the NB-IoT nodes during the initial deployment based on the computed and sorted RSSI values of the received interest messages.

The received RSSI values are computed as follows:

- Through the analysis of the RSSI, it is found that the RSSI value decreases as the distance from the NB-IoT node to the BS increases. Based on this consideration, the free space model (FSM) is used as the RSSI-Based Ranging Model. The FSM is expressed as follows,

$$PL = 20 \times \log(d) + 20 \times \log(f) - 27.55 \quad (5.3)$$

where PL , d and f represent the path loss of the signal energy, the distance between the NB-IoT node and the BS and the transmission frequency being used respectively.

- Furthermore, it is also found that the path loss decreases as the antenna height increases. Based on this consideration, a two-way ground model can be represented as

$$PL = 40 \times \log(d) - 20 \times \log(h_n) - 20 \times \log(h_{BS}) \quad (5.4)$$

where h_n is the transmitting NB-IoT device height and h_{BS} is the effective height of the Base Station.

- In this approach, a two-way ground level model is considered with an average LTE BS effective height of 27.81 m (Colpaert, 2018) and an average NB-IoT elevation level h_n of 7.8 m for most NB-IoT urban applications scenarios (Khan, 2019).
- Considering the NB-IoT antenna gain g_a of 6 dBi (Bao, 2018), and a transmit power P_{TX} , the $RSSI$ value can be computed as

$$\begin{cases} RSSI_{dBm} = P_{TX(dB)} + g_{a(dB)} - PL_{dB} \\ RSSI_{dBm} = P_{TX(dB)} + 6 - PL_{dB} \end{cases} \quad (5.5)$$

The obtained RSSI values are then sorted as

$$x_{n,(0 \leq n < j)} = RSSI_{n,(0 \leq n < j)} \quad (5.6)$$

The initial seed is distributed as part of the downlink broadcast packet to all the NB-IoT nodes. The initial seed is used to form the MLFG sequence that is used by the selected CHs for dynamic frequency hopping and channel selection within the available 200 kHz narrowband bandwidth either deployed in standalone, in-band or guard-band mode. This dynamic frequency hopping and channel selection is performed by CHs as they relay aggregated data packets received from the respective member nodes (MNs) within their clusters to the BS. The proposed dynamic frequency hopping spread spectrum approach is used to mitigate the interlink interference within the cell as the various nodes attempt to reach the BS. It is further supplemented by the clustering approach as described and boosts the overall network security, energy

efficiency, and robustness of the network but most importantly, enhances the possibility for more nodes to join the network without compromising its overall network performance.

5.3.2.2 The proposed energy efficient and scalable clustering and network coding approach

This section describes the proposed cluster groups formation as well as the energy and RSSI aware CHs selection process. The BS is equipped with GPS devices in cooperation with two NB-IoT nodes with reliable source power and is used as anchor nodes for locating other NB-IoT nodes inside the cell as follows. The coordinates of the two selected anchor nodes and the BS are known and modelled as (x_1, y_1) , (x_2, y_2) and (x_{BS}, y_{BS}) respectively. From the broadcast of interest packets as the various nodes join the network, the two nodes and the BS will work out three Euclidean distance values to each of the $(j - 2)$ nodes, as per figure 5.1, as follows

$$\begin{cases} (x_n - x_1)^2 + (y_n - y_1)^2 = d_1^2 \\ (x_n - x_2)^2 + (y_n - y_2)^2 = d_2^2 \\ (x_n - x_{BS})^2 + (y_n - y_{BS})^2 = d_{BS}^2 \end{cases} \quad (5.7)$$

The solution of equation 5.7 leads to solving the matrix equation: $AX_n = B$ such as

$$\left\{ \begin{array}{l} A = \begin{bmatrix} -2(x_1 - x_{BS}) & -2(y_1 - y_{BS}) \\ -2(x_2 - x_{BS}) & -2(y_2 - y_{BS}) \end{bmatrix} \\ X_n = \begin{bmatrix} x_n \\ y_n \end{bmatrix} \\ B = \begin{bmatrix} d_1^2 - d_{BS}^2 - x_1^2 + x_{BS}^2 - y_1^2 + y_{BS}^2 \\ d_2^2 - d_{BS}^2 - x_2^2 + x_{BS}^2 - y_2^2 + y_{BS}^2 \end{bmatrix} \end{array} \right. \quad (5.8)$$

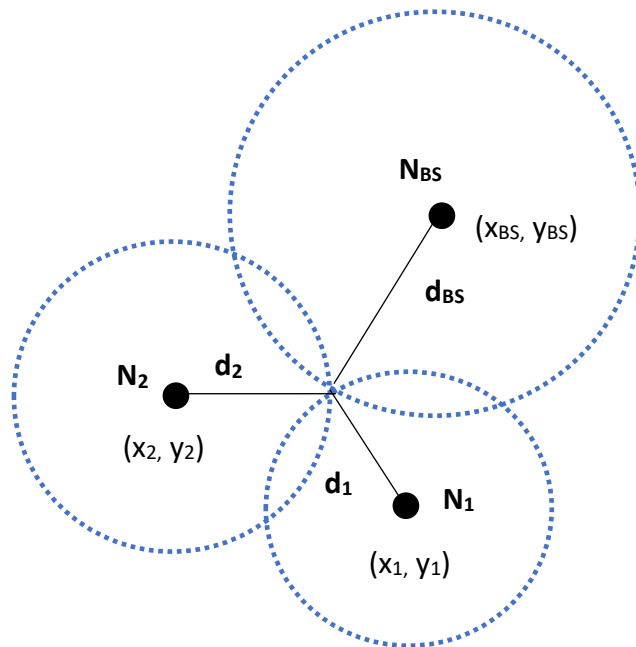


Figure 5.1: NB-IoT Nodes localization Approach

After the geographical localization of nodes within the cell, the BS through its down-link reply packet does not only distribute the initial adaptive spread spectrum fre-

quency hopping seed. It also sends information that geographically groups NB-IoT nodes that are close to each other into clusters. A typical illustration of a typical cluster formation within an NB-IoT cell is shown in figure 5.2

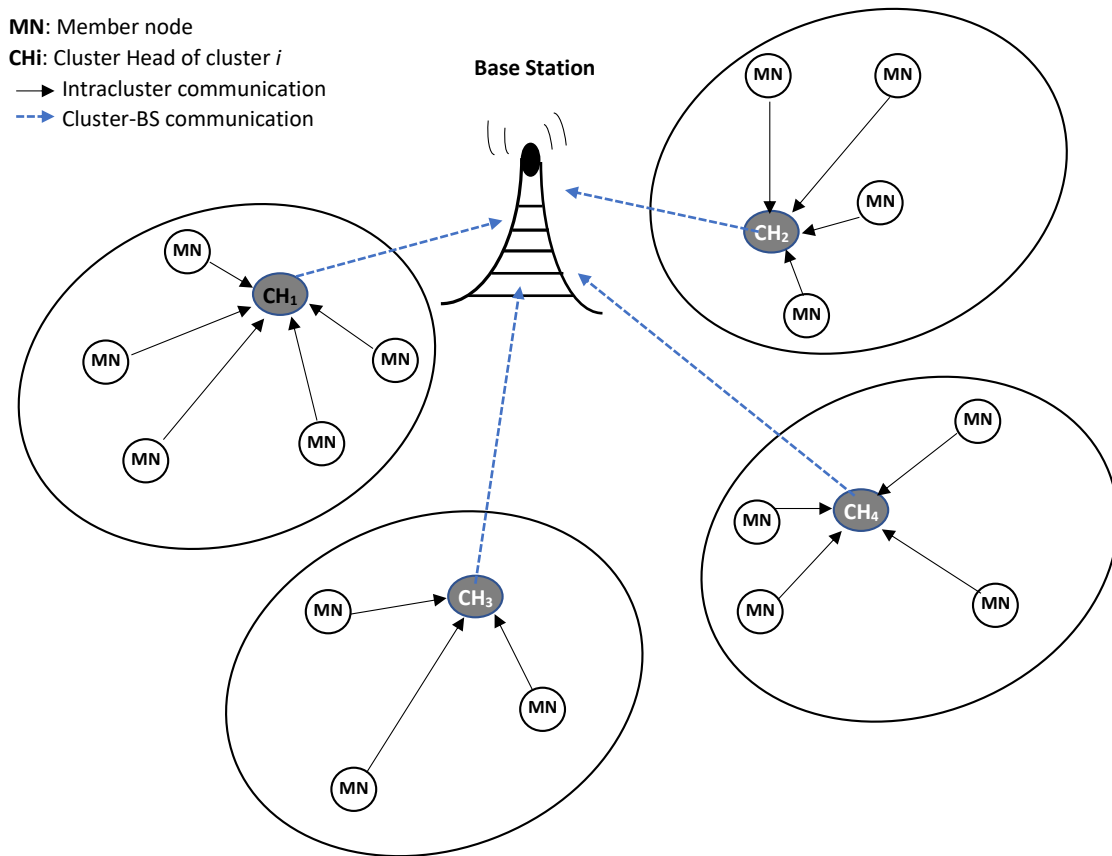


Figure 5.2: NB-IoT cell cluster formation

The following steps are taken for clusters formation and CH selection.

- Step 1: Determining the neighbour nodes of each node within the cell by the use of predefined transmission range threshold d_{th} or an optimum number of clusters

p_{opt} . The problem of least energy number of clusters is a well-studied optimization problem (Wang et. al., 2009) in energy-efficient wireless sensor networks clustering research which is normally formulated as

$$p_{opt} = \arg \min_{1 \leq p \leq j} E_{avg}(p) \quad (5.9)$$

subject to: $0 \leq P_t \leq P_{t_{max}}$. where $E_{avg}(p)$ is the average energy consumption of the j nodes within the cell as modelled in (Migabo et. al., 2018) and $P_t, P_{t_{max}}$ are the transmission power and the maximum transmission powers respectively.

- It is observed that in an adaptive clusters formation and CHs selection, the process should be dynamic to ensure not only energy efficiency but also energy consumption balance. This is because, as the overall average remaining energy efficiency reduces, the number of clusters should be reduced. This means much bigger clusters should be formed to ensure greater energy balance and to make sure some CHs do not die faster than others. It is also true that the bigger the transmission range threshold used for clusters formation, the smaller the number of clusters. This means that the average residual energy is inversely proportional to the transmission range threshold d_{th} .
- On the other hand, the higher the average RSSI value, the more eligible CHs as more nodes can directly reach the BS. This also translates to a smaller number of clusters which means that the transmission range threshold will be higher. This means that the average RSSI value is directly proportional to the maximum transmission range threshold.

The above considerations leads to a maximum transmission range d_{th} given by

$$d_{th} = \frac{K \times (MAX(d_n) + MIN(d_n))}{2} \quad (5.10)$$

where $K = \frac{RSSI_{avg}}{RP_{avg}}$, $RSSI_{avg}$ is the average RSSI value, and RP_{avg} is the average residual power as observed by the BS after the broadcasting of interest messages during network deployment.

The proposed approach opts for the use of the threshold transmission distance to form the different network clusters. Considering the set of all nodes denoted as N , the set of neighbour nodes of node n denoted as N_b can be computed as

$$N_b = \sum_{b \in N, b \neq n} d(b, n) < d_{th} \quad (5.11)$$

where $d(b, n)$ is the Euclidean distance between NB-IoT nodes b and n . This approach comes with the advantage that it avoids the chaining issue.

- Step 2: For every node n , all the distances with the neighbors in its cluster is computed as

$$d_{sum} = \sum_{b \in N_b} d(n, b) \quad (5.12)$$

- Step 3: The average residual energy of each cluster i denoted as RE_{CH_i} is computed as

$$RE_{CH_i} = \frac{1}{sizeof(N_b)} \times \sum_{b \in N_b} RE_{ni} \quad (5.13)$$

where RE_{ni} represents the residual energy of node n belonging to cluster i .

- Step 4: For each formed cluster i , the BS computes a mixed residual energy and signal strength aware cluster head selection gradient SG_{ni} as

$$SG_{ni} = \alpha \times \left(\frac{RE_{ni}}{RI_{ni}} \right) + \beta \times (RSSI_{ni}) \quad (5.14)$$

where RI_{ni} is the initial energy level of node n in cluster i and $RSSI_{ni}$ is the RSSI value of node n in cluster i with respect to the BS. $RSSI_{ni}$ is computed as per equation 5.5. The parameters α and β are the cost weights of the residual energy consideration and the reliability of communication aspect respectively. The cost weights α and β are selected in each cluster i based on the following criteria:

$$\begin{cases} \alpha + \beta = 1 \\ \frac{RE_{CHi}}{RSSI_{CHi}} = \frac{\alpha}{\beta} \end{cases} \quad (5.15)$$

The criteria in equations 5.15 expresses the fact that the sum of cost weights (α and β) is equal to unity and the higher the average residual energy in a cluster i (RE_{CHi}) compared to the average $RSSI$ of nodes in cluster i ($RSSI_{CHi}$), the higher the weight cost α of the residual energy consideration in the definition of the CH selection gradient when compared to the weight cost of the RSSI consideration β and vice-versa.

- Step 5: In each cluster i , the node with the highest selection gradient S_{Gn} within a cluster is selected to be the CH.
- Step 6: Each time a CH receives data packets form various member nodes in its cluster, it applies Random Linear Network Coding (RLNC) (data aggregation) before transmitting it to the BS. In the typical two-hops clustering approach as

considered in this study, the focus of this approach is mainly on the global network coding approaches as the data aggregation point is the CH after which the aggregated data is immediately forwarded to the BS where its decoding occurs. Furthermore, the proposed network coding approach is an intersession network coding scheme in which data packets from various member nodes within the network are aggregated together before being transmitted as a single packet to the BS.

The m independent data packets (d_i) from the m member nodes of the network cluster i are linearly combined by means of m random coefficients (C_i) from the GF of order 2^S . The value S is a positive number equal to the size of a single NB-IoT packet. The m packets are combined to form a single aggregated packet of the same size S as each one of them. A GF as generated by each CH is also made known to the BS for the sake of the decoding process. The aggregated (encoded) packet A is obtained as

$$A = \sum_{i=1}^m C_i \times d_i \quad (5.16)$$

The key challenge associated with the network coding technique is that the decoding of the encoded packet is performed by Gaussian elimination, and therefore, requires the reception of at least m packets to occur. The decoding process on the BS side is performed by forming a $m \times m$ coefficient matrix $C_{m \times m}$ from the received m encoded packets and by reducing it using the row-echelon form. Considering that the linear independence of encoded packets, the set of m linearly independent equations is solved to retrieve each originally encoded packet. One key advantage of this proposed RLNC approach is that the choice of encoding coefficients from a GF, enhances the probability of linear independence among the encoded packets which then translates

in high decoding reliability.

The combination of the proposed dynamic frequency hopping and the energy-RSSI aware clustering with network coding approaches form the mixed proposed strategy for enhancing the overall network scalability, energy efficiency and latency of the network. MATLAB version 2019b was used to implement and evaluate the performance of the proposed NB-IoT Mixed Approach with Network Coding (N-MANC) in comparison the NB-IoT with the adaptive frequency hopping spread spectrum at PHY layer only (N-AFHSS) (Kim and Rim, 2018), then with respect to the NB-IoT with LEACH clustering at network layer (N-LEACH) (Xu et. al., 2017), and finally with the NB-IoT Mixed approach with no network coding (N-MANNC). The main performance comparison metrics considered are network scalability, energy efficiency, network reliability and network lifetime; as described in section 5.4.

5.4 Performance Evaluation and Obtained Results

This section presents the performance evaluation in terms of the simulation parameter considerations, the simulation scenarios as well as the obtained performance results and their discussion.

5.4.1 Evaluation set-up

The performance evaluation of the proposed N-MANC approach versus the N-AFHSS, the N-LEACH and the N-MANNC is performed under the network considerations

as summarized in table 5.1. It is important to note that a simulation is conducted for each of the compared approaches with the objective to elucidate the actual contribution of a specific addition or modification to an approach in terms of network scalability, energy efficiency, network reliability and network lifetime. The proposed approach as well as the approaches to which it is compared are all simulated under the same simulation conditions to ensure fair performance comparison.

Table 5.1: Key Simulation parameters.

Transmitting device (h_n) average height	7.8 m
Effective Height of the BS (h_{BS})	27.81 m
Antenna Gain (G_a)	6 dBi
System bandwidth	200 kHz
Carrier frequency	900 MHz
Residual Frequency Error	$\pm 50 Hz$
Average NB-IoT cell radius range	10 km (urban)
Number of Nodes per cell (T)	[1k,10k,50k,100k,150k]
Communication period (P)	1 hour
Maximum payload length	1600 bytes
Localization Technique	<i>RSSI – based</i>
Channel estimation for NPDCCH	Sequential Channel Estimation in the presence of Random Phase Noise (Rusek and Hu, 2017)
Interference Rejection Combiner	MRC
Number of Tx antennas	1
Number of Rx antennas	2
Duplex mode	Half-Duplex Frequency division Duplex (HD-FDD)
Initial NB-IoT node energy (Power capacity)	$3 \times AA$ Batteries Nominal voltage= $3 \times 1.5 = 4.5V$ Each AA has 1500 mAh Initial Energy = $6.75 J$
BS power	43 dBm
Receiving Sensitivity level	-90 dBm
Time offset period	2.5 μs
Channel Model	Time-invariant slow fading with random phase noise following Additive White Gaussian Noise (AWGN) distribution
Slow or almost no nodes mobility considered	Static nodes No fading channel consideration
LTE Modulation Scheme	Quadrature Phase Shift Keying (QPSK)

It is also important to note that eNodeBs of the LTE network are often designed to handle QPSK, 16 QAM and 64 QAM modulations schemes for the Downlink(DL) communications. However, due to the limited computational ability of the NB-IoT node, often micro-controller based in majority of IoT applications such as smart water, electricity metering etc.), the modulation scheme of choice is the QPSK as specified in table 5.1 (Schlienz and Raddino, 2016).

5.4.2 Real-Life Application Scenario under Simulation

The realistic case scenario considered in our study is one of the smart water metering applications. As we know, the water meter, unlike the other utility meters, is very energy-critical because of the regulation in many countries like South Africa which forbids to bring electrical lines on a water utility. Most water supply companies request a guaranteed minimum of 10 years lifetime of smart water meter design. The smart water meters are fixed sensor nodes and the ones considered for this research are assumed to have a Tunnel Magneto Resistance (TMR) active magnetic sensor to detect and convert the turning of the mechanical register. Every turning cycle of the mechanical register corresponds to a well-defined water flow value and results in a digital pulse transition on the output of the TMR sensor. The digital processor of the smart water meter counts the number of digital pulses it receives. The water volume flow is computed based on the total number of counted TMR digital pulses. The smart water meter is also able to detect any tampering activities. There is an NB-IoT radio module in each smart water meter and the assumption that there is one smart water meter per household. The choice of 1000 to 150,000 NB-

IoT nodes represents the number of smart water meters and other battery-powered environment monitoring smart devices such as geyser leak detectors, door sensors, room occupancy detection sensors, fire detection sensors, water tank level monitoring systems, smart fridges, smart TVs etc. The set of nodes considered in this study are normally static sensors and limited in terms of energy resources. With the increasing number of IoT devices applications, this study caters for up to 150,000 nodes within the geographical area of an NB-IoT cell. In terms of the data traffic, data packets are sent on an average of 1 packet per day by these devices. Hence our consideration of up to 3960 rounds of transmission packets for 11 years of operation. The daily data packet sent as an uplink packet by each smart water meter contains information about the device's status (water meter daily consumption, any sensed possible leaks as well as the remaining battery level percentage of the smart water meter for example). The other environment monitoring smart devices are also assumed to send their daily status once a day either in the case of a triggering event (alarm) or around midnight for a summary daily report. The traffic data model used in our simulation is therefore made up of a combination of deterministic daily packet transmissions coupled with a uniformly distributed stochastic event-triggered packet transmission. In essence, every single node has a minimum of 1 packet per day.

5.4.3 Obtained Results, Analysis & Discussion

This subsection presents the results obtained for the performance evaluation for the various simulation scenarios considered.

5.4.3.1 Energy Consumption Performance Results

First, the average energy consumption performance of the proposed N-MANC mixed approach is assessed as the network scalability is progressively increased, in comparison with the N-AFHSS, N-LEACH and N-MANNC. The results obtained for a single communication period (P) are captured in figure 5.3,

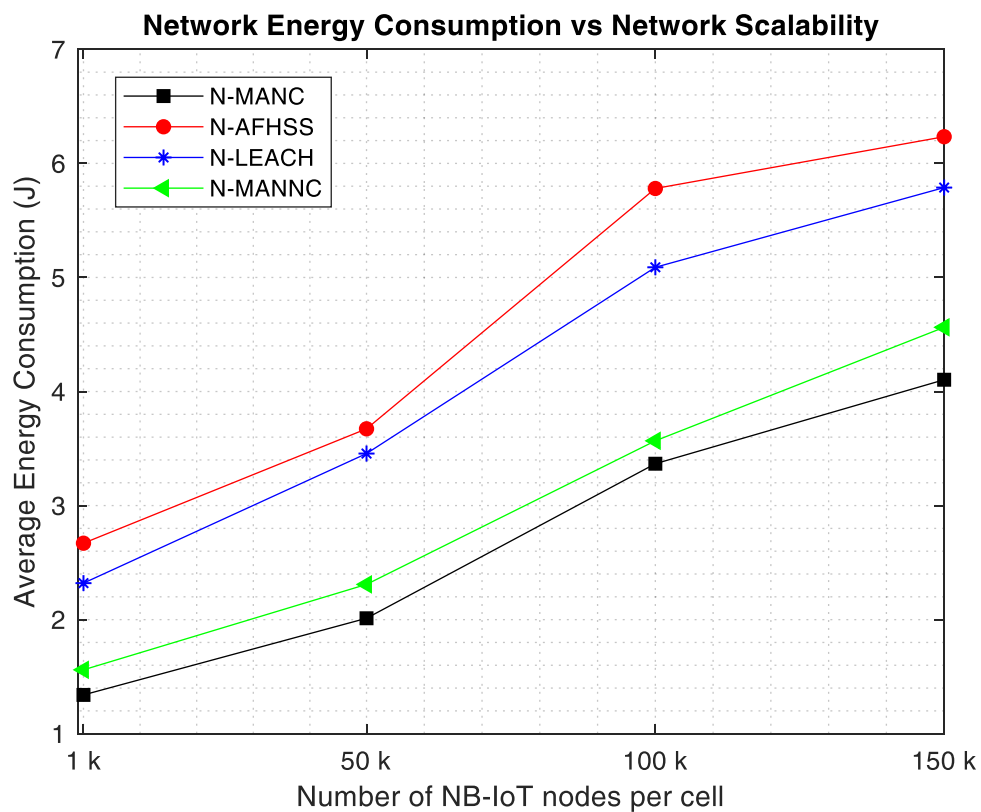


Figure 5.3: Average Energy Consumption versus Network Scalability

It is important to mention that the results shown in figure 5.3 have been obtained by simulating each of the approaches under comparison one at a time and for a trans-

mission period T of one hour with a varying cell density from 1000 to 150000 nodes with each node having an initial energy level of $7J$. As can be observed in figure 5.3, the average energy consumption within the cell increases for all the four approaches as more nodes are added within the cell. This behaviour is expected because as more devices join the network, the probability of successful up-link transmission reduces because of more interlink interference. However, as can be noticed, despite the increase in the average energy consumption of the network, the proposed N-MANC maintains a much lower energy consumption when compared to the N-AFHSS and the N-LEACH and maintains a significantly lower energy consumption when compared to the N-MANNC. The N-MANC consumes an average of 41.04% less energy than the N-AFHSS, 35.01% less than the N-LEACH, and only 9.81% less than the N-MANNC. This is justified by the fact that due to its mixed approach strategy, it taps into both the network reliability of the AFHSS, the network clustering network density reduction of the clustering, and the number of transmitted packets as added by the network coding approach. The N-MANC saves a significant amount of energy when compared to the N-AFHSS which only enhances the network reliability and the N-LEACH which only addresses the network density reduction aspect. It is important to notice the 9.81% energy consumption reduction contributed by the random linear network coding approach when compared to the N-MANNC which does not have any network coding. This sufficiently demonstrates that packet aggregation with an enhanced reliable communication as a pre-requisite can greatly help in the reduction of energy within the NB-IoT network, despite the increasing number of nodes within the cell. This demonstrates that, the proposed N-MANC scales in a

more energy-efficient manner when compared to the N-AFHSS, the N-LEACH, and the N-MANNC.

5.4.3.2 Network Reliability Performance Evaluation Results

The average rate of successful up-link transmissions is assessed for comparison of the proposed N-MANC to the other approaches (N-AFHSS, N-LEACH, and the N-MANNC). This average rate of successful transmissions is computed as the various number of nodes per cell is increased to assess the impact of the network scalability on the network transmission reliability of the network. The obtained results are illustrated in figure [5.4](#).

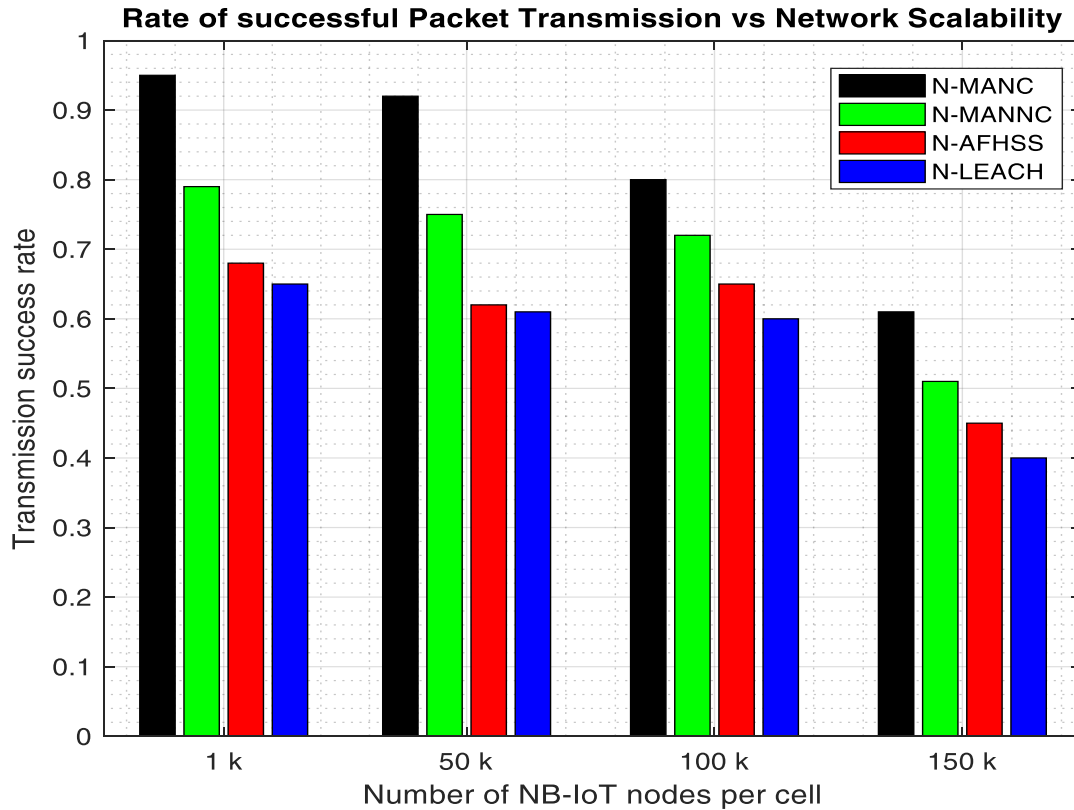


Figure 5.4: Packets Transmission Success Rate versus Network Scalability

It can be observed from figure 5.4 that the rate of successful transmissions drops as the number of NB-IoT nodes increases in the cell for all the assessed approaches. However, the proposed mixed approach (N-MANC) maintains the highest probability of successful transmission when compared to the N-MANNC, the N-AFHSS, and the N-LEACH respectively. On average, the proposed N-MANC maintains a 5.86% higher transmission success rate compared to the N-MANNC, 10.83% higher than the N-AFHSS, and 55.84% higher than the N-LEACH respectively. It is important

to notice that the N-AFHSS approach outperforms the N-LEACH in terms of up-link transmission reliability. This is because the N-AFHSS, unlike the N-LEACH, is primarily designed to mitigate the inter-link interference which is one of the main causes of unsuccessful up-link transmissions unlike the N-LEACH which is mainly focused on reducing the network communication traffic to primarily enhance its energy efficiency. It is however important to note the N-LEACH approach also contributes towards improving the network communication reliability and, therefore, the proposed mixed N-MANC demonstrates a much better transmission success rate as it taps into the benefits of the N-AFHSS as well as the N-LEACH approach. On the other hand, the improved transmission reliability enhances the RLNC performance in terms of its decoding process. This results in the RLNC further contributing towards enhanced network transmission reliability when compared to the mixed approach with no network coding (N-MANNC) despite the increase in the number of nodes within the cell.

5.4.3.3 Network Lifetime Performance Evaluation Results

It was also crucial to assess the contribution of the proposed approach towards enhancing the network's lifetime. To assess the network lifetime performance, the number of simulation runs was performed to compute the number of remaining active nodes as the rounds of packet transmissions was increased to evaluate the rate at which the network dies when the proposed N-MANC approach is used compared to the N-LEACH, N-MANNC and the N-AFHSS. The results obtained are shown in figure 5.5.

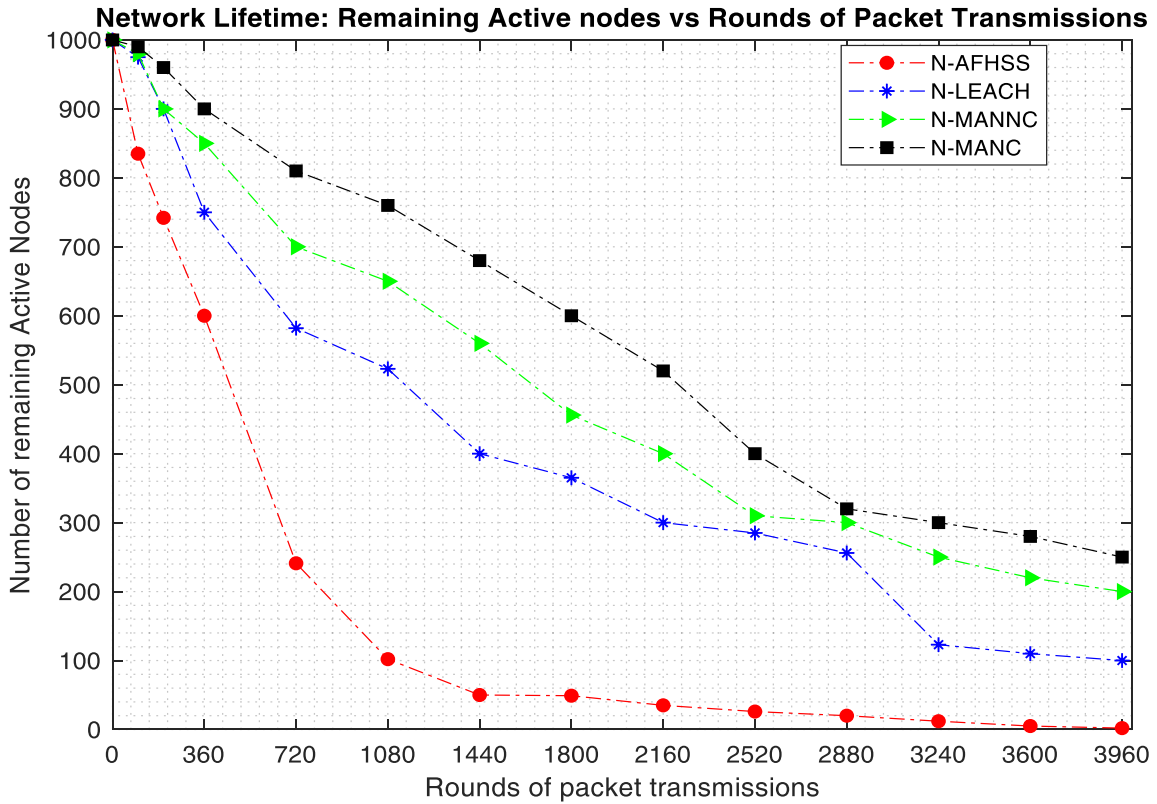


Figure 5.5: Network Lifetime: Remaining Nodes versus Round of Transmission Packets

It can be observed in figure 5.5 that the number of remaining active nodes reduces as the number of rounds of packet transmissions increases. Since most of the NB-IoT applications work based on periodic packet transmissions, the rounds of packet transmissions often correspond to the number of packet transmission periods. For a typical smart water metering application with a daily water consumption packet transmission, the maximum round of packet transmissions considered for the simulations (3660) corresponds to a total of almost 11 years of operation for a yearly

number of days of roughly 365 days considering that the NB-IoT node is in deep sleep mode for the rest of the day where it consumes almost no power.

It can also be noticed in figure 5.5 that the number of remaining active NB-IoT nodes when the proposed N-MANC approach is used remains always higher compared to when the N-MANNC, the N-LEACH, and the N-AFHSS are used respectively. It is also important to mention that with the use of the N-AFHSS, the network dies much faster compared to the others (N-LEACH, N-MANNC, and N-MANC) respectively. This demonstrates that the energy consumption reduction of the proposed mixed approach (N-MANC) as depicted in figure 5.3 coupled with its enhanced network reliability as shown in figure 5.4 contributes towards significantly extending the NB-IoT network lifetime.

The results in figure 5.5 are further confirmed by the results of the evaluation of the average remaining energy per node of the proposed N-MANC approach compared to the N-MANNC, N-LEACH, and the N-AFHSS as shown in figure 5.6.

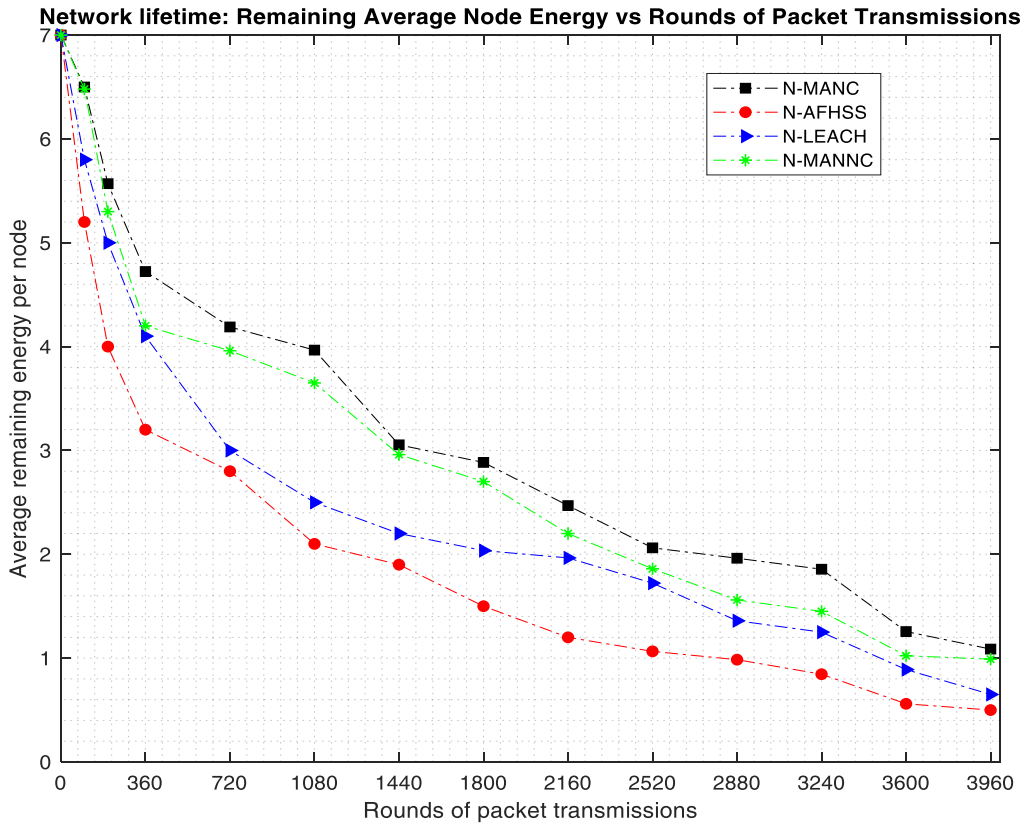


Figure 5.6: Network Lifetime: Remaining Average Energy versus Round of Transmission Packets

The findings in figure 5.6 clearly show that just as the amount of remaining active nodes in figure 5.5 is transmitted as more rounds of packets, so the average remaining energy per node also decreases.

The results in figure 5.6 also show that the N-MANC approach maintains the highest average remaining energy per node for all the considered rounds of packet transmissions compared to the N-MANNC, the N-LEACH, and the N-AFHSS respectively.

5.5 Conclusion

This chapter presented a novel NB-IoT mixed spread spectrum with Network Coding (N-MANC) to enhance the NB-IoT network scalability while improving its energy efficiency, network reliability, and network lifetime performance. The N-MANC is proposed as a step towards enabling the massive connections of IoT objects to the cellular network (5G and beyond) within the licensed band. After establishing through the literature survey that the enhanced scalability of the NB-IoT network is a cross-layers effort, this research study proposed a mixed approach which proposes an adaptive frequency hopping spread spectrum technique at the physical layer using a lightweight pseudo-random sequence generator coupled with the clustering and network coding techniques at the network layer. The proposed approach was described in detail in terms of its implementation and underlying concepts.

Based on the results obtained and the evaluation of the results, it can be concluded that the proposed N-MANC approach helps mitigate the scarcity of the available spectrum coupled with the interlink interference to enable more NB-IoT nodes to join the network cell while ensuring the offloading of the BS using an energy and RSSI aware formation of network clusters and selection of CHs. It can be further concluded that the offloading of the BS together with the aggregation of data packets at each CH using the proposed RLNC technique demonstrates the ability to significantly improve the energy efficiency, network reliability and network lifetime of the network as compared to the N-AFHSS (with adaptive frequency hopping spread spectrum only), the N-LEACH (with energy-efficient clustering only), and N-MANNC (Mixed approach with no network coding) respectively. As a typical application scenario to smart water metering, it can be deduced that the proposed mixed approach would help significantly reduce the network energy consumption of the smart water meters and extend the overall network lifetime. This would translate in fewer maintenance

cost. At the same time, the enhanced communication reliability would ensure timely and accurate generation of water consumption bills by the water management utility which also translates in significant reduction of operational cost.

Chapter 6 Conclusions and Rec- ommendations for future work

6.1 Introduction

This chapter provides concluding remarks of the research study. First, a short and concise overview of the objectives of the study is provided. The achievements of the study are then highlighted. Finally, the recommendations for further research are identified and potential future work are formulated before an overall conclusion regarding the study is made.

6.2 The stated research objectives and achievements of the Study

The general problem identified in this study is the fact that despite the increasing number of connected devices, the increase in applications, and the benefits associated with the NB-IoT technology within the licensed band, the NB-IoT designs remain

constrained in terms of their energy efficiency, low data rates, network reliability, and spectrum sharing performance. These challenges were identified in this research study as key aspects that prevent efficient NB-IoT network scalability.

The present study focused on providing a multi-layers solution to the problem as stated above. Firstly, the objective of this study was to study, review, analyze, and compare the existing NB-IoT PHY and network layers techniques in terms of channel coding, MCS selection schemes, spectrum management and clustering approaches. The first part of the study was aimed at identifying the advantages and disadvantages of each approach. The literature survey that was summarized in chapter 2 resulted in the identification of open research problems and the formulation of research opportunities to enhance the resource management performance of the NB-IoT network.

Secondly, the objective of this study was to develop, evaluate, and validate a scientifically well-supported PHY layer performance mathematical model of the NB-IoT within its three deployment modes. The focus of the developed model was on the energy consumption, data rate, and downlink processing delay as described in chapter 3. Based on this objective, this part of the study has systematically considered the NB-IoT model design and realization in terms of NB-IoT PHY characteristics in the uplink and downlink. It further discussed mathematically the energy consumption versus data rate performance dilemma encountered with the NB-IoT designs and modeled the expected energy consumption of the NB-IoT network before proposing and assessing a predictive processing delay model of the NB-IoT network.

Thirdly, this study proposed enhancing, at the physical layer level the energy efficiency performance of existing traditional repetition and NBLA channel coding,

MCS selection and link adaptation approaches. This has been achieved by proposing a novel 2-D energy-efficient and adaptive channel coding approach (EEACC) as described in chapter 4. The proposed EEACC approach was designed to select the appropriate MCS and number of repetitions based on the channel conditions to enhance the energy efficiency of the network while ensuring that network reliability is maintained or even improved. The obtained results have demonstrated that the proposed EEACC approach not only enhances the overall energy efficiency of the network but also improves the data rate, the network reliability, and transmission latency performance of the network.

Finally, this study proposed a mixed adaptive spread spectrum and clustering approach with network coding (N-MANC) at both the PHY and network layers respectively. The proposed N-MANC, as described in chapter 5, uses a lightweight pseudorandom number generation technique for an efficient adaptive frequency spread spectrum model on the narrowband available frequency band and also proposes an energy and signal strength aware technique for CHs selection coupled with data aggregation at each selected CH before forwarding data to the BS. The N-MANC has been proposed to firstly manage efficiently the constrained available narrowband spectrum as a way to mitigate interlink interference and enable more and more devices to be connected within a cell without degrading the network transmission reliability. Secondly, the N-MANC approach was proposed to offload the BS as a result of the formation of clusters within the cell to prolong the network lifetime and to further enhance energy efficiency due to its network coding technique at each selected CH.

6.3 Benefits of the study

After successful completion of the proposed approaches in this study, the following benefits have been achieved:

1. Considering the limited number of existing surveys of resources management performance enhancement approaches in terms of energy efficiency, data rate performance and scalability, and also the non-existence, to the best of our knowledge, of a comparative survey, this research work has elaborated, described, analysed and compared the performances of such resources management approaches.
2. The mathematical modelling of the NB-IoT PHY layer performance has sufficiently demonstrated that to enable a licensed massive IoT network, there was a need for developing novel PHY layer channel coding, modulation coding scheme selection and link adaptation techniques.
3. The developed EEACC algorithm has significantly improved the energy efficiency of the NB-IoT network by allowing for a dynamic MCS selection and repetition number variation based on pre-assessed channel conditions as obtained from previous network reliability performance. The EEACC has further demonstrated better network reliability, data rate, and latency performance as compared to the existing traditional repetition and the NBLA approaches. This enhanced overall performance of the NB-IoT is a key enabler for its network scalability.
4. The developed N-MANC mixed algorithm has considerably improved the efficiency in sharing the limited NB-IoT narrowband spectrum and has simultane-

ously allowed the offloading of the BS using the formed clusters and the proposed energy-aware CH selection resulting in prolonging the network lifetime of an NB-IoT cell when compared to the existing spread spectrum only (AFHSS), nodes clustering only(N-LEACH), and mixed approach with no network coding approaches (N-MANNC).

5. The additional network coding aspect at each selected CH as proposed by the N-MANNC algorithm has allowed for data aggregation before their forwarding to the BS. This has come with the benefit of further enhancing the overall energy efficiency of the NB-IoT network within a cell.

Overall, the present research study has provided to both the scientific and the industrial community within the licensed band IoT field in general and the NB-IoT field in particular, with useful tools for further research, development and implementation considerations in critical and massive IoT applications.

6.4 Recommendations for Future study

Firstly, although this research work developed a well supported NB-IoT PHY layer performance and predictive downlink processing delay models, it did not perform a real-life scenario validation test with real NB-IoT nodes and measurements for validation of the proposed model. It would be of interest research work to physically investigate the validity of the proposed model as proposed in the present work.

Secondly, the proposed energy efficiency approach (EEACC) has been demonstrated to be an energy efficient approach when compared to the traditional repetition and

the NBLA approaches. Similarly, the proposed NB-IoT Mixed spread spectrum frequency hopping and clustering approach with network coding (N-MANC) has demonstrated enhancement of the network scalability while improving the overall energy efficiency, transmission reliability, and lifetime of the NB-IoT. Therefore, the proposed future research work consists of first of all implementing and assessing the proposed energy-efficient approach on-chip by using an application scenario such as smart water metering or environmental monitoring sensor network to further practically validate the proposed approach. Additionally, a theoretical assessment of the energy enhancement using a well-formulated optimization approach can be investigated.

6.5 Overall Conclusions

In short, this research study has led to the modelling of the NB-IoT PHY layer performance in its three deployment modes followed by the development of an energy-efficient and adaptive channel coding (EEACC) approach as well as a mixed spread spectrum frequency hopping and clustering approach with network coding (N-MANC) as a multi-layers solution towards enabling the NB-IoT network scalability while maintaining good QoS performance.

The obtained results have in general revealed that the objectives of the present research work have been satisfactorily met as their energy efficiency, network reliability, data rate, network latency, and scalability has been proven to be enhanced as compared to existing traditional repetition channel coding and energy-efficient clustering

approaches.

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