SERVICES PROVISIONING BY USING INTELLIGENT LEARNING FOR LONG RANGE WIDE AREA NETWORK (LoRaWAN)

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DEDICATION

To my beloved family, teachers, and friends.

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This voyage can never be so interesting and overwhelming with mixed emotions without the amazing people I met along. I can remember the time, when I told my father that, I have completed my MS and got a smiley response, son, PhD awaits you. Perhaps that was the first motivation towards this voyage. Or, it was the unsaid desire of my parents to get a doctoral decorum. Either way, the dream of so many loved ones and teachers during multiple phases of life would not have come true so interestingly, if I have not come across Dr. Kashif Naseer Qureshi, my mentor, my inspiration and above all a brotherly figure.

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ABSTRACT

The exponential growth of Internet of Things (IoT) services and ecosystems is recently emerged with a novel type of communication network known as Low Power Wide Area Network (LPWAN). This standard enables the low power long range communication at low data rate. Besides, Long Range Wide Area Network (LoRaWAN), is a recent standard of LPWAN that incorporates LoRa Wireless into a networked infrastructure. Consequently, Quality of Service (QoS) efficient service provisioning is a major challenge due to highly dense network environment, limited battery lifetime of LoRa based End Devices (EDs), spectrum coverage and data collisions. Intelligent and efficient service provisioning is a dire need of network to streamline and address these problems. This study proposes a novel and Intelligent Learning (IL) based framework for efficient service provisioning without placing any extra burden on the network and its resource constraint LoRaWAN EDs. The proposed framework intelligently learns from varied underlying potential parameters such as real-time Packet Error Rate, data throughput, data delay, data collisions and energy consumption to improve the overall network performance. The proposed framework is extensively simulated and evaluated with current state of the art benchmark algorithms using standard and extended evaluation metrics. Slotted Aloha with Markov chain model mitigate collision and enhanced performance of LoRaWAN by 38% in terms of data throughput. Results of Slotted Aloha with Markov chain model is compared with Pure Aloha used by conventional LoRaWAN. Adaptive Scheduling Algorithm (ASA) with Gaussian Mixture Model (GMM) is extensively compared with conventional LoRaWAN and Dynamic PST (Priority Scheduling Technique). ASA with GMM enhanced performance in terms of delay by 5% in LoRaWAN environment. Dynamic Reinforcement Learning Resource Allocation significantly reduced energy consumption of EDs by 20% measured in Jouls. Results of Dynamic Reinforcement Learning Resource Allocation is compared with conventional LoRaWAN and Adaptive Priority-aware Resource Allocation (APRA). The proposed work is properly cross-validated to utterly show unbiased results.

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LIST OF ABBREVIATIONS

Notation Used	Portrayals
A_ED_t	Action for *ED* at time *t*
ADR	Adaptive Data Rate
BN	Back logged nodes
BP	blood pressure
BW	Bandwidth
CR	Coding Rate
CSS	Chirp spread spectrum
DS	Descriptive study
DT	Decision Tree
$(ED_j)Prof_{HLP}$	End devices from profile having high priority
$(ED_j)Prof_{LLP}$	End devices from profile having low priority
ED	End devices
F	Frequency
Fcnt	Frame Count
FP	Fuzzy Profiling
$G\ ED_j$	Average value of end device *j*
$G\ Prof_k$	Average value of Profile *k*
GW	Gateway
GW's	Gateways
HPP	High Priority Profile
HR	and heart rate
I_ED_t	Information of *ED* at time *t*
IoT	Internet of things
IT	Information technology
LoRa	Long Range
LoRaWAN	Long Range Wide Area Network
LPP	Low Priority Profile
LPWAN	Low Power Wide Area Network
M2M	Machine-to-Machine
$Max(G\ Prof_k)$	Maximum average value of Profile *k*
$Max(P_r)$	Maximum Priority
ML	Machine Learning
MPP	Middle Priority Profile
N_ED_t	Network parameters assigned to *ED* at time *t*
N_PCKT_COLLISION	Number of packets collided
N_PCKT_Loss	Number of packets loss
N_PCKT_R	Number of packets successfully received
N_PCKT_S	Number of packets sent towards gateway
NB-IoT	Narrow Band- Internet of Things
PDR	Packet Delivery Rate
PER	Packet Error Rate

PPD	Propagation path delay
PR	pulse rate
P_r	Priority
Prof	Profile
PSR	Packet Success Ratio
QoS	Quality of Service
QoS	Quality of Service
R_ED_t	Reward of *ED* at time *t*
RL	Reinforcement Learning
RLA	Reinforcement Learning Agents
Rx1	Receiving window 1
Rx2	Receiving window 2
SA	Slotted Aloha
SF	Spreading Factor
SLR	Systematic literature review
SNR	Signal to Noise Ratio
TD	Transmission Delay
T_{sym}	Symbol duration

CHAPTER 1

INTRODUCTION

1.1 Overview

This chapter presents the introduction of Low Power Wide Area Network (LPWAN) and its usage in IoT networks. Chapter also covers the applications, problem background, problem statement, research questions, research objectives and study scope regourously. Chapter concludes with thesis organization and contents detail.

1.2 Internet of Things

The Internet of Things (IoT) is an interconnected network of smart devices, vehicles, buildings, and other items embedded with sensors and other technologies. These smart devices retrieve or collect and share data with other smart devices and the cloud, allowing them to perform a variety of functions and also provide a various services. The IoT has changed the way we interact with our surroundings by permitting smart nodes or users to remotely monitor and operate gadgets in our homes, businesses, and cities. Smart thermostats, security cameras, wearable fitness trackers, and even self-driving automobiles are examples of IoT gadgets. The massive amounts of data generated by these smart devices can be analyzed to take decision in industries as diverse as healthcare, transportation, and agriculture. While IoT has the potential to provide several benefits, such as enhanced efficiency and safety, it also poses privacy and security concerns. As the number of IoT devices grows rapidly, it is critical to address these concerns and ensure that they are developed and executed in a way that secures users data while also maintaining their faith in the technology.

Objects of daily life are connected with for data communication called Internet of Things (IoT). Requirements of next generation communication systems are high speed networks by using 5G and 6G data communication standards [1]. One of the major requirements of 5G network is End Devices (EDs) long lasting battery life and should be seamlessly integrated with

IoT services. Some other key challenges like scalability, cost effectiveness, battery life, processing power, indoor coverage, throughput, and persistent connection should be addressed [2]. The term IoT is generally used to specify diverse technologies and research disciplines that are somehow intended to enable the Internet to access the real world physical objects.

Several wireless technologies are used for diverse Machine-to-Machine (M2M) communications to achieve long range, low power and low data rate connectivity [3]. According to the survey conducted by Ericsson's [4], by 2020 two billion terminals used for M2M communication are expected to use cellular infrastructure. The authors in [4], discuss all the issues like collision, throughput and delay. Different LPWAN standards are discussed and compared in terms of attributes like modulation scheme, MAC scheme, data rate, receiver sensitivity levels and in addictiveness. Several potential directions are also deeply observed and elaborated for future researchers. In another survey, approximately 28 % of Machine Type Communication (MTC) [5] is handled by LPWAN and 78 % of the market is captured by 3GPP. Several attributes are required to enable M2M communication such as long or short range, low bandwidth and ability to connect higher number of devices [6]. Comparison of different wireless technologies in terms of bandwidth and range are provided in Figure 1.1.

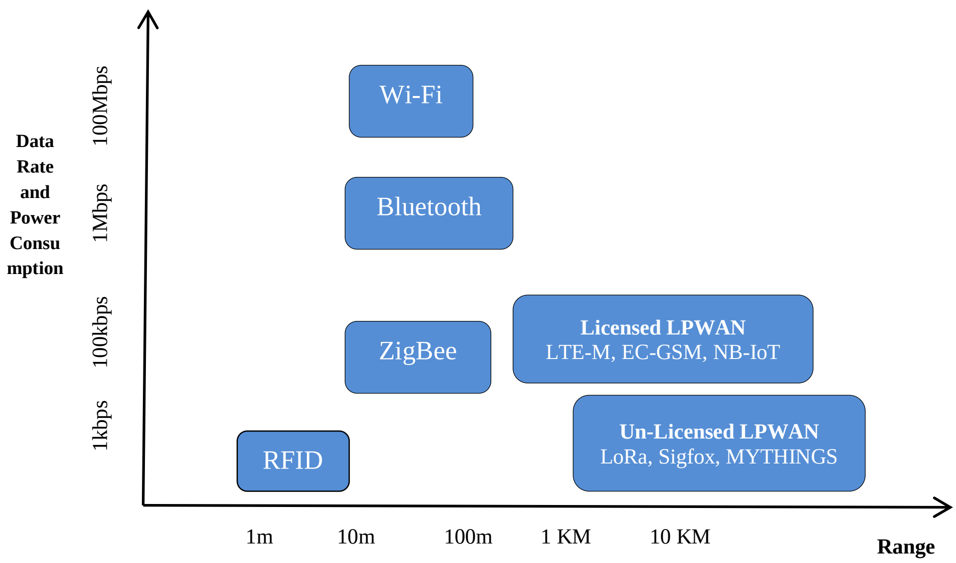

Figure 1.1 Comparison of Wireless Technologies in terms of Range and Bandwidth [7]

There are various IoT wireless technologies available for device connectivity, some of the most common of which are:

Wi-Fi is a popular wireless technology for Internet of Things smart devices [8]. It features high-speed connectivity and a wide area of coverage, making it perfect for smart home devices and other high-bandwidth applications. Bluetooth is a wireless technology with a limited range that is commonly utilized in IoT devices such as wearables, sensors, and smart home devices. It is simple to use and consumes little power, making it suitable for battery-powered devices [8]. Zigbee is a low-power wireless technology designed for low-cost, low-power Internet of Things (IoT) applications such as smart lighting, home automation, and industrial automation. It has a greater range than Bluetooth and requires less power, making it perfect for devices that run on batteries. Z-Wave is a wireless technology that was created primarily for home automation applications including smart thermostats, door locks, and security systems. It has a greater range than Zigbee and requires less power, making it perfect for devices that run on batteries.

Some of the most popular IoT technologies used for several IoT applications are Radio Frequency Identifiers (RFID) [8], short-range Wireless Communication Technologies (NFC, Bluetooth, ZigBee), Wireless Sensor Networks (WSNs), Cellular Technology (2G, 3G, 4G) and Wireless Body Area Networks (WBANs) [9]. WBANs often send data from smart wearable devices to a central relaying hub or network server using low-power wireless technologies such as Bluetooth, Zigbee, or Wi-Fi. The data generated from the sensors can be used for a variety of applications, including medical monitoring, fitness tracking, and sports performance analysis. All these technologies have attributes of short range and low-power communication capabilities, which limit the coverage area within the buildings or inside an area. Some of the promising LPWAN standards are Sigfox, Weightless [10], Narrow Band Internet of Things (NB-IoT) [11] and LoRaWAN, which will be used in future to meet the requirements of different IoT applications. LoRaWAN is considered to be competitive LPWAN technology for different IoT use cases. Moreover, LoRaWAN gateway is able to extract the data from millions of IoT devices from a considerable range in kilometers. Due to short range of LPWAN, multi-hop communication is necessary to complete a desired task [12]. Cellular networks also suffered with the ubiquitous and transparent coverage, and to achieve this, IoT enabled devices need to be placed on desired location [13]. Massive connectivity of IoT devices with a Base Station (BS) may adversely affect the signal strength and control messages. These important concerns make current cellular network technologies unsuitable to fully support the envisioned IoT scenarios. Due to rapid increase in number of connected devices, another technology known as

LPWAN, has been introduced, which is best suited for massive connectivity scenarios. Similar to cellular networks, LPWAN technologies are characterized by long range, i.e., in kilometers. These networks are based on star topologies where EDs are connected directly to the gateway, which relays packets towards a network server. Several applications are are using LPWAN technologies such as in smart city applications, personal IoT applications, smart grid, consumer applications, smart metering, logistics, industrial monitoring and agriculture monitoring applications. Approximately 25 billion devices [14] are connected in 2020 with Internet where networks suffered from data analysis, data processing for intelligent decisions. The US National Intelligence Council (NIC) has embarked IoT as one of the six ‘‘Disruptive Civil Technologies” (National Intelligence Council, 2008) [15]. Figure 1.2 shows IoT applications.

Figure 1.2 Applications of LPWAN Technologies Across different Sectors

1.3 IoT applications

The IoT smart devices will be approximately more than 200 billion by the end of 2025 [16]. In [16], McKinsey Global Institute reported that the number of devices has grown 300% over the last 5 years. The area of smart homes is more dominant among all other area of IoT networks. IoT applications for smart city make life much easier with smart devices for water distribution management, environment monitoring, and traffic control. The concept of smart health is another area that has enormous potential for the betterment of people and their health. IoT industry is also working for smart supply chain solutions. This includes smart devices for tracking goods at the time of transportation and also used for exchanging inventory information among suppliers. The market covered by IoT applications in various sectors by 2020 [17] are presented in Figure 1.3.

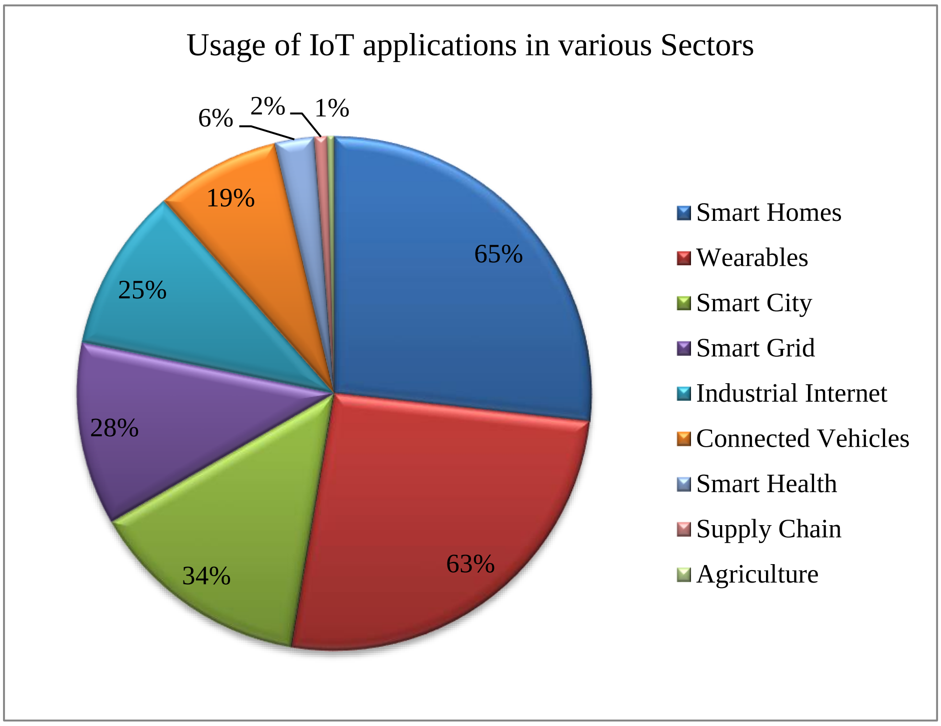

Figure 1.3 Market share of dominant IoT applications

Here are some examples of IoT applications, explained in different catagories:

1. IoT technology can be utilized to build a smart home environment in which End Devices (EDs) such as smart thermostats, lighting systems, and security cameras can be managed and automated via a central access point or hub. This gives you more control over all of your functions in home and improves energy efficiency.

2. IoT EDs can be used to track and monitor assets such as vehicles, equipment, and inventory. This can assist industry in optimizing operations, preventing loss or theft, and increasing overall efficiency.

3. IoT sensors and EDs can be used to monitor equipment performance, track inventory levels, and optimize production processes in manufacturing and other industrial contexts. IoT EDs such as wearable fitness trackers and medical sensors can collect and communicate patient health data.

4. Smart Cities IoT technology can be used to regulate traffic flow, optimize energy use, and monitor environmental aspects in cities. EDs or smart nodes or sensors can be used to observe soil moisture levels, measure crop growth, and regulate irrigation systems, assisting farmers in increasing crop yields while reducing waste. By monitoring usage patterns and automatically altering lighting and temperature settings, IoT technology can be utilized to optimize energy consumption in buildings. EDs or smart sensors can be used to monitor air and water quality, weather, and other environmental issues. This data can be utilized to create more effective conservation plans.

5. IoT EDs can be used in retailers to watch customer behavior and analyses purchasing trends in order to improve store layouts, optimize product presentations, and increase sales.

6. IoT EDs can be used to track shipments, check inventory levels, and optimize distribution networks, boosting overall efficiency and lowering costs.

7. IoT smart sensors may be used to monitor animal health, track fertilizer and pesticide usage, and optimize irrigation and crop management strategies in smart farming.

8. IoT technology can be used to automate building services such as lighting, temperature control, and security systems, increasing energy efficiency and lowering maintenance costs.

9. Internet of Things (IoT) technology is important for the development of self-driving cars, which rely on real-time data from sensors, cameras, and other devices to navigate roadways and make choices.

10. IoT devices such as smart watches and fitness trackers can gather and analyses data on users activity levels, heart rate, and other health measurements.

11. Internet of Things EDs or smart sensors can be used to monitor and regulate power grid systems, increasing energy efficiency and lowering costs.

12. Using data analytics to deliver customized recommendations and promotions, IoT technology may be leveraged to create personalized shopping experiences for customers.

13. IoT sensors and devices can be used to monitor equipment performance and predict when maintenance is required, saving downtime and repair costs.

14. Internet of Things devices can be used to remotely monitor assets such as pipelines, oil rigs, and other equipment in hazardous or difficult-to-reach areas.

1.4 IoT challenges

Some of the most prominent challenges in IoT are Scalability, Smart Health System, energy efficiency, Education and data storage and its processing. All these are briefly discussed in below section.

A. **Scalability**

One of the biggest issues with IoT implementations is scalability. The number of connected devices in IoT systems is continuously expanding, and as more devices are added to the network, managing and scaling the system becomes increasingly complicated. With the amount of sensor nodes required simultaneous connectivity it becomes difficult to scale the network. Mostly two types of scalability are performed like vertical scalability and horizontal scalability. Despite of all these efforts by researchers, various challenges still exist in terms of scalability [18].

Here are some of the scalability issues that IoT deployments face: Network bandwidth is the mostly discussed challenge in IoT applications, as more EDs are added to the network, the amount of data transferred and received grows exponentially, necessitating greater bandwidth. As a result, network congestion, delays, and dropped connections may occur. With so many gadgets producing so much data, storing and analyzing this data becomes a huge difficulty. Traditional databases may be incapable of dealing with the volume, velocity, and variety of data created by IoT devices. Scaling an IoT deployment can be costly, as extra hardware, infrastructure, and staff may be required. When planning for scalability, cost factors must be taken into account.

To address these scalability issues, IoT EDs implementations must be planned with scalability. To ensure that the system can handle the exponential growth of EDs and data quantities, efficient planning, architecture design, and implementation of the appropriate tools and technologies are required. Some of the technologies that can aid in the development of scalable IoT systems include cloud-based IoT platforms, edge computing, and machine learning techniques.

B. **Smart health system**

By enabling the creation of smart health systems, the Internet of Things (IoT) has the potential to revolutionize healthcare. However, certain hurdles must be overcome in order to fully realize the potential of IoT in healthcare. Here are a few of the major challenges:
IoT devices collect sensitive data, such as patient health information, which must be protected from unauthorized access or cyber assaults. IoT devices frequently employ distinct communication protocols and data formats, making integration into existing healthcare systems difficult. The vast amount and variety of data provided by IoT devices might be overwhelming for healthcare practitioners. Healthcare organizations must devise strategies for properly integrating and managing this data. In order to function properly, IoT EDs must be both dependable and accurate. Healthcare practitioners must follow a variety of rules pertaining to the usage of IoT EDs, including those pertaining to data privacy, safety, and efficacy. The usage of IoT EDs poses ethical and legal concerns around patient permission, data ownership, and liability. Healthcare providers must ensure that proper procedures are in place to handle these challenges. Implementing and maintaining IoT EDs can be costly. Healthcare organizations must carefully weigh the costs and benefits of incorporating IoT EDs into their operations.

Smart Health System nearly takes over our traditional health care system, but still have to cater a lot of challenges. Several standards are discussed in literature like SmartBAN or IEEE 802.15.6 but these devices are still not available in market. Privacy of data is another main challenge that health monitoring applications had to address. In general, overcoming these issues is critical to ensuring the safe and effective use of IoT in healthcare.

C. **Energy efficiency**

The Internet of Things (IoT) has the potential to revolutionize many industries, but it also poses a number of energy-efficiency challenges. Here are some of the major issues in this area:

In order to function, IoT EDs require a continual source of power, and many of them are designed to be always on. This can result in excessive power usage and limited battery life. Improving IoT smart device energy efficiency can assist increase battery life and eliminate the need for frequent recharging. IoT devices link to the internet through wireless communication technologies such as Wi-Fi, Bluetooth, and cellular networks. These technologies can consume a lot of electricity, especially when transmitting big volumes of data. To minimizing the consumption of power is one of the big challenge. Many IoT smart devices perform sophisticated computations on the data they retrieve, which can consume huge amount of computing power. This can result in undue power consumption, especially for smart devices with low computational capacity. Improving IoT processor energy efficiency can assist minimize power usage and improve battery life. IoT smart devices generate massive amount of data, which must be processed, analyzed, and saved. This can necessitate a significant amount of energy, especially for systems that create big amounts of data at high frequencies. Improving data processing and storage energy efficiency can help reduce the overall energy consumption of IoT devices. The manufacture and disposal of IoT smart devices have the potential to have a substantial environmental impact. Reducing IoT device energy usage can assist minimize their carbon footprint and increase environmental sustainability.

Energy efficiency is another key challenge that is inherent in smart IoT devices. Researchers are working to design IoT smart devices that are efficient in as far as energy is concerned. Several algorithms are developed that targets optimization of medium, to lower computation on node side and other adaptive approaches to increase the energy efficiency of end node. Overall, improving the energy efficiency of IoT smart EDs is critical for lowering environmental impact and enabling widespread adoption. To address these issues, a combination of technology innovation, regulatory measures, and consumer education will be required.

D. **Education**

The Internet of Things (IoT) is a complicated and quickly expanding field that provides a variety of educational challenges. Here are a few of the major challenges:

IoT smart systems incorporate a diverse set of technologies and disciplines, such as sensors, networks and software development. Educating others on these complicated topics can be difficult, especially for those who don’t have a technical background. The Internet of Things industry is continually evolving, with new technology and applications emerging at an alarming rate. To guarantee that their students are equipped for the difficulties of IoT development, educators must stay current on the newest advances in the industry. Hands-on experience with hardware and several software tools is frequently required for IoT systems development. Giving children access to these technologies can be costly and difficult, especially in schools with limited resources. The Internet of Things area, like many others must try to address this issue by fostering a friendly and comprehensive learning environment that raises involvement from people of various backgrounds.

In the field of education IoT plays critical role. Researchers use IoT sensor nodes for collection of data from remote areas like agriculture and factories etc. To understand the patterns and behavior of these datasets are extremely vital. However we have certain challenges like wireless coverage, cost of nodes, life time of devices and absence of privacy standard. Overall, resolving these difficulties is critical for establishing a trained workforce capable of designing, implementing, and managing IoT systems. This will necessitate a combination of creative educational approaches and industry-academia collaboration.

E. **Storage of data and its processing**

The Internet of Things (IoT) creates massive amounts of data, which offers a number of storage and processing issues. Here are a few of the major challenges:

IoT smart devices generate large volumes of data, traditional data storage systems can quickly become overwhelmed. Storing and analyzing this data necessitates substantial computational resources, which can be costly and time-consuming. IoT data is created in real-time, necessitating quick processing and storage. Slow data processing and storage might result in data loss or incorrect data interpretation, reducing the usefulness of IoT devices. IoT data is available in a variety of formats, including text, audio, video, and sensor data. Processing and analyzing this data necessitates the use of specialized tools and techniques that might be difficult to adopt and integrate with current systems. IoT data can be noisy and incomplete, lowering the accuracy and utility of data analysis. To ensure data quality, complex data cleaning and preprocessing techniques are required. Multiple parties, including device manufacturers, service providers, and end users, frequently acquire IoT data. Defining and enforcing data ownership and access rights can be difficult, and clear legal and regulatory frameworks are required.

Storage of data and its processing is another challenge for IoT as large number of devices is generating data on daily basis. As most of IoT devices are battery driven, that keeps researchers away to process this on smart node side. Storage of data is also not possible because of the energy reservations. Overall, overcoming these obstacles is critical for successfully storing and analyzing IoT data. This will necessitate a combination of technological advancements, data management tactics, and legislative frameworks to secure the privacy and security of IoT data.

The term IoT describes a huge network that connects numerous objects and intelligent gadgets. Sensing, processing and data transmission are the three crucial elements of the IoT. Security is becoming increasingly important for IoT systems due to the exchange of critical data produced by EDs. Additionally, IoT need simple encryption methods. Table 1.1 presents some of the fundamental challenges that IoT systems must offer like, authorization, authentication, confidentiality, availability and integrity.

Table 1.1 IoT Challenges and Key Issues

Services	**Perception**	**IoT layers Networking**	**Application**
Authentication	✔	✔	✔
Authorization	✔	✔	✔
Confidentiality	✔		
Availability	✔	✔	
Integrity	✔	✔	✔

1.5 Problem background

This thesis focuses on aspects of LoRaWAN, based on star topology [5], where all EDs directly communicate with a gateway. The single hop LoRaWAN simplifies the network design and also provides a centralized control over all type of resources. However, in such networks, EDs have important requirements of transmission power, antenna gain, and data rate to accomplish the communication with gateway. Further, if the gateway is located far from EDs, high power levels are required to transmit frames, which may lead to rapid energy consumption. The summary of key contributions in this thesis is discussed below:

1.5.1 Degradation in performance of LoRa network by Pure Aloha

The LoRa protocol has a patented modulation mechanism that allows it to achieve great sensitivity and long-range communication while consuming little power. Pure Aloha, on the other hand, is a simple channel access protocol that allows several users to share a single communication channel. In Pure Aloha, each smart ED sends data packets at random times, with no collaboration with other smart EDs. This might cause packet collisions, resulting in decreased network speed and poorer throughput. When used to a LoRa network, Pure Aloha can cause a comparable performance decrease. Because LoRa networks are designed to operate in unlicensed frequency bands, many LoRa devices can send data on the same channel at the same time. Collisions can occur if certain smart EDs use Pure Aloha to send their data, resulting in a loss in network performance. Issues like collision, Packet Error Rate (PER), throughput and latency of EDs are observed depending on the size of the payload and the number of EDs [19]. The probability of collision exponentially increasing in LoRa network, as LoRa network don't have the ability to sense the channel before transmitting packets towards gateway [20]. Another factor of increased number of collisions observed in LoRaWAN is the increase in time for transmitting packet with the increase in Spreading Factor (SF). For application like smart health (Smart Blood Pressure, Smart Proximity Sensor, Smart Heart Rate), where huge amount of packets are generated by smart EDs towards gateway, these issues severely affect network capacity and reliability of LoRa network [21].

1.5.2 QoS-aware efficient service provisioning to optimize transmission delay

LoRaWAN, transmission latency might have a substantial impact on performance. The time it takes for a message to be transferred from an ED to a gateway in a LoRaWAN network is referred to as transmission delay. This delay can be caused by a number of variables, including distance, signal quality, network congestion, and interference from other devices. The longer the transmission delay, the more influence on network performance there is, including: Longer transmission delays cause end devices to take much more time to send and receive data readings (packets), potentially reducing network capacity. Longer transmission delays might affect the response from IoT applications and services by increasing total network latency. Longer transmission delays can enhance the risk of packet loss, lowering the networks overall reliability.

QoS efficient service provisioning is a major challenge due to highly dense wireless environment, limited battery lifetime of LoRa EDs, spectrum coverage, interference and collisions [22]. All these QoS-aware potential parameters drastically affect the performance of LoRa network in terms of delay. By using current LoRa framework for applications like smart health, where huge amount of data being transmitted, will ultimately contribute towards real-time PER, low throughput, high number of collisions, re-transmissions. Inter-packet arrival is another issue that affects LoRa network performance, as same packets from ED are received from multiple gateways by Network Server [23]. All these issues contribute hugely towards transmission delay. Intelligent QoS-aware efficient service provisioning is a dire need of the day to better streamline this problem that directly impacts the QoS of such networks [24].

Several strategies can be employed to mitigate the effect of transmission delay on LoRaWAN performance, including: Network operators can shorten transmission lengths and increase network performance by strategically installing gateways. Adaptive Data Rate (ADR) is a LoRaWAN feature that adjusts the transmission rate adaptively based on signal quality and network congestion, reducing transmission latency and energy usage. Network congestion can be minimized by regulating the number of end devices on a network and optimizing data scheduling, which can enhance overall network performance.

1.5.3 Dynamic Reinforcement Learning to optimize energy consumption

Efficient resource allocation is critical for improving the performance of LoRaWAN networks in terms of energy consumption, which are commonly utilized for low-power, wide-area IoT applications. LoRaWAN uses an unlicensed spectrum and a star-of-stars network topology, with gateways connecting smart end devices to the network server. Efficient LoRaWAN resource allocation can have a substantial impact on several elements of network performance, including: Efficient resource allocation can aid in the efficient use of available network resources such as bandwidth and airtime, hence increasing overall network capacity. This allows for more smart devices to be connected to the network and bigger traffic levels to be supported. Most LoRaWAN smart end devices are battery-powered and intended for long-term use. Efficient resource allocation can help to mitigate device energy consumption by minimizing the amount of airtime necessary for communication, which can increase device battery life. By minimizing the time necessary for smart end devices to transmit and receive data readings, efficient resource allocation can help to reduce latency in LoRaWAN networks. This has the potential to improve the responsiveness of IoT applications and services. Efficient resource allocation can help to improve LoRaWAN network dependability by reducing the packet loss and collision factor.

Various strategies can be utilized to accomplish efficient resource allocation in LoRaWAN. By optimizing gateway location, regulating the number of smart end devices on the network, and optimizing data readings scheduling, careful network planning and optimization can help to deploy network resources more efficiently. QoS management can help in the prioritization of critical data traffic and the allocation of network resources like data rate, spreading factor, transmit power and bandwidth etc, to support the most critical IoT applications.

In smart health monitoring scenario, where extremely sensitive data readings of patients (Pulse Oximeter, Blood Pressure, Heart Rate), had to be reached on time to take further necessary action. With more than 1000 EDs or smart nodes using Pure Aloha, this lead towards challenges like resource allocation and channel congestion in smart health monitoring scenario, ultimately affect the network performance in terms of consumption and capacity [25]. With static nature of smart EDs in LoRa network, EDs that are far from gateways need high value of transmit power. Further individual handling of EDs by ADR algorithm in LoRaWAN is another issue that needs to cater. Figure 1.4 shows the taxonomic view of LoRaWAN issues.

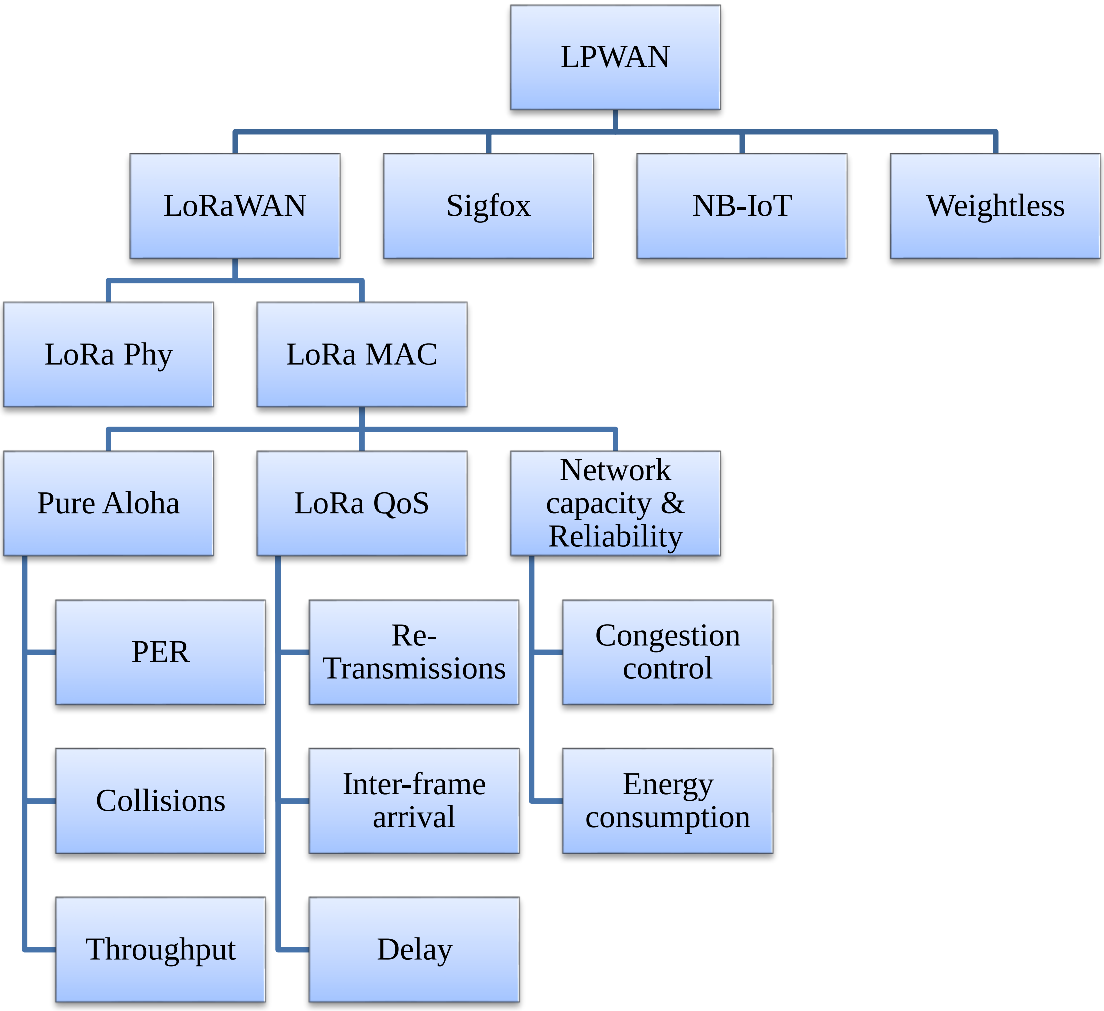

Figure 1.4 Taxonomic View of LoRaWAN Issues

Under massive traffic scenarios in single hop communication, massive number of EDs are aggravate the overhead, thereby affecting the performance of LoRaWAN. Further to multi-hop solutions, a number of other challenges including: ADR, multiple access, and propagation considerations is an open issues, which plays vital roles in the performance of LoRaWAN [26]. Thus, how to enable multi-hop communication architecture with revisited ADR and multiple access schemes is an open issue.

1.6 Problem statement

Pure Aloha performance in LoRaWAN is hampered by an increase in ED density and different throughput demands. With the ease and simplicity we get with Pure Aloha, it also brings issues related to network capacity and reliability on table. These limitations are increase in number of collisions, degrade performance in terms of throughput, PER, and latency [27]. With smart health monitoring scenario where some of the patients are extremely critical, we need a reliable network that can forward reading of different smart wearable EDs on time. For this it's really vital to address all the above mentioned issues. QoS efficient service provisioning is a major challenge due to highly dense wireless environment, limited battery lifetime of LoRa EDs, spectrum coverage, interference, collisions, and delay [28]. With thousands of smart EDs deployed in a specific geographical area, addressing the issue of delay has become critical. Packet delays are also a source of inter-frame interference, which contributes to packet losses. These losses increase number of re-transmissions from EDs which contributes heavily towards transmission delay. In a smart health monitoring scenario, where we have extremely sensitive patient data readings (Pulse Oximeter, Blood Pressure, Heart Rate), we had to be reached on time to take additional essential action. With more than 2500 to 3000 EDs or smart nodes using Pure Aloha and with the mechanism of allocating resources through conventional ADR, this leads towards channel congestion, which ultimately affect the network performance and capacity in terms of energy consumption [29]. With channel congestion, resource allocation is another issue that plays a vital role in the enhancement of performance in LoRaWAN.

1.7 Research Questions

i) How to enhance performance of LoRa network, with number of EDs transmit simultaneously in terms of collision, PER and throughput?

ii) How to mitigate delay without placing any extra burden on the underlying resource constraint smart EDs and to make it QoS-aware efficient service provisioning network?

iii) How to optimize energy consumption of smart EDs in LoRa network by analyzing channel condition, network capacity and its reliability?

1.8 Research Objectives

i) To examine the behavior of Pure Aloha in LoRa network and enhance performance in terms of collision, PER and throughput.

ii) To achieve the least possible transmission delay by resource optimization in QoS-aware efficient service provisioning network.

iii) To optimize energy consumption by efficiently allocating resources in LoRa network.

1.9 Research Scope

The exponential growth of IoT devices and ecosystems is recently emerged with a novel type of communication network known as LoRaWAN. LoRaWAN enables low power long range communication at low data rate and cost. To improve performance of LoRaWAN, in terms of collision, PER and throughput, we design an approach Slotted Aloha with Markov Chain model. Consequently, QoS efficient service provisioning is a major challenge due to densely populated LoRa environment, limited battery lifetime of LoRa EDs, interference and collisions. LPWAN technologies especially LoRaWAN have certain challenges such as massive connectivity, reliability, retransmissions, duty cycling and limited downlink [30]. To mitigate delay without placing any extra burden on the underlying resource constraint smart EDs, a novel un-supervised Learning algorithm ASA with GMM is developed. Efficient resource allocation mechanisms are designed to optimize energy consumption of smart EDs in LoRaWAN by analyzing channel condition, network capacity and its reliability. A dynamic Reinforcement Learning algorithm is used to intelligently learn from varied underlying potential parameters such as real-time PER, throughput, delay, collisions and energy consumption to improve the overall network performance. The proposed research framework is extensively simulated, rigorously evaluated with current state of the art benchmark algorithms using standard and extended evaluation metrics.

1.10 Thesis Organization

Preliminary work in chapter 1 provides basic knowledge to domain and state of the art literature regarding LoRaWAN solutions. Chapter 2 gives basic idea about IoT applications and LPWAN standards. Furthermore, a comparative analysis of major LPWAN technologies is also performed. Chapter 3 provides detail discussion on research methodology followed in this thesis. Chapter 4 presents proposed methodology or framework that includes, analytical modeling of BackLogged (BL) and Non-BackLogged (NBL) nodes with addition to extensive simulations of Slotted Aloha in LoRaWAN environment, introduces an intelligent learning algorithm with Adaptive Scheduling Algorithm (ASA) to prioritize traffic from different profiles and dynamic RL resource allocation on the basis of channel congestion and other defined parameters. Chapter 5 explains the conclusion and future endeavors of thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter discusses Internet of Things (IoT) networks, its applications, various existing technologies and standards. The detail literature review also highlights the existing issues and challenges in LPWAN technologies. The Quality of Service (QoS) issues are also elaborated in detail. Summary of different existing studies and their limitations are provided. Further this chapter also highlights the main challenges regarding of QoS, delay and energy consumption existing solutions [31]. Chapter concludes with main literature findings to design an efficient LoRaWAN for better data throughput, less delay and efficient energy consumption.

2.2 IoT in perspective of LPWAN

Requirements of next generation communication systems are generally under consideration by several researchers [32]. One of the major requirements of 5G networks is battery life of End Devices (EDs) and integration with IoT services. Some key challenges like scalability, device cost, battery life, processing power, indoor coverage, data throughput, and persistent connection should be addressed [33]. The term IoT is broadly used to indicate different technologies that are somehow intended to enable Internet. Several attributes are required to enable IoT devices to communicate by using long or short range standards, low bandwidth utilization and ability to connect with other devices. However, it's understandable that LPWAN is one of the best suitable wireless technologies adopted for IoT applications. Among the most popular technologies associated with IoT are, Radio Frequency Identifiers (RFID), short-range Wireless Communication Technologies (NFC, Bluetooth, ZigBee), Wireless Sensor Networks (WSNs), Cellular Technology (2G, 3G, 4G) and Wireless Body Area Networks (WBANs) [34]. All these technologies have attributes of short range and low-power communication capabilities, which limit the coverage area within the buildings.

2.2.1 Components of IoT in perspective of LPWAN

The Internet of Things (IoT) is a network of interconnected smart devices that share or exchange data and interact with one another to complete a task or achieve a common objective. The term LPWAN (Low Power Wide Area Network) refers to a wireless communication technology that enables long-distance, low-power data transfer between IoT smart devices and the internet. In terms of LPWAN, the components of IoT can be split into three categories: The physical devices that are linked to the internet and communicate with one another via LPWAN technology. Sensors, actuators, and controllers are examples of IoT smart devices. These devices are often battery-powered and are designed to require extremely little electricity. LPWAN network is another component that consists of network infrastructure that allows IoT smart devices to communicate with the outside world through internet. LPWAN networks are intended to give IoT devices with long-range coverage, low-power consumption, and low-cost connectivity. LoRaWAN, Sigfox, and NB-IoT are examples of LPWAN networks. Last component is the software platform responsible for managing and analyzing the data generated by IoT smart devices. IoT platforms offer a variety of services, including data storage, processing, and visualization. They also allow developers to create and deploy IoT applications capable of automating jobs, optimizing operations, and increasing efficiency.

The prominent components of IoT in perspective of LPWAN are rigorously discussed in this section. Building blocks of LPWAN help us for better understand actual insight functionality [35]. Certain components are required to deliver the required functionality in LPWAN. Figure 2.1 shows components that are required to deliver the desired functionality.

2.2.1.1 Identification

Identification is a critical component of IoT systems because it provides the safe and reliable authentication of network devices, users and services. To create trust, prevent unauthorized access and assure data privacy and integrity, IoT end devices must be individually identifiable. In IoT systems, numerous types of identification are routinely employed, including: MAC address, IP address, RFID tags, QR codes and Bio-metric authentication. Identification is critical for any smart devices in LPWAN to provide services according to their demands. Different methods are available for identification of smart devices in LPWAN such as Electronic Product Codes (EPC) and Ubiquitous Codes (uCode). Furthermore, it’s important to distinguish smart object IDs and smart object addresses. For example, smart object ID means name of smart sensor such as "STemp" to measure the temperature and smart object address for the smart objects in LoRaWAN. Since we are more interested in identification of smart objects in LoRaWAN, it needs following information: a Device Address (DevAddr) and an Application Identifier (AppEUI) [36].

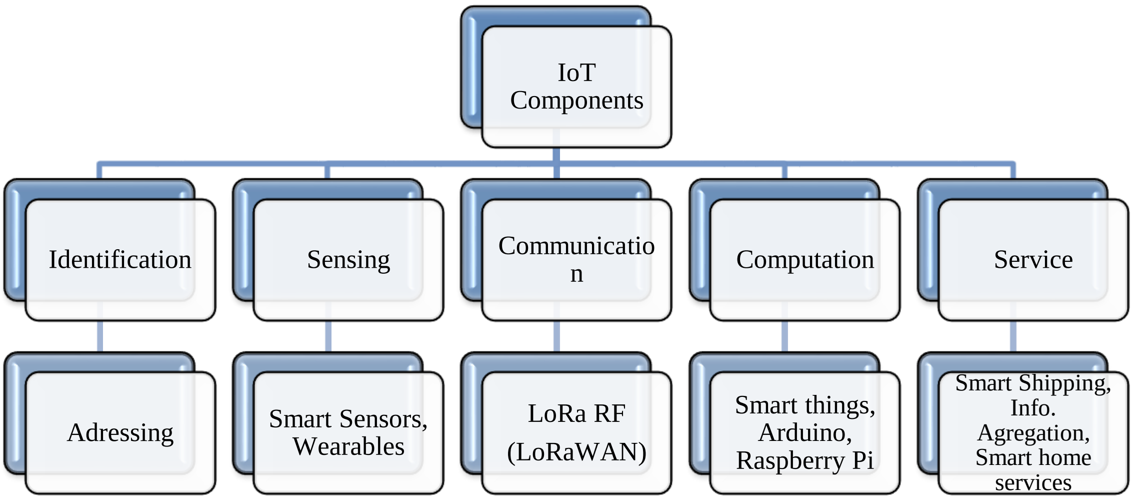

Figure 2.1 Components of IoT to deliver functionality

2.2.1.2 Sensing

Sensing is an important component of IoT systems because it allows smart devices to collect data from their environment and create insights that can be utilized to automate processes, optimize operations, and make better decisions. Sensing in IoT systems is accomplished by the use of various sensors and devices capable of detecting physical phenomena such as temperature, humidity, pressure, light, sound, motion, and location. Some commonly used sensors are: Temperature sensor, humidity sensor, pressure, light sensor and GPS sensor. Sensing means collection of data from relevant smart objects inside the communication network and forwards it to a data warehouse or cloud to take further action. After data is collected by sensing, it is analyzed to take further actions based on required services. The IoT sensors can be smart sensors or wearable sensing devices. For example, different companies like Wemo, Revolv and SmartThings provide mobile applications that help people to control millions of smart devices and appliances inside buildings using their smartphones [37]. In summary, sensing in IoT systems requires the employment of various sensors and smart devices capable of detecting physical events and extracting data that can be utilized to optimize operations, automate processes, and improve decision-making. IoT systems can build a more efficient and smarter environment by utilizing sensor technologies, resulting in considerable benefits for both individuals and organizations.

2.2.1.3 Communication

Communication is an essential component of IoT systems because it allows objects to communicate data with one another and with the internet, allowing them to perform a variety of functions. In IoT systems, communication entails the use of various communication technologies and protocols that allow devices to connect to one another and to the internet. Some of the most prevalent communication methods and protocols used in IoT systems are: WiFi, Bluetooth, Zigbee, LoRaWAN etc.

To provide smart services several objects are connected by IoT communication technologies. Various protocols are used in IoT technologies are WiFi, IEEE 802.15.4 [38], Z-wave and Bluetooth. All these technologies have their own limitations in terms of transmit power, communication range and interference. Specifically, in LoRaWAN communication between smart nodes are performed with ultra-low power in noisy environment. The modulation scheme used by LoRaWAN provides immunity in terms of noise and interference [39]. The sensitivity level at receiver is better than other IoT technologies. To summarize, communication is an important part of IoT systems, and numerous communication technologies and protocols, can be used to allow smart devices to share data with one another and with the internet. IoT systems can build a more connected and smarter environment by utilizing communication technologies, resulting in considerable benefits for both individuals and organizations.

2.2.1.4 Computation

Computation is a critical component of IoT systems because it allows smart end devices to process data, make assessments, and take certain actions on the basis of information they have extracted or recieved. In IoT systems, computation entails the use of different technologies and architectures that allow smart end devices to conduct computation efficiently. The following are some of the most often utilized compute technologies and architectures in IoT systems like Microcontrollers, edge computing devices, cloud computing, quantam computing etc. Several processing units (e.g., Microcontrollers, Microprocessors, SOCs, FPGAs) and applications are available to perform computation for smart objects. Various hardware platforms are provided to run different applications such as Arduino, FriendlyARM, Intel Galileo, Raspberry PI, Gadgeteer, WiSense, and T-Mote Sky [40]. Furthermore, software platforms are also available to provide desired functionalities like Operating Systems of a smart sensor that run for the whole activation time [41]. Overall, computation is an important component of IoT systems. IoT systems can build a more intelligent and automated environment by utilizing computation technologies, resulting in considerable benefits for both individuals and organizations.

2.2.1.5 Services

Services are an important component of IoT systems because they allow smart end devices to bring value to consumers and organizations by performing specified duties and providing data insights. The employment of diverse technologies and architectures in IoT systems enables devices to deliver specialized functions and data insights to end-users . Services that are often used in IoT systems include: device management, data management, predictive maintenance, asset tracking etc. There are several services used in IoT devices like smart shipping services, information aggregation, smart home services, smart city services, agriculture services and environmental services [42]. The services related to smart health and smart grid falls into the information aggregation category and smart home, smart buildings and Intelligent Transportation Systems (ITS) lie in collaborative-aware category [43]. Examples of collaborative-aware category are how to monitor and control appliances like air conditioner, heating systems and energy consumption meters etc. remotely. The IoT services related to smart home make life of people much easier by monitoring and operating all the appliances remotely.

In conclusion, services are an important aspect of IoT systems, and various service technologies and architectures. IoT systems can create value for organizations and end-users by utilizing services, resulting in huge benefits for all stakeholders.

2.3 Applications and standards

LPWAN network or Low-Power Network (LPN) are the wireless technologies designed to allow long range, ultra-low power and low bit rate among things, such as sensors or EDs operated on a battery [44]. These features distinguish LPWAN from other wireless WAN technologies that are designed to establish sessions among users or businesses, and carry huge amount of data, using high power [45].

2.3.1 Low Power Wide Area Network

LPWAN intends to extend range, to operate on low power, and to achieve scalability. LPWAN has become a "big thing" in the IoT over the last few years [46]. This is a terminology that is used for a variety of technologies to provide connectivity among EDs (sensor nodes) and controllers (gateways) to the server at cloud without any traditional WiFi or cellular. Several applications are monitored for decades, but the title LPWAN is used to describe a portion of the IoT and Machine-to-Machine (M2M) market [47]. Some of the emerging LPWAN technologies are extensively compared and highlighted in Table 2.1.

Table 2.1 LPWAN Technologies

	SigFox	**LoRaWAN**	**NB-IoT**	**Weightless-W**	**Weightless-P**
Modulation	UNB DBPSK(UL), GFSK(DL)	CSS	QPSK	BPSK, QPSK, DBPSK	GMSK, Offset-QPSK
Data Rate	100 bps(UL), 600 bps(DL)	0.3-37.5 kbps (LoRa), 50 kbps (FSK)	200 Kbps	1 kbps to 10 Mbps	200 bps to 100 kbps (UL & DL)
Adaptive Data Rate	No	Yes	No	Yes	Yes
MAC	unslotted Aloha	unslotted Aloha	OFDMA /TDMA	FDMA and TDMA	FDMA and TDMA
Authentication & Encryption	encryption not supported	AES 128 bit	AS and NAS	AES 128 bit [22]	AES-128/256
Range	10 km (URBAN), 50 km (RURAL)	5 km(URBAN), 15 km (RURAL)	22 Km	5 km (URBAN) [22]	2 km (URBAN)
Num. of channels	360 channels	10 in EU, 64+8(U	12 subcarriers of 15	16 or 24 channels (UL) [22]	16 or 24 channels (UL)

/ orthogonal Signals		L) and 8(DL) in US plus multiple SFs	kHz in DL using OFDM and 3.75/ 15 kHz in UL using SC-FDMA		
Topology	Star	star of stars	Star	Star	Star
Mobility Support	No	Yes, better than NB-IoT	No connecte d mobility (only idle mode reselectio n) / stationar y nodes	Yes	Yes
Deployment Cost	$2 for EU, less than $3 for American and Asian markets	$1-5 per module (Ref-LPWAN survey)	low, which is under $5 per module	less than $2 per module	less than $2 per module
Status	In deployment	Specific ation released June 2015, in deploym ent	In deploym ent	In deployment awaiting spectrum availability	In deployment awaiting spectrum availability
Link Budget (decibles)	155 dB	154 dB	150 dB	153 dB	140-160 dB

2.3.2 Sigfox

Modulation scheme is used in EDs to connect with BS is Binary Phase Shift Keying (BPSK) [48]. Sigfox network efficiently utilizes bandwidth, and keeps low noise level due to its ultra-narrow band. It aims to achieve a throughput of 100 bps. A downlink message is only generated after successful uplink transmission. Sigfox uses different data rates for both uplink and downlink transmissions, i.e., 100 bps for uplink, and 600 bps for downlink. Regional regulation decides number and size of messages transmitted in this network, where the number and size of uplink messages is limited to 140 messages each of 12 bytes in a day. Channel access in Sigfox is asymmetric, means 4 messages of 8 bytes per day over the downlink from the BS to the EDs. It means acknowledgment of each uplink message is not supported.

2.3.3 NB-IoT

Narrowband IoT (NB-IoT) is a Low Power Wide Area Network (LPWAN) technology designed to enable long-range communication between IoT devices using cellular networks. It operates on licensed spectrum and offers low power consumption, extended coverage, and low data rates, making it ideal for IoT applications that require long battery life, low data transfer speeds, and remote communication.

NB-IoT uses narrowband technology, which allows it to transmit data over a narrow frequency range, using less power and reducing the risk of interference with other wireless signals. This makes it well-suited for applications that require communication over long distances and in hard-to-reach areas. NB-IoT offers several advantages over other LPWAN technologies, such as Sigfox and LoRa. First, it operates on licensed spectrum, which means that it offers more reliable and secure connectivity than unlicensed LPWANs. Second, it is compatible with existing cellular infrastructure, which means that it can be easily deployed by mobile network operators without requiring significant investment in new infrastructure. In addition, NB-IoT offers strong support for mobility, making it well-suited for applications that require tracking of moving objects, such as logistics and transportation. It also supports two-way communication, which enables real-time control and monitoring of IoT devices. NB-IoT has been widely adopted by mobile network operators around the world and is expected to become one of the dominant LPWAN technologies for IoT applications in the coming years. Its low power consumption, extended coverage, and low data rates make it well-suited for a wide range of applications, including smart cities, smart homes, industrial automation, and agriculture.

This technology is specifically designed for IoT, and based on international standard called 3GPP. Its major attributes including low data rate, longer coverage area, and longer battery life [49]. NB-IoT devices have very low power consumption, therefore may extend their battery life up to 10 years. Latency experienced by NB-IoT networks for uplink transmission is less than 10 seconds. Cost of one Narrow Band Internet of Things (NB-IoT) module is under $5, which is extremely low as compared to other IoT devices. NB-IoT uses a frequency spectrum which ranges between 700MHz to 900MHz, with transmission power varying between +20 dBm or +23 dBm. As data rate requirements of IoT devices are low, therefore, NB-IoT devices have data rate support up to 200 kbps.

2.3.4 Weightless-W

Weightless-W is a Low Power Wide Area Network (LPWAN) technology that is intended for Internet of Things (IoT) applications that require long-range communication, low power consumption, and low data rates. It uses unlicensed sub-gigahertz spectrum and narrowband technology to transmit data over a narrow frequency range while using less power and reducing the risk of interference with other wireless signals. The Weightless Special Interest Group (SIG), a group of companies and organizations dedicated to developing and promoting open standards for LPWANs, created Weightless-W. The technology is based on the Time Division Duplex (TDD) protocol, which allows for bi-directional communication and real-time control and monitoring of IoT devices.

One of the most important characteristics of Weightless-W is its ability to support both low-power and high-power sources. It has multiple modes, allowing it to support a wide range of IoT devices, from battery-powered sensors to power-hungry devices like gateways and routers. It also supports data rates ranging from 100 bits per second (bps) to 100 kilobits per second (kbps), making it suitable for a wide variety of applications. Weightless-W also supports mobility, making it ideal for tracking moving objects in applications such as logistics and transportation. Furthermore, it provides robust security features such as encryption and authentication to ensure the privacy and security of data transmitted over the network. Weightless-W has been used in a variety of Internet of Things (IoT) applications, including smart cities, agriculture, and industrial automation. It is distinguished by its low power consumption, extended range, and support for bi-directional communication. Well-suited for a wide range of applications, particularly those that require long battery life and reliable connectivity in hard-to-reach areas.

Overall, Weightless-W is an exciting LPWAN technology that has several advantages over competing LPWAN technologies. Because of its open standard approach and support for both low-power and high-power modes, it is versatile and adaptable to a wide range of IoT applications. One of the cheapest technology in IoT is Weightless-W and operated on an unlicensed environment, where interference caused by others cannot be predicted. Therefore it must be avoided. The modulation scheme used by weightless-W is differential BPSK, or QPSK, or DBPSK. The data rates used by EDs in Weightless-W, range from 1 kbps to 10 mbps, with a coverage of approximately 5 km, in an urban environment. The multiple access schemes used by Weightless-W are FDMA/TDMA with 16 or 24 channels for uplink (UL).

2.3.5 LoRaWAN

The LoRaWAN is an open standard as its specification is easily available. The modulation scheme used by LoRaWAN is Chirp Spread Spectrum (CSS). CSS spreads the narrow band signal over a wide band. To achieve orthogonal transmission, an end device in LoRaWAN, uses SF from 7 to 12, where SF tradeoffs between data rate and range. Higher the SF, higher is the transmission range with low data rates. LoRaWAN also relies on Forward Error Correction (FEC) for reliable transmission of frames. Data rates for LoRaWAN ranges from 300 bps to 37.5 kbps, and depends on bandwidth and SF [50]. In case of Frequency Shift Keying (FSK) modulation scheme, maximum data rate is upto 50 kbps. Table 2.2 shows the technical specification of LPWAN.

Table 2.2 Technical specification of LPWAN [28]

Parameters / **LPWAN Standards**	**Multi-hop Comm.**	**ADR**	**FEC**	**Mobility Support**	**Co-existence**	**Interference Immunity**	**Power Efficiency**	**Link Symmetry**
LoRaWAN	☒	☑	☑	☒	☑	☑	☑	☒
Sigfox	☒	☒	☒	☒	☒	☒	☑	☒

NB-IoT	☑	☒	☒	☑	☑	☒	☒	☑
Weightless-W	☒	☑	☑	☒	☒	☒	☒	☑
Weightless-P	☒	☑	☑	☒	☑	☒	☒	☒

Coverage area achieved by LoRaWAN in urban areas is approximately 5 km, and in rural areas it is up to 15 km. Link budget is another factor that plays important part in the success of any wireless technology. The Link budget for LoRaWAN is much less as compared to other LPWAN technologies. LoRaWAN EDs rely on ADR to assign data rates to all EDs individually. The main purpose of using ADR is to optimize the performance of network and provide scalability. LoRaWAN also provides reliability with Forward Error Correction (FEC) that is a signal processing technique used to increase the consistency and reliability of data by adding redundant bits. A study evaluated LoRaWAN by performing real life experiments to measure the coverage of LoRa technology. The measurements show that on ground up to 5 km, the amount of successfully delivered packets exceeds 80%. On sea level, almost 30 km communication range was reached and about 70% of the packets are successfully delivered at a distance below 15 km.

The LoRa Alliance is an open, non-profit association formed to nurture an environment for certain LPWAN technology. It has about 400 member companies throughout North America, Europe, Africa, and Asia, and its founding members include IBM, MicroChip, Cisco, Semtech, Bouygues Telecom, Singtel, KPN, Swisscom, Fastnet, and Belgacom. LoRaWAN is an open-standard governed by the LoRa Alliance. However, it is not truly open since the underlying chip, to implement a full LoRaWAN stack is only available via Semtech. Basically, LoRa is the physical layer: the chip. LoRaWAN is the MAC layer: software that is embedded in the chip to enable networking. The working of LoRaWAN is almost similar to SigFox, as it is primarily used for uplink-only applications (data from EDs to a gateway). LoRaWAN focuses on spread spectrum techniques, instead of using narrowband transmission. These transmissions are less likely to collide and interfere with one another thereby increasing the capacity of the gateway.

2.4 LoRaWAN system architecture

LoRaWAN is a Low-Power Wide-Area Network (LPWAN) technology designed for long-range communication for low-power EDs, such as sensors nodes and relaying devices. LoRaWAN has grown in popularity as a low-power, long-range connectivity option for Internet of Things (IoT) applications. End devices, gateways, and a network server are the three main components of the LoRaWAN system architecture.
LoRaWAN is based on star-of-stars topology, where all EDs are connected to one or more gateways. EDs communicate with the LoRa gateways by using single-hop communication. LoRa concentrator or gateway relays messages of EDs to a network server, where gateway is connected to the network server via standard internet technologies. After receiving a message from the EDs via LoRa gateway, the network server responds by selecting one of the gateways. LoRaWAN System architecture is shown in Figure 2.2.

A brief description of three main components of LoRaWAN technology is as follows.

2.4.1 LoRa End Devices

End devices are battery-powered sensors or other devices that use the air interface to communicate with gateways. They typically consume little power and transmit small amounts of data over long distances. LoRa modulation is used by end devices to send signals to gateways. LoRa EDs are mainly categorized in three bidirectional classes: A, B, and C. Different applications are supported by these three classes in order to fulfill requirements and optimization of applications. The descriptions of all these EDs classes are as follow:

2.4.1.1 Class A

By default, all EDs operate in class A. Bi-directional communication is followed by class A EDs. Each uplink transmission by class A ED is followed by two receive windows, denoted as *Rx1* and *Rx2*. Whenever, an end device wants to transmit, it accesses the medium based on Aloha. Class A end device opens first receive window Rx1, at the end of its last bit of uplink transmission. However, duration of these receive windows should be long enough, to receive response from the network server via a gateway. If an end device receives response from the network server within the duration of Rx1, then it does not open Rx2.

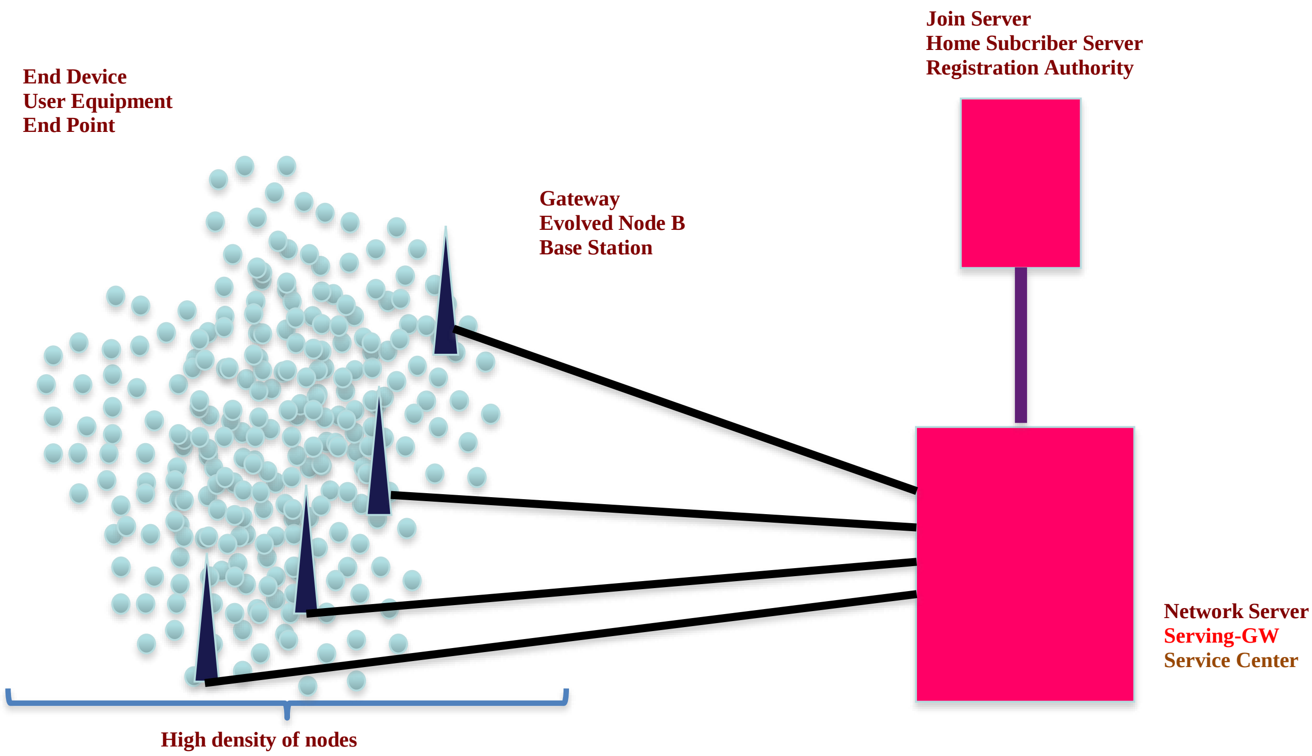

Figure 2.2 LoRaWAN system architecture

2.4.1.2 Class B

Additional slots are used for class B EDs to get synchronized with the network server. Class B EDs open this extra receive window slots after receiving a beacon from the gateway. This helps the network server to know about the status of ED.

2.4.1.3 Class C

Class C EDs constantly keeps their receive windows open, and only close them while transmitting towards a gateway. Class C EDs requires more power to operate, however, they offer lowest latency for network server among all the classes. All the differences and attributes of class A, class B, and class C EDs are summarized in Table 2.3.

Table 2.3 Comparison of class A, class B, class C in LoRaWAN [39]

Class A	Class B	Class C
High Latency	High Latency	Low Latency
Bidirectional communications	Bidirectional with scheduled receive slots	Bidirectional communications
Unicast messages	Unicast and Multicast messages	Unicast and Multicast messages

Small size of payloads, long intervals	Small size of payloads, long intervals, Periodic beacon from gateway	Small payloads
End-device initiates communication (UL)	Extra receive window (ping slot)	Server can initiate transmission at any time
Server respond to end-device (DL) during response windows	Server initiate transmission at specific intervals	End-device is continuously listening

2.4.1.4 LoRa Gateway

Gateways receive signals from EDs and transmit them to network servers via wired or wireless connections. They typically cover a few Km's in cities and up to tens of Km's in rural areas. Gateways are in charge of managing the communication of thousands of EDs. The main responsibility of LoRa gateway is to relay message from EDs towards a network server. Gateways aim to receive data, process it, and forward it to some appropriate network server. Different gateway models are available with varying number of channels. Some channels are dedicated for ADR communication, and some are used for FSK modulated packets. The packets forwarded by end device towards gateway are received by multiple gateways. However, multiple copies of same uplink packet are received by a network server. Further, a network server performs other functions including: authentication and decryption.

2.4.1.5 LoRa Network Server

The Network Server (NS) is in charge of coordinating communication between EDs and applications. It receives data from gateways, decrypts and verify it, and then forwards it to the concerned application server. It also manages the LoRaWAN network, which includes device registration, network security, and bandwidth allocation. All the decisions and complex operations are performed by a network server. Packets forwarded by EDs are received by multiple gateways, and all these gateways forward the packet towards a NS. Further, a network server filters redundant packets, decrypts payload, performs security checks, and sends acknowledgments through an optimal gateway.

Overall, the LoRaWAN architecture enables efficient and low-power communication over long range distances between EDs and concerned applications, making it an overwhelming choice for a wide range of IoT applications.

2.5 Uncoordinated channel access schemes

In wireless communication systems, uncoordinated channel access schemes allow multiple EDs to transmit data over a shared channel without centralized coordination. These schemes are also known as random access schemes because EDs access the channel in a probabilistic manner with no set schedule. Uncoordinated channel access schemes include the following:

Pure Aloha is a widely used and simple channel access scheme for wireless communication. EDs transmit packets whenever they have data reaings to send under this scheme. If at any time collision occurs, the EDs that collided will retransmit after a random amount of time according to some algorithm. Several wireless LAN and satellite communication systems used this scheme. Pure Aloha is one of the simplest multiple access protocol for medium access, where a node transmits data without any coordination. When two or more nodes transmit data simultaneously, it causes a collision. After transmitting data, the node waits for an acknowledgment [51]. If the node does not receive any acknowledgement for a specific amount of time, it assumes that the packet is lost. After a collision, node waits for a random amount of time and retransmits data again. Figure 2.3 shows the design of Pure Aloha.

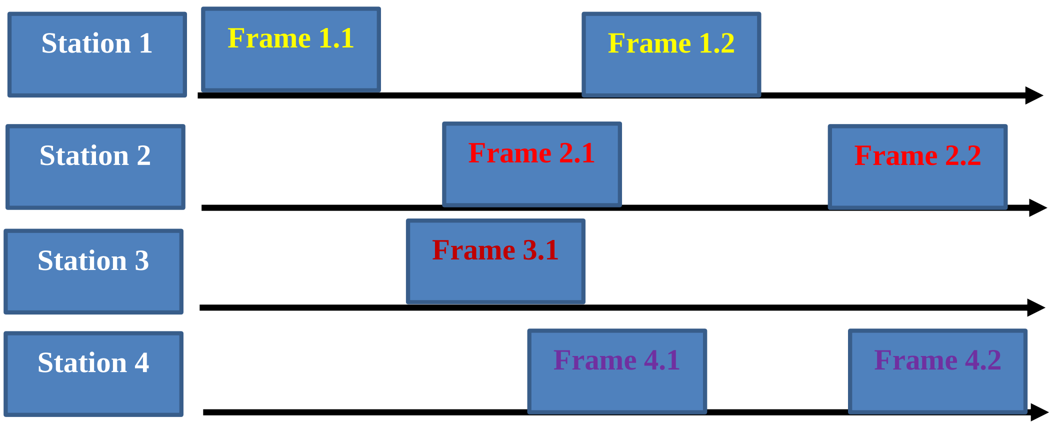

Figure 2.3 Design of Pure Aloha

Let station 1 transmits a frame (Frame 1.1). After some time, station 3 also transmits data as Frame 3.1. In the meanwhile, stations 1 and 2, have frames to transmit [52]. The overlapping region in Figure 2.3 shows the collision as multiple stations transmit the frames at same time. Table 2.4 presents several **c**hannel access schemes in different IoT-Enabled wireless technologies.

Table 2.4 Channel access schemes in different IoT-Enabled Wireless Technologies [53]

Multiple Access Schemes	**Technologies**
Pure Aloha	SigFox, LoRa
Slotted Aloha	RFID, NB-IOT, Weightless
Non-Slotted CSMA/CA	ZigBee, WiFi
Slotted CSMA/CA	ZigBee

Another well-known uncoordinated channel access scheme is Carrier Sense Multiple Access (CSMA). EDs in this scheme listen to the channel to know about other EDs transmissions. If the channel is not in use by any other ED, the concerned ED will send its data. If the channel is busy and in use by other ED, the ED will retry after a random amount of time. Many wireless LAN systems employ CSMA, but this ultimately increase the factor of delay. The Code Division Multiple Access (CDMA) scheme allows multiple EDs to share the same frequency channel. In this scheme, each ED is assigned with a separate code. Although all EDs transmit at the same time, the receiver can only decode the signal intended for it. Some cellular communication systems employ CDMA.

Most of the research in this field deals with different MAC layer protocols based on Aloha. The performance of these protocols is satisfactory when limited number of devices is transmitting simultaneously. However, if the number of devices increases exponentially, they suffered with severe congestion. Some researchers also adopted random access methods to share the communication channel [54]. Most of the existing methods are based on variations of Aloha with carrier sensing, i.e., Carrier Sense Multiple Access (CSMA). All these influential approaches are summarized in Table 2.4. LoRaWAN is based on Aloha with small number of acknowledgments and Packet Error Rate (PER) of 50%. With 50 % of PER, Aloha is not suitable for industrial applications where 0 % PER is a requirement. Whenever class A EDs have any data to transmit, they use Pure Aloha with listen before talk. This kind of approach is suitable for applications, which wait for downlink response immediately after sending the uplink data. Another drawback of Pure Aloha is energy consumption of EDs incurred due to PER. With over 50 % PER, most of the packets must be retransmitted by EDs, which affect LoRaWAN capacity [55].

These channel access schemes are simple to implement and do not require any centralized coordination or control, making them suitable for large-scale systems with many devices. These schemes, however, may suffer from low channel utilization and high collision rates, resulting in poor system performance. As a result, to improve performance, some systems may employ coordinated channel access schemes such as TDMA (Time Division Multiple Access) or FDMA (Frequency Division Multiple Access).

2.6 LoRa physical layer

LoRaWAN employs a patented physical layer modulation scheme known as LoRa (Long Range). LoRa modulation offers low rate, long-range, and low power consumption, making it suitable for several Internet of Things (IoT) applications. The LoRa modulation spreads the signal over a wide frequency band, typically between 125 kHz and 500 kHz, using chirp spread spectrum technology. This provides excellent immunity to interference and noise, which is critical for long-distance communication. The spread spectrum technique also prevents multipath fading, which is a common issue in wireless communication. LoRa modulation modulates the signal using different Spreading Factors (SF), which determines the bandwidth and data rate of transmission. SF range from SF7 to SF12, with SF7 having the most bandwidth and the highest data rate and SF12 having the least bandwidth and the lowest data rate. The LoRa physical layer also includes a several features, which are implemented to improve the performance of the link. These features include Adaptive Data Rate (ADR), which adjusts the spreading factor and data rate based on signal quality, and frequency hopping, which changes the frequency band to reduce the effects of interference and improve the robustness of the communication link.

LoRa uses CSS as a modulation technique [56]. To achieve synchronization and accuracy, special symbols are used in the physical layer packet header. The LoRa modulation consists of three major components: bandwidth, spreading factor, and coding rate. The length of a symbol is computed by using the following formula:

$$\mathrm{T_s} = 2^{\mathrm{SF}}\mathrm{T_c} \qquad 2.1$$

$$\mathrm{T_c} = \frac{1}{\mathrm{BW}} \qquad 2.2$$

Where *BW* denotes the bandwidth, T_s represents the symbol length, and T_c is the number of bits required to represent a symbol [57]. The third component of LoRa called coding rate determines the error rate. The term coding rate is used to analyze the amount of Forward Error Correction (FEC). FEC is a signal processing technique used to increase the consistency of data. By using FEC technique some redundant data is added to the actual payload to enhance the reliability of frames to be transmitted. The bit rate of the desired payload is computed as follows.

Overall, the LoRaWAN physical layer provides a dependable and efficient method of transmitting data over long distances while consuming little power, making it an overwhelming choice for various sectors that require durable and long battery life and long-range communication.

2.7 Adaptive Data Rate

LoRaWAN is a protocol used in IoT networks. ADR stands for Adaptive Data Rate. ADR LoRaWAN is a protocol feature that allows the LoRa network to adaptively adjust the data rate and transmit power based on the attributes of radio link quality between the EDs and the relaying device i.e gateway. The main objective of ADR is to improve or enhance network performance and ED battery life time. When the radio link quality or performance is best, the ED can transmit at a higher data rate with less power, which results in much faster transmission and longer battery life time. When the radio link quality is not up to the mark, the ED will reduce its rate by decreasing data rate and in that case more power is required to ensure best possible communication.

LoRaWAN EDs rely on ADR to assign data rates to all EDs individually. The main purpose of using ADR is to optimize the performance of network and provide scalability [58]. EDs that are placed near to the gateway uses high data rates, as compared to the EDs that are far away. By assigning high data rates to EDs that are near to the gateway, LoRaWAN network avoids collisions between frames and transmitted with same data rates. Initially, an end device transmits data with an initial static configured data rate; however, static data rate causes massive congestion on the Access Point (AP), or coordinator adversely affecting the LoRaWAN capacity. An increase in the number of dropped packets increases the number of re-transmissions, which directly affects energy efficiency. MAC commands that are used for successful implementation of ADR in LoRaWAN are given below in Table 2.5.

The data rates can be configured by both EDs and network. ADR bit is configured for this purpose. If the ADR bit is enabled, or set in the frame control field, the network manages the data rate for EDs by exchanging certain MAC commands. If ADR bit is not set, then network is not responsible to control the data rate of an end device. However, to extend the life time of EDs and network capacity, the ADR scheme should be enabled. If an end-device whose data rate is optimized by the network to use a data rate higher than its default data rate, it periodically needs to validate that the network still receives the uplink frames. An EDs increments the counter ADR_ACK_CNT each time, it sends an uplink frames. If the value of ADR_ACK_CNT counter exceeds ADR_ACK_LIMIT without any downlink response from network server, the end device sets ADRACKReq bit. Afterwards, network responds to the ADRACKReq within a time frame allowed by ADR_ACK_DELAY. The value of ADR_ACK_CNT counter is reset after receiving any of the downlink response. If no response is received within allowed time frame, i.e., ADR_ACK_DELAY, then the end device retry to connect by moving to small data rates to achieve longer range.

Table 2.5 List of MAC commands to adjust ADR [47]

Serial No	MAC Commands	Descriptions
0	ADR	Possess value 1 or 0.
1	ADR_ACK_CNT	Maintain at end device for uplink frames.
2	ADR_ACK_LIMIT	Limit defined for uplink frames without any downlink response.
3	ADR_ACK_CNT >= ADR_ACK_LIMIT	Condition to set ADRACKReq bit.
4	ADRACKReq	Possess value 1 or 0.
5	ADR_ACK_DELAY	Duration after which end device switch towards lower data rates and regain connectivity.
6	LinkADRReq	4 bytes long MAC command transmitted by network to request node to change its transmit parameters.

The control messages exchanged and extra computation required on EDs, they affect the battery life time of EDs. If ADR bit is enabled, it requires acknowledgments from the network towards EDs which may incur extra overhead. In case of loss acknowledgments, the ED configures lower data rates and regains connectivity. The energy consumption due to extra computation at EDs and network capacity are two main issues that degrade the performance of LoRa network in a long run. The data rate and size of frames depends on the distance between nearest gateway and the type of data being transmitted.

LoRaWAN networks can achieve better network scalability and longer battery life for EDs while maintaining a high level of reliability by utilizing ADR. This makes it an overwhelming choice for smart applications in which EDs must operate for large or extended time without requiring any maintenance or change of battery.

2.8 Existing Challenges

While LoRaWAN is one of the auspicious technology for smart IoT networks, but still there are some issues that need to be sort out. Some of the generic current challenges for LoRaWAN are:
LoRaWAN operates on unlicensed bands, there might be possibility of huge congestion in environment where we have more number of users or congested environment. This ultimately results in mitigated capacity and increased in terms of delay. Another major concern is regarding security, with any wireless communication technology. LoRaWAN networks can be exposed to several attacks which includes spoofing, eavesdropping, and Denial-of-Service (DoS). Interference is another issue that may degrade performance of LoRa network, as it operates in unlicensed bands, it is more inclined to interference from other smart wireless EDs and networks, which ultimately mitigate the performance and its reliabilit1y. Battery life of EDs are designed to support or run on low power, with this battery life can still be an issue, especially for EDs that need to transmit data on regular basis. LoRaWAN EDs and gateways can be expensive, especially for applications that require a large number of EDs or huge coverage. Overall, we have several advantages, but in some scenarios it is critical to sort these challenges in order for it to provide reliable, secure, and cost-effective IoT networks.

Several challenges are discussed in the preceding section, but because we are dealing with a smart health monitoring scenario based on LoRaWAN, we will focus on the challenges listed below. Key challenges are scalability, network capacity, collision, PER and QoS parameters. Smart Health System are nearly take over the traditional health care system, but still have to cater a lot of challenges. However cellular network has other issues mainly factor of cost. LPWAN suffered from other QoS issues like energy consumption, delay and latency. Data Privacy is another main challenge that health monitoring applications had to address. Keeping in mind smart health monitoring system where bulk of data is transmitted from smart nodes towards gateway several times a day, LoRaWAN may suffer from collision, collision, throughput, delay and energy consumption. All these issues are discussed in detail below:

2.8.1 QoS provisioning

In LoRaWAN, Quality of Service (QoS) provisioning is critical to ensuring that EDs transmit data reliably and efficiently over the LoRa network. Typically, QoS is defined by three most important parameters: reliability, latency, and throughput. This network provide high level of of reliability, because of its use of Adaptive Data Rate (ADR) and Forward Error Correction (FEC). ADR ensures that EDs transmit data at the optimized rate based on the attributes of link, whereas FEC allows EDs to detect and correct those errors in received data. Another target parameter that improve or enhance performance of LoRa network is latency. LoRaWAN is intended to support low-latency applications, as actual latency can vary on the basis of network configuration and the rate at which ED transmit data readings. To optimize data transmission time, LoRaWAN networks can be configured to to best possible configurable parameters. With the narrow bandwidth of LoRaWAN networks, it can be some time very difficult to support high-bandwidth smart applications. LoRaWAN, on the other hand, can support a large number of EDs at once, making it a best choice for smart applications requiring a huge number of low-bandwidth connections. Network operators or vendors can configure several parameters such as data rate, transmit power, and Time on Air (ToA) to enhance the network's performance for wide variety of smart applications when provisioning QoS in LoRaWAN. Another important factor is to place LoRaWAN gateways intelligently to minimize the effect of interference, improving overall network reliability and performance.

With millions of EDs transmitting simultaneously, issues like PER, throughput, delay, and energy consumptions drastically affect the performance of LoRa network. LoRa is a long-range, low power, single-hop wireless technology designed for IoT applications with battery-powered nodes. However, the performance of Pure Aloha in LoRaWAN is hampered by the growth in ED numbers and the wide range of throughput requirements. Various kind of collision may occur in LoRa network like in terms of SF, frequency, power and time.

Researchers in [59] propose an unsupervised learning approach to prioritize packets at different levels. On an average of 1000 smart nodes send data towards gateway. K-Means is used as an unsupervised technique to extract different clusters on the basis of reading received from smart applications like humidity and weather temperature. Different weights are calculated on the basis of reading received from smart nodes on gateway. These weights contribute towards placing smart nodes in different clusters. Overall this approach works well to enhance performance in terms of delay and energy. Priority Scheduling Algorithms (PST) is used to mitigate the delay and energy consumption considerably. While the dynamic PST enables the gateway to set the node's transmission intervals in accordance with the respective clusters' transmission priority. Different simulations are performed to show the behavior of throughput, error rate, delay and energy consumption.

The authors of [60] discussed a variety of factors that influence the number of collisions that cannot be resolved using traditional time series analysis algorithms. As a result, deep learning methods are used to predict collisions in an LPWAN system by analyzing these factors. Long Short-Term Memory Extended Kalman Filter (LSTMEKF) model is proposed in this paper for collision prediction in LPWAN in terms of temporal correlation, which can improve LSTM performance. Expected growth of smart IoT devices is 32% annually with a claim by most of the well reputed research papers that over 21 billion EDs are used to transmit and receive the data. Various studies in the literature have evaluated the transmission capacity and outage probability of Slotted Aloha by modelling the transmitters under the Poisson distribution. Another study in [61], analyze the behavior of Slotted Aloha under different transmission configurations and found that it performed nearly twice as compared to CSMA. In another work [62], authors analyze the collision probability of Aloha by using stochastic geometry approach. Further, they also have analyzed the maximum load capacity under various packet loss rate. Authors in [63], investigated the performance of carrier frequency under Slotted Aloha. In another recent work [64], authors analyze the throughput of Slotted Aloha in cognitive radio networks with constant power under Rayleigh fading.

2.8.2 Transmission delay in LoRaWAN

The time it takes for an ED to transmit data readings towards gateway and receive a feedback response in LoRaWAN is referred to as transmission delay. There are several factors that influence this delay, including the distance between the ED and the gateway, the data rate used, and the amount of data to be transmitted. The transmission delay in LoRaWAN is primarily determined by the data readings Time on Air (ToA). ToA is the time it takes to send a data packet from a smart ED towards a gateway, and it is affected by parameters like data rate, spreading factor, and bandwidth. The transmission delay can also be influenced by the total number of EDs in the network and more specifically the number of EDs competing for gateway access. To avoid and ED collisions, LoRaWAN employs a random access mechanism; however, in a congested network, the delay can increase as devices wait for an available time slot. Several techniques, such as; improving the quality of signal by and mitigating interference and by allocation of optimized parameters to EDs. By increasing number of gateways in LoRa environment, we can improve range and also optimize the distance between EDs and gateways. We can reduce ToA by using higher data rates, which ultimately shorten the size of payload. Adaptive data rate (ADR) can also be used to optimize data rate based on signal quality of respective ED. Prioritizing low-latency applications and reducing data transmission volume to reduce transmission delay. Overall, minimizing transmission latency is critical to ensure, that LoRaWAN networks can provide reliable and efficient communication for IoT applications, especially those with strict latency requirements.

Having thousands of smart EDs deployed in a defined geographical area it becomes really important to tackle the issue of transmission delay. There is a high likelihood that numerous collisions will take place, wasting precious wireless resources which further enhances delay. The amount of collisions is affected by a variety of factors, many of which cannot be resolved by conventional time series analysis tools. Authors in [65], present a long short-term memory extended Kalman filter (LSTMEKF) model for collision prediction in the LPWAN based on the temporal correlation that can enhance LSTM performance. In this study, a LoRaSim simulated dataset is provided to show the effectiveness of model. Delay of packets also becomes the reason of inter-frame interference that ultimately contributes in losses of packets. These losses increase number of re-transmissions from EDs [66]. The most distant smart EDs in LoRa networks typically influence network longevity because single-hop communication is still popular. Although LoRa networks allow up to eight retransmissions and packet retransmission helps recover lost packets, network lifetime can decrease dramatically when nodes are forced to transmit additional packets. It would be crucial to anticipate the effects of each retransmission in a network in order to know the effect on network lifetime and the quantity of packet retransmissions. Smart health monitoring scenarios where we have critical data reading from patients in severe condition are not in a position to tolerate these delays.

Researchers in [67] proposed an unsupervised learning approach to prioritize packets at different levels. On an average of 1000 smart nodes send data towards gateway. K-Means is used as an unsupervised technique to extract different clusters on the basis of reading received from smart applications like humidity and weather temperature. Different weights are calculated on the basis of reading received from smart nodes on gateway. These weights contribute towards placing smart nodes in different clusters. Overall this approach works well to enhance performance in terms of delay and energy. Priority Scheduling Algorithms PST are used and result shows that it reduces the delay and consumption considerably. Different simulations are performed to show the behavior of throughput, error rate, delay and energy consumption.

In [68], authors used resource scheduling algorithms to mitigate the delay in wireless communication. Authors used banker’s algorithms to manage resources efficiently in this study. The execution time of this algorithm is also taking in to account for fair allocation of resources. As we know that LoRaWAN performance is highly dependent on resource allocation, so Adaptive Data Rate (ADR) plays an important role specifically in allocation of data rate and transmit power. Further Cuomo et al. [69], proposed two different SF allocation schemes, EXPLoRa-SF and EXPLoRa-TA. These schemes provide low interference in cluster based environment with enhanced Time on Air (ToA). Also EXPLoRa-SF algorithm, assign same SF and performs successful transmission without any collision. The simulation suggests that high value of SF provide long coverage but sometimes they contribute in high number of collisions. Delobel et al. [70], simulated the LoRaWAN environment where the gateway is not able to send ACK back towards EDs. By doing this authors achieve less delay as compared to confirmed network. Another limitation is the conflict between class A and class B EDs. Due to the random transmission nature of class A EDs, class B EDs suffers low throughput as they are dependent on beacon from gateway. To cater this limitation, Markov Chain model is introduced to enhance the performance in terms of data rate.

2.8.3 Optimization of energy consumption in LoRaWAN

LoRaWAN is a low-power, long-distance wireless communication protocol specifically used for smart Internet of Things (IoT) applications. The following strategies can be used to optimize energy consumption in LoRaWAN:

The transmission power used by EDs is one of the biggest energy consumers in a LoRaWAN network. Energy consumption can be significantly reduced by lowering transmission power. However, this must be balanced against the application's range requirements. Duty cycle is another parameter that need to be smartly adjusted for efficient energy consumption of EDs. The duty cycle is the percentage of time that an ED is permitted to transmit within a given time frame. Increased duty cycle allows the ED to transmit more frequently, improving network reliability. This, however, increases energy consumption, which must be balanced with transmission power. ADR plays important role in mitigating the energy consumption of LoRa enabled EDs. The network can maintain a reliable link while consuming less energy by employing ADR.

Energy efficiency is another key challenge that is inherent in smart IoT devices. Researchers have been working to design IoT smart devices that are efficient in as far as energy is concerned. Authors in [71], creates prediction models of various IoT application performance metrics in a single-gateway LoRa IoT network based on a variety of heterogeneous device configurations for factors like distance from gateway, data rate, and packet generation rate, which are more important inputs for network provisioning. First, simulation experiments are used to gather performance data on packet loss, average packet delay, and high-percentile delays. The data is then fitted to binomial regression, linear regression, and neural network models. According to our findings, neural network regression, a widely used technique, can provide excellent prediction accuracy with prediction errors ranging from 1.5 to 5.3% on the test dataset, depending on the application performance criteria. The proposed algorithms significantly outperform the conventional ADR in an environment where large number of devices is deployed. Several algorithms are developed that targets optimization of mediums, to lower computation on node side and other adaptive approaches to increase the energy efficiency of end nodes' [72].

In smart health monitoring scenario, where we have extremely sensitive data readings of patients (Pulse Oximeter, Blood Pressure, Heart Rate), had to be reached on time to take further necessary action. With more than 2500 to 3000 EDs or smart nodes using Pure Aloha, this leads towards channel congestion in smart health monitoring scenario, ultimately affect the network performance and capacity in terms of energy consumption. With channel congestion, resource allocation is another issue that plays a vital role in the enhancement of performance in LoRaWAN. The focus is on resource allocation like (Channel frequency, SF, Data Rate and Transmit Power) on the basis of Reinforcement Learning and channel utilization. Research in [73] targeted the concept of network slicing in LoRaWAN using different slicing techniques. A slicing resource allocation algorithm is developed on the basis of estimation to prioritize traffic from different slices. Intra slicing technique is also elaborated in this paper for allocation of resources to enhance QoS requirements. Extensive simulation is performed by authors to evaluate the results of resource allocation. The problem addressed in [74] is the unfairness of data rates assigning to nodes. This is because traditional LoRa network perform capture effect of a signal which is strong enough and then allocate data rate to that node. The technique of fairly allocation of data rates to smart EDs in LoRa network is proposed. Before assigning data rate to EDs the probability of collision is also calculated to allocate suitable data rate to smart EDs among various data rates. Another achievement of this research is to design a power control algorithm that balanced the power of received signal irrespective of the distance from gateway. The result shows promising change as compared to traditional LoRaWAN.

The ADR scheme is used by LoRaWAN allocates data rate and transmit power to EDs on the basis of several parameters. In case of ADR last 20 logged messages send by concerned ED is retrievd by network server [75]. From these 20 messages in formation like No. of GW's, signal to noise (SNR), Frame Count (Fcnt). After the information of retrieved from network server, the ADR algorithm perform certain calculation to calculate updated SF and transmit power. However, this algorithm works well in the context of energy saving and packet delivery rate, but to analyze the channel condition we introduce another scheme called dynamic priority aware resource allocation that works with ADR to further enhance performance in terms of network capacity and reliability. Sometimes it results in interference as ADR looks for same SNR and SF in all frames. The study in [76], examines the effectiveness of the random access back-off algorithm in the Long Term Evolution (LTE) system while accounting for physical loss. For system performance parameters including throughput, drop probability, and medium access delay, analytical results are provided. These analytical findings have all been validated through simulation. For instance, the ideal back-off window size should be set to 1 and the attempt limit should be set to 2 or 3 under a physical loss chance of 1%.

The Energy-Aware Adaptive Kernel Density Estimation algorithm (EAKDE) is proposed in [77], which is a new uneven clustering approach presented, strives to balance the energy dissipation among the cluster heads. EAKDE uses fuzzy logic to assess the relative importance of the nodes vying for cluster head. The proper uneven cluster radius is assigned to sensor nodes using the adaptive kernel density estimation algorithm in order to accommodate the dynamic change of node conditions. In various scenarios, EAKDE outperforms other well-known algorithms in terms of session stability and energy efficiency according to simulation results. In [78], a Slotted Aloha is in cooperated in LoRaWAN to mitigate number of collisions and ultimately enhance throughput.

To optimize the effect of delay in smart health monitoring scenario, Adaptive Scheduling Algorithm (ASA) with Un-Supervised Learning approach GMM with K Means is developed [79]. The proposed technique in [80], makes SF allocation flexible by allowing for various user distributions over SFs. These distributions depends heavily on the nature of application. The simulation results show how the distance from the gateway and EDs in each SF affect transmission reliability by taking into account various network scenarios and realistic parameters. The average coverage probability of the network is increased by our SF allocation strategy by up to 5 % points when compared to the baseline model, according to simulation results. Furthermore, our findings point to a more equitable network operation where the performance gap between the best and worst-case nodes is noticeably smaller. Table 2.6 presents the research studies regarding QoS, optimization of delay and resource allocation to optimize the energy consumption.

Table 2.6 Studies regarding QoS, delay and energy optimization in LoRaWAN

Studies provide analysis of QoS parameters in LoRaWAN				
S No	**Techniques**	**Simulation Tools**	**Findings**	**Limitations**
1	LoRa Single-Hop System Architecture Pure Aloha with ADR [4]	PYTHON	Different aspects of LoRa network are elaborated. Issues like collision and interference are discussed. Issues like throughput and delay are analyzed.	Duty Cycle limitation are not implemented
2	LoRa CSS, Pure Aloha with ADR [5]	MATLAB	Comparison of LPWAN standards is provided.	Duty Cycle limitation are not implemented
3	LoRa Single-Hop System Architecture, LoRa CSS, Pure Aloha with ADR. [22]	PYTHON	Our network is composed of one network server, one gateway and one ED. Received signal quality is measured from different locations, in order to cover an entire building. The signal quality is not degraded by walls between the rooms and the lab.	Gateways deployed in basement experienced degradations.
4	LoRa Single-Hop System Architecture with Unsupervised Learning on GW Unsupervised	PYTHON	To mitigate collision resource allocation is performed, Mitigate number of collisions	With duty cycle limitation and having 1 GW

	learning approach K Means with Pure Aloha [59]			further decrease throughput.
5	LoRa Single-Hop Architecture with LSTMEKF Long Short-Term Memory Extended Kalman Filter (LSTMEKF) [65]	PYTHON	Deep learning methods are applied by authors to predict collisions in an LPWAN system. LSTMEKF model is proposed to predict collisions in LPWAN using temporal correlation, which can improve LSTM performance.	Not enough mathematical or probabilistic approaches are provided.
Research studies focuses on delay				
1	LoRa CSS, Pure Aloha with decoding algorithm. [27]	PYTHON	Simulation demonstrates that at the time of collision, throughput is reduced due to packet loss and retransmissions occur. A decoding algorithm is proposed to mitigate packet loss due to collision.	Lack of Mathematical expressions.
2	LoRa CSS, Pure Aloha with ADR [45]	MATLAB	- Examine the expected delay and energy required to join the network (OTAA). -Expected delay and energy consumption depends on: -Inactivated nodes (0%, 50%, 100%), No. of channels per sub-band, No. of sub-bands, Gateway configuration.	Targets delay and energy consumption only at the time of joining the LoRa Network.
3	LoRa CSS, Pure Aloha Scheme [46]	PYTHON	Investigates the feasibility of using the LPWAN protocol LoRaWAN with an event-triggered control scheme. LoRaWAN is capable of meeting the maximum delay and message loss requirements of an event-triggered controller for certain classes of applications.	Path Loss and propagation delay are not addressed.
4	LoRa CSS, LoRa Single-Hop System Architecture [71][68] LoRa CSS, Pure Aloha Scheme Used	PYTHON	Resource scheduling algorithms are proposed to mitigate delay in wireless communication.	Lack of Mathematical expressions.
Resource Allocation studies to optimize energy consumption				

1	LoRa CSS, Pure Aloha with Novel ADR	PYTHON	Novel ADR scheme is developed. Two reasons due to which the data rate is adaptively increased or decreased. Wireless link failure. Network congestion.(not a network connectivity problem) Congestion classiifier and modified data rate controller is introduced. Back-off timer is used to avoid congestion.	Novel ADR need some Mathematical details that is not provided.
2	LoRa CSS, Pure Aloha, LoRa Single-Hop System Architecture [70]	PYTHON	LoRaWAN resource allocation with adaptive priority awareness for Internet of Things applications. APRA improves results in terms of energy consumption by 95% and increases the EDs battery discharge time by up to 5 years while yielding high packet delivery.	
3	LoRa CSS, Pure Aloha,Adaptive Dynamic Inter Slicing Resource Reservation Algorithm	PYTHON	Enhance QoS, Allocate resources like SF, BW to optimize energy.	Comparison with LoRaWAN ADR is not provided.
4	LoRa CSS, Pure Aloha Scheme, Algorithm to allocate Transmit Power and Data Rate	PYTHON	Analyze unfairness of LoRaWAN in terms of allocation. Allocation is performed on the basis of SF, BW.	
5	LoRa CSS, Pure Aloha Scheme, EXPLoRa-SF	PYTHON	Mitigate number of collisions, Simulation results show that EXPLoRa-AT outperform the basic ADR strategy.	Lack of probabilistic expressions.

2.9 Summary

This chapter discussed the overall overview of LPWAN. All the LPWAN standards are rigorously analyzed and discussed in different sections. Detailed analysis of Sigfox, NB-IoT, Weightless-w and LoRaWAN are presented. Various attributes of LPWAN standards are elaborated. Overview of applications for various LPWAN standards is provided. LoRaWAN system architecture is based on star topology, where all EDs are connected to one or more gateways. EDs communicate with the LoRa gateways by using single-hop communication. LoRa concentrator or gateway relays messages of EDs to a network server, where gateway is connected to the network server via standard internet technologies. After receiving a message from the EDs via LoRa gateway, the network server responds by selecting one of the gateways. A brief description of three main components of LoRaWAN technology (class A,B,C; LoRa Physical Layer; LoRa ADR) is also discussed. Some of the existing challenges like collision, PER, data throughput, data delay and energy consumptions are provided with tabular details.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview

The research approach used to accomplish the major goals of this study is presented in this chapter. The research methodology is divided in to three main modules including research investigation, design & development, performance and evaluation. This chapter also discusses the simulation setup to test the proposed architecture and performance parameters.

3.2 Research Methodology Framework

For the research methodology, this research proposed a three-module based strategy where the three main modules are involved to design and develop the proposed research methodology framework. In the first module, the problem investigation discusses the problem which is extracted from literature after analyzing the existing work in the domain. The last module discusses the performance evaluation of proposed work where all the performance parameters, its inclusion, and exclusion criteria's and results generation process are discussing. The complete research framework shows in Figure 3.1.

3.2.1 Research investigation phase

In this module, the problem background is discussed which is extracted from the literature review after studying several research papers collected from different platforms like journals, thesis, conferences, and books. This chapter focuses on QoS issues that drastically degrade the performance of Long Range Wide Area Network (LoRaWAN), based on star topology, where all End Devices (EDs) directly communicate with a gateway. However, in such networks, EDs have important requirements of transmission power, antenna gain, and data rate etc. to accomplish the communication with gateway. Further, if the gateway is located far from EDs, high power levels are required to transmit frames, which may lead to rapid energy consumption. Due to random increase in number of EDs and varying throughput requirements, drastically affect Pure Aloha performance in LoRaWAN. To successfully monitor the performance of LoRaWAN, it is also necessary to do an analytical examination of backlogged and non-backlogged traffic in a Slotted Aloha LoRaWAN environment. Quality of Service (QoS) efficient service provisioning is a major challenge due to highly densed wireless environment, limited battery lifetime of LoRa EDs, spectrum coverage, interference, collisions, and energy consumption.

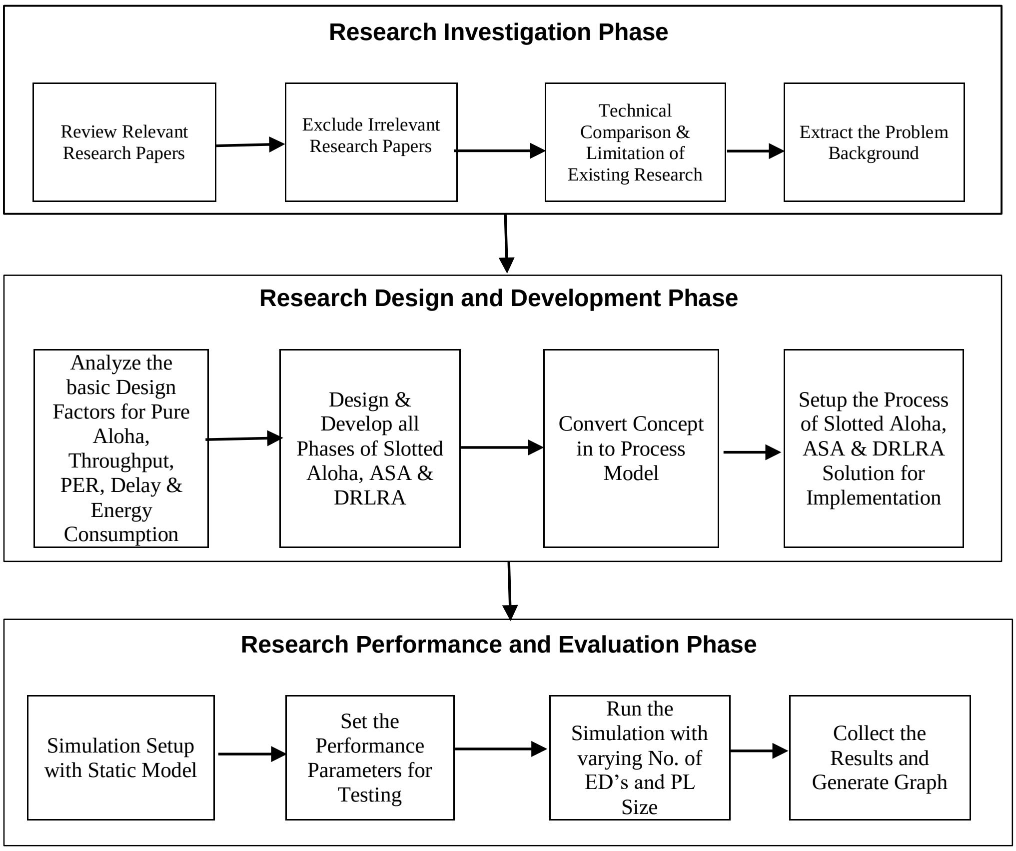

Figure 3.1 Research Methodology Framework

Intelligent QoS-aware efficient service provisioning is a dire need of the day to better streamline this problem that directly impacts the QoS of such networks. In smart health monitoring scenario, where we have extremely sensitive data readings of patients (Pulse Oximeter, Blood Pressure, Heart Rate), had to be reached on time to take further necessary action. With more than 1000 EDs or smart nodes using Pure Aloha, this leads towards channel congestion in smart health monitoring scenario, ultimately affect the network performance and capacity. With channel congestion, resource allocation is another issue that plays a vital role in the enhancement of performance in LoRaWAN ultimately effect the energy consumption of ED. Further a path loss model is also need to be evaluated to cater all the attributes of channel.

3.2.2 Research design and development phase

For design and development phase different techniques and approaches are followed to optimize QoS issues in LoRaWAN. Considering the limitations of LoRaWAN in terms of collision, PER and throughput, delay and energy consumption we design algorithms to mitigate the effect QoS parameters. Firstly, Slotted Aloha is in cooperated in LoRaWAN to mitigate number of collisions and ultimately enhance throughput. In smart health monitoring scenario EDs like Smart Blood Pressure (SBP), Smart Proximity (SP) and Smart Heart Monitoring (SHM) generate huge amount of frames in small size. To cater the effect of collision, PER and throughput Slotted Aloha approach is followed. Markov Chain model is used to observe the Backlogged BL and Non-Backlogged NBL EDs.

To optimize the effect of delay in smart health monitoring scenario, Adaptive Scheduling Algorithm (ASA) with Un-Supervised Learning approach GMM with K Means is developed [79]. To prioritize traffic of EDs, first of all we have to design profiles (HPP, MPP, LPP). After designing profiles, EDs are assigned to these profiles on the basis of readings received. EDs with critical readings are assigned to HPP and have high priority to transmit frames. EDs with semi critical readings are assigned to MPP which can transmit its frames after the EDs in HPP. The proposed framework is extensively simulated, rigorously evaluated with current state of the art benchmark algorithms using standard and extended evaluation metrics. In smart health monitoring scenario, where extremely sensitive data readings of patients (Pulse Oximeter, Blood Pressure, Heart Rate), had to be reached on time to take further necessary action. With more than 1000 EDs or smart nodes using Pure Aloha, this leads towards challenges like resource allocation and channel congestion in smart health monitoring scenario, ultimately affect the network performance and capacity [80]. Dynamic Reinforcement Learning Resource Allocation (DRLRA) algorithm is designed to enhance performance in terms of energy consumption. Certain parameters are dynamically allocated to EDs like (Channel frequency, Data Rate and Transmit Power) on the basis of current information of ED, action taken by relevant Reinforcement Learning Agent (RLA) [81] and calculating reward. An intelligent learning probabilistic algorithm Gaussian Mixture Model (GMM) is followed to design profiles and then all these profiles is analyzed for channel congestion and inter arrival of frames. Further a path loss model is also be used to cater all the attributes of channel. Extensive simulations are performed to extract the results in LoRaWAN environment.

3.2.3 Research performance and evaluation phase

In research performane and evaluation phase a simulation environment with static model is developed. Python is used to simulate the whole network environment. The simulation is performed by using well known libraries of python used to create wireless network environment. The idea behind using Python libraries to create network environment is its flexibility to control and manage all network related functions. Different objects are assembled and configured as well as scheduled certain discrete events. Some of th Python libraries used in simulation setup are: For martrix calculation numpy library is used. For normalization and Probability Density Function computation scipy library is used in our simulation environment. Simpy library is used to implement multi-agent systems with both simulated and real communication. Processes in SimPy are simple Python generator functions and are used to model active components like nodes, Servers, customers, vehicles or agents. Python library matplotlib.pyplot is used for plotting graphs. Table 3.1 provides all the details about parameters used during simulation.

Table 3.1 Simulation Environment

Parameters	Values
Application Scenario	Smart Health Monitoring Scenario (SBP, SPO, SHR)
Area	5-6 Km^2
Spreading Factor	7, 8, 9, 10, 11, 12
Bandwidth	125 Khz, 250 Khz
Channels (8)	868 MHz EU Standard
End devices	2500-3000
T_x Power (SX1272/73)	2dBm-20dBm
ADR	Enabled
No. of gateways	2
CR	4/5
Packet Size	20 bytes
Optimal Profiles	$Prof_k$ =3
Req. Voltage (SX1272/73)	3.3 V
I_idle (SX1272/73)	I_idle=1.5 μA
I_R_x (SX1272/73)	I_R_x=10.5 mA
Simulation Time	1 Hour

Python libraries provide several services to user by creating a flexible environment with the help of which user can easily perform research tasks. Python is used for both simulator and connectivity generating library. The performance parameter presented in this research is No. of collision, PER, PSR, throughput, payload size, delay and energy consumption. LoRa network is extensively simulated and analyzed for all these parameters. Unsupervised machine learning algorithms are used to enhance the performance in terms of QoS service provisioning, delay, resource allocation and energy consumption.

Packet Success Ratio (PSR) is an effective approach to explore and analyze the *EDs* deployment in LoRa network. *GWs* deployed will be in a better position to analyze *PSR* of different HPP. Mathematical equation for *PSR* is as follow:

$$\mathrm{PSR} = \frac{\mathrm{N\_PCKT\_R}}{\mathrm{N\_PCKT\_S}} \qquad 3.1$$

The *PER* is another factor that needs to be explore to know about the number of erroneous packets received at the *GW*. *CRC* algorithm is used to add some redundant bits with original payload on the basis of generated polynomial. This information is also shared with GW, so that *GW* also runs its own *CRC* algorithm to know about the packets validity. If the contents received are same as transmitted by *EDs* then it is successfully forward towards *NS* but if there are erroneous bits received by *GW* as per *CRC* algorithm, the *PER* counter is incremented.

Mathematical equation for Received Signal Strength ($RSS_{i,j}$) (*RSS* of node *i* at GW_j) becomes [83]:

$$\mathrm{RSS_{i,j}} = (\mathrm{T_p} + \mathrm{G_{ant}} + \mathrm{PL}) \qquad 3.2$$

Where T_p is the transmit power, G_{ant} is the antenna gain and *PL* is the path loss factor [84].
Time on Air (ToA) is another metric that need to be evaluated carefully to understand the performance of network [85][86]. *ToA* depends on several parameters like *SF*, *CR* and packet size. ToA increases with the increase in *SF* and decrease in *DR*. For *ToA* we have to calculate preamble duration ($PREA_d$) and ($PAYL_d$), where *NPS* is the number of payload symbols. Formulae's are given below [87]:

$$\mathrm{PREA_d} = \left(\mathrm{N_{preamble}} + 4.25\right) * \mathrm{Dura_{Sym}} \qquad 3.3$$

$$\mathrm{Dura_{Sym}} = 2^{\mathrm{SF}} / \mathrm{BW} \qquad 3.4$$

$$\mathrm{PAYL_d} = \left(\mathrm{NPS} * \mathrm{Dura_{Sym}}\right) \quad 3.5$$

$$\mathrm{NPS} = 8 + \max(\mathrm{Ceil}\left(\frac{(8\mathrm{PL}-4\mathrm{SF}+28+16-20\mathrm{H})*(\mathrm{CR}+4)}{4(\mathrm{SF}-2\mathrm{DE})}\right), 0) \quad 3.6$$

Where *PL* is payload size, *H* and *DE* are Boolean values. These are control variables used to optimize the performance of network [88]. So mathematical equation for *ToA* becomes:

$$\boldsymbol{ToA} = (\boldsymbol{PREA_d} + \boldsymbol{PAYL_D}) \quad 3.7$$

Transmission delay is one of the important factors to rectify for QoS enhancement in LoRaWAN. Transmission delay (*TD*) is directly proportional to frame bits transmitted or bitrate. *TD* in LoRaWAN environment depends on number of bits in frame transmitted and bit rate [89]:

$$\mathrm{TD} = \frac{\text{No.of bits inside frame}}{\text{bit rate}} \quad 3.8$$

The bit rate in above equation is given as [50]:

$$\text{bit rate} = \frac{\mathrm{SF\ x\ BW}}{2^{\mathrm{SF}}} \quad \frac{4}{4+\mathrm{CR}} \quad 3.9$$

SF is the spreading factor and it is adjusted by LoRa ADR algorithm according to network performance. *BW* is the bandwidth and it is configured as 125Khz [90]. Coding Rate (*CR*) is the ratio of actual and redundant bits. LoRa ADR will be responsible to configure those parameters for *EDs*, which best suited according to the network environment on run time. Further details about *SF*, *BW* and *CR* are in. As thousands of EDs are transmitting towards gateway in LoRa network, so possibility of collision is also exponentially increased [91]. This section exhibits the behavior of collision in LoRa network when multiple LoRa transmissions are received at gateway. Some of the transmissions that are orthogonal to others are decoded successfully by the receiver, but transmissions that overlap in terms of *SF*, frequency, time or in power domain will result in collision. All these categories of collision are discussed in detail in this section.

Overlapping of LoRa transmissions at gateway is one of the serious concern for LoRa network [92]. Assume that interval at which packets are overlapped, starts from P_i and ends at Q_i such that (P_i, Q_i), whereas *i* is any packet. The gateway receives packet *i* during time P_i and Q_i. According to these parameters we can easily define midpoint and distance of the said interval. $MP_i = \frac{(Pi+Qi)}{2}$, $DIST = \frac{(Qi-Pi)}{2}$. Now overlapping condition fulfills when two packets *x* and *y* arrives at receiver during same reception interval.

$$\mathrm{Overlap(x,y) = MP_x - MP_y < (DIST_x + DIST_y)} \qquad 3.10$$

LoRa network used spreading factor to achieve long range, resilience against interference and to receive simultaneous transmission at the same time. However when we have multiple transmitters that transmit packets having same spreading factor, it lead towards collision [93]. The condition for collision in terms of spreading factor is $SF_x = SF_y$, where SF_x and SF_y are spreading factors for transmitters *x* and *y*. Transmissions with different frequencies are still orthogonal and can be easily decoded by receiver. However overlapping region in terms of frequency is defined as the difference of frequencies and offset. We have certain overlapping cases discussed below:

1. For 125Khz bandwidth: IF $(Freq_{pck1} - Freq_{pck2}) \leq 30\ Khz$, *pck1* and *pck2* are packets from different transmitters.
2. For 250Khz bandwidth: IF $(Freq_{pck1} - Freq_{pck2}) \leq 60\ Khz$, *pck1* and *pck2* are packets from different transmitters.
3. For 500 Khz bandwidth: IF $(Freq_{pck1} - Freq_{pck2}) \leq 120\ Khz$, *pck1* and *pck2* are packets from different transmitters.

Energy consumption for all *EDs* are measured as the energy consumed during the *ED* is in active mode. *ToA* also effect the energy consumption of *ED*. In [94][95], the authors only consider the successfully demodulated packets to calculate energy consumption and battery discharge time. But the practical approach is to consider those packets as well that are not received successfully at *GW* due to any reason. We are also incorporating one extra condition on *EDs*, that only those current readings are forwarded towards *GW* that are different from previous readings. Mathematically energy consumption will be calculated as [58][96]:

$$\mathrm{E_{cons} = \sum_i \sum_{packets} (V).(I).(ToA)} \qquad 3.11$$

Where *V* is Volts and is taken from spreadsheet used for LoRa chip SX1276. I is the current used for transmitting packets and other processing. E_{cons} is measured in *Jouls (J).*

3.3 Assumptions and limitations

One major assumption is the static nature of LoRa EDs and we also deploy these EDs statically. Due to its static nature EDs that are far from gateway, needs more transmit power to perform successful transmission. This leads towards high energy consumption of EDs. Another limitation is the absence of dedicated LoRa simulator available in market. Simulations are performed using Python. No such dedicated library or third party tools are available to provide help. This is the reason we perform all these extensive simulations in Python.

Multiple GWs are used in our Smart Health Application Scenario as we are dealing in critical data of patients that must reach GW on time. By configuring multiple GWs we have multiple HPP with critical patient's data readings. Further multiple GWs increase throughput but it also contribute towards interference and cost factor. Interference is one of our limitations, as our first priority is to transmit critical data readings of patients successfully in such constrained LoRa network. In our case we are using GMM with K Means probabilistic approach to create profiles and ultimately minimize the number of EDs per profile. This definitely increases throughput as number of collision automatically decreased with the small number of EDs transmitting data at one time. To optimize energy consumption of EDs, an adaptive dynamic Reinforcement Learning approach is adapted, to assign optimized resources to EDs [97]. As we are simulating LoRa network in Python, so we have several limitations. The EDs randomly deployed in the mentioned area and transmit data according to Gaussian distribution. This method is somewhat according to real environment but not exactly the one.

3.4 Summary

Research method for this study is based on literature review research and extensive study. In this strategy we have to combine certain components to achieve the goal. In the first phase collection of information from different data source takes place. In the second phase brief analysis of collect information will be held. After that, the issues faced by LoRa networks are discussed and also briefly explain the components of our research. Like what are they and what challenges they facing. Now the solution related to our problem is identified and gathers all related solutions. To reach the problem solution, there is a need of extensive simulation environment for retrieval of data from LoRa EDs and gateways. Through this simulator we will make a simulation scenario in which smart static EDs transmit data towards gateway. After that it apply unsupervised probabilistic approach to mitigate delay and dynamic Reinforcement

Learning to enhance performance in terms of energy consumption [98]. After that it generates the results from simulation and rigorously analyze them.

CHAPTER 4

PROPOSED FRAMEWORK

4.1 Overview

This chapter presents the proposed framework for Slotted Aloha with Markov Chain Model in LoRaWAN. Backlogged (BL) and Non-Backlogged (NBL) EDs are also designed by using Markov Chain Model with the process and state diagrams to understand to effect of using Slotted Aloha with Markov Chain Model. Further it highlights the issues caused due to Quality of Service (QoS) parameters. To address this problem, an unsupervised probabilistic approach is used to perform profiling. After profiling a scheduling algorithm ASA is proposed to assign priorities to profiles. In another subsection, the proposed Dynamic Reinforcement Learning Resource Allocation (DRLRA) algorithm, its process and integeration in LoRa network is discussed. The main objective is to optimize energy consumption of End Devices (EDs) in LoRaWAN. Mathematical expressions and probabilistic relations are regourously provided to justify the simulation results. The chapter also provides the process and physical model to understand the communication between end device and gateway.

4.1.1 Optimize performance of LoRaWAN in IoT

There are several key factors to consider when optimizing LoRaWAN performance specifically for IoT applications: The LoRaWAN network architecture can have a significant impact on overall performance. A well-designed network architecture can increase network capacity, improve coverage, and mitigate packet loss. Several factors like placement of gateway to mitigate the effect of interference, EDs density, and the use of Medium Access Control (MAC) protocols. Channel access scheme: The LoRaWAN channel access scheme, which combines random access schemes and scheduled access schemes, can have major impact on overall network performance. Selecting the best possible channel access scheme for the smart EDs can increase network efficiency and reliability. The LoRaWAN network's security is critical for preventing attacks and ensuring data privacy. By lowering the risk of data breaches and network downtime, appropriate security measures, such as encryption and authentication, can improve network performance. The application layer has a big influence on LoRaWAN performance. Increasing network efficiency and lowering energy consumption can be accomplished by optimizing the application layer protocol and data payload size.

Transmission parameters, such as data rate, coding rate, and transmit power, can influence the range, reliability, and battery life of LoRaWAN nodes. These parameters can be optimised for the specific use case to improve network performance.

Throughput, latency, and energy consumption of smart EDs under various payload sizes and variable number of EDs are used as benchmarks to optimise Slotted Aloha performance in LoRaWAN using extensive simulations [98]. When compared to Pure Aloha, the simulation results overcomes the performance of PER and throughput. However, a delay increase was observed during the experimental evaluation. Overall we endorse Slotted Aloha LoRaWAN [99] for the Green IoT Environment. LoRaWAN is an LPWAN standard with a long range, low power, and a single hop that was specially designed for Internet of Things (IoT) applications that use battery-powered smart nodes. However, the performance of Pure Aloha in LoRaWAN is hampered by the growth in end device numbers and the wide range of throughput requirements [100]. We use in-depth simulations to assess the effectiveness of Slotted Aloha in LoRaWAN taking these restrictions into account. As a benchmark, we used the PER, throughput, latency, and energy consumption of devices with various payload sizes and numbers of EDs [101]. Additionally, in the Slotted Aloha LoRaWAN environment, an analytical examination of backlogged and non-backlogged traffic is also carried out.

4.1.2 Existing research using Pure Aloha

Pure Aloha is a simple random access protocol for sharing a channel among multiple smart devices, in which any user can send a packet towards Access Point (AP) at any time. LoRaWAN, on the other hand, is a more sophisticated protocol that manages communication in a huge covered area by combining random access and scheduled access approaches.

Recently, an advent to the Internet of Things (IoT) has demonstrated significant applications in industry, healthcare, smart agriculture, smart cities, connected vehicles and environmental monitoring. LoRaWAN is considered as one of the popular low power wide area network technologies, which provides long range, low power, low cost, and secure bi-directional communication [102]. A recent advancement in virtualization and cloud computing has motivated the telecommunication industry to rethink the conventional proprietary approaches to networking. The primary infrastructure used by the telecommunication industry lacks the capabilities which we wish should be enabled with the 5G. The next era of IoT is expected to bring along a range of flexible and automated applications for the end users. In order to make 5G a reality, LoRaWAN due to its capability and feasibility in IoT can be considered as one of the strong candidate enabler which can be integrated with the 5G [103]. A massive increase in the number of IoT devices in the decade to come is expected to impose huge capacity requirements on the backbone connectivity provided by the low power wide area network (LPWAN) technologies. LoRaWAN due to its low power, long range and low cost is expected to outstand other LPWAN technologies [104]. Figure 4.1 shows MAC issues in LoRaWAN.

Expected growth of smart IoT devices is 32% annually with a claim by most of the well reputed research papers that over 21 billion smart nodes are there to transmit and receive data. It also discusses pros and cons of smart devices and its design aspects specifically in terms of smart applications used in urban areas [105]. Given the future uptake of LoRaWAN for innovative IoT applications, recently a significant research has been dedicated to the strengthen the robustness of medium access mechanisms in LoRaWAN. Although the performance of Slotted Aloha has been well studied in different literature for LTE, wireless networks, and cognitive radio networks.

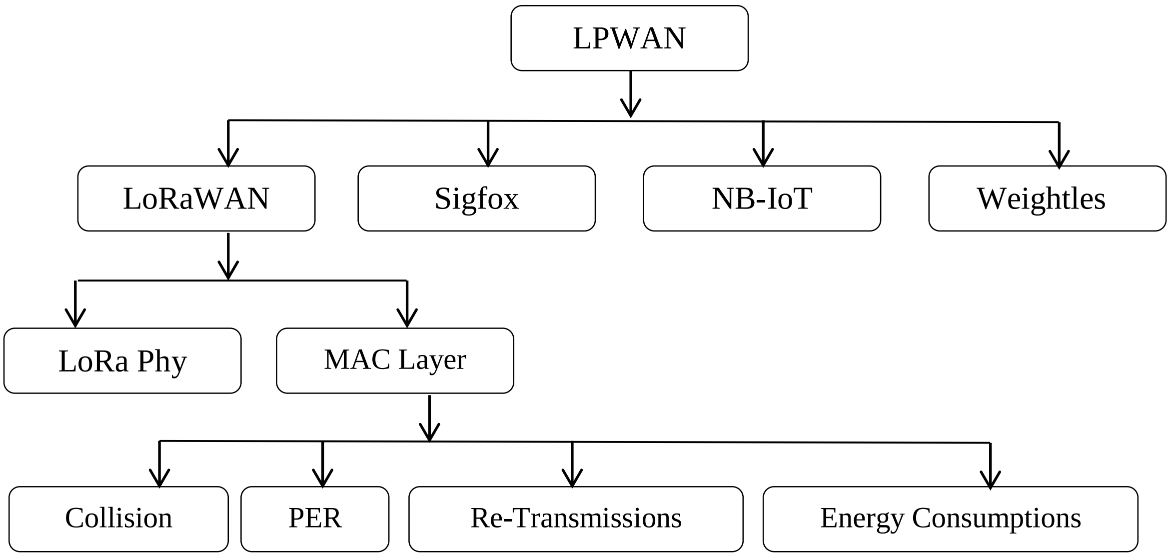

Figure 4.1 Taxonomic view of MAC Issues in LoRaWAN

However, to the best of our knowledge no work about performance analysis of slotted Aloha for the BL and NBL nodes has been considered for LoRaWAN [106]. An analytical model is proposed to study BL and NBL under Slotted Aloha LoRaWAN environment. In the analysis, the main objective is to analyze the probability of collisions for both the BL and NBL nodes. We then perform simulations to analyze the performance of Slotted Aloha in terms of energy efficiency, throughput, and PER, and delay under varying packet load sizes and number of EDs.

4.1.3 Challenges in LPWAN channel access schemes

LPWAN (Low Power Wide Area Network) channel access schemes are intended to enable long-distance communication while using minimal power. However, several challenges must be overcome when implementing these channel access schemes. Among the major challenges are: LPWANs are designed to connect a large number of smart EDs covering huge geographical area. The scalability of the channel access scheme becomes critical as the number of EDs increases exponentially. Another factor is regarding interference, as LPWANs operate in unlicensed frequency bands, they are exposed to interference from other EDs operating in the same frequency band. This can result in huge number of collisions and losses, which can have a major impact on LoRa network performance. Latency: Low-power, low-data-rate LPWANs are typically designed for such applications. Some applications, however, may require low latency, which can be difficult for LPWANs due to their slow data transmission rates.

In literature, a significant analysis of contention-based MAC techniques has been performed. Several IoT applications as discussed in recent literature are based on Aloha. In, authors analyze the performance of Aloha in homogenous networks, where nodes generate traffic according to random distribution. Authors analyze the throughput performance of the work along with delay incurred due to path loss. However with the evolution of IoT enablers, in particularly LoRaWAN, the random packet generation models must be revised according to the requirements of user and dynamics of system. For example, large number of sensors is deployed to monitor vibration of infrastructure like buildings etc. These sensors generate packets on regular basis to provide feedback, which will lead to congestions. Smart metering is another example of delay tolerant application [107], which generates short messages of readings from water, gas, electricity at regular intervals [108]. Although, LoRaWAN is one of the emerging technologies used for IoT applications nowadays. However, there are number of challenges including massive number of collisions, re-transmissions, low throughput, energy consumption, Packet Error Rate (PER), and delay etc., that we should be addressed, effectively. Table 4.1 shows the multiple access methods in different wireless technologies.

Table 4.1 Overview of multiple access methods in different Wireless Technologies [4]

	Pure Aloha	Slotted Aloha	Slotted CSMA/ CA	FDMA	TDM A	CDM A	CSS	FHSS	DSSS
LoRaWAN	X						X		
Sigfox	X								
NB-IoT		X		X		X			
Weightless		X		X	X			X	X
Zigbee			X				X		X
WiFi				X					X
RFID		X							

Most of LPWAN technologies used for IoT applications are based on Aloha type multiple access mechanism. Although, Aloha appears an attractive choice for limited number of EDs. However, massive number of M2M devices may qualify it as an unwise channel access mechanism [110]. Therefore, need an access mechanism in LoRaWAN which can have go slightly wiser than Aloha, while still keeping transmit packets in first attempt or do not have any packet to transmit. It means in case of NBL, no queues buildup.

4.1.4 Markov chain model for Slotted Aloha

Assume that we have m users that are sharing a channel using Slotted Aloha (SA). To analyze the impact of BL and NBL nodes on SA, it is important to understand the terms BL and NBL. BL nodes are those who always have packet to transmit, as these users experience collisions or packet loss in their first attempt. NBL nodes are those who either successfully transmit packets in first attempt or do not have any packet to transmit. It means in case of NBL, no queues buildup. The preamble portion of packet consists of 5 bytes needs for synchronization of EDs with GW. PHY Header takes 5 bytes and consists of all configurable parameters like *SF*, *DR*, T_p, *CR* and packet length. MAC Header has two portions *MType* and *Major bit*. The packet format for slotted Aloha is depicted below in Figure 4.2:

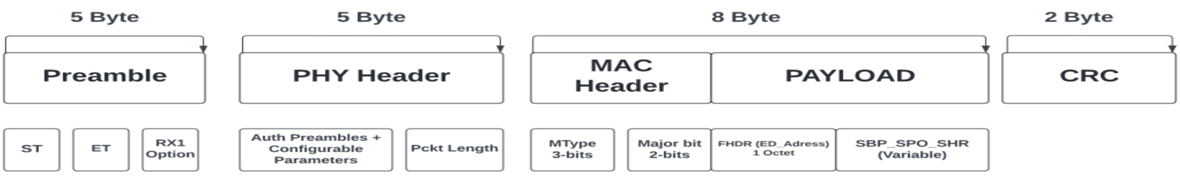

Figure 4.2 Packet format used in Slotted Aloha

MType tells us about MAC messages like Join Request, Join Accept, Confirmed Uplink, Confirmed Downlink, Un-Confirmed Uplink or Un-Confirmed Downlink. After this we have PAYLOAD followed by CRC.

Assume that out of these m users, n users are in BL state. So *(m – n)* remains in NBL state. Let *a* denotes the probability of NBL nodes to transmit packet in a particular slot. Value of *a* is usually very small because in wireless networks like LoRaWAN users are in BL state most of the time. Let *b* be the probability of BL nodes, which have packet to transmit. It is important to understand that probability *b* is not generation of new packets. It is similar to re-transmission of a packet. Network performance highly depends on the value of *b*. We can optimize the value of *b* for our system. However, we do not have any control on the value of *a*. Given values of *m, n, a* and *b* describes throughput of our system. Algorithm that elaborates all processing SA with Markov Chain Model. The algorithm for analytical modeling of SA with Markov Chain Model is discussed below. Algorithm 1 presents the step by step procedure of analytical modeling for Slotted Aloha with Markov Chain model.

Algorithm 1: Analytical modeling of Slotted Aloha with Markov chain model

Algorithm for Analytical Modeling of SA with Markov chain model.

Data: Initial Configuration

Distance between smart End Devices (EDs) and Gateway (GW) (D) = 500m. Payload Size (PL) = [20, 25, 30, 35, 40].

Number of transmitters (N) = 500. Initial transmit power (Tp) = 14dbm. Initial SF = 12.

Data Channels=[CH0, CH1, CH2, CH3, CH4, CH5, CH6, CH7]

ADR = Enabled.

Results: Analysis of Collision and PER.

```
begin    for all EDs do
             Free space path loss model is used for channel modeling.
             Randomly select from 8 data channel [CH0, CH1, CH2, CH3, CH4, CH5, CH6, CH7]
             Slot Size will be according to SF:  [7, 8, 9, 10, 11, 12]
             Packets = [p1,p2].
                 if ED[j] send JOIN REQ towards NS
                     NS Lookup in SA Table.
                     Select data channel from [CH0, CH1, CH2, CH3, CH4, CH5, CH6, CH7] according to SF.
             for i=0 to 7      // i is for No of Channels. As we have 8 No of data channels.
                         if CH[i] == FREE for respected SF
```

```
                    CALCULATE Slot Size W.R.T SF (ToA is calculated based on: SF, CR, PL, BW)
                        Assign slot to ED[j].
                    else if CH[i] != FREE for respected SF     // i indicates No of channels.
                            INCREMENT i to check other channels Slots
                            Check all other channels for FREE slots. goto for loop
    To Check Collision:
                if Req received for ED[j+1] for channel slot at same time   //j indicates No of EDs.
                        NS Lookup in SA Table
                if ED[j+1].SF.ReqTime == ED[j].CH[i].SF .ReqTime
                //Channel Slot already in use, j are number of nodes and i indicates  channel.
                                Assign same slot to ED[j+1] as ED[j].
                            Collision Occurs.  (Collision occurs and PER gets incremented.)
                else if  ED[j].SF.RSSI ≤ Sensitivity[SF] AND back-off slots ≥8.
                        Packet lost.
                else
                        goto Line No 9 to check for free slot W.R.T channel.
                else
                        Packet transmitted successfully.
            end
        end
    end
end
```

The flow diagram shown in Figure 4.3 depicts the overall processing of Slotted Aloha approach in LoRa network environment. First of all the EDs wil be statically deployed in an area of 5 Km^2. These static EDs are manually configured with parameters like data rate, bandwidth, payload size, channel frequency and spreading factor. Now these EDs send Join Request message towards gateway. If this Join Request message is encoded and validated by respective gateway accordingly. Once the Join Request message is accepted, the gateway give response in form of Join Accept message. With this Join Accept response, the gateway also check for suitable slot (if available) for EDs. The slot duration should be according to the initial spreading factor used by ED. Higher spreading factor mean we have large ToA and lower spreading factor should have less ToA. Once the slot is assigned to an ED, now the ED is allowed to transmit packets in respective time slot. No other ED is allowed to use same time slot duration for their transmission. Certain conditions are applied to check number of collided packets, lost packets and successfully

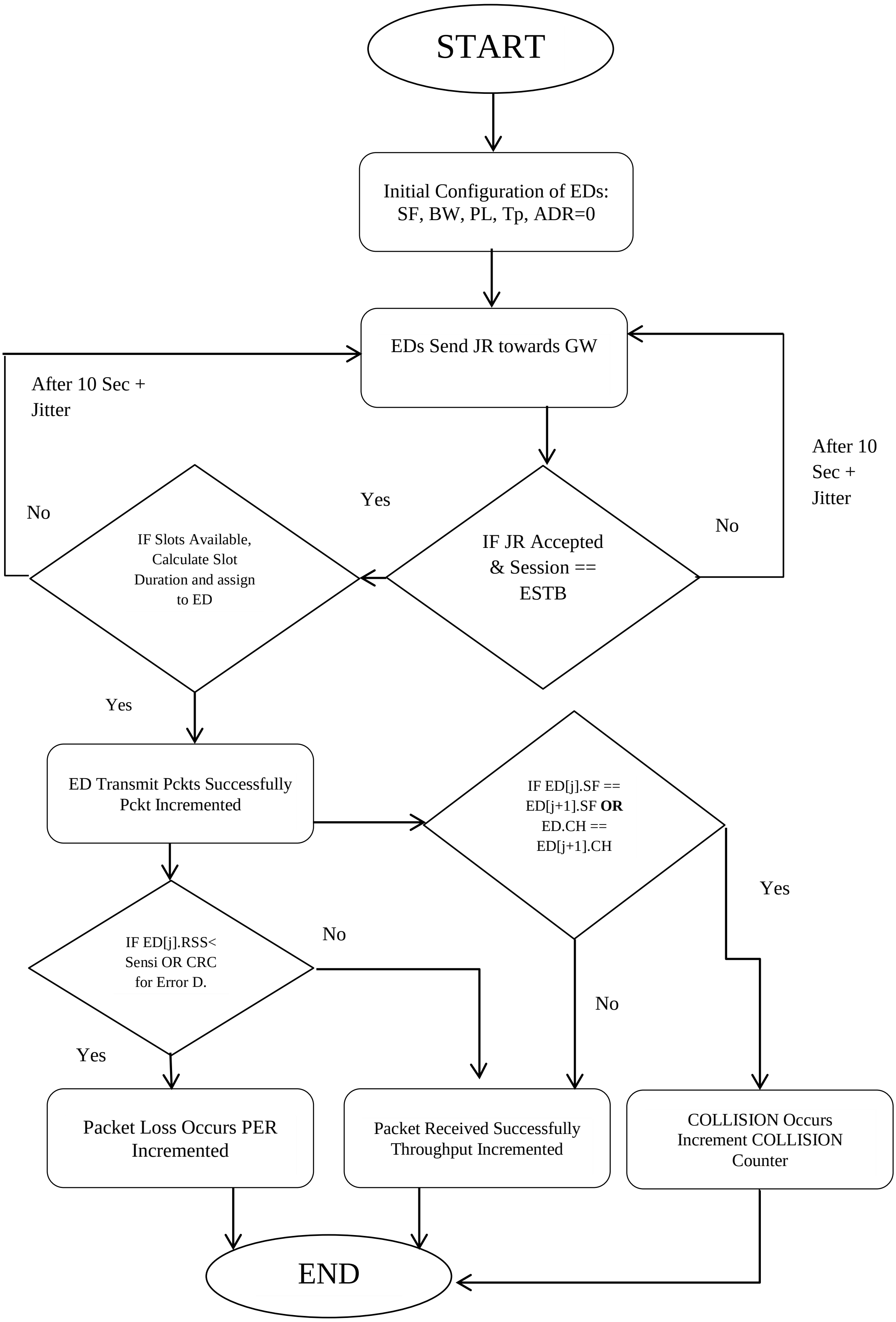

Figure 4.3 Flow diagram of Slotted Aloha for LoRaWAN

received packets at gateway. In case the Join Request is not accepted by gateway or slot is not available, in that case the ED has to wait for 10 seconds plus Jitter. The Jitter is equal to 1 second plus (0-20)% time of that 1 second. This Jitter is included to lower the collision in terms of Join Request messages. If all Join Request is transmitted towards gateway at the same time, so chances of losses are on a higher side, that's why we introduce the factor of Jitter.

Assume, *A(i,n)* is the probability of exactly *i* NBL nodes, that can transmit in a slot as given in Equation 4.1.

$$A(i,n) = \sum_{i=0}^{m-n} \binom{m-n}{i} a^{i} (1-a)^{m-n-i} \qquad 4.1$$

Let *B(i,n)* is the probability that exactly *i* BL nodes re-transmit in a slot as represented in Equation 4.2.

$$B(i,n) = \sum_{i=0}^{n} \binom{n}{i} b^{i} (1-b)^{n-i} \qquad 4.2$$

Let *n* represents the process state. As it can be seen in Figure 4.4, in the start we have no BL nodes so our system states start from *n* = 0, which becomes our starting state and then we have one BL node and so on.

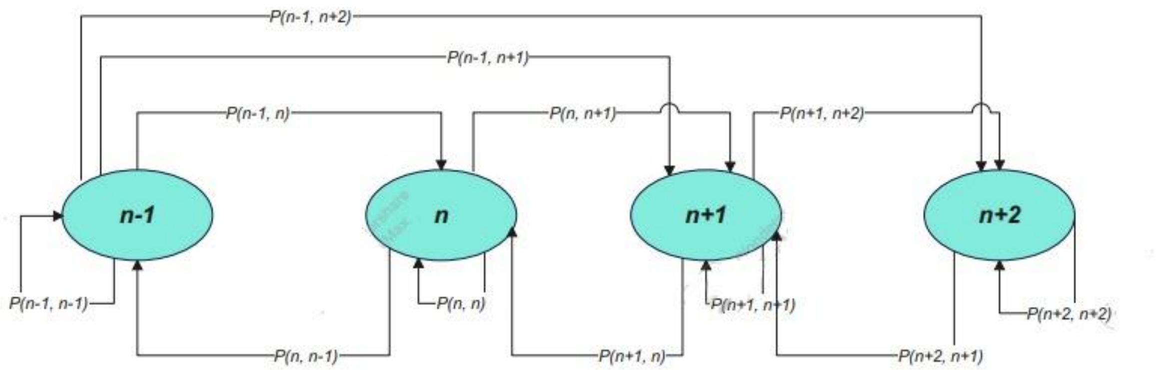

Figure 4.4 State transition diagram for BL nodes

P(n,n) denotes the probability that node remains on the same state *n* after occurrence of any transaction, and *P(n,n+1)* is the probability that a node moves from state *n* to state

$n+1$. For Slotted Aloha $P(n,n)$ indicates same number of BL nodes in the beginning and end of timeslot as shown in Equation 4.3.

$$P(n,n) = [A(1,n) * B(0,n)] + [A(0,n) * (1 - B(1,n))] \qquad 4.3$$

In Equation 4.3, $A(1,n)$ denotes only one NBL node in transmit state, and $B(0,n)$ means none of the BL nodes is in transmit state. $A(0,n)$ represents that no NBL node has data to transmit, and $1\text{-}B(1,n)$ indicates an exactly one BL node in transmit state. Similarly $P(n,n+1)$ becomes,

$$P(n,n+1) = [A(1,n) * (1 - B(0,n))] \qquad 4.4$$

In Equation 4.4, $A(1,n)$ indicates that only one NBL node can transmit packet and $1\text{-}B(0,n)$ depicts at least one BL node that will try to send. We can also find the probability $P(n,n\text{-}1)$ as,

$$P(n,n-1) = [A(0,n) * B(1,n)] \qquad 4.5$$

According to the above equation exactly one BL user will transmit.

We can also generalize the case when we have more than one NBL node who wants to transmit. Such a case is translated as follows:

$$P(n,n+i) = [A(i,n)] \qquad 4.6$$

where, $2 \le i \le m\text{-}n$

With every state n in Figure 4.4, we have a reward r that determines that either packet is successfully transmitted or not. The throughput of system highly depends on reward r. Let, r_n indicates reward of state n, which determines probability of successful transmission at state n as given in Equation 4.7.

$$r_n = [A(0,n) * B(1,n)] + [A(1,n) * B(0,n))] \qquad 4.7$$

The above expression r_n indicates that for successful transmission either one BL node or NBL node can be in the transmit state.

4.1.5 Simulation results of Slotted Aloha in LoRaWAN

This section presents simulation results of Slotted Aloha for LoRaWAN. Each LoRaWAN gateway covers 100 to 1000 EDs, where each node has a fixed payload size. The distance between EDs and gateway varies from 3 Km to 5 Km. Several numbers of packets (in bytes) are transmitted by EDs per simulation, to know its impact on LoRa network. Each simulation is performed at least 100 times to get average values of all parameters. All the possible cases are taken in to considerations to analyze the performance of Slotted Aloha in LoRaWAN. LoRa technology defines 3 data channels for the European standard, i.e., 868.1, 868.3, 868.5 for EDs transmit its data towards gateway with 6 *SFs*, i.e., 7,8,9,10,11,12. Some of the simulations results are taken over single *SF* like for *SF*=12 and so on. ADR must be disabled if we want to perform simulation with single *SF*. With 3 data channels and 6 *SF*, logically we have 18 virtual channels that can be used simultaneously without any interference. For the scenarios where we obtain results by using single *SF*, transmit power remains constant with a value 14 dbm for the time of simulation. In all other scenarios, we keep the ADR enabled. The simulations results clearly shows for all the above scenarios that slotted Aloha is more suitable for delay tolerant applications. *PER* is observed for different *SFs* for varying payload sizes. The curves for different *SFs* are plotted to get exact information from simulations. By keeping ADR enabled, we analyze the average throughput in bits per second for LoRaWAN using Slotted Aloha. Further, we also evaluate the Slotted Aloha in terms of slotted Average delay for different *SFs* under varying payload sizes.

a. Limitations of 1% duty cycle in Slotted Aloha

As LoRaWAN is a constrained technology by respecting duty cycle of 1% imposed by regulations. Duty cycle indicates that each LoRa end device can use a channel or sub-channel (sub-band) for 1% of the time in 24 hours. This duty cycle limitation prevents LoRa network from collisions, and therefore *PER*. Due to duty cycle constraints, each node only transmits limited number of packets. In this article, all the simulations have been performed 1% duty cycle.

The simulation results in Figure 4.5 show *PER* (in percentage) in terms of different payload size (in bytes). We have used 3 data channels in this scenario and these channels are randomly assigned to *EDs*. Each end device is configured with a bandwidth of 125 khz.

EDs and gateway are separated with distance of 5 Km. ADR is disabled for this simulation because we want to observe the performance of Slotted Aloha under different *SFs*. If we observe the curve of Slotted Aloha in LoRaWAN for *SF*=12 and *SF*=7 with payload size of 20 bytes, we can observe that *PER* is almost 25% and 5%. For the same configurations in LoRaWAN using Aloha, almost 78% of *PER* is observed with *SF*=12 and 60% with *SF*=7. Simulation runs for one hour each time (almost 50 tests). In Figure 4.6, the effect of *PER* is observed with respect to payload size with ADR enabled. Performance of both Slotted Aloha and Pure Aloha is rigorously analyzed in LoRaWAN. Significant amount of improvement is observed in case of Slotted Aloha, when compared with pure Aloha. Figures 4.5 and 4.6 show the analysis of *PER* w.r.t payload size with varying *SFs* and payload size w.r.t *PER* in percentage with ADR enabled.

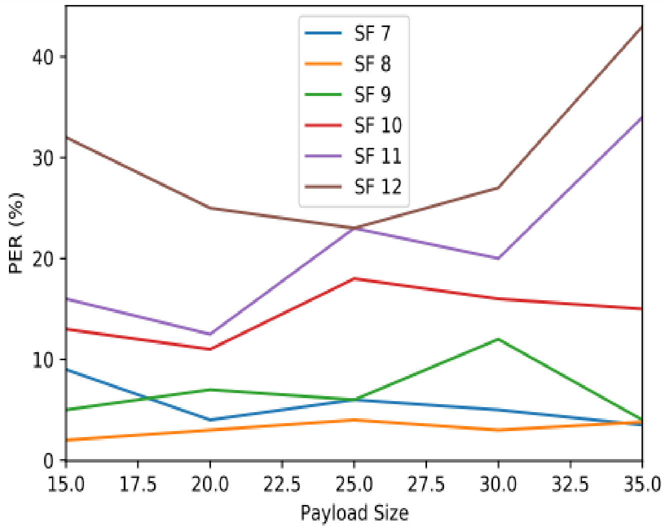

Figure 4.5 Analysis of PER W.R.T payload size with varying SFs

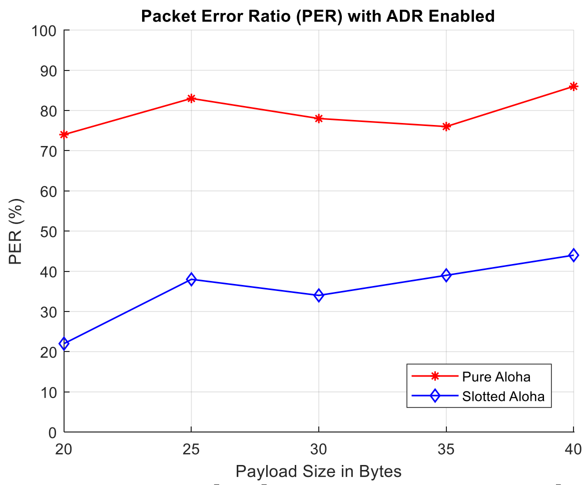

Figure 4.6 PER W.R.T payload size in percentage with ADR enabled

The performance of Slotted Aloha is ominously enhanced with ADR enabled. ADR is responsible for adjusting data rate and transmit power adaptively with the help of MAC commands. Initially, each EDs are configured with *SF*=12 and transmit power 14 dbm with 500 patients (approximately 1500 EDs), where distance between EDs and gateway is 5 km. It can be observed from the Figure that when packets size is 20 bytes, *PER* is more reduced to 22%. We can see from the figure that for packet size of 30 bytes, *PER* is further reduced to 27%.

Comparison of *PER*, for both Slotted Aloha and Pure Aloha is performed and presented in Table 4.2. From numerical results we clearly observe that for discussed configuration, results of Slotted Aloha are better than Pure Aloha with 1% duty cycle limitation. Algorithm below illustrates the steps which are involved in collisions and therefore in *PER*. There are three conditions that can cause collisions. These conditions include: If more than one nodes use same SF to transmit packet, or if more than one nodes access same slot at same time, or if they are using same channel. A packet loss occurs when received signal strength of a packet is below the sensitivity level at receiver or node takes at least 8 *BEB.* Otherwise signal is successfully transmitted and received. Algorithm below defines all the steps that are performed in simulations. Table 4.2 shows the numerical analysis of *PER* with varying parameters.

Table 4.2 Numerical analysis of PER with varying parameters

Spreading Factor (SF)	BW	ED	PER (in %)	Distance (Km)	ADR	Payload Size (in bytes)	Duty Cycle
12	125 Khz	500	25%	5 Km	Disabled	20	1%
11	125 Khz	500	13.5%	5 Km	Disabled	20	1%
10	125 Khz	500	12%	5 Km	Disabled	20	1%
9	125 Khz	500	8%	5 Km	Disabled	20	1%
8	125 Khz	500	5%	5 Km	Disabled	20	1%
7	125 Khz	500	5%	5 Km	Disabled	20	1%

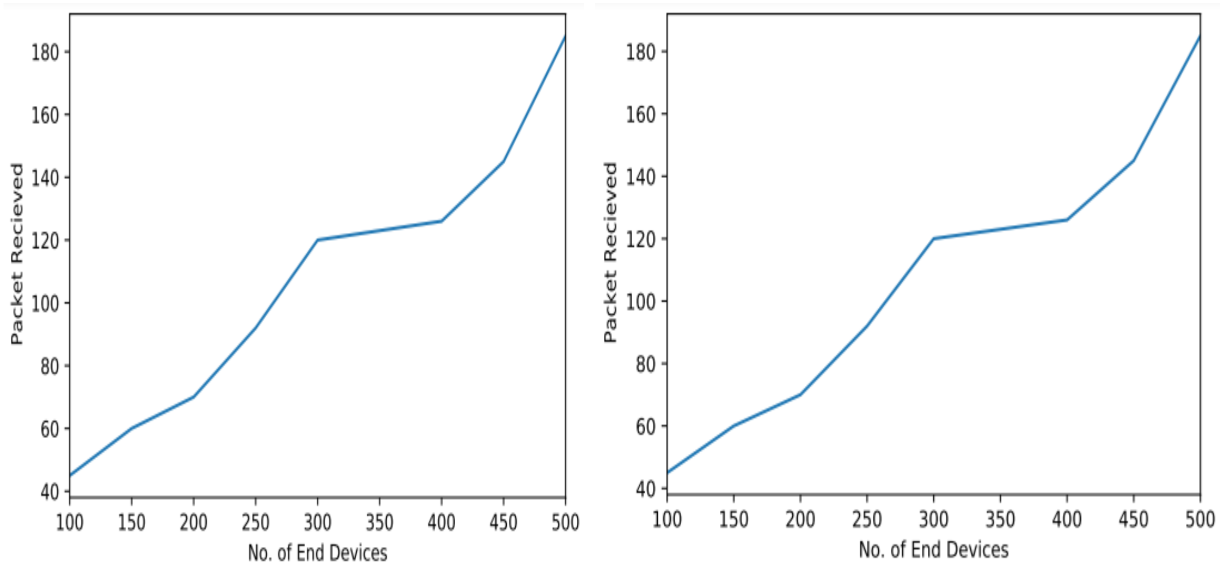

Figure 4.7 Average number of packets received W.R.T No. of EDs with ADR enabled (a) d=3 Km (b) d=5 Km

Figure 4.7 shows impact of successfully received packets by varying number of EDs. Data rate and transmit power of nodes are adaptively managed by LoRa network as ADR is enabled for this simulation. Packet size used for below simulation is 20 bytes. With 3 data channels and ADR enabled, we have 18 virtual channels that are simultaneously used by EDs to transmit data packets. Distance between end device and gateway are taken as 500m. Figure 4.7 (a) is for *d*=3 Km and (b) is for *d*=5 Km. Distance has significant effect on total number of average successfully received packets. Further to distance, the number of EDs also affect the number of received packets. If we increase the number of EDs from 500, the percentage of received packets are drastically decreased. Figure 4.8, shows the behavior of average received packets with varying number of EDs. Having ADR enabled, number of packets received in Slotted Aloha is greater than Pure Aloha LoRaWAN. For this simulation payload size remains constant. A packet of 20 bytes are transmitted by varying number of EDs. Results clearly demonstrate that with payload size of 20 bytes and 3 Km of distance between ED and gateway, Slotted Aloha out-performs Pure Aloha. With 300 EDs, number of received packets in Slotted Aloha are significantly more than Pure Aloha. Further, when we have 500 EDs per gateway transmitting packets simultaneously, average packets received in Slotted Aloha are greater than Pure Aloha.

Table 4.3 E = Enabled; initial SF=12; initial Transmit Power=14DBM

ADR	BW	ED	SA PER (in %)	Pure Aloha PER (in %)	Distance (Km)	Payload Size (in bytes)	Duty Cycle
E/SF12	125 Khz	500	25%	67%	5 Km	20	1%
E	125 Khz	500	23%	66%	5 Km	20	1%
E	125 Khz	500	34%	70%	5 Km	20	1%
E	125 Khz	500	29%	68.3%	5 Km	20	1%
E	125 Khz	500	32%	65.5%	5 Km	20	1%
E	125 Khz	500	43.5%	69.4%	5 Km	20	1%

Table 4.4 E = Enabled; initial SF=12; initial Transmit Power=14Dbm

ADR	BW	ED	Throughput (in %)	Distance (Km)	Payload Size (in bytes)	Duty Cycle
E/SF12	125 Khz	100	86%	3 Km	20	1%
E	125 Khz	100	86%	3 Km	20	1%
E	125 Khz	200	95%	3 Km	20	1%
E	125 Khz	300	92%	3 Km	20	1%
E	125 Khz	400	50%	3 Km	20	1%
E	125 Khz	500	61%	5 Km	20	1%
E	125 Khz	100	47.65%	5 Km	20	1%
E	125 Khz	200	49.5%	5 Km	20	1%
E	125 Khz	300	49.0%	5 Km	20	1%
E	125 Khz	400	48.65%	5 Km	20	1%
E	125 Khz	500	45%	5 Km	20	1%

The throughput of Slotted Aloha in LoRaWAN is presented in Figure 4.9. Initially, nodes configure their *SF* as 12 with a transmit power of 14 dbm, accordingly. As ADR is enabled, so after first transmission, the data rate and transmit power of a node is adaptively controlled. We perform simulations to analyze the throughput of Slotted Aloha in LoRaWAN environment by varying distance between EDs and gateway.

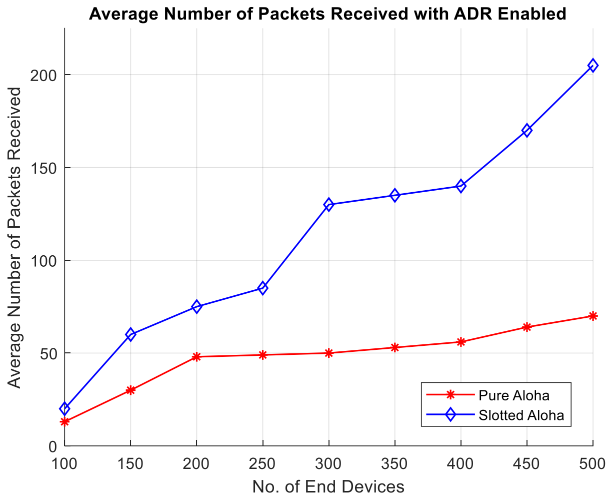

Figure 4.8 Average number of packets received W.R.T No. of EDs with ADR enabled

We have kept the packet size as 20 bytes for the simulations. We can observe from Figure 4.9(a) that the throughput of Slotted Aloha is 40% better than Aloha. We can observe that for 500 EDs having distance 5 Km between end device and gateway, transmitting a packet of 20 bytes results in a 68% of throughput. In case of Aloha in LoRaWAN environment, the throughput for same set of parameters is 28%. Further decrease in throughput is observed by increasing distance between end device and gateway from 3 Km to 5 Km in Figure 4.9(b). Figure 4.10 demonstrates the delay with respect to payload size. As LoRa nodes follow duty cycle limitation of 1%, the delay factor in LoRa network is really important to analyze rigorously. Before transmission of packets towards gateway, LoRa nodes have to select a random slot. This random slot duration is according to the *SF* used for transmission. This slot selection by LoRa nodes causes delay, which definitely increases the *ToA* for that packet. However, for the delay tolerant IoT applications, this increase in delay generated by Slotted Aloha is acceptable. We have kept the number of nodes for this scenario as 200. The delay showed in Figure 4.10 is in milliseconds. For *SF* 12, we have higher delay, which decreases significantly with the lower *SF*. One of the major factors in higher delay is *BEB* mechanism used for back-off in Slotted Aloha. By default, LoRa EDs use Aloha for transmission of packets. Although, Pure Aloha seems simple choice to transmission, however it may lead to massive number of collisions affecting the LoRaWAN throughput. In this article, we have used Slotted Aloha for transmissions. In case of Slotted Aloha, EDs have to randomly select slot before transmission starts. However, unlike Aloha in Slotted Aloha end device can only transmit the data in the start of a time slot. Figure 4.9 shows the throughput percentage w.r.t no of nodes with ADR.

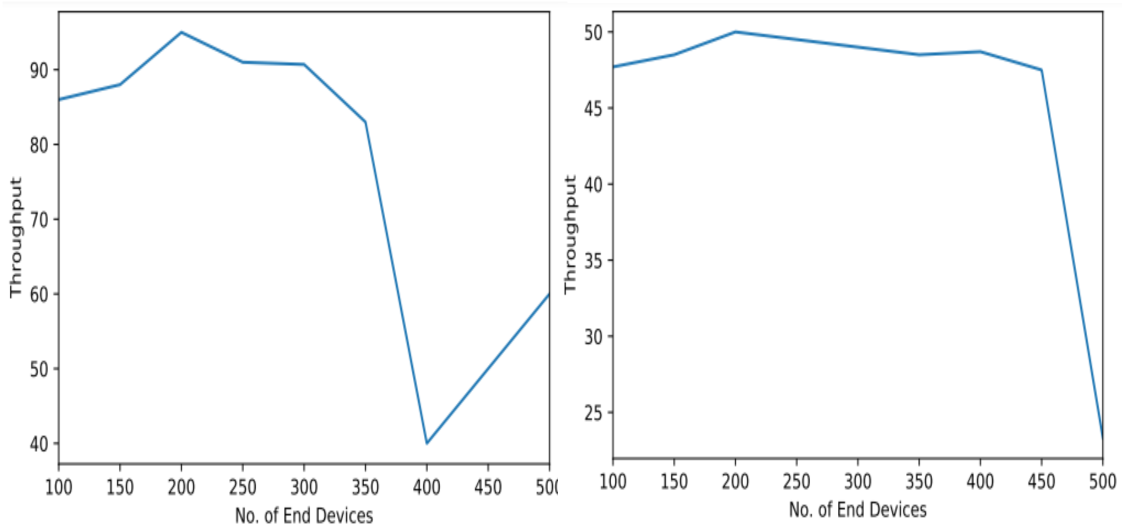

Figure 4.9 Percentage throughput W.R.T No of nodes with ADR (a) d=3 Km (b) d=5 Km

Our results show that by using Slotted Aloha, energy consumption is on a higher side as compared to Aloha due to the time spent by EDs in listening mode for most of its time for slot selection. In Figure 4.10, it analyzes behavior of EDs that transmits different size of payload with different *SFs*.

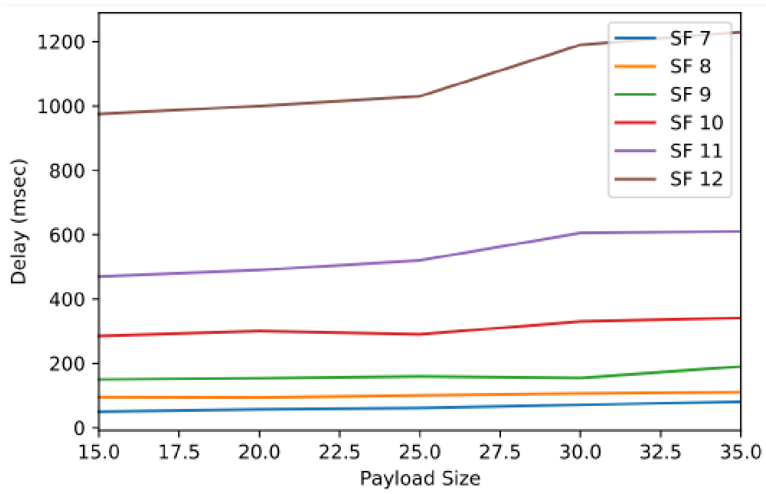

Figure 4.10 Delay W.R.T payload size for different SFs

One interesting result in Figure 4.11 is for the payload size of 30 bytes. As the size of packet is large enough and with duty cycle limitation of 1%, it is not possible to transmit whole packet of size 30 byte in simulation time of 1 hour. This is the reason that energy consumption of LoRa ED with 30 bytes payload is on a lower side as compared to others.

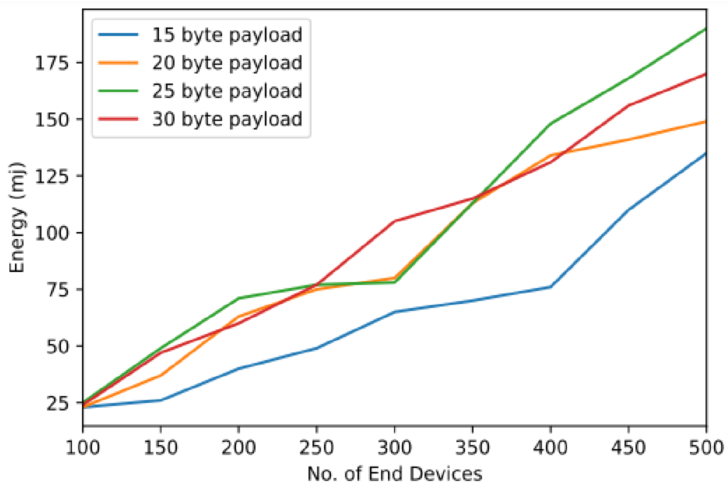

Figure 4.11 Effect of No. of EDs on energy (in milliJouls)

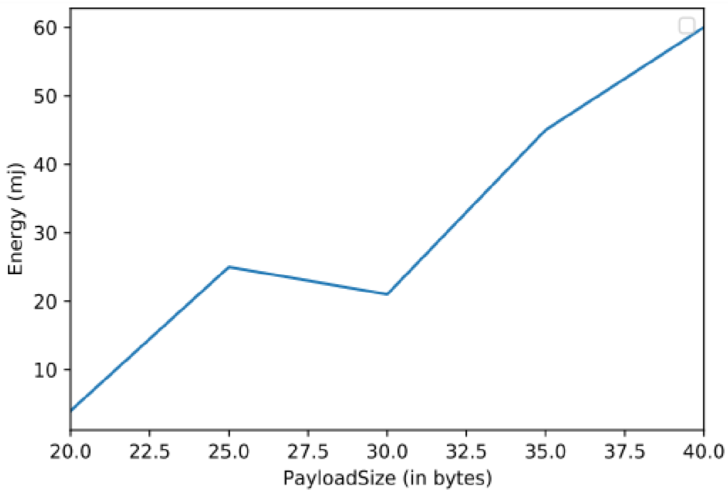

Figure 4.12 Effect of EDs on energy (in milliJouls) having ADR enabled

Results in Figure 4.12 shows the impact of varying payload size on energy with the ADR enabled. Initially EDs statically configures *SF*=12 and transmit power 14 dbm. After this both these parameters are adaptively controlled by LoRa network. By enabling ADR, energy of nodes is significantly optimized.

4.2 Unsupervised probabilistic approach with adaptive scheduling

This section highlights the issues caused due to delay in LoRaWAN. To address this problem, an unsupervised probabilistic approach is used to perform profiling. After profiling a scheduling algorithm ASA is proposed to assign priorities to profiles. Mathematical expressions and probabilistic relations are regourously provided to justify the simulation results.

4.2.1 Unsupervised scheme to enhance QoS provisioning

The Low-Power Wide Area Networks (LPWAN) technologies have been increasingly researched and overwhelming choice because of the huge number of IoT devices. Several LPWAN technologies are used by various researchers to address specific issues, but LoRaWAN is the most appropriate and appealing in terms of cost and energy consumption. The issue with LoRaWAN is the high rate of packet drop due to collision. The main cause of this packet drop rate is the MAC channel access scheme Pure Aloha used by LoRaWAN for frame transmission. LoRa EDs initiate communication with Aloha, resulting in a large number of re-transmissions. These re-transmissions will further depreciate delay factor and consumption issues. In order to accomplish well-organized application of LoRaWAN, it's important to define target application. This chapter focuses on heterogeneous IoT applications used mainly for smart health monitoring scenarios. An intelligent learning using unlabeled scheme is applied in this chapter because of the low power nature (battery driven EDs) of LoRa network. An optimal profiling algorithm is applies to by gateway to perform profiling of EDs. An efficient profiling algorithm selects as ultimate target is to optimize delay because of re-transmissions. K-Means intelligent learning algorithm is more suitable choice for making profiles of EDs on behalf of certain parameters as compared to other learning algorithms. Ultimate target is to group those EDs that exhibit same behavior at gateway level without involving nodes. By doing all this processing on gateway, the overhead of computation regarding EDs are mitigated.

On the basis of GMM probabilistic algorithm with K Means, profiling of EDs are performed by gateway. Further an Adaptive Scheduling Algorithm (ASA) is implemented on gateway to prioritize frames from different profiles. The gateway is solely responsible for transmission intervals defined for different profiles. Another important functionality of gateway, in addition to adaptive scheduling algorithm the inter-arrival frames from prioritized profile are deployed and examined to enhance the data throughput. This adaptive learning algorithm significantly enhances success ratio rate of frames from end device, hence re-transmissions on a lower side and delay is ultimately mitigated. The authors in [111], performed clustering where EDs workload is shifted towards another cluster but multi-hop scenario drastically enhance computation of EDs in LoRaWAN, hence also increase delay and energy consumption. The proposed work in [112], also performs K-Means learning for clustering. On the basis of these clusters scheduling algorithm is designed to prioritize packets. Authors use only spreading factor (SF) 7 for transmission of frames towards gateway. The reason behind using SF=7, as with this we can get minimum Time on Air (ToA). Only one gateway is used for simulation. The debatable issue is that, LoRaWAN adaptive data rate algorithm dynamically adjust Data Rate (DR) and transmit power of EDs. By using one single SF for whole simulation environment kills that adaptively provide by ADR. So in this chapter we discussed and address all these issues. This chapter details the basic intelligent learning solution in LoRaWAN environment by adaptively schedule traffic from different profiles of EDs and enhances performance in terms of delay.

4.2.2 Intelligent learning in LoRaWAN

LoRaWAN is more suitable option for IoT applications like smart energy meter, smart gas meter and smart health monitoring. Overwhelming choice of LoRaWAN is because of its simplicity and less calculations on edge devices for transmission of data. For IoT applications, where low latency is not that critical, LoRaWAN is an ultimate requirement. But most of the time, major setback in LoRaWAN that researchers face is high number of collisions, low throughput, increased number of re-transmissions and high delay. All these issues question the reliability of LoRaWAN. Although several features that enhance reliability and flexibility of LoRaWAN are Spreading Factor (SF), Coding Rate (CR) and ADR. To provide flexibility and reliability intelligent learning algorithms and techniques are discussed and used in LoRaWAN. An enhanced scheme to predict collision of packets based on LSTM model is developed. Online training schemes are used to achieve high accuracy. Further this also motivates Cui and Joe to combine LSTM with State Space Model (SSM). All these schemes are integrated in LoRaWAN protocol suit that drastically increase the computation overhead. Having limited resource technologies like LoRaWAN, these computations further degrade performance in terms of delay, energy consumption and latency. In another study Cuomo et al, proposed K-Mean clustering and also provide acknowledgment for random transmissions. Similar transmission characteristics are taken in to account to perform profiling of EDs. Decision Tree (DT) and LSTM models are used in this research to optimize allocation of resources.

Reinforcement Learning (RL) schemes are used to enhance throughput of EDs. Configuration parameters for EDs play vital role in the performance of LoRaWAN network. The best possible parameters are analyzed by Reinforcement scheme and update the future configuration parameter accordingly. Similar study is proposed in [113], by using RL and Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA) to reduce number of collisions in LoRa network. Q-Learning scheme is used to assign best possible configuration parameters to EDs. Their analysis reveals that main cause of collision in LoRa network is simultaneous transmissions from EDs. In this research the LoRa gateway allows the EDs to forward the packets on channels using CSMA/CA. However, throughput and delay is still main concern for LoRaWAN that needs to be addressed.

4.2.3 Methodical concerns with intelligent learning in LoRaWAN

The use of intelligent learning algorithm is inevitable as the severity of problems like collision, throughput, frame error rate, delay and energy consumption in LoRaWAN are exponentially grown when we have huge number of EDs. But the concerns of using intelligent learning in LoRaWAN are its computation that ends up with high energy consumption. These concerns make learning approaches more vulnerable especially for LoRaWAN. The study in [114], revealed that because of the resource limitation of IoT nodes machine learning algorithms are that efficient choice. As in these schemes EDs need certain level of coordination with access point. Keeping in mind all these facts, un-supervised learning techniques (K-Means) are used with scheduling algorithm to prioritize traffic of clusters. The main purpose of using K means is to make partitions of EDs on the basis of certain parameters. After this the access point assigns nodes to these clusters. So by doing this some of the computation burden is lift from EDs but still there are tradeoff between energy consumption and delay. Needing higher throughput which definitely compromise delay and consumption parameters.

4.2.4 System model of intelligent learning and formulation

The model developed in this chapter for intelligent learning, is considered as well populated smart health monitoring scenario. First of all, un-supervised probabilistic approach GMM with K-Means are used for profiling in a densely defined populated area. The GMM with K Means is performed by gateway in LoRaWAN environment. After the optimum profiles are defined by GMM algorithm, the EDs are assigned to each profile. On the basis of Adaptive Scheduling Algorithm (ASA), traffic from different profiles is prioritized in terms of Low Priority Profile (LPP), Middle Priority Profile (MPP) and High Priority Profile (HPP).

4.2.4.1 System modeling

The system modeling depicts smart health monitoring scenario in residential area: such as smart pulse Oximeter, smart blood pressure and smart heart rate. The said scenario is implemented with the help of two Gateways *(GWs)* and all the nodes are randomly distributed over an area of 5 Km^2. All the ED_j are initially configured using LoRa model SX1272, where j are from $1 \leq j \leq 3000$. All the nodes ED_j are static and for interaction with *GW* they are using class A LoRaWAN protocol. Class A EDs use two receiving windows (Rx1 and Rx2) for responses from gateway in case of confirmed communication. As we have to perform profiling for all of considered nodes in area span of 5 km^2, so for this we have to use some intelligent learning algorithm are used. As dealing with very time sensitive data, so the idea of taking two gateways in proposed network. Sometimes multiple *GWs* increase interference, but to deploy these *GWs* on points where interference between *EDs* which is negligible as possible. Another point about using multiple *GWs* is using Pure Aloha for transmission of packets from nodes so energy consumption is not an issue. Further with Chirp Spread Spectrum (CSS) method used by LoRa modulation which allows LoRa *GWs* to serve thousands of *EDs* in a densely populated area. With this huge number of *EDs* transmitting towards *GWs*, the main challenge is to keep packet acceptance rate high. Achieving high throughput, mean low number of re-transmissions that drastically mitigate transmission delay of transmitting *EDs.* Figure 4.13 present the smart health monitoring scenario for LoRaWAN network.

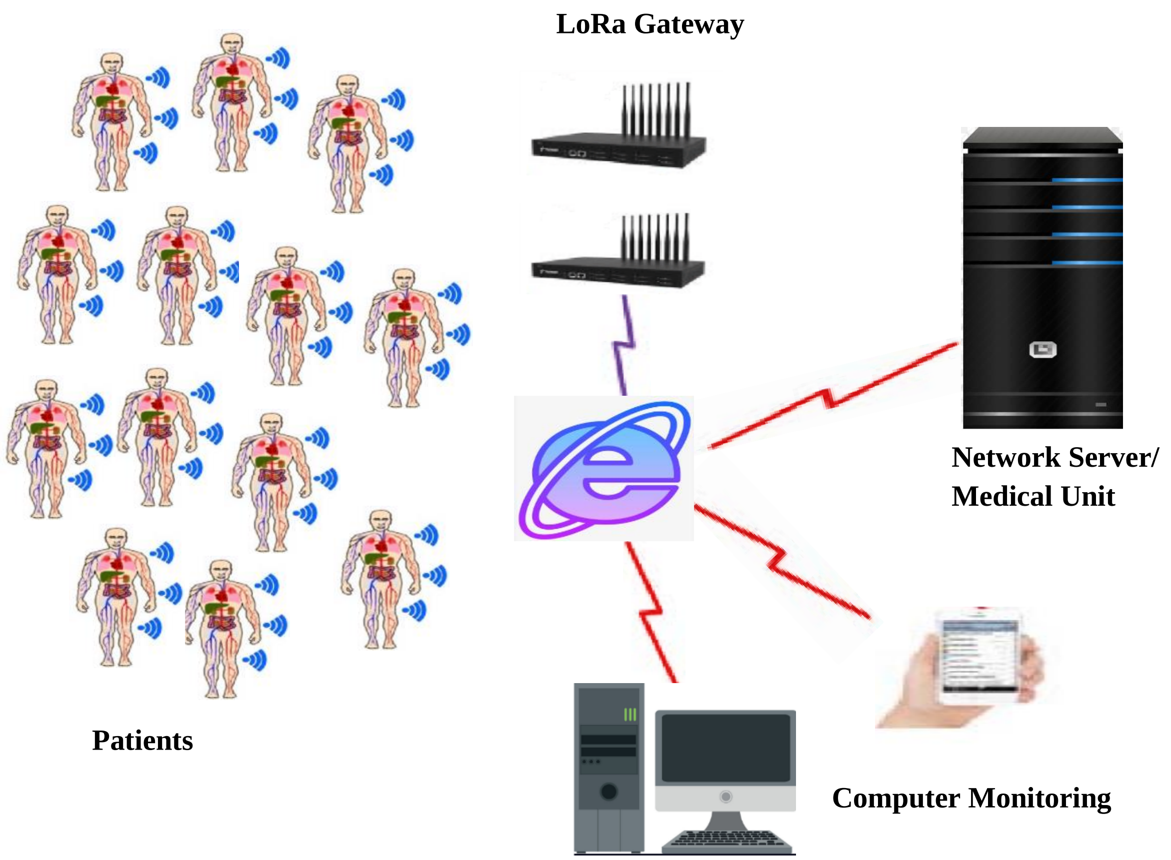

Figure 4.13 Smart Health Monitoring Scenario for LoRaWAN network

The target is Smart health monitoring applications, so for this the set of random values *(P)*, *(Q)* and *(R)* that are assigned to ED_j by using Gaussian distribution. These values are transmitted by smart nodes ED_j towards *GWs*, on which profiling is designed. On the account of these values, *GWs* assign smart nodes ED_j to different profiles. The main objective of this is to prioritize traffic from profiles that have critical readings of pulse rate *(P)*, blood pressure *(Q)* and heart rate *(R)* in the prescribed area. Most of the time, distance between *GW* and smart nodes ED_{j_d} has a very prodigious impact on throughput. In environment where we have high rise buildings, smart nodes ED_j that are deployed at 500m *(do)* away from *GW* such that $(ED_{j\_d} \geq (do))$ suffers from bad channel condition and having Packet Delivery Rate (PDR) between 50% to 90%. In addition to all these the $ED_j s$ transmits packets towards the *GWs* using different Spreading Factor *(SF)*. LoRaWAN provides six *SF* (7, 8, 9, 10, 11, 12) and four different Coding Rates (CR). LoRaWAN uses ADR algorithm to adjust DR of (ED_j) accordingly. Further the system model designed in this thesis is in densely populated area within a range of 5 km^2.

The sole objective of this research is to enhance the performance of LoRaWAN network in terms of transmission delay by using intelligent learning schemes that mitigate the collision hence re-transmissions. Packets transmitted by smart nodes collided in LoRaWAN, if they have same *SF*, channel frequency and at same time. LoRaWAN is single hop wireless technology that espouses Pure Aloha for transmission of frames from EDs towards gateways. To formulate this behavior of LoRa we use poisson distribution, where *P* is the probability of frame collision and is given as,

$$\mathrm{p} = \mathrm{e}^{-2\mathrm{R}} \qquad 4.8$$

Where *R* is the transmission rate of frames per end device. Further with the increase in the number of *ED*, this probability is exponentially increasing which leads towards QoS issues in LoRa network. As we already discussed that LoRaWAN uses Pure Aloha for transmission of frames towards *GW*. With the application scenario already discussed above and random transmission from EDs, our main objective is split smart nodes in different profiles. So end device profiling play important role in minimizing the random traffic towards GWs. Gaussian Mixture Model (GMM) with K Means are applied on $\mathrm{GW_j}$ to construct optimum number of profiles for the *EDs* on the basis of values transmitted from *EDs*. After the GW_j completes its profiling, now the GW_j implements Adaptive Scheduling Algorithm (ASA) to prioritize traffic from different profiles. In all this processing the *EDs* limited resources is key for us to keep in mind. Since the main objective is to mitigate the transmissions delay, so that we can check the effect of *ED* profiling by using intelligent un-supervised learning algorithm GMM. Mathematical formulation of transmission delay, GMM, Inter-arrival-frames from individual profiles and ASA is performed in next section.

4.2.5 Transmission delay formulation

Transmission delay is one of the important factors to rectify for QoS enhancement in LoRaWAN. Transmission Delay *(TD)* is directly proportional to frame bits transmitted or bitrate [115]. *TD* in LoRaWAN environment depends on number of bits in frame transmitted and bit rate as shows on Equation:

$$TD = \frac{\text{No.of bits inside frame}}{bit\ rate} \qquad 4.9$$

The bit rate in above equation is given as:

$$bit\ rate = \frac{\text{SF x BW}}{2^{SF}} \quad \frac{4}{4+CR} \qquad 4.10$$

SF is the spreading factor and it is adjusted by LoRa ADR algorithm according to network performance. *BW* is the bandwidth and it is adjusted to 125Khz. *CR* is the ratio of actual and redundant bits. LoRa ADR is responsible to configure those parameters for ED, that best suited according to the network environment on run time. Further details about SF, BW and CR are in [115].

In proposed Adaptive Scheduling Algorithm (ASA), GW adaptively assigns priority *(P_r)* to different profiles *(Prof)* on the basis of values *P, Q* and *R* received from ED_j. Number of profiles are denoted by $Prof_k$ where *k*: (1, 2, 3, ….., k). LoRa nodes ED_j belongs to LPP waits until the transmission from node ED_j belongs to HPP profile *(Prof)* completed successfully. So nodes belong to lower priority profile waits for certain amount of time and that delay is described below:

$$TD(Prof) = \sum_{j=1}^{k}(D_{prof1}, D_{prof2}, \dots \dots, D_{profk}) \qquad 4.11$$

Where *k* is the number of profiles in LoRa network, D_{profk} is the total transmission delay of *ED* in a profile of $Prof_k$ and given in equation below. Further *(ED)*. $Prof_k$ is the total number of all ED_j in the corresponding $Prof_K$; and $Z(j) = D\ (D_{init} + D_{Rc} + D_{Rch})$; D_{init} is initial transmission delay of each node ED_j; D_{Rc} is the delay of the retransmission caused by ED_j collided packet; D_{Rch} is the delay of the retransmission caused by ED_j lost packet because of bad channel condition. The *GW* must have knowledge about the terminologies like initial transmission, collision and bad channel condition. Transmission from ED_j that are in a LPP $Prof_{LPP}$ in a state of back-off until the transmission from ED_j that are in HPP $Prof_{HPP}$ is completed. The delay expression of LPP becomes$D_{Prof_{LPP}}$.

$$D_{Prof_{LPP}} = D_{Prof_{HPP}} + Z(i) \qquad 4.12$$

Where *i* is the summation starts from 1 and goes to ED_J $D_{Prof_{LPP}}$ and $D_{Prof_{HPP}}$is the delay of high priority profile.

4.2.6 Unsupervised Gaussian mixture profiling algorithm

With the number of IoT devices increasing day by day it's really important to make the networks more and more intelligent. To make the LoRa network more robust, intelligent learning unsupervised technique Gaussian Mixture Model (GMM) Profiling is used to mitigate the probability of collision. To do this, GMM algorithm is adopted to make optimum number of profiles and further assign ED_j to those profiles. K-Means is one of the mostly used non-probabilistic approaches for profiling. The problem with K-Means approach is, that most of the time it converges to local minimum. To get the global minimum we have to run simulation several times with different configuration parameters. Another drawback of K-Means approach is that; it performs hard profiling. Hard profiling means that each object is assigned only to one profile. There are no probabilities assigned to nodes or objects during simulations. Given the $ED_{i's}$ in large geographical are of 5 Km^2, where $i \in 1, 2, 3, \ldots\ldots, 3000$. So $X = x_1, x_2, x_3, \ldots\ldots x_n \in R^3$. As we are starting with K-Means profiling so the intuition is to find the local minima or initial center point $C_p = C_1, C_2, C_3$, where $p \in 1, 2, 3$ for each profile *prof* that is near to the ED_i in that profile in terms of readings. As already discussed that three number of prof (HPP, MPP, LPP). One measure to know about the center C_p of each prof is the sum of its distances from C_p. Mahematically L becomes,

$$L = \sum_{p=1}^{3} \sum^{n}_{\substack{i:\, x_i \\ is \\ assigned \\ to\ p}} ||\, x_i - C_p\, ||^2 \qquad 4.13$$

We can also write the above equation as,

$$L = \sum_{p=1}^{3} \sum_{i=1}^{n} a_{ip}\ ||\, x_i - C_p\, ||^2 \qquad 4.14$$

Where, a_{ip} is a coefficient having values 1 or 0:

$$a_{ip} = \begin{cases} 1 & x_i assigned\ to\ p \\ 0 & otherwise \end{cases}$$

Further K-Means trying to minimize L w.r.t a and C by following steps.

i. Choose optimal a for fixed C.

ii. Choose optimal C for fixed a.

iii. Repeat (i) and (ii) until convergence.

This is essentially a special case of EM algorithm; in which we are trying to find estimated parameters. Now the above step (i) is mathematically expressed as,

$$a_{ip} = \begin{cases} 1 & if\ p = \underset{l}{\arg min} \;||\, x_i - C_p \,||^2 \\ 0 & otherwise \end{cases} \qquad 4.15$$

We know that minimizing the Euclidean distance is same as minimizing its square.

Researchers round the globe are moving towards another solution for profiling known as GMM profiling approach. The Expectation Maximization (EM) model is used for convergence by GMM algorithm. Another benefit of using GMM is its shape of decision boundaries. With its covariance matrix the decision boundaries are more elliptical as compared to the circular boundaries in K-Means. However, an interesting fact about GMM is its assigning probabilities to each object. By assigning the probabilities to each object, we can easily see how strong our belief that a given object belongs to a specific profile. If we compare both algorithms, the GMM seems to be more robust. However, GMM usually tend to be slower than K-Means because it takes more iterations of the EM algorithm to reach the convergence. They can also quickly converge to a local minimum that is not a very optimal solution. The problem with GMM is that they have converged quickly to a local minimum that is not very optimal for said object. To avoid this issue, GMM are usually initialized with K-Means. This usually works quite well and it improves profiles (clusters) generated with K-Means. We can create GMM with K-Means initializer by changing one parameter in the GMM approach. Mathematical formulation of GMM and EM probabilistic algorithm is as follow:

Given the ED_i in large geographical are of 5 Km^2, where $i \in \{1, 2, 3, \ldots\ldots, 3000\}$. So $X=\{ x_1, x_2, x_3, \ldots.. x_n \} \in R^3$. The main aim of GMM is to define optimum number of profiles with global minima. The derivation of K-Means profiling is already presented in previous section. Now for GMM profiling the initial center point $C_p = \{C_1, C_2, C_3\}$, where $p \in \{1, 2, 3\}$ for each profile prof that is near to the ED_i in that profile in terms of readings. Generic Gaussian distribution is presented in the form of Probability Distribution Function (PDF) as,

$$P_x(x) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad 4.16$$

$P_x(x)$ is the probability density function representing patients lying in different regions depends on readings. μ, σ and σ^2 are variable terminologies depicts average (mean), standard deviation and variance of bell shape curve.

Mathematically, for 3-dimensions Gaussian distribution of EDs or a vector representation of these EDs becomes, $X = \{x_1, x_2, x_3, .. x_n\} \in R^3$. To know about profile k of x_i. $z_i | w$ is nearly equal to categorical(w), which means,

$$P(Z_i = k|w) = W_k \qquad 4.17$$

$P(Z_i = k|w)$ means that ED_i belongs to profile k. W_k is a mixture weight of k which is equal to 1, if the value of mixture is between 0 and 1.

$$\sum_k W_k = 1, \quad \text{if} \quad 0 \leq W_k \leq 1 \qquad 4.18$$

As each profile has its own center and co-variance so generate X_i from profile distribution as below,

$$X_i \,|Z_i = k \sim N(\mu_k, \Sigma_k) \qquad 4.19$$

μ_k is considered as profile center and $\sum_k$ is the co-variance of profile.

Given the profile center and its co-variance, we can compute probability P for specific value of X_i.

$$P(X_i = \; x_i \;\mid\; \mu_k, \Sigma_k) \qquad 4.20$$

$$P(x/c) = \frac{1}{\sqrt{2\pi.|\Sigma c|}} . e^{-\frac{1}{2}(x_i - \mu_c)^T \Sigma_c^{-1}(x_i - \mu_c)} \qquad 4.21$$

$P(x/c)$ is probability density function of i^{th} node with respect to center point of profiles c. After this in exponential component we are subtracting mean component from the i^{th} instance of EDs $(x_i - \mu_c)^T$ and in the middle we are multiplying it by inverse of co-variance $\sum_c^{-1}(x_i - \mu_c)$. The co-variance component describes the shape of Gaussian distribution.

4.2.7 Proposed Adaptive Scheduling Algorithm (ASA)

This section covers all the aspects of proposed Adaptive Scheduling Algorithm (ASA), where the *GW* is responsible for scheduling the transmission of ED_j on the basis of different priorities (priorities are set according to the reading received from sensors). Firstly the *GW* received different values $G.ED_j$ from ED_j and after processing assigns it to different profiles prof. After the profiles are formed, now the *GW* assigns ED_j to these profiles on the basis of certain parameters (reading/data received from end nodes). Assume that $G.\ Prof_k$ becomes the average value of all $G.Ed_j$ with in the same profile. Further on the basis of $G.\ Prof_k$ the *GW* implements ASA to schedule and assign p_r to different *prof*. Since the optimum number of profiles *k* selected in this research 3, so p_r assign are LPP, MPP and HPP respectively. Once the GMM with K-Means probabilistically design optimum number of profiles, now the ED_i is assigned to these profiles according to the readings/data. Further, the ED_i from HPP is allowed to transmit data for 15 minutes at maximum. The reason behind this is that, having 20 bytes of complete packet with *SF* 12, *BW* 125 Khz and *CR* 4/5, it takes 1318.912 milliseconds to reach GW_j. Having 15 minutes for ED_i in HPP, we have 900 seconds and 900000 milliseconds for all the ED_i in HPP. If we allow ED_i*'s* to transmit second packet only if current reading is 5% to 10% different from previous reading. By doing this the ED_i*'s* in HPP is capable to transmit multiple times towards GW_j*'s*.

4.2.8 Transmission scheduling

As we already discussed that scheduling algorithm ASA is implemented on *GW*. The *GW* assigns highest P_r to ED_j that have maximum value of $G\ ED_j$. Just to remind that *G* is the difference of value *P, Q* and *R*, where *P* denotes smart pulse oximeter, *Q* denotes smart blood pressure monitoring and *R* is for smart heart rate. Various normalization techniques [116][117], are used in literature to calculate normalized values. Each LoRa node generates these 3 values and these values differ from one another in terms of its unit. The maximum P_r is considered as $Max(P_r)$ and its equal to $Max(G\ Prof_k)$. Where $G(ED_j)$ denotes the average value of *G* in the corresponding profile $Prof_K$.

The P_r of $Prof_k$ is directly proportional to average value of profile $G(Prof_k)$. It means higher the value of $G(Prof_k)$, the higher P_r of that profile. Based on priority of $Prof_k$, the *GW* schedules the transmission of node ED_j from that $Prof_k$. The nodes traffic from Low priority profile $(ED_j)Prof_{HLP}$ is blocked until the transmission from nodes in high priority profile

$(ED_j)Prof_{LLP}$ block is completed. The above statement to block the traffic from Low priority profile $(EDj)Prof_{LPP}$ is some time degraded the performance of network, because of unnecessary traffic from high priority profile $(EDj)Prof_{HPP.}$ In order to prioritize the traffic from profiles Adaptive Scheduling Algorithm (ASA) is designed. This algorithm is implemented on *GW*. According to the assumptions, *GW* had to schedule the transmission from each ED_j of corresponding profile. As *GW* take decision on the value $G(ED_j)$ received from earlier transmissions. After every successful transmission value of $G(ED_j)$ is updated. Each ED_j correspond from Prof transmits one packet after every 5 minutes. If there is any collision due to bad channel condition, only one re-transmission is allowed by ASA.

Figure 4.14 elaborates technical flow of Adaptive Scheduling Algorithm with unsupervised learning approach GMM. The flow diagram shown in Figure 4.14 depicts the overall processing of ASA with unsupervised learning approach GMM in LoRa network environment. First of all the EDs are statically deployed in an area of 5 Km^2. These static EDs are manually configured with parameters like data rate, bandwidth, payload size, channel frequency and spreading factor. Now these EDs send Join Request message towards gateway. Join Request message is encoded and validated by respective gateway accordingly. Once the Join Request message is accepted, the gateway give response in form of Join Accept message. The MAC scheme used in this algorithm is Pure Aloha with Extended Aloha. Initially EDs transmit packets towards gateway using Pure Aloha, after this the ED follow all the steps of Extended Aloha which states that if current reading deviates from previous reading by 5%, then EDs are allowed to transmit again.

Upon receiving first packet from EDs, the gateway used unsupervised learning algorithm called GMM. GMM assigns probabilities to all EDs with the help of probability density function. On the basis of these probabilities EDs are assigned to certain profiles like HPP, MPP or LPP. Critical data readings are assigned to HPP, semi-critical readings are assigned to MPP and normal data readings are assigned to LPP. Now EDs in HPP are allowed to transmit for 15 minutes as we have critical patients in this profile. After 15 minutes EDs in MPP are allowed to transmit packets towards gateway for 5 minutes. EDs pat of LPP are not allowed to transmit, as we have normal patients in this profile.

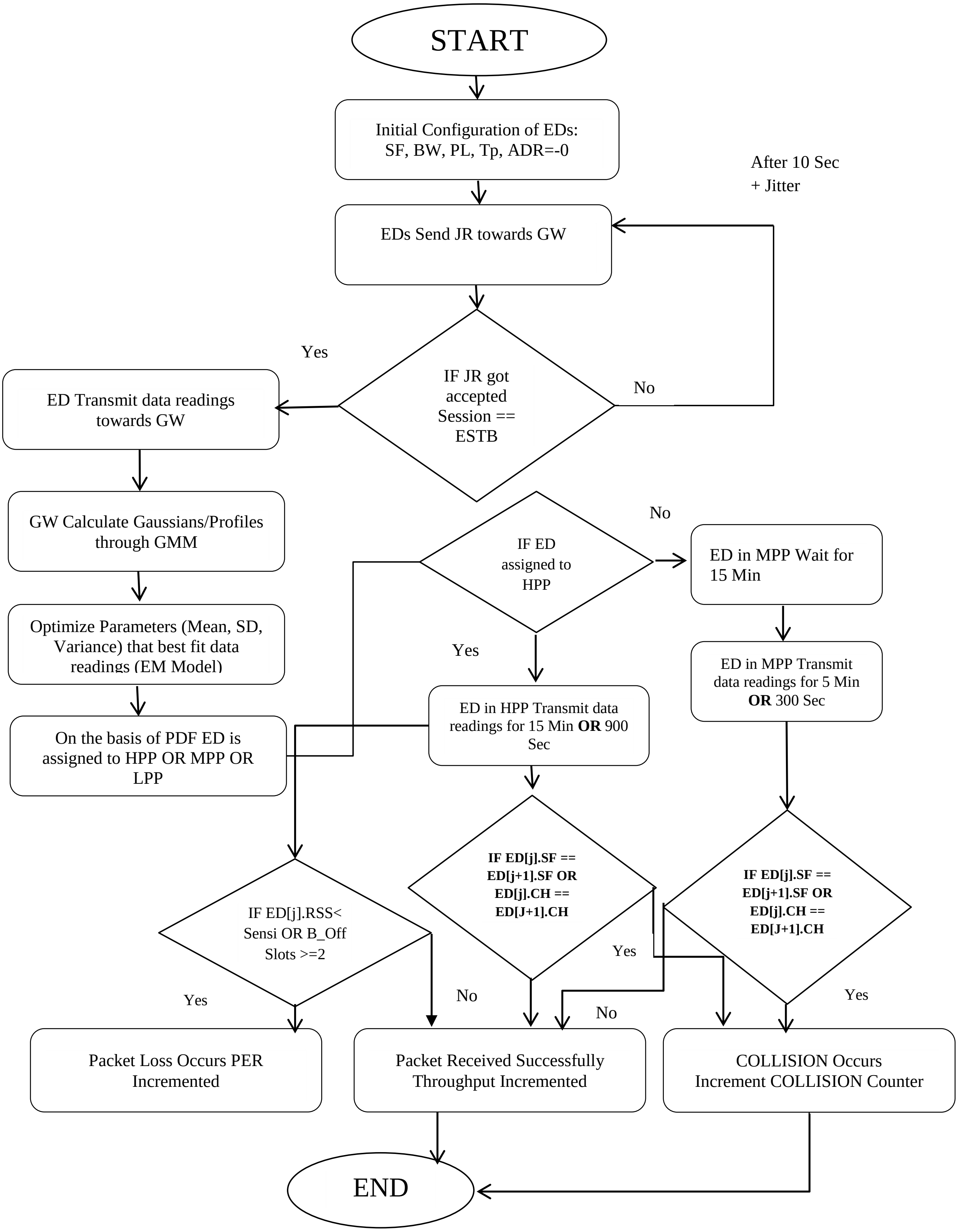

Figure 4.14 Technical flow of Adaptive Scheduling Algorithm

To estimate best possible parameters for these profiles or to design a best Gaussian class or profile, GMM use Expectation Maximization (EM) algorithm. Certain conditions are applied to check number of collided packets, lost packets and successfully received packets at gateway. In case the Join Request is not accepted by gateway or slot is not available, in that case the ED has to wait for 10 seconds plus Jitter. The Jitter is equal to 1 second plus (0-20)% time of that 1 second. This Jitter is included to lower the collision in terms of Join Request messages. If all Join Request is transmitted towards gateway at the same time, so chances of losses are on a higher side, that's why we introduce the factor of Jitter.

Algorithm 2 presents the step by step procedure of Adaptive Scheduling Algorithm with unsupervised learning approach GMM to prioritize traffic in LoRaWAN.

Algorithm 2: Adaptive Scheduling Algorithm to prioritize traffic in LoRaWAN

Adaptive Scheduling Algorithm to prioritize traffic

Declare variables: *TD*, ED_j, $G(ED_j)$, $(ED_j)_{Pr}$, P_r **BELONGS TO** [LPP, MPP, HPP]
To mitigate *TD:*

START LOOP for EDj do
1. ***if*** ED[j] send JOIN REQ towards NS
2. NS Respond with Channel CH[i]
3. ***If*** Session == ESTB Then
4. ED[j] Transmits data readings towards GW
5. **CALCULATE** $N(x|\mu, \Sigma)$ through EM Model, $P(X_i \in \text{Prof}_k)$ for ED[j]
6. Mathematical Optimization $\theta^* = \arg\max_\theta P(X|\theta)$
to best fit data with selected parameters like μ_j, SD and Variance.
7. On the basis of PDF, ED[j] is assigned to Profiles [HPP, MPP, LPP]
9. ***if*** EDj BELONGS TO HPP
10. EDj := (EDj)HPP AND (EDj)HPP is allowed to transmit for 15 Min
11. ***else if*** EDj BELONGS TO MPP AND (EDj)HPP = 0
12. EDj := (EDj)MPP AND (EDj)MPP is allowed to transmit for 5 Min.
14. ***if*** New_Reading deviate by 5% Than Current_Reading
15. OR
16. ***if*** Last_Ack Not Received
17. EDs in MPP is allowed to transmit multiple times during this 5 Min.

```
    else if EDj  BELONGS TO LPP AND [(EDj )HPP , (EDj )MPP ] = 0 THEN
            EDj  := (EDj )LPP  AND (EDj )LPP  AND ignore transmission.
    else
            (EDj)Pr   = 0
    end if
END LOOP
PERFORM GMM with Adaptive Scheduling AND goto START LOOP.
```

4.2.9 Collision behavior of EDs inside profiles

As thousands of EDs are transmitting towards gateway in LoRa network, so possibility of collision is also exponentially increased. This section exhibits the behavior of collision in LoRa network when multiple LoRa transmissions are received at gateway. Some of the transmissions that are orthogonal to others are decoded successfully by the receiver, but transmissions that overlap in terms of *SF*, frequency, time or in power domain leads to collision. All these categories of collision discussed in detail in this section.

4.2.9.1 Collision in terms of overlapping region

Overlapping of LoRa transmissions at gateway is one of the serious concern for LoRa network. Assume that interval at which packet overlaps starts from P_i and ends at Q_i such that (P_i, Q_i), whereas i is any packet. The gateway receives packet i during time P_i and Q_i. According to these parameters we can easily define midpoint and distance of the said interval. $MP_i = \frac{(Pi+Qi)}{2}$, $DIST = \frac{(Qi-Pi)}{2}$. Now overlapping condition fulfills when two packets x and y arrives at receiver during same reception interval.

$$Overlap(x, y) = MP_x - MP_y < (DIST_x + DIST_y) \qquad 4.22$$

4.2.9.2 Collision in terms of spreading factor

LoRa network used spreading factor to achieve long range, resilience against interference and to receive simultaneous transmission at the same time. However, when we have multiple transmitters that transmit packets having same spreading factor, it leads towards collision. The condition for collision in terms of spreading factor is $SF_x = SF_y$, where SF_x and SF_y are spreading factors for transmitters x and y.

4.2.9.3 Collision in terms of carrier frequency

Transmissions with different frequencies are still orthogonal and can be easily decoded by receiver. However, overlapping region in terms of frequency is defined as the difference of frequencies and offset. We have certain overlapping cases discussed below:

1. For 125Khz bandwidth: IF $(Freq_{pck1} - Freq_{pck2}) \leq 30$ Khz , *pck1* and *pck2* are packets from different transmitters.
2. For 250Khz bandwidth: IF $(Freq_{pck1} - Freq_{pck2}) \leq 60$ Khz , *pck1* and *pck2* are packets from different transmitters.
4. For 500 Khz bandwidth: IF $(Freq_{pck1} - Freq_{pck2}) \leq 120$ Khz , *pck1* and *pck2* are packets from different transmitters.

As GW_j assigned three different priorities P_r (HPP, MPP, LPP) to *prof*, so different simulations are performed to know the behavior of ED_i in terms of Packet Success Ratio (PSR), PER and collisions. The normalized values of PSR, PER and collisions is calculated for all prof. The simulation carried out two GW_j in the scenario that built, so at one time *EDs* from two HPP transmits there frames. The reason to choose HPP for each GW_j individually is that we may have critical readings from other *EDi* as well. To keep in mind, the severity of patients in smart health monitoring scenario we want that maximum number of ED_i can send data at one time but keeping in mind the QoS as well.

GW_j*'s* deployment is another important factor in the mentioned geographical area. As used two number of GW_j*'s* so to keep interference as low as possible the distance between GW_j*'s* is intelligently decided.

Let $X = \{x_1, x_2, x_3, \ldots\ldots x_n\}$ be the ED_i*'s* $\in R^2$ and GW_j*'s* $G = \{g_1, g_2\} \in R^2$. So to optimize the distance *d* between two GW_j*'s* g_1 and g_2, $\| g_1 - g_2 \| > Threshold$: where the minimum value of *Theshold* is 1 Km.

$$min \sum_{j=1}^{2} \sum_{i=1}^{n} \| g_j - x_i \| \qquad 4.23$$

After both the GW_j select there HPP and MPP profiles, now the ED_i in HPP is allowed to transmit packets. The behavior of PSR with varying number of nodes are rigorously analyzed.

As the packet size for our simulation environment is 20 bytes. The structure of complete packet used in simulation is presented in Table 4.5.

Table 4.5 Packet Structure

Node ID	Preamble	Physical Header	MAC Header	**Payload**			CRC
				SBP	**SPO**	**SHR**	

4.2.10 Simulations to optimize delay using probabilistic approach

As GW_j assigned three different priorities P_r (HPP, MPP, LPP) to *prof*, so different simulations are performed to know the behavior of ED_i in terms of *PSR, PER* and collisions. The normalized values of *PSR*, *PER* and collisions are calculated for all prof. The simulation carried out two GW_j in the scenario that we built, so at one time we have two HPP. The reason to choose HPP for each GW_j individually is that we may have critical readings from other ED_i as well. To keep in mind, the severity of patients in smart health monitoring scenario where there is a need maximum number of ED_i can send data at one time but keeping in mind the QoS as well. GW_js deployment is another important factor in the mentioned geographical area. As two number of GW_js, so to keep interference as low as possible the distance between GW_j*'s* will be intelligently decided.

Let $X= \{x_1, x_2, x_3, ... x_n\}$ be the ED_i*'s* $\in R^2$ and GW_j*'s* $G= \{g_1, g_2\} \in R^2$.

So to optimize the distance d between two GW_j*'s* g_1 and g_2, $\| g_1 - g_2 \|$ > Threshold: where the minimum value of *Theshold* is 1 Km.

$$min \sum_{j=1}^{2} \sum_{i=1}^{n} \ || \, g_j - x_i \, || \qquad 4.24$$

After both the GW_j select there HPP and MPP profiles, now the ED_i in HPP will be allowed to transmit packets. The behavior of *PSR* with varying number of nodes will be rigorously analyzed. The packet size for our simulation environment is 20 bytes. As in simulation environment, there are total 1000 patients, but each of these patient is equipped with 3 different smart LoRa enabled wearable's like (Smart blood pressure monitoring, Smart Pulse Oximeter, Smart Heart rate monitoring). Figure 4.15, shows the behavior of Packet Collision Rate *(PCR)* in percentage (%) with varying number of nodes. In this simulation total number 1000 patients with 3 smart wearables transmit data towards GW_j. Initially ED_i transmit data with *SF* 12, *BW* 125 Khz and T_p 14 dBm. ADR is enabled after the first uplink for all the ED_i in said geographical area. As in smart health monitoring system the ED_i generates small amount of data, so payload size is limited to 20 bytes. The behavior for conventional LoRaWAN is presented in Figure 4.15, that shows severe increase in *PCR* with the increase of ED_i. So in health monitoring scenario, where we have some critical patients conventional LoRaWAN strongly failed.

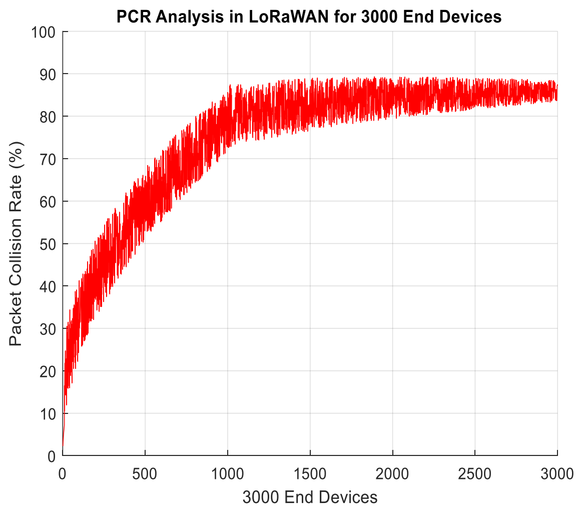

Figure 4.15 PCR analysis in LoRaWAN for 3000 EDs

As shown in Figure 4.15, ED_i follow Pure Aloha to transmit data towards GW_j. It is clearly seen that if all ED_j transmit data at one time so *PCR* is almost 85%. So the reason to perform profiling and adaptive scheduling on GW_j, is that most of the readings are successfully received by GW_j. After sending first uplink packet by an ED_i, the second packet is forwarded towards GW_j if and only if, there is significant difference between previous and current readings. By doing this, unnecessary traffic has been blocked and also manages the network capacity efficiently. Figure 4.16 presented results of *PCR* for HPP. GMM with K-Means are used to perform profiling on the basis of probabilities assigned to ED_i. After running the simulation, the GMM with K-Means distributes ED_i in to three profiles (HPP, MPP, LPP). In first attempt, the 300 ED_i are included in HPP by GMM with K-Means algorithm. In total of 3000 ED_i, approximately 300 ED_i are of those with critical readings. The GW_j assign priorities to profiles on the basis of Adaptive Scheduling Algorithm (ASA). After assigning priorities, now all ED_i in HPP is allowed to transmit data towards designated GW_j. Figure 4.16 shows the *PCR* behavior with varying number of ED_i. By limiting the number of ED_i, which can easily send critical data of patients towards GW_j.

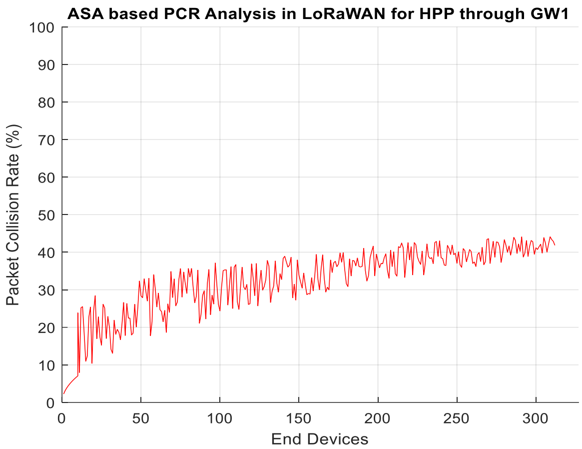

Figure 4.16 ASA based PCR analysis in LoRaWAN for HPP through GW1

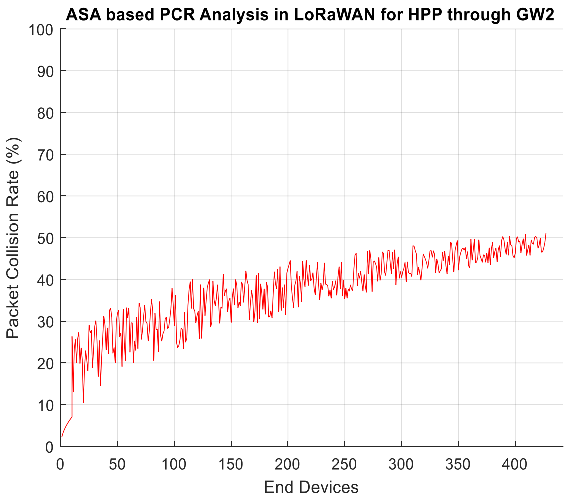

Figure 4.17 ASA Based PCR analysis in LoRaWAN for HPP through GW2

As we have 2 *GWs* deployed for smart health monitoring scenario. Further both the *GWs* will select his own HPP. With this approach we cater more *EDs* having critical readings. Figure 4.17 presents the results of second gateway *GW2* serve 425 *EDs* (GMM with K Means approach running on *GW2* select 425 *EDs* in HPP on the basis of readings). Now these 425 *EDs* are on a priority to transmit there frames towards *GW2*. With the increase in number of *EDs* in this HPP serve by *GW2*, the *PCR* ratio is little bit on a higher side as compared to HPP served by *GW1* specifically after more than 300 smart nodes transmitting. Gaussian or normal distribution is followed to generate data of all these patients in simulation. The reason behind Gaussian distribution is that, in real environment critical patients with severe readings of blood pressure or pulse Oximeter or heart rate are on a lower side. As in Gaussian distribution the Probability Density Function (PDF) of peak belongs to normal patients. The patient with critical values is on a right or left side and these patients are less in number. Figure 4.18, gives us idea about Gaussian distribution for patients of blood pressure with systolic (first reading) and diastolic (second reading) terminologies.

$$P_x(x) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad 4.25$$

$P_x(x)$ is the probability patients lying in different regions depends on readings. μ, σ and σ^2 are variable terminologies depicts average (mean), standard deviation and variance of bell shape curve. μ is the average number of patients that have normal blood pressure readings in Figure 4.18. Where σ and σ^2 tells us about the patients with critical readings that are low in number.

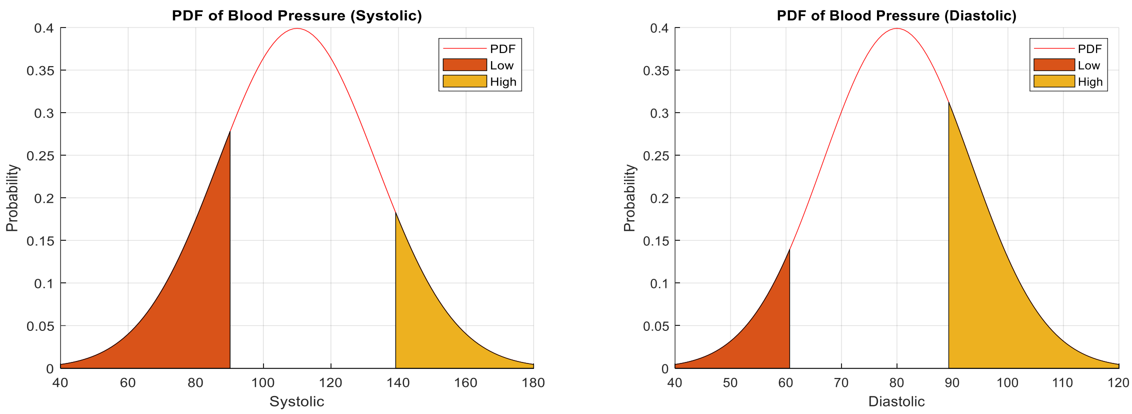

Figure 4.18 Gaussian distribution of Smart Blood Pressure wearable in terms of Systolic & Diastolic

Figure 4.19, presented the result of PSR in both conventional LoRaWAN, Dynamic PST and by using Adaptive Scheduling Algorithm (ASA) w.r.t varying number of nodes. As ASA approach prioritize profiles in different categories. Ultimately the number of critical EDs in HPP, forward packets towards GW_j. This eventually enhances the performance in terms *PSR*. The increase in *PSR*, definitely affect the performance of LoRa network in terms of delay.

Another important factor that, this simulation scenario consists of two GW_js. ASA approach is followed by both these gateways GW_js, deployed on a certain position assuming that there is not any interference between the GW_js. By installing two GW_j*'s* the data extraction rate is increased, because of ED_i from two HPP (may have semi-critical readings from ED_j that need attention), transmitting data towards GW_js. Further performance of ASA clearly outperforms conventional LoRaWAN by 39% and Dynamic *PST* by 5% in terms of *PSR*.

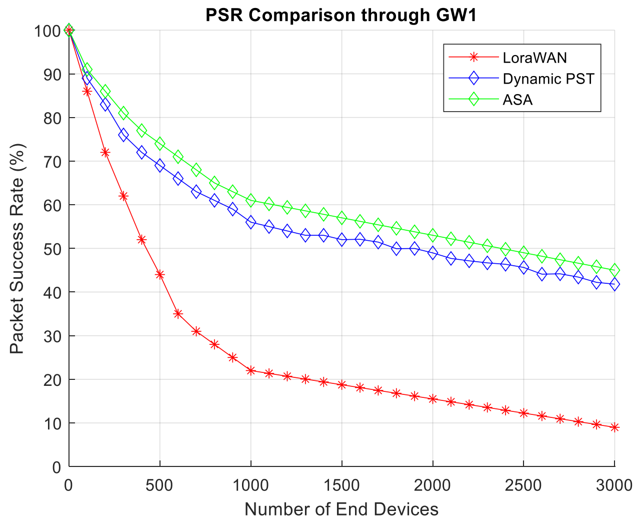

Figure 4.19 Comparison of conventional LoRaWAN with ASA in terms of PSR

With the introduction of multi gateways GW_j, issues like interference may arise as the ED_i from multiple HPP transmitting data towards GW_j*,s*. In previous section, certain equations for placement of GW_js at suitable locations are derived. Further, if distance between GW_js increases, the *PSR* of a deployed ED_i*'s* in LoRa network increases as expected. As the distance between multiple GW_js increases, *PSR* also increases. Another simulation is carried out that shows the behavior of *PSR* with both single and multiple GW_js. To achieve the maximum *PSR*, GW_js has to be deployed intelligently. Figure 4.20 shows the effect of delay with varying number of nodes in LoRa network. ASA achieves promising results in terms of delay as compared to conventional LoRaWAN and Dynamic PST. Conventional LoRa network, Dynamic PST and ASA results are simulated by using two GW_j's. Re-transmission only happens when the collision or packet loss occur. ASA intelligently mitigating the traffic by reducing the number of $ED_{i's}$ to transmit simultaneously. This approach significantly reduces the collision probability and hence re-transmission of packets. Once achieves this factor, the transmission delay is ultimately reduced as presented in below graph. ASA outperforms both LoRa network and Dynamic PST in terms of delay by 91% and 79%.

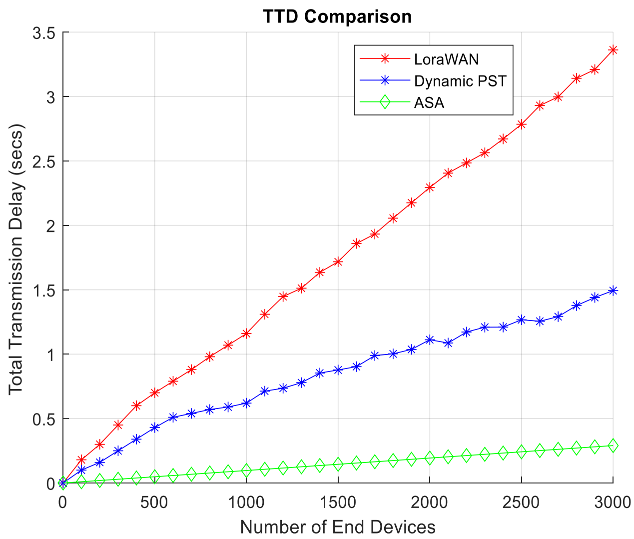

Figure 4.20 Enhancement of performance in terms of delay through ASA

4.3 Priority-Aware Dynamic Resource Allocation in LoRaWAN

This section presents the proposed Dynamic Reinforcement Learning Resource Allocation (DRLRA) algorithm, its process and integeration in LoRa network. The main objective is to optimize energy consumption of EDs in LoRaWAN. Mathematical expressions and probabilistic relations are regourously provided to justify the simulation results. The section also provides the process and physical model to understand the communication between EDs and gateway.

4.3.1 Priority-aware RL Resource Allocation

A long-range wide area network (LoRaWAN), have the ability to cater massive number of IoT devices because of its ability to refuge huge coverage area and robustness. In smart health monitoring scenario, where extremely sensitive data readings of patients (Pulse Oximeter, Blood Pressure, Heart Rate), had to be reached on time to take further necessary action. With more than 1000 EDs or smart nodes using Pure Aloha, this leads towards the channel congestion in smart health monitoring scenario, ultimately affect the network performance and capacity. With channel congestion, resource allocation is another issue that plays a vital role in the enhancement of performance in LoRaWAN. This chapter focuses on resource allocation like

(Channel frequency, Data Rate, bandwidth and Transmit Power) on the basis of Dynamic Reinforcement Learning Resource Allocation (DRLRA) profiling algorithm and to analyze congestion in channels. An intelligent learning probabilistic algorithm Gaussian Mixture Model (GMM) is followed to design profiles and then all these profiles are analyzed for channel congestion and inter arrival of frames. Further a path loss model is also used to cater all the attributes of channel. Extensive simulations are performed to extract the results in LoRaWAN environment.

LoRaWAN is wireless technology with low power and long coverage. Because of its attributes like low cost, low power and long coverage, LoRaWAN is widely deployed over the countries. LoRa is a MAC layer communication technology using Pure Aloha for transmission of frames. Industry and academia researchers are doing its best to analyze different aspect of LoRaWAN because of its lucrative features. Having Pure Aloha for layer two communications, LoRaWAN uses Chirp Spread Spectrum (CSS) scheme at physical layer to achieve long range and efficient energy consumption. With the number of EDs increases exponentially, a lot of issues are encountered by researchers like network delay, packet error rate, throughput, collision, retransmission and depletion in energy. LoRaWAN introduces three different classes for EDs to cater with different issues discussed above (class A, class B and class C). Class A EDs support both bi-directional and uni-directional communication with concerned gateway (GW). Two different receiving windows are kept open by class A ED after completion of every uplink transmission. Both these receiving windows Rx1 and Rx2 are open for 1 second each. If response is not received during first Rx1, second Rx2 are open for 1 second. Six Spreading Factors (SF's) are used by LoRaWAN specially to address orthogonal transmission. With thousands of IoT EDs transmission using Pure Aloha, it becomes difficult to cater QoS [52]. SF also tells us about the Data Rate (DR) at any given time. High SF mean low DR and low SF mean High DR. SF also effects the Time on Air parameter (ToA) of transmission. The channel was assigned to these EDs randomly by network server for uplink transmission. For every uplink transmission network server had to assign different data channel. This technique further increases the probability of data extraction rate. Sometimes failure of re-transmissions also occurs because of bad channel condition. This problem of re-transmissions can be solved by switching the ED towards high SF, but it also come up with enhancing ToA. To overcome the effect, we come across with the idea of adaptive channel assignment after analyzing the congestion. To mitigate the effect of SF interference in LoRaWAN, authors in allocates SF to

ED on the basis of distance between EDs and GW. This technique is based on fixed ring approach used in. Some other researchers GW sensitivity and Signal to Noise Ratio (SNR) based technique to allocated SF to nodes. However, in networks where nodes are transmitting simultaneously in high number, bi-directional communication leads towards more packet loss and congestion. So the proposed adaptive resource allocation is different from SF allocation, as in this we have to analyze the channel parameters and on the basis of this channel is allocated to EDs.

LoRaWAN supports various IoT applications to be deployed in its network space. Because of this heterogeneity LoRa technology faced a lot of issues such as delay and reliability. These issues also arise certain questions for researchers relevant to resource allocation. Resource allocation in terms of channels are addressed in this chapter, as this is only way to efficiently utilize channels. This chapter introduces a novel priority aware dynamic resource allocation scheme. The main aim of dynamic resource allocation is to enhance QoS in terms of scalability. First of all a machine learning approach, Gaussian Mixture Model (GMM) with K Means is implemented on GW to make optimum number of profiles. After this the optimized resources like (channel, Spreading factor, transmit power) is assigned to EDs to enhance performance in terms of reliability and scalability.

Research conducted in recent years on resource allocation in LoRa network are summarized in Table 4.6. After thoroughly study all mentioned papers and extract the main objective of authors regarding resource allocation. It is concluded that only a few works provided energy efficiency through transmission power TP fine-tuning or SF allocation. Application requirements are not addressed in. None of the author addressed SF, TP and BW's as a parameter to enhance performance in terms of scalability and reliability. To the best of our knowledge, only the priority aware dynamic resource allocation with adaptive congestion control at profile level gives optimum results in terms of network capacity and reliability.

Table 4.6 Resource Allocation schemes for a heterogeneous scenario

Research Papers	Publication Year	Objective	Energy	Application Requirements	Spreading Factor (SF)	Bandwidth (BW)	Transmit Power (TP)
ADR	2016	Increase transmission range	Yes	No	Yes	Yes	Yes
[29]	2020	Increase utilization of channel and mitigate collision	Yes	No	Yes	No	No
[58]	2020	Improve the noise resilience	Yes	No	Yes	Yes	No
[59]	2019	Mitigate number of collisions	No	Yes	No	No	No
[69]	2017	Mitigate number of collisions	Yes	No	Yes	No	No
[73]	2019	Enhance QoS	Yes	Yes	Yes	Yes	No
[74]	2018	Analyze unfairness of LoRaWAN in terms of Allocation	Yes	No	Yes	Yes	No

4.3.2 Dynamic Reinforcement Learning procedure

Reinforcement Learning (RL) method is used in wireless network to dynamically extract parameters from the environment according to requirement. RL agents extract desired information from the network deployed, take appropriate action and then update the reward accordingly. Through reward, that action taken by RL agent was appropriate or not. Generically RLA's are designed using Markov Decision Process (MDP) model. The main objective of RLA is to continuously refine the policy to get enhance the reward for future. Mathematical expression for future reward becomes.

$$P_t = \sum_{z=t}^{T} R_{z+1} \qquad 4.26$$

R_{z+1} is the reward at time *z*.

There are various RL algorithms that define certain states S. In this chapter, our dynamic RL algorithm first define the initial state S_T at time T, take certain action on the basis of collected information A_T at time T and achieve the reward R_{T+1}. So this information is really important to gather throughout the learning process. The function that is involved in learning process depends on Q values. The Q function depends on current state information and action taken.

$$Q(s,a) = E_{\pi}[P_t | \, S_T = S, A_T = A] \qquad 4.27$$

4.3.3 Impetus of proposed Dynamic Reinforcement Learning

To achieve best performance from LoRa nodes it becomes really important that suitable transmit power, bandwidth and SF are selected for EDs. Another factor that plays important role is the distance between ED and GW. With the increase in distance between EDs and gateway, the mechanism of transmit power need to be addressed. LoRaWAN solve these problems through ADR, but to keep the complexity as low as possible LoRa ADR allocates resources in network environment where we have limited number of smart nodes. The total number of received packets is increased by conventional ADR for class A ED but ultimately this enhances energy consumption as well. So to mitigate the energy consumption we propose to integrate a dynamic Reinforcement Learning in LoRa network. As we know that all attributes of EDs transmitting packets towards gateways are received by central terminal called Network Server (NS). So NS runs dynamic Reinforcement Learning algorithm to update the parameters like transmit power, SF, BW and channel for ED. The main contribution of our proposed technique is:

i) After adjusting profiles by GMM with K Means we address not only PSR, PER and delay but also optimize energy consumption of ED.

ii) After assigning EDs to various profiles like HPP or MPP, the dynamic Reinforcement Learning take distance and its RSS between ED and GW in to account on NS.

iii) After dynamic Reinforcement Learning the NS allocates parameters accordingly.

4.3.4 Dynamic Reinforcement Learning Resource Allocation based on GMM Profiling

This section highlights the novel approach of dynamic Reinforcement Learning Resource Allocation based on Gaussian Mixture Model (GMM) profiling (DRLRA). Almost the impact of all LoRa parameters is discussed. This scheme is mainly used to enhance the network scalability and efficiency in terms of energy.

4.3.4.1 Proposed methodology

Total of 1000 patients are considered in our smart health scenario, so it means that we have to deal with 3000 *ED* at one time. After performing profiling with GMM we assign *ED* to HPP, MPP or LPP. Now we have to implement Reinforcement Learning Agents (RLA) on NS for each terminal part of LoRa network. The reason behind using different RLA's for every ED in selected profile is, because each ED is involved in different actions at various times. Further to keep state of all the information regarding that particular ED and to allocate resources after learning will be responsibility of that particular RLA. One RLA is not enough because with the increase in number of *EDs* it becomes difficult for one RLA to collect information and allocate resources. On the basis of collected information from *EDs*, the reward *r* to each *ED* is responded by concerned RLA. The model presented in this chapter dynamically creates RLA for each *ED* joining the LoRa Network on *NS*. The explanation of DRLRAP model, that how it is applied in LoRaWAN environment is provided below.

4.3.4.2 Network and system model

A smart health monitoring scenario composed of n number of (ED_i) where $i \in \{1, 2, 3, \ldots\ldots n\}$ deployed in a densely populated area. A Gateway (GW) is deployed based on certain criteria. All the ED_i and *GW* are randomly deployed on certain location and we can identify these devices based on its geographical coordinates. Moreover, the location of ED_i are represented as (x_i, y_i, z_i) and GW_j will be represented by (x_j, y_j, z_j). As LoRaWAN is a single hop network between Ed_i and *GW*. The communication between *Edi* and *GW* is accomplished with the help of several channels and these channels are dynamically assigned to ED_i on the basis of traffic.

A dense smart health scenario is considered of ED_i from 1000 to 1500. First of all, *GW* is responsible for making profiles by using a probabilistic approach. A probabilistic approach known as GMM already discussed in earlier section, it is used to design optimum number of profiles prof. After the number of prof are decided, the *GW* is assigned different priorities P_r to *prof*. The mechanism of priorities P_r assigned by *GW* to prof are already discussed in previous sections (HPP, MPP, LPP). The scheduling algorithm discussed in previous section adaptively assign these priorities. As addressing smart health monitoring scenario, extremely sensitive data of patients to be delivered to medical center or to any individual on time. Sometimes it's also possible, to get some critical readings from *EDi* of prof belongs to medium priority. To address this issue, *GW* is deployed which covered geographical area. After establishing the priorities for each prof, to manage the traffic intelligently from multiple profiles, only critical readings are forwarded by ED_i towards *GW*. By doing this, intelligently handling the network capacity and also enhance performance in terms of energy consumption. As we are taking smart pulse monitoring ED_i, smart blood pressure monitoring ED_i and smart heart rate monitoring ED_i. Generally, each ED_i generates all three readings. But in this section, ED_i is more intelligent by forwarding only those readings that are critical.

Resource allocation is one of the overwhelming areas for researchers in LoRaWAN [119]. A lot of researchers are working on resource allocation mentioned in Table 4.5. In this particular chapter, we consider distance *(d)*, Current *ToA* (extracted from current *SF*), current *SF*, current T_p, Received Signal Strength *(RSS)* at *GW* and current channel usage by concerned ED_j in percentage (%). All this information is collected and given to DRLRA algorithm for further processing. The resources like transmit power and *SF* are allocated by ADR in conventional LoRa network. In our model of dynamic Reinforcement Learning, the *GW* performs extra functionality of RLA. Sometimes it is also possible that we have single RLA for more than one *EDs*. This decision will be purely on the basis of distance of that *EDs* from *GW*. More *RLAs* mean more computation from *GW* and *NS* hence more delay is observed. As we are already designing profiles (HPP, MPP, LPP), so proposed algorithm dynamically check the parameter distance of all these *EDs* in any particular profile. As in our smart health scenario, *EDs* from HPP are transmitting packets towards *GW* after for 15 minutes at maximum. After 15 minutes *EDs* from MPP is allowed to transmit readings towards *GW* for 5 minute. The *RLA* is designed for each *ED* on *GW*, which automatically update the allocation parameters for *ED* according to requirement. The main objective of this research is to observe LoRa network performance in terms of energy consumption under DRLRA. Certain parameters are maintained by Reinforcement Learning algorithms. *ED* information is provided by I_ED_t at time t, the network parameters is presented by N_ED_t at time t, reward is denoted as R_ED_t and A_ED_t is denoted as action. The main agents used in our dynamic Reinforcement Learning model are extracted from.

4.3.5 End Device state

Now the dynamic Reinforcement Learning can only allocate best parameters to *ED*, if and only if more information is provided to agents for learning about network environment. The action A_ED_t can be taken by agent according to the initial state or information of that particular *ED*. Attributes like *ED ID*, *ED P_Num*, *ED_PS* packet size generated, *ED* initial *SF*, *ED* initial *TP*, *ED BW*, *ED SNR*, *ED RSS*, *ED CH* and ED_e energy consumption are learned by RLA's. ED_e is the energy consumed by *ED* to transmit packet. ED_e is calculates by following the approach in. All this information are helpful for agent to take best action and provide reward accordingly. Algorithm 3 present the step by step procedure of DRLRA based on GMM.

Algorithm 3: Dynamic Reinforcement Learning Resource Allocation based on GMM Profiling (DRLRA)

DRLRA based on GMM Profiling.
Declare variables: Ed_i, distance (d), Initial SF, Initial DR, Initial T_p, BW, ToA, Channel Usage (CH_US), $(ED_j)_{Pr}$, P_r To mitigate Energy Consumption, Delay:
START LOOP for ED_i **do** ***if*** ED_i BELONGS TO **HPP** OR ED_i with Maximum value (Pr) in **HPP** Initially $\mathbf{ED_i}$ transmit packets at Maximum value of **SF** i.e **SF12 & TP 20 dBm.** Dynamic RL define Groups inside HPP on the basis of d and RSS. Design RLA for each Group inside HPP. RLA checks EDi State, takes Action & calculate Reward. RLA use Q Function to calculate future Reward. At GATEWAY ***if*** **RSS** of $\mathbf{ED_i}$ < $\mathbf{SENSI_{EDi,\ SFi}}$ **AND CH_US** $_{\mathbf{EDi}}$ > 70% Then Perform ***if*** $\mathbf{SF_{EDi}}$ is 12, Keep it same,

11. *else* **DECREASE** $\mathbf{SF}_{\mathbf{EDi}}$ by 1.
12. **UPDATE** $\mathbf{ED}_{\mathbf{i}}$ with new $\mathbf{SF}_{\mathbf{i}}$**, BW** and $\mathbf{DR}_{\mathbf{i}}$**.**
10. At $\mathbf{GW}_{\mathbf{j}}$, **REPEAT**
11. ***if*** **RSS** of $\mathbf{ED}_{\mathbf{i}}$ >= $\mathbf{SENSI}_{\mathbf{EDi, SFi}}$ **AND** $\mathbf{CH\_US}_{\mathbf{EDi}}$ > 50%
12. Then Perform
12. ***if*** $\mathbf{SF}_{\mathbf{EDi}}$ is 12, **DECREASE** $\mathbf{SF}_{\mathbf{EDi}}$ by 1. (**INCREASE DR**)
13. **UPDATE** $\mathbf{ED}_{\mathbf{i}}$ with new $\mathbf{SF}_{\mathbf{i}}$**, BW**, $\mathbf{DR}_{\mathbf{i}}$ and Adjust $\mathbf{TP}_{\mathbf{EDi}}$
14. **Set** $\mathbf{RSS}_{\mathbf{Thresh}}$ and $\mathbf{TP}_{\mathrm{V}}$ (TP Inc/Dec value)
15. **REPEAT**
16. ***if*** $\mathbf{SENSI}_{\mathbf{SF\ EDi}}$ > $\mathbf{RSS}_{\mathbf{Thresh}}$
17. TP= TP - TP_{V}
18. **UPDATE** $\mathbf{ED}_{\mathbf{i}}$ with new $\mathbf{SF}_{\mathbf{i}}$**, BW**, $\mathbf{DR}_{\mathbf{i}}$ and Adjust $\mathbf{TP}_{\mathbf{EDi}}$

4.3.6 End Device Action

The most prominent parameters affecting the performance of LoRaWAN network are *SF, TP, BW* and Channel attributes. So the dynamic RLA must be well equipped in terms of learning before allocating resources to *EDs*. The data channels used by LoRa network are 868 Mhz and 6 *SF* from 7 to 12 are used. *TP* used in our model are from 2 dbm to 14 dbm with spacing of 3 dbm. With 6 *SFs*, 5 different combinations of *TP, 2 BW* options (125 & 250 Khz) and 8 data channels, total of 480 different possible actions can be performed by RLAs.

4.3.7 End Device Reward

On the basis of collected parameters in previous section, dynamic RLA responded with a reward in terms of updated configuration. The reward according to corresponding actions is calculated as:

$$EDr = c\,\frac{\sum_{i=0}^{N} F_i}{\sum_{i=0}^{N} E_i} \qquad 4.28$$

As, *N* is the number of EDs and *F* is total number of frames received at gateway for specific duration and *E* is the total energy consumed during the active duration of *ED*. The reward for concerned ED_r increases with the increase in total number of frames. With the increase in consumption of energy the reward for ED_r decreases. The reward *r* is automatically varies with the change occur in state of *ED*. To optimize the reward we have to give priority to the success rate of frames by multiplying it with term *c*.

4.3.8 Reinforcement Learning methodology

This section describes the Reinforcement learning methodology in LoRa network. After the *EDs* is distributed in different profiles now the Reinforcement Learning procedure will be applied on *NS*. First of all, different groups are formed on the basis of distance *d* and Received Signal Strength *RSS* of *EDs* inside HPP or MPP profiles. Once the groups are decided, then the algorithm has to generate *RLA* for each group. The main purpose of designing groups is to make the process as simple as we can. In smart health monitoring scenario, 2500 to 3000 *EDs*, so it becomes difficult for system that we have *RLA* for each *ED* separately. Design *RLA* for each group is much better option when thousands of *EDs* are transmitting at one time. Another benefit of designing groups inside profiles is to make resource allocation easier. When the frame from *EDs* inside any group is received by *NS*, the corresponding *RLA* is invoked to collect current state information from header. After collecting all information now the *RLA* has to take certain action. Last step is to calculate reward for that particular *ED* and on the basis of reward; updated resources to *EDs* or group of *EDs* are allocated. The same methodology will be applied up to maximum simulation time.

DRLRA make use of Reinforcement Learning to extract nodes current state *S*. There are agents that take action *A* according to policy π. Reward *R* is denoted by function *F* which depends on State *S* and Action *A* it takes:

$$\text{Reward: } F: S * A \rightarrow R$$

As a result of Action *A*, there is also a change in state *S*. Now there are two types of changes. One is deterministic change, in which all actions are pre-defined and the other is probabilistic change, in which changes takes place on the basis of probabilistic approach. Mathematically it can be expressed as: Deterministic Change: $T: S * A \rightarrow S'$ and Probabilistic Change: $P(S' \mid S,A)$, where S' is new state. Agent also has certain policies. This policy is going to dictate its behavior. It is denoted by function π: Policy: $\pi: S \rightarrow A$. Mean once we are in State *S*, we have to choose these Actions according to policy π. With the passage of time the agent also have to learn the optimal policy. Optimal policy is denoted by V_π. Value of Optimal Policy is: $V_\pi : S \rightarrow R$. By following policy π in State *S*, we are getting value of Reward *R*. V_π is the optimal value of policy depends on the cumulative Reward R. The way to think about this cumulative Reward is to find an expected value.

$$V_\pi(St) = E[\, R_{t+1} + \partial \; R_{t+2} + \partial^2 \; R_{t+3} + \dots\dots],\ 0 \le \partial < 1 \qquad 4.29$$

where ∂ is weighted value or discount rate. Practically we are more interested in immediate Reward, that's why we need ∂=0, to reduce the effect of other Rewards.

$$V_\pi(St)=E\left(\sum_{i=1}^{\infty} \partial^{i-1} R_{t+i}\right) \qquad 4.30$$

Optimal Policy becomes: $\pi^* : V*(St) = MAX(\pi)\ V^{\pi}(St)$ for all St

$Q^*(S_t,A_t)$ is the commulative reward we get if we are in state St and take action A.

Dynamic RL Resource Allocation based on GMM Profiling (DRLRA), is implemented on Network Server. Firstly, to initialize some variables that is used in this process of resource allocation. These variables are Ed_i, distance (d), Initial SF, Initial DR, Initial $T_{p,}$ BW, ToA, Channel Usage (CH_US), $(ED_j)_{Pr,}$ P_r . The main purpose of resource allocation or assigning optimized parameters to ED_i is to efficiently utilize network capacity and address energy efficiency matters. First of all, by GMM probabilistic approach certain priorities are assigned to profiles prof. After assigning p_r to prof, we would in co-operate some intelligence on ED_i side also. The application that we are addressing is: smart pulse Oximeter, smart blood pressure monitoring and smart heart rate monitoring. In proposed scenario, the Ed_i have to check the readings generated and only those values from particular application are forwarded to GW_j that are critical. Further only those ED_i can transmit data towards GW_j that belongs to HPP. Initially the ED_i transmit data with maximum value of SF 12. Maximum value of SF_i means low DR_i. DRLRA profiling algorithm performs certain steps like it checks that the Received Signal Strength (RSS) of ED_i meets the receiver sensitivity $SENSI_{\,EDi\ SFi}$ requirement or not. We rigorously monitor channel utilization for allocation of optimized resources to ED_i. The RSS_{Thresh} value depends on SF, BW_i and transmits power value TP_V (TP Inc/Dec value) depends on path loss factor and distance d between ED_i and GW_j. Figure 4.21 shows the flow of DRLRA with RLA procedure.

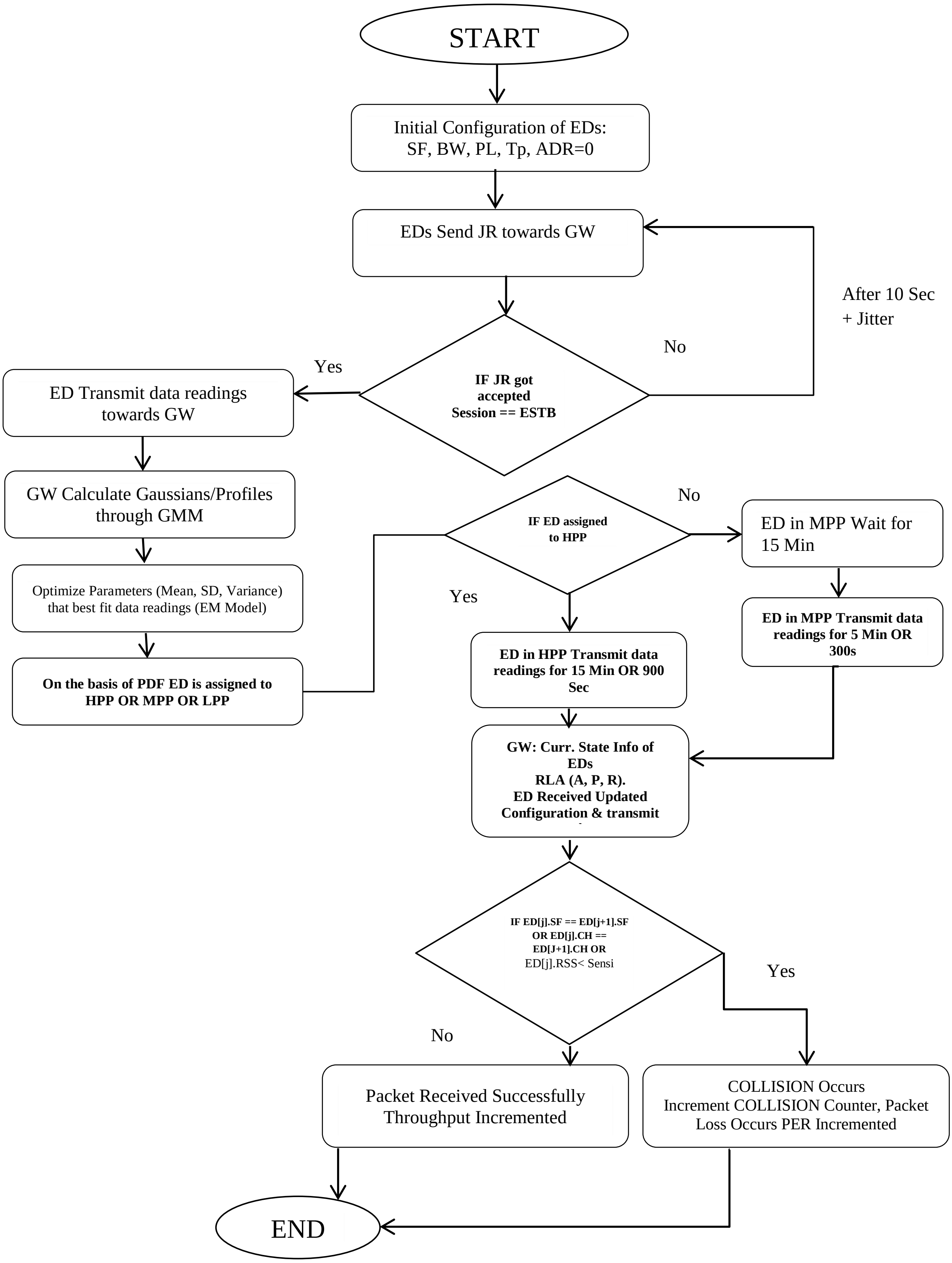

Figure 4.21 RLA procedure in DRLRA

The flow diagram shown in Figure 4.21 depicts the overall processing of DRLRA algorithm. Statically deployed EDs are manually configured with parameters like data rate, bandwidth, payload size, channel frequency and spreading factor. Now these EDs send Join Request message towards gateway. Join Request message is encoded and validated by respective gateway accordingly. Once the Join Request message is accepted, the gateway give response in form of Join Accept message.

Resource Learning agents are also introduced to allocate efficient resources towards EDs. ASA with GMM approach is used to design profiles. Q Learning is Reinforcement Learning approach used in DRLRA algorithm. Q Learning generalize the LoRa environment through Markov Decision process (MDP). MDP consist of certain components that describe the environment like states of EDs, events, set of actions and rewards. The reward is in the form of efficient parameters like data rate, spreading factor, transmit power and channel frequency. The MAC scheme used in this algorithm is Pure Aloha with Extended Aloha. Initially EDs transmit packets towards gateway using Pure Aloha, after this the ED follow all the steps of Extended Aloha which states that if current reading deviates from previous reading by 5%, then EDs are allowed to transmit again.

Certain conditions are applied to check number of collided packets, lost packets and successfully received packets at gateway. In case the Join Request is not accepted by gateway or slot is not available, in that case the ED has to wait for 10 seconds plus Jitter. The Jitter is equal to 1 second plus (0-20)% time of that 1 second. This Jitter is included to lower the collision in terms of Join Request messages. If all Join Request is transmitted towards gateway at the same time, so chances of losses are on a higher side, that’s why we introduce the factor of Jitter.

Table 4.7 shows the sensitivity according to *DR, SF* and *BW* for SX1272 LoRa module.

Table 4.7 Sensitivity according to DR, SF and BW for SX1272 LoRa module

Data Rate (DR)	**SF with Bandwidth (BW)**	**Sensitivity of ED w.r.t SF**	**Bit Rate of concerned ED**
DR5	SF 7 AND BW 125 Khz	-123 dBm	5470

DR4	SF 8 AND BW 125 Khz	-126 dBm	3125
DR3	SF 9 AND BW 125 Khz	-129 dBm	1760
DR2	SF 10 AND BW 125 Khz	-132 dBm	980
DR1	SF 11 AND BW 125 Khz	-134 dBm	440
DR0	SF 12 AND BW 125 Khz	-137 dBm	250

4.3.9 Performance metrics

This particular section elaborates the environment in which simulation is performed. However metrics used to enhance performance in densely populated area are rigorously evaluated. The simulator used to implement LoRaWAN environment for resource allocation on the basis of DRLRA is Python. All the *EDs* are randomly deployed in an area of 5 km^2 with two numbers of *GWs*. Maximum of 3000 *EDs* are deployed and expected to use LoRa network. A smart health monitoring scenario is considered with different set of applications like (smart pulse Oximeter, smart blood pressure, smart heart rate) having different set of readings. All these IoT applications have various QoS requirements [120]. Time on Air *(ToA)* is one of the important parameter that can affect the performance of network in terms of energy consumption. The *ToA* of those *EDs* that belong to HPP will be on a lower side, as we assign low *SF* to those *EDs*. Allocation of lower *SF* to *EDs* of HPP also depends on its distance from *GWs. ToA* also affects the energy consumption of *EDs*. After setting up profiles prof and assign priorities P_r, now in our scenario each *EDs* have to generate 3 types of readings. With huge number of IoT *EDs* and applications that we consider LoRa network will end up with large number of losses. To cater this, *EDs* must be little bit intelligent. The *EDs* has to forward those reading (data) that are critical most. By adapting this approach we can efficiently utilize the network capacity and energy consumption will also be on a lower side. The *EDs* forward packets after every 5 minutes, only if non-congested channel is allocated. To allocate optimize resources, standards of LoRa network to be followed as maximum as we can. Several research papers target on *SF*

7 that gives us lower *ToA* to optimize energy. But by doing this we are not following the factor of adaptiveness as it gives us much flexibility. The proposed algorithm DRLRA allocates optimized *SF*, T_p, *BW* and channels *CHs* on the basis several parameters extracted from the initial transmission from *EDs*. The parameters that are used by DRLRA algorithm for resource allocation include: *SF*, *BW*, T_p, *RSS*, *d*, *CH_US* (congestion level in %) and *ToA*. On the basis of these parameters DRLRA algorithm allocates optimized parameters to *EDs* for future transmission. Approximately 1500 *EDs* are deployed in a geographic area of 5 km^2, and each dot represent an *ED* at location *(x,y)*. The blue dots represent the *GWs* in the mentioned area. Understanding of these metrics are really important, to know about current state, actions, rewards, Packet Success Ratio *(PSR)*, Packet Error Rate *(PER)* and energy consumption.

The *PSR* is an effective approach to explore and analyze the *EDs* deployment in LoRa network. *GWs* deployed will be in a better position to analyze *PSR* of different HPP. *PSR* is effectively calculated with the help of total number of packets transmitted towards *GW* from *EDs* in a HPP and total number of packets that are successfully received.

$$\mathrm{PSR} = \frac{\mathrm{N\_PCKT\_R}}{\mathrm{N\_PCKT\_S}} \qquad 4.31$$

The *PER* is another factor that needs to be explore to know about the number of erroneous packets received at the *GW*. *CRC* algorithm is used to add some redundant bits with original payload on the basis of generated polynomial. This information is also shared with *GW*, so that *GW* also runs its own *CRC* algorithm to know about the packets validity. If the contents received are same as transmitted by *EDs* then it is successfully forward towards NS but if there are erroneous bits received by *GW* as per *CRC* algorithm, the *PER* counter is incremented.

Table 6.3 shows receiver sensitivity for each SF. Received Signal Strength *(RSS)* of ED_i indicates the strength of signal at the time of reception at GW_j. The ED_i transmitted payload towards GW_j which must have sufficient $RSS_{i,j}$, so that demodulation process performed successfully [121]. Mathematical equation for $RSS_{i,j}$ (*RSS* of node *i* at *GW j*) becomes:

$$\mathrm{RSS_{i,j}} = (\mathrm{T_p} + \mathrm{G_{ant}} + \mathrm{PL}) \qquad 4.32$$

Where T_p is the transmit power, G_{ant} is the antenna gain and PL is the path loss factor.

ToA is another metric that need to be evaluated carefully to understand the performance of network [122]. ToA depends on several parameters like *SF, CR* and packet size. *ToA* increases with the increase in *SF* and decrease in *DR*. That's why it's vital to assign optimal *SF* to *EDs*. *ToA* is measured in milliseconds. For *ToA*, it calculates preamble duration *($PREA_d$)* and *($PAYL_d$)*, where *NPS* is the number of payload symbols. Formulae's are given below:

$$\mathrm{PREA_d} = \left(\mathrm{N_{preamble}} + 4.25\right) * \mathrm{Dura_{Sym}} \qquad 4.33$$

$$\mathrm{Dura_{Sym}} = 2^{\mathrm{SF}} / \mathrm{BW} \qquad 4.34$$

$$\mathrm{PAYL_d} = \left(\mathrm{NPS} * \mathrm{Dura_{Sym}}\right) \qquad 4.35$$

$$\mathrm{NPS} = 8 + \max(\mathrm{Ceil}\left(\frac{(8\mathrm{PL} - 4\mathrm{SF} + 28 + 16 - 20\mathrm{H}) * (\mathrm{CR} + 4)}{4(\mathrm{SF} - 2\mathrm{DE})}\right), 0) \qquad 4.36$$

Where *PL* is payload size, *H* and *DE* are Boolean values. These are control variables used to optimize the performance of network. So we can get the expression for *ToA* by adding duration of preamble with duration of payload.

$$\mathrm{ToA} = (\mathrm{PREA_d} + \mathrm{PAYL_D}) \qquad 4.37$$

Energy consumption for all *EDs* are measured as the energy consumed during the *ED* is in active mode. In active mode the *ED* may be in T_x State or in R_x state. We have different consumptions for T_x State, R_x State and idle states. According to the SX1272/73, the voltage required for *EDs* to fully functional is 3.3 Volts, and the current consumptions at idle, transmit (at 20 dBm), and receive states are: *Iidle*=1.5 μA, *ITx*=125 mA, and *IRx*=10.5 mA, respectively [123]. The energy consumption is calculated by multiplying the voltage *Vp* by the current and the time duration of the corresponding sate.

ToA also effect the energy consumption of *ED* [123]. In this research, the authors only considered successfully demodulated packets to calculate energy consumption and battery discharge time. But the practical approach is to consider those packets as well that are not received successfully at *GW* due to any reason. We are also incorporating one extra condition on EDs that only those current readings are forwarded towards *GWs* that are different from previous readings by 5 to 10%. On this way considerable amount of energy efficiency enhanced for LoRa *EDs* as limited number of packets are forwarded towards *GW*. Mathematically energy consumption is calculated as [58]:

$$\mathrm{E_{cons}} = \sum_{\mathrm{i}} \sum_{\mathrm{packets}} (\mathrm{V}).(\mathrm{I}).(\mathrm{ToA}) \qquad 4.38$$

Where *V* is volts and is taken from spreadsheet used for LoRa chip SX1276. I is the current used for transmitting packets and other processing. E_{cons} is measured in Jouls (J).

LoRaWAN is one of the long range technologies and this claim of covering large geographical area is because of its CSS modulation scheme. In our smart health monitoring scenario, once we have 1000 patients so it means that we have 3000 EDs or nodes generating data (each patient have 3 wearable sensors). The ADR prevents connection problems when allocating the SF by extracting the last 20 EDs packets. ADR sets EDs close to the gateway to the lowest SFs and EDs far away to the gateway to the highest SF. APRA in [73], considers only RSSI value for resource allocation. APRA sets priorities according to application requirements. It set SF 7 to SF 8 for high priority applications and SF 11 to SF 12 for low priority applications. Dynamic RL Resource Allocation mechanism allocates parameters like SF, BW, T_p and data channel. As we have 8 data channels and 6 SF, so logically we have 48 data channels that give us liberty to transmit simultaneously. However, assigning a non-congested data channel to EDs in HPP, MPP and LPP further enhances the performance in terms of QoS and network capacity.

4.3.10 Simulation results to optimize energy consumption by DRLRA to profiles

LoRaWAN is one of the long range technology and this claim of covering large geographical area is because of its CSS modulation scheme. Figure below shows the SF, T_p and Channel allocation after deploying 1500 *EDs* with 2 *GWs*. In proposed smart health monitoring scenario, once reaches to the 1000 patients so it means that 3000 *EDs* or nodes generating the data (each patient have 3 wearable sensors). The ADR prevents connection problems when allocating the *SF* by extracting the last 20 *EDs* packets. ADR sets *EDs* close to the gateway to the lowest *SFs* and *EDs* far away to the gateway to the highest *SF*. APRA in, considers only

RSSI value for resource allocation. APRA sets priorities according to application requirements. It set *SF* 7 to *SF* 8 for high priority applications and *SF* 11 to *SF* 12 for low priority applications.

Dynamic resource allocation mechanism allocates parameters like *SF*, *BW*, T_p and data channel. With these entire parameters DRLRA profiling algorithm takes help from channel utilization classifier. As the 8 data channels and 6 *SF*, so logically there are 48 data channels that give us liberty to transmit simultaneously. However, assigning a non-congested data channel to *EDs* in HPP, MPP and LPP are further enhances the performance in terms of QoS and network capacity.

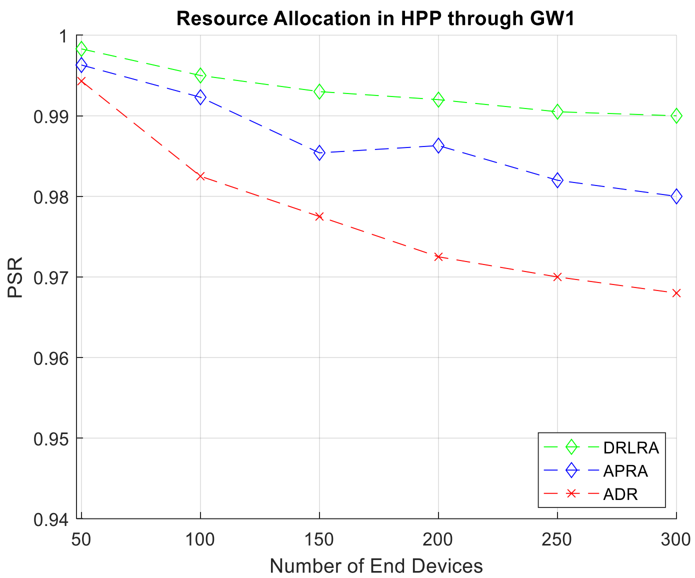

Figure 4.22 PSR W.R.T DRLRA for HPP and comparison with ADR and APRA

Dynamic Resource Allocation is performed on the basis of profiling with the help of extensive simulation to show packet success ratio *PSR* for HPP. First of all, profiling is performed on the basis of GMM with K-Means. Gaussian distribution is used to generate values from ED_i and on the basis of critical readings from ED_i HPP is formed. DRLRA allocates resources like *SF*, *BW*, Channel and *Tp* on the basis network environment. For HPP *BW* of 250 Khz is assigned to ED_i, so that data reached its destination smoothly. Figure 4.22 demonstrates DRLRA algorithm in terms of *PSR* for HPP. These results are associated with GW1. The desired results of DRLRA is extensively compared with state of the art algorithms APRA and ADR. Results of DRLRA outperforms ADR and APRA by 2.2% and 0.975% in terms of *PSR*. *PSR* of about 97 % is achieved with the help of profiling and DRLRA algorithm.

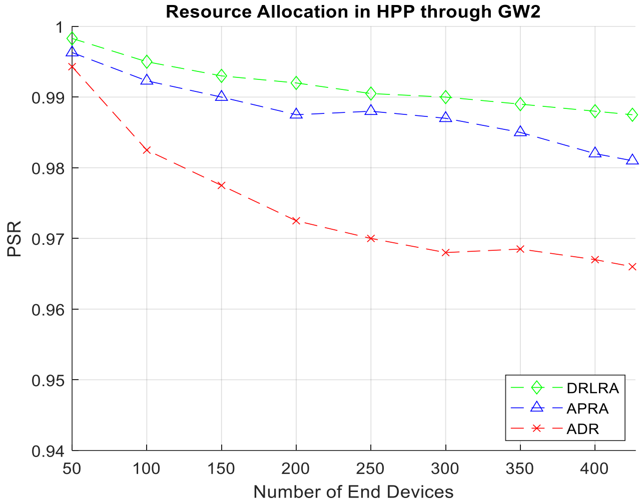

Figure 4.23 PSR W.R.T DRLRA for HPP and comparison with ADR and APRA

Results in Figure 4.23, shows performance of DRLRA algorithm by dynamically allocating resources in HPP through *GW2*. For this simulation, GMM with K Means assigns 425 *EDs* to HPP on the basis of critical readings received. GMM with K Means assign probabilities with the help of probability density function. Inside HPP we have several groups of EDs decided on the basis of distance *d* and *RSS*. *RLA* is responsible to assign resources to *EDs* inside the group on the basis of Reward. Overall the performance of DRLRA algorithm is enhanced in terms of *PSR*, when compared to conventional ADR and APRA. In numerical terms the performance of DRLRA is optimized by 2.1% and 0.5% as compared to ADR and APRA. Figure 4.24 shows the behavior of *PSR* for MPP through GW1. Approximately 900 smart EDs are assigned to MPP depending on the data readings and probabilities assigned to these EDs through probability density function. The results of *PSR* after allocating resources by DRLRA outperform the conventional ADR and APRA by 1.6% and 0.5%.

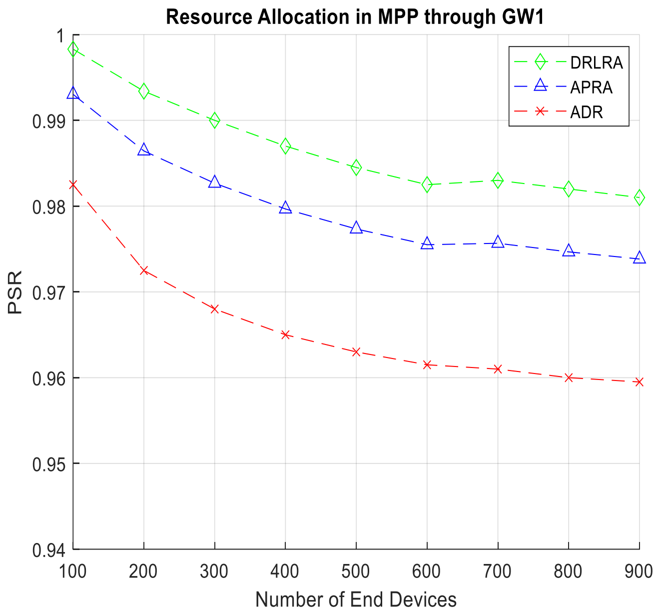

Figure 4.24 PSR W.R.T DRLRA for MPP and comparison with ADR and APRA

Figure 4.25 depicts the performance of LoRa network in terms of *PER* w.r.t number of *EDs*. Gaussian Mixture Model assigns 300 EDs to HPP as discussed earlier. The behavior of these 300 EDs are observed in terms of *PSR*. Overall DRLRA profiling algorithm outperforms conventional ADR by increasing *PSR* and mitigating the effect of *PER.* The results of DRLRA algorithm also outperform APRA in terms of *PER*. With the increase in throughput *PER* drastically decreased.

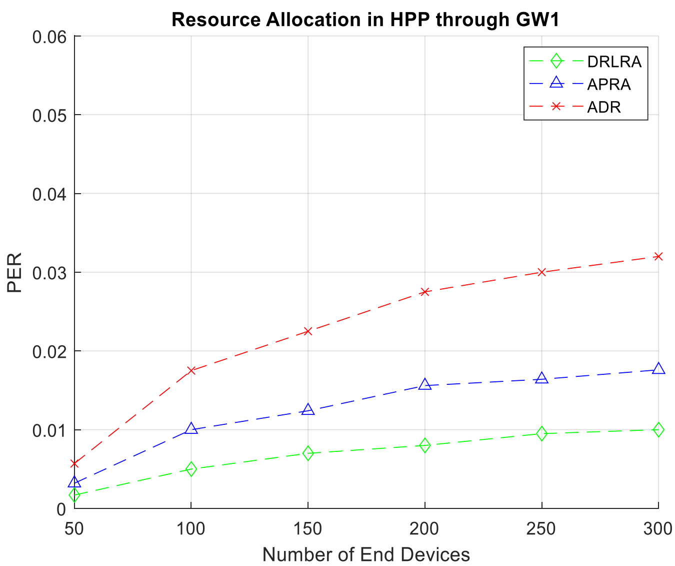

Figure 4.25 PER W.R.T DRLRA for HPP and comparison with ADR and APRA

Figure 4.26 presents results of *PER* for *EDs* in MPP through GW1. All these data readings are from semi-critical patients. GMM with EM algorithm is used to assign these EDs to MPP. With the increase in number of *EDs* inside MPP, *PER* is little bit on a higher side but still DRLRA profiling outperforms both ADR and APRA by achieving mitigated *PER*. Mitigated PER is also because of Extended Aloha used for second transmission from EDs. Extended Aloha states that only those EDs will send packets towards gateway, whose data readings are deviated by 5% from previous transmission.

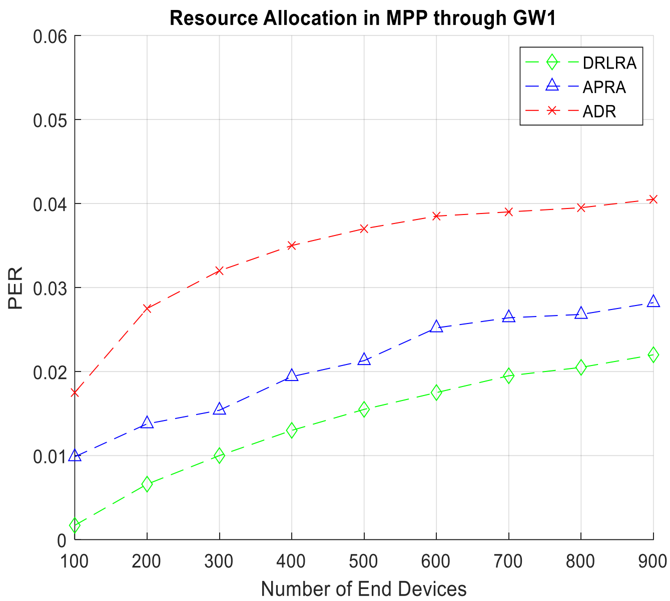

Figure 4.26 PER W.R.T DRLRA for MPP and comparison with ADR and APRA

Figure 4.27 depicts the simulation of energy consumption for dynamic reinforcement learning resource allocation algorithm, adaptive data rate and adaptive priority-aware resource allocation in HPP through GW1. The energy consumption is calculated on the basis of voltage consumed by EDs, current consumption at the time of transmission, current consumption at idle state of EDs and more specifically ToA. Overall DRLRA algorithm outperform the results of conventional ADR and APRA by mitigating the energy consumption of EDs. This is due to the efficient resource allocation towards EDs.

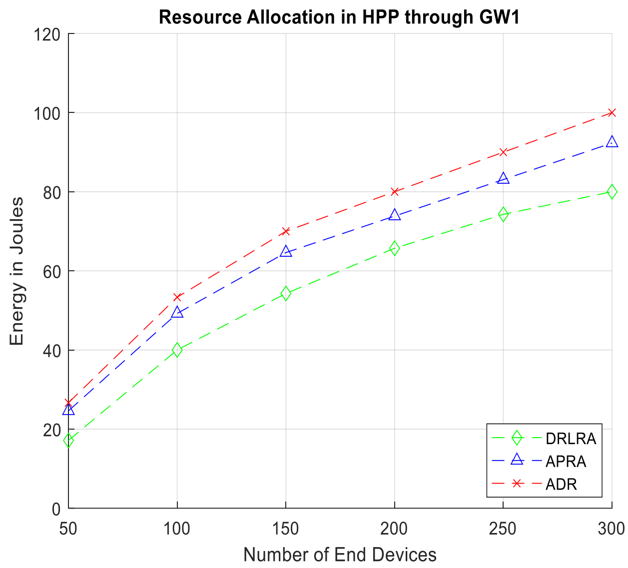

Figure 4.27 Energy consumption after allocating resources in HPP through GW1

To compute energy consumption, it considers several parameters like current drainage, voltage, processing of packets and *ToA* of packets transmitted according to *SF*. Figure 4.28 presents the results of energy consumption for DRLRA, ADR and APRA in HPP through *GW2*. To compute energy consumption, it considers several parameters like current drainage, voltage, processing of frames and ToA of frames transmitted according to *SF* adaptively.

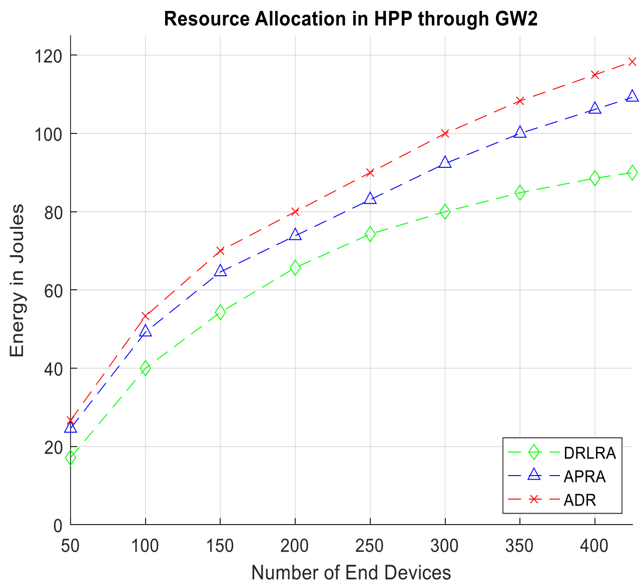

Figure 4.28 Energy consumption after allocating resources in HPP through GW2

With unsupervised learning approach GMM used for profiling and efficient resource allocation through dynamic reinforcement leaning resource allocation algorithm, we optimize overall performance of LoRaWAN in terms of energy consumption and network capacity.

4.4 Summary

Recently, IoT preferably use LPWAN as the most promising and prevalent technology for a wide range of applications such as smart homes, agriculture, and smart metering. Extant literature mostly focuses on the use of LoRaWAN under Pure Aloha that may not be suitable for certain delay tolerant applications. We thoroughly assess Slotted Aloha's performance in LoRaWAN for delay-tolerant applications. Results of Slotted Aloha outperforms in terms of PER, collision, and throughput. Further, increase in delay has been observed; however, that is affordable by delay tolerant applications. The advancement of the Green IoT can be significantly aided by out-performance in terms of PER, throughput, collision, and lower energy usage. Last but not least, it supported Slotted Aloha LoRaWAN for IoT. The proposal also recommends using adaptive Reinforcement Learning algorithms to alter duty cycles and channel allocations for dynamic IoT scenarios.

The use of Intelligent Learning (IL) approaches can lead towards inefficient in delay when applied to low power networks with limited resources. This is because IL approaches usually require coordination between the *EDs* and the *GWs*. However, the use of unsupervised profiling probabilistic approach GMM with K-Means in LoRaWAN network has shown a great impact in mitigating the re-transmissions and ultimately delays. This is mainly due to partitioning the end nodes into different profiles, which in return reduces simultaneous transmissions as a result of using the ASA to configure the nodes with different transmission intervals based on the profile priority. Given the same network density, the adaptive ASA reduced delay by 20.9% from the typical LoRaWAN. Despite the slight improvement to delay the ASA significantly enhanced the *PDR* when compared to typical LoRaWAN.

The massive use of IoT in smart spaces is transforming everything around the world and it is paving the way for the creation of smart cities. It is needed to improve the use of LoRaWAN with a better channel utilization schemes, SF, DR and T_P. This chapter presented DRLRA, which is an efficient priority-aware method for distributing configurable ratio parameters (such as SF, T_P and channel) for LoRaWAN. Due to the optimal T_P configuration, DRLRA significantly reduces the total amount of network energy consumption compared to state-of-the art algorithms ADR and it also significantly increases the battery discharge time of the EDs. Moreover, the proposed resource allocation mechanism exhibited a robust gain in terms of ToA for high and medium priorities EDs, and better results in PDR for all priority groups compared to the other mechanisms. Hence, DRLRA shows promise as a reliable solution for meeting the QoS requirements of applications while significantly enhance performance of LoRaWAN's energy consumption. In future DRLRA, it will be able to change the radio parameters of the EDs in case there is any change in the network.

CHAPTER 5

CONCLUSION AND FUTURE ENDEAVORS

5.1 Conclusion

LPWAN is the most promising and prevalent technology for a wide range of applications such as smart homes, agriculture, and smart metering etc. Extant literature mostly focus on the use of LoRaWAN under Pure Aloha that may not be suitable for certain delay tolerant applications. Slotted Aloha is a basic but efficient random access protocol that is utilized in wireless communication systems such as LoRaWAN. The slotted Aloha protocol is used in the LoRaWAN uplink direction, when EDs transmit messages to the gateway. One of the success of adopting slotted Aloha in LoRaWAN is its simplicity and efficiency in large-device Low Power Wide Area Networks (LPWANs). Slotted Aloha lets numerous smart EDs to send messages at his own designated slot duration, reducing data transmission time and increasing network capacity overall. However, slotted Aloha has several downsides, such as the possibility of collisions and the need for device synchronization. Furthermore, because it gives no guarantees, it may not be ideal for time-sensitive applications. Overall, slotted Aloha is a common protocol in LoRaWAN networks due to its ease of use and efficiency in dealing with a large number of devices at low data rates. It's a suitable option for applications that don't require real-time data transfer, like smart agriculture or asset tracking. We thoroughly assess Slotted Aloha's performance in LoRaWAN for delay-tolerant applications. Results of Slotted Aloha outperforms in terms of PER, collision, and throughput. Slotted Aloha with Markov chain model mitigate collision and enhanced performance of LoRaWAN by 38% in terms of data throughput.

Further, increase in delay has been observed due to re-transmissions and inter-packet arrival. H owever, to achieve optimum performance in LoRaWAN we must mitigate delay. To achieve optimum performance in terms of delay un-supervised probabilistic approach called GMM with K-Means is introduced. Further to prioritize traffic from profiles ASA is used. Results shows that in environment where thousands of EDs are transmitting ASA with un-supervised probabilistic approach drastically mitigate the factor of delay for smart EDs. ASA with GMM enhanced performance in terms of delay by 5% in LoRaWAN environment. The Adaptive Scheduling Algorithm with Gaussian Mixture Model is a potential solution for scheduling LoRaWAN broadcasts. The algorithm estimates the traffic load using a probabilistic model and adjusts the transmission rate accordingly. Finally, the probabilistic method outperforms existing scheduling algorithms in various ways, including best network performance, lower the number of retransmissions, increased the packet success ratio and optimized transmission delay. The algorithm is capable of adapting to changes in traffic patterns and network circumstances, making it appropriate for dynamic and diverse LoRaWAN environments. However, the algorithm's performance is determined by the accuracy of the traffic model and the quality of the channel estimation. Furthermore, the algorithm's implementation necessitates significant processing resources and may not be suited for low-power devices. Overall, the ASA with GMM algorithm has significant potential for enhancing the performance and efficiency of LoRaWAN networks, but more research and development is needed to optimize the algorithm and overcome its limitations.

Another objective regarding energy consumption of EDs are rigorously analyzed and addressed in LoRa network. Dynamic Reinforcement Learning Resource Allocation is used to allocate resources to EDs in different profiles. Inside the profiles we define different groups on the basis of distance and RSS. This help RLA to allocate resources inside the group to EDs that are far from each other. Further, comparison with other benchmark resource allocation techniques is also provided. Results of algorithm for dynamic allocation of resources outperform conventional ADR in terms of energy consumption. Dynamic Reinforcement Learning Resource Allocation significantly reduced energy consumption of EDs by 20% measured in Jouls. The out-performance in terms of PER, throughput, collision, and reduced energy consumption can substantially lead towards Green IoT. The Dynamic Reinforcement Learning Resource Allocation (DRLRA) algorithm is a machine learning-based approach to resource allocation in LPWANs like LoRaWAN. The system use a deep reinforcement learning technique to learn the best resource allocation policy for the network. Various simulations and experiments have yielded encouraging results for the DRLRA algorithm. In terms of network capacity, energy efficiency, and fairness, it outperforms alternative resource distribution approaches. It also responds well to changes in traffic and topology on the network, making it suited for dynamic environments. The key advantage of the method is that it does not require prior knowledge of the network's features or traffic patterns. Instead, it learns from past mistakes and adapts its policies accordingly. Finally, the DRLRA algorithm appears to be a promising solution for optimizing resource allocation in LoRaWAN and other LPWANs. More research and development are required to increase the algorithm's scalability and resilience, as well as to make it acceptable for real-world deployments.

5.2 Future endeavours

The LoRaWAN (Long Range Wide Area Network) technology has already demonstrated significant promise in smart health monitoring systems. LoRaWAN is well-suited for healthcare applications that require remote monitoring and tracking of patients' health problems due to its low power consumption, long-range connectivity, and capacity to support a large number of connected devices. LoRaWAN is projected to play an important role in smart health monitoring systems in the future. Here are a few possible applications for LoRaWAN:

1. LoRaWAN-based sensors could be used to monitor vital indicators in patients recovering from surgery or suffering from chronic illnesses, including as blood pressure, heart rate, and oxygen levels. The data obtained by these sensors might be wirelessly communicated to healthcare providers.
2. Medical equipment, such as hospital beds, infusion pumps, and wheelchairs, might be tracked using LoRaWAN technology. This would assist healthcare professionals in tracking the location and usage of equipment, enhancing efficiency and lowering the risk of loss or theft.
3. Monitoring of environmental conditions in hospitals and other healthcare facilities: LoRaWAN sensors could be used to monitor environmental conditions in hospitals and other healthcare facilities. Temperature and humidity monitoring, as well as air quality monitoring, could be used to detect hazardous contaminants and improve patient safety.
4. LoRaWAN could be used to remotely monitor patients taking part in clinical trials. Researchers would be able to collect data more efficiently and correctly, decreasing the need for in-person visits and increasing patient engagement.
5. Moreover, data aggregation and data compression schemes, when applied in multiple access environments can significantly reduce the collision rate, and also maximize network capacity in LoRaWAN.
6. LoRaWAN network aims to achieve longer distances, while EDs communicate to a gateway. Longer distances can contribute to propagation path delay, specifically in single-hop LoRaWAN scenarios. Another aim of our research is to analyze PPD under 3D scattering model

in LoRaWAN. This analysis may help to decide an optimal placement for gateways for the LoRaWAN scenarios, which may improve delay experienced by EDs and their energy efficiency.

7. Up to now all research is only for static EDs in LoRaWAN, because its existing ADR works well with static EDs only. We are also aiming to design an ADR algorithm for LoRa network that works well for mobile EDs as well.

Current LoRaWAN supports single hop communication between EDs and gateways. However, single hop communication is subject to several problems. In single hop communication, EDs transmit at maximum power level that directly affects their battery life. In LoRaWAN, gateway is the central point to relay all frames from ED to network server, and vice versa. A gateway also assigns channels and desired frequencies to all EDs with the help of MAC commands. Hence, all these tasks and processing, overburden the gateway, which ultimately affects LoRaWAN network performance. Another main aim of our research is to develop an ADR mechanism using deep learning approach in LoRaWAN, which can efficiently improve network capacity, and also reduces the overhead by offloading ADR computation from both EDs and network according to traffic requirements. Our proposed Dynamic Resource Allocation scheme aims to improve network throughput and network lifetime, while reducing the complexity of gateways, specifically in scenarios, where millions of EDs may transmit frames towards gateways. Overall, the future of LoRaWAN in smart health monitoring systems appears to be quite promising, with more novel applications of this technology expected in the next years.

5.3 Publications within thesis

1. **Ali, Z.**, Henna, S., Islam, S. U., & Akhunzada, A. (2018). Evaluation of Propagation Path Delay Using 3D Scattered Model in LoRaWAN. Adhoc & Sensor Wireless Networks, 40.
2. **Zufiqar Ali,** Shagufta Henna, A-Akhunzada; Raza, M., & Kim, S. W. (2019). “Performance evaluation of LoRaWAN for green internet of things”. IEEE Access.
3. **Zulfiqar Ali,** KN Qureshi, K Mustafa, R Bukhsh, S Aslam, H Mujlid, KZ Ghafoor. (2022). “Edge based priority-aware dynamic resource allocation for Internet of Things networks”, Entropy 24 (11), 1607.

4. **Zulfiqar Ali,** KN Qureshi, AS Al-Shamayleh, A Akhunzada, A Raza, MFU Butt IEEE Access 11, 2545-2556 (2023). “Delay Optimization in LoRaWAN by Employing Adaptive Scheduling Algorithm With Unsupervised Learning”, Entropy 24 (11), 1607.

6 References

[1] Li, S., Da Xu, L., & Zhao, S. (2018). 5G Internet of Things: A survey. *Journal of Industrial Information Integration*, *10*, 1-9.

[2] Haroon, A., Shah, M. A., Asim, Y., Naeem, W., Kamran, M., & Javaid, Q. (2016). Constraints in the IoT: the world in 2020 and beyond. *International Journal of Advanced Computer Science and Applications*, *7*(11).

[3] Berni, A., & Gregg, W. O. (1973). On the utility of chirp modulation for digital signaling. *IEEE Transactions on Communications*, *21*(6), 748-751.

[4] Raza, U., Kulkarni, P., & Sooriyabandara, M. (2017). Low power wide area networks: An overview. *ieee communications surveys & tutorials*, *19*(2), 855-873.

[5] Vangelista, L., Zanella, A., & Zorzi, M. (2015, September). Long-range IoT technologies: The dawn of LoRa™. In *Future access enablers of ubiquitous and intelligent infrastructures* (pp. 51-58). Springer, Cham.

[6] Paul, A., & Rho, S. (2016). Probabilistic model for M2M in IoT networking and communication. *Telecommunication Systems*, *62*(1), 59-66.

[7] Zalyubovskiy, V., Erzin, A., Astrakov, S., & Choo, H. (2009, June). Energy-efficient area coverage by sensors with two adjustable ranges. In *2009 7th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks* (pp. 1-8). IEEE.

[8] Landaluce, H., Arjona, L., Perallos, A., Falcone, F., Angulo, I., & Muralter, F. (2020). A review of IoT sensing applications and challenges using RFID and wireless sensor networks. *Sensors*, *20*(9), 2495.

[9] Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future generation computer systems*, *29*(7), 1645-1660.

[10] Barrachina-Munoz, S., Bellalta, B., Adame, T., & Bel, A. (2017). Multi-hop communication in the uplink for LPWANs. *Computer Networks*, *123*, 153-168.

[11] Mikhaylov, K., Petaejaejaervi, J., & Haenninen, T. (2016, May). Analysis of capacity and scalability of the LoRa low power wide area network technology. In *European Wireless 2016; 22th European Wireless Conference* (pp. 1-6). VDE.

[12] Baccelli, F., Blaszczyszyn, B., & Muhlethaler, P. (2006). An Aloha protocol for multihop

mobile wireless networks. *IEEE transactions on information theory*, *52*(2), 421-436.

[13] Biral, A., Centenaro, M., Zanella, A., Vangelista, L., & Zorzi, M. (2015). The challenges of M2M massive access in wireless cellular networks. *Digital Communications and Networks*, *1*(1), 1-19.

[14] Glaroudis, D., Iossifides, A., & Chatzimisios, P. (2020). Survey, comparison and research challenges of IoT application protocols for smart farming. *Computer Networks*, *168*, 107037.

[15] Uckelmann, D., Harrison, M., & Michahelles, F. (Eds.). (2011). *Architecting the internet of things*. Springer Science & Business Media.

[16] S. Madakam, R. Ramaswamy, and S. Tripathi, “Internet of Things (IoT): A Literature Review,” *J. Comput. Commun.*, vol. 03, no. 05, pp. 164–173, 2015, doi: 10.4236/jcc.2015.35021.

[17] Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of things: A survey on enabling technologies, protocols, and applications. *IEEE communications surveys & tutorials*, *17*(4), 2347-2376.

[18] Gupta, A., Christie, R., & Manjula, R. (2017). Scalability in internet of things: features, techniques and research challenges. *Int. J. Comput. Intell. Res*, *13*(7), 1617-1627.

[19] Centenaro, M., Vangelista, L., Zanella, A., & Zorzi, M. (2016). Long-range communications in unlicensed bands: The rising stars in the IoT and smart city scenarios. *IEEE Wireless Communications*, *23*(5), 60-67.

[20] Park, G., Lee, W., & Joe, I. (2020). Network resource optimization with reinforcement learning for low power wide area networks. *EURASIP Journal on Wireless Communications and Networking*, *2020*(1), 1-20.

[21] Petajajarvi, J., Mikhaylov, K., Roivainen, A., Hanninen, T., & Pettissalo, M. (2015, December). On the coverage of LPWANs: range evaluation and channel attenuation model for LoRa technology. In *2015 14th international conference on its telecommunications (itst)* (pp. 55-59). IEEE.

[22] Neumann, P., Montavont, J., & Noel, T. (2016, October). Indoor deployment of low-power wide area networks (LPWAN): A LoRaWAN case study. In *2016 IEEE 12th international conference on wireless and mobile computing, networking and communications (WiMob)* (pp. 1-8). IEEE.

[23] Sornin, N., Luis, M., Eirich, T., Kramp, T., & Hersent, O. (2015). Lorawan

specification. *LoRa alliance*, *1*.

[24] Dardari, D., Tralli, V., & Verdone, R. (2000). On the capacity of slotted Aloha with Rayleigh fading: the role played by the number of interferers. *IEEE Communications Letters*, *4*(5), 155-157.

[25] Kumar, R., & Kumar, D. (2016). Hybrid swarm intelligence energy efficient clustered routing algorithm for wireless sensor networks. *Journal of sensors*, *2016*.

[26] Teng, H., Liu, X., Liu, A., Shen, H., Huang, C., & Wang, T. (2018). Adaptive transmission power control for reliable data forwarding in sensor based networks. *Wireless Communications and Mobile Computing*, *2018*.

[27] El Rachkidy, N., Guitton, A., & Kaneko, M. (2019). Collision resolution protocol for delay and energy efficient LoRa networks. *IEEE Transactions on Green Communications and Networking*, *3*(2), 535-551.

[28] Delobel, F., El Rachkidy, N., & Guitton, A. (2017, June). Analysis of the delay of confirmed downlink frames in class B of LoRaWAN. In *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)* (pp. 1-6). IEEE.

[29] Moraes, J., Matni, N., Riker, A., Oliveira, H., Cerqueira, E., Both, C., & Rosário, D. (2020, July). An efficient heuristic LoRaWAN adaptive resource allocation for IoT applications. In *2020 IEEE Symposium on Computers and Communications (ISCC)* (pp. 1-6). IEEE.

[30] Zorbas, D., Papadopoulos, G. Z., Maille, P., Montavont, N., & Douligeris, C. (2018, June). Improving LoRa network capacity using multiple spreading factor configurations. In *2018 25th International Conference on Telecommunications (ICT)* (pp. 516-520). IEEE.

[31] Martinez-Caro, J. M., & Cano, M. D. (2021). A novel holistic approach for performance evaluation in Internet of Things. *International Journal of Communication Systems*, *34*(2), e4454.

[32] Salih, A. A., Zeebaree, S. R., Abdulraheem, A. S., Zebari, R. R., Sadeeq, M. A., & Ahmed, O. M. (2020). Evolution of mobile wireless communication to 5G revolution. *Technology Reports of Kansai University*, *62*(5), 2139-2151.

[33] Chinchilla-Romero, N., Navarro-Ortiz, J., Muñoz, P., & Ameigeiras, P. (2021). Collision avoidance resource allocation for LoRaWAN. *Sensors*, *21*(4), 1218.

[34] Zourmand, A., Hing, A. L. K., Hung, C. W., & AbdulRehman, M. (2019, June). Internet

of things (IoT) using LoRa technology. In *2019 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)* (pp. 324-330). IEEE.

[35] Zaidan, A. A., Zaidan, B. B., Qahtan, M. Y., Albahri, O. S., Albahri, A. S., Alaa, M., ... & Lim, C. K. (2018). A survey on communication components for IoT-based technologies in smart homes. *Telecommunication Systems*, *69*(1), 1-25.

[36] Marais, J. M., Abu-Mahfouz, A. M., & Hancke, G. P. (2020). A Survey on the Viability of Confirmed Traffic in a LoRaWAN. *Ieee Access*, *8*, 9296-9311.

[37] Mdhaffar, A., Chaari, T., Larbi, K., Jmaiel, M., & Freisleben, B. (2017, July). IoT-based health monitoring via LoRaWAN. In *IEEE EUROCON 2017-17th international conference on smart technologies* (pp. 519-524). IEEE.

[38] Molisch, A. F., Balakrishnan, K., Chong, C. C., Emami, S., Fort, A., Karedal, J., ... & Siwiak, K. (2004). IEEE 802.15. 4a channel model-final report. *IEEE P802*, *15*(04), 0662.

[39] Almuhaya, M. A., Jabbar, W. A., Sulaiman, N., & Abdulmalek, S. (2022). A survey on Lorawan technology: Recent trends, opportunities, simulation tools and future directions. *Electronics*, *11*(1), 164.

[40] Jaffar, J., Malik, A. F. A., Zuhairi, M. F. A., Sajak, A. A. B., & Ismail, M. T. (2020, January). Development of the lorawan-based movement tracking system. In *2020 14th International Conference on Ubiquitous Information Management and Communication (IMCOM)* (pp. 1-6). IEEE.

[41] Niles, K., Ray, J., Niles, K., Maxwell, A., & Netchaev, A. (2021). Monitoring for Analytes through LoRa and LoRaWAN Technology. *Procedia Computer Science*, *185*, 152-159.

[42] Manzano, L. G., Boukabache, H., Danzeca, S., Heracleous, N., Murtas, F., Perrin, D., ... & Silari, M. (2021). An IoT LoRaWAN network for environmental radiation monitoring. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-12.

[43] Safi, A., Ahmad, Z., Jehangiri, A. I., Latip, R., Zaman, S. K. U., Khan, M. A., & Ghoniem, R. M. (2022). A fault tolerant surveillance system for fire detection and prevention using LoRaWAN in smart buildings. *Sensors*, *22*(21), 8411.

[44] Bankov, D., Khorov, E., & Lyakhov, A. (2016, November). On the limits of LoRaWAN channel access. In *2016 International conference on engineering and telecommunication (EnT)* (pp. 10-14). IEEE.

[45] Toussaint, J., El Rachkidy, N., & Guitton, A. (2016, October). Performance analysis of the on-the-air activation in LoRaWAN. In *2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)* (pp. 1-7). IEEE.

[46] Tomic, I., Bhatia, L., Breza, M. J., & McCann, J. A. (2018, September). The limits of LoRaWAN in event-triggered wireless networked control systems. In *2018 UKACC 12th International Conference on Control (CONTROL)* (pp. 101-106). IEEE.

[47] A. Lavric and A. I. Petrariu, "LoRaWAN communication protocol: The new era of IoT," *2018 14th Int. Conf. Dev. Appl. Syst. DAS 2018 - Proc.*, pp. 74–77, Jun. 2018, doi: 10.1109/DAAS.2018.8396074.

[48] Johnston, S. J., Basford, P. J., Bulot, F. M., Apetroaie-Cristea, M., Easton, N. H., Davenport, C. & Cox, S. J. (2019). City scale particulate matter monitoring using LoRaWAN based air quality IoT devices. *Sensors*, *19*(1), 209.

[49] Ruano Lin, E. (2016). LoRa protocol. Evaluations, limitations and practical test.

[50] Lavric, A., Petrariu, A. I., Coca, E., & Popa, V. (2020, May). LoRaWAN analysis from a high-density internet of things perspective. In *2020 International Conference on Development and Application Systems (DAS)* (pp. 94-97). IEEE.

[51] Laya, A., Kalalas, C., Vazquez-Gallego, F., Alonso, L., & Alonso-Zarate, J. (2016). Goodbye, aloha! *IEEE access*, *4*, 2029-2044.

[52] Haxhibeqiri, J., Van den Abeele, F., Moerman, I., & Hoebeke, J. (2017). LoRa scalability: A simulation model based on interference measurements. *Sensors*, *17*(6), 1193.

[53] Bianchi, G. (2000). Performance analysis of the IEEE 802.11 distributed coordination function. *IEEE Journal on selected areas in communications*, *18*(3), 535-547.

[54] Haenggi, M. (2005, September). Outage and throughput bounds for stochastic wireless networks. In *Proceedings. International Symposium on Information Theory, 2005. ISIT 2005.* (pp. 2070-2074). IEEE.

[55] Bor, M. C., Roedig, U., Voigt, T., & Alonso, J. M. (2016, November). Do LoRa low-power wide-area networks scale?. In *Proceedings of the 19th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems* (pp. 59-67).

[56] Yi, J., Clausen, T. H., & Townsley, W. M. (2016). C. Systems,"A study of LoRa: long

range & low power networks for the Internet of Things,”. *Sensors*, *16*(9).

[57] Miorandi, D., Sicari, S., De Pellegrini, F., & Chlamtac, I. (2012). Internet of things: Vision, applications and research challenges. *Ad hoc networks*, *10*(7), 1497-1516.

[58] Babaki, J., Rasti, M., & Aslani, R. (2020, August). Dynamic spreading factor and power allocation of LoRa networks for dense IoT deployments. In *2020 IEEE 31St annual international symposium on personal, indoor and mobile radio communications* (pp. 1-6). IEEE.

[59] Alenezi, M., Chai, K. K., Jimaa, S., & Chen, Y. (2019, October). Use of unsupervised learning clustering algorithm to reduce collisions and delay within LoRa system for dense applications. In *2019 international conference on wireless and mobile computing, networking and communications (WiMob)* (pp. 1-5). IEEE.

[60] Cuomo, F., Garlisi, D., Martino, A., & Martino, A. (2020). Predicting lorawan behavior: How machine learning can help. *Computers*, *9*(3), 60.

[61] Ferrari, G., & Tonguz, O. K. (2003, October). MAC protocols and transport capacity in ad hoc wireless networks: Aloha versus PR-CSMA. In *IEEE Military Communications Conference, 2003. MILCOM 2003.* (Vol. 2, pp. 1311-1318). IEEE.

[62] Sorensen, R. B., Kim, D. M., Nielsen, J. J., & Popovski, P. (2017). Analysis of latency and MAC-layer performance for class a LoRaWAN. *IEEE Wireless Communications Letters*, *6*(5), 566-569.

[63] Li, Z., Zozor, S., Brossier, J. M., Varsier, N., & Lampin, Q. (2017, May). 2D time-frequency interference modelling using stochastic geometry for performance evaluation in low-power wide-area networks. In *2017 IEEE International Conference on Communications (ICC)* (pp. 1-7). IEEE.

[64] Wang, J., Jiang, C., Zhang, H., Ren, Y., Chen, K. C., & Hanzo, L. (2020). Thirty years of machine learning: The road to Pareto-optimal wireless networks. *IEEE Communications Surveys & Tutorials*, *22*(3), 1472-1514.

[65] Cui, S., & Joe, I. (2020). Collision prediction for a low power wide area network using deep learning methods. *Journal of Communications and Networks*, *22*(3), 205-214.

[66] Paul, B. (2020). A novel mathematical model to evaluate the impact of packet retransmissions in lorawan. *IEEE Sensors Letters*, *4*(5), 1-4.

[67] Alenezi, M., Chai, K. K., Alam, A. S., Chen, Y., & Jimaa, S. (2020). Unsupervised learning clustering and dynamic transmission scheduling for efficient dense LoRaWAN

networks. *IEEE Access*, *8*, 191495-191509.

[68] Kumar, J. S., Zaveri, M. A., & Choksi, M. (2017). Task based resource scheduling in IoT environment for disaster management. *Procedia computer science*, *115*, 846-852.

[69] Cuomo, F., Campo, M., Caponi, A., Bianchi, G., Rossini, G., & Pisani, P. (2017, October). EXPLoRa: Extending the performance of LoRa by suitable spreading factor allocations. In *2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)* (pp. 1-8). IEEE.

[70] Lima, E., Moraes, J., Oliveira, H., Cerqueira, E., Zeadally, S., & Rosário, D. (2021). Adaptive priority-aware LoRaWAN resource allocation for Internet of Things applications. *Ad Hoc Networks*, *122*, 102598.

[71] Chungsawat, N., & Siripongwutikorn, P. (2020, July). Predicting application performance in LoRa IoT networks. In *Proceedings of the 11th International Conference on Advances in Information Technology* (pp. 1-7).

[72] Kim, D. H., Lee, E. K., & Kim, J. (2019). Experiencing LoRa network establishment on a smart energy campus testbed. *Sustainability*, *11*(7), 1917.

[73] Dawaliby, S., Bradai, A., & Pousset, Y. (2019). Adaptive dynamic network slicing in LoRa networks. *Future generation computer systems*, *98*, 697-707.

[74] Abdelfadeel, K. Q., Cionca, V., & Pesch, D. (2018, June). Fair adaptive data rate allocation and power control in LoRaWAN. In *2018 IEEE 19th International Symposium on" A World of Wireless, Mobile and Multimedia Networks"(WoWMoM)* (pp. 14-15). IEEE.

[75] Benkahla, N., Tounsi, H., Ye-Qiong, S. O. N. G., & Frikha, M. (2019, June). Enhanced ADR for LoRaWAN networks with mobility. In *2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC)* (pp. 1-6). IEEE.

[76] Yang, X., Fapojuwo, A., & Egbogah, E. (2012, September). Performance analysis and parameter optimization of random access backoff algorithm in LTE. In *2012 IEEE Vehicular Technology Conference (VTC Fall)* (pp. 1-5). IEEE.

[77] Sivakumar, N. R. (2020). Stabilizing energy consumption in unequal clusters of wireless sensor networks. *Comput. Mater. Contin*, *64*, 81-96.

[78] Ali, Z. (2016). Shagufta Henna, Adnan Akhunzada, Mohsin Raza, and Sung Won Kim.«. *Performance Evaluation of LoRaWAN for Green Internet of Things'. IEEE Access*, *4*.

[79] Balakrishna, S., Thirumaran, M., & Solanki, V. (2020). Machine Learning based Improved Gaussian Mixture Model for IoT Real-Time Data Analysis: Análisis de los datos. *Ingeniería Solidaria*, *16*(1).

[80] Asad Ullah, M., Iqbal, J., Hoeller, A., Souza, R. D., & Alves, H. (2019). K-means spreading factor allocation for large-scale LoRa networks. *Sensors*, *19*(21), 4723.

[81] Uprety, A., & Rawat, D. B. (2020). Reinforcement learning for IoT Security: A Comprehensive Survey. IEEE Internet Things J.,(2021).

[82] Zeb, A., Ali, Q., Saleem, M. Q., Awan, K. M., Alowayr, A. S., Uddin, J., ... & Bashir, F. (2019). A proposed IoT-enabled smart waste bin management system and efficient route selection. *Journal of Computer Networks and Communications*, *2019*.

[83] van Roermund, T. (2019). In-Vehicle Networks and Security. *Automotive Systems and Software Engineering: State of the Art and Future Trends*, 265-282.

[84] Duangsuwan, S., & Maw, M. M. (2021). Comparison of Path Loss Prediction Models for UAV and IoT Air-to-Ground Communication System in Rural Precision Farming Environment. *J. Commun.*, *16*(2), 60-66.

[85] Benammar, M., Abdaoui, A., Ahmad, S. H., Touati, F., & Kadri, A. (2018). A modular IoT platform for real-time indoor air quality monitoring. *Sensors*, *18*(2), 581.

[86] Basford, P. J., Bulot, F. M., Apetroaie-Cristea, M., Cox, S. J., & Ossont, S. J. (2020). LoRaWAN for smart city IoT deployments: A long term evaluation. *Sensors*, *20*(3), 648.

[87] Haxhibeqiri, J., De Poorter, E., Moerman, I., & Hoebeke, J. (2018). A survey of LoRaWAN for IoT: From technology to application. *Sensors*, *18*(11), 3995.

[88] Hossain, T., Doi, Y., Tazin, T., Ahad, M. A. R., & Inoue, S. (2018, October). Study of lorawan technology for activity recognition. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers* (pp. 1449-1453).

[89] Ortín, J., Cesana, M., & Redondi, A. (2018, September). How do ALOHA and listen before talk coexist in LoRaWAN?. In *2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)* (pp. 1-7). IEEE.

[90] Phung, K. H., Tran, H., Nguyen, Q., Huong, T. T., & Nguyen, T. L. (2018, January). Analysis and assessment of LoRaWAN. In *2018 2nd International Conference on Recent Advances in Signal Processing, Telecommunications & Computing (SigTelCom)* (pp. 241-246). IEEE.

[91] Chinchilla-Romero, N., Navarro-Ortiz, J., Muñoz, P., & Ameigeiras, P. (2021). Collision avoidance resource allocation for LoRaWAN. *Sensors*, *21*(4), 1218.

[92] Rahmadhani, A., & Kuipers, F. (2018, October). When lorawan frames collide. In *Proceedings of the 12th International Workshop on Wireless Network Testbeds, Experimental Evaluation & Characterization* (pp. 89-97).

[93] Efimov, S. E., Stepanov, N. V., & Turlikov, A. M. (2021, May). Research LoRaWAN collide signals with used SDR. In *2021 Wave Electronics and its Application in Information and Telecommunication Systems (WECONF)* (pp. 1-5). IEEE.

[94] Marini, R., Mikhaylov, K., Pasolini, G., & Buratti, C. (2021). Lorawansim: A flexible simulator for lorawan networks. *Sensors*, *21*(3), 695.

[95] Ertürk, M. A., Aydın, M. A., Büyükakkaşlar, M. T., & Evirgen, H. (2019). A survey on LoRaWAN architecture, protocol and technologies. *Future Internet*, *11*(10), 216.

[96] Callebaut, G., Ottoy, G., & Van der Perre, L. (2019, April). Cross-layer framework and optimization for efficient use of the energy budget of IoT Nodes. In *2019 IEEE Wireless Communications and Networking Conference (WCNC)* (pp. 1-6). IEEE.

[97] Kufakunesu, R., Hancke, G. P., & Abu-Mahfouz, A. M. (2020). A survey on adaptive data rate optimization in lorawan: Recent solutions and major challenges. *Sensors*, *20*(18), 5044.

[98] Ilahi, I., Usama, M., Farooq, M. O., Janjua, M. U., & Qadir, J. (2020, November). LoRaDRL: deep reinforcement learning based adaptive PHY layer transmission parameters selection for LoRaWAN. In *2020 IEEE 45th Conference on Local Computer Networks (LCN)* (pp. 457-460). IEEE.

[99] Polonelli, T., Brunelli, D., Marzocchi, A., & Benini, L. (2019). Slotted aloha on lorawan-design, analysis, and deployment. *Sensors*, *19*(4), 838.

[100] Ortín, J., Cesana, M., & Redondi, A. (2019). Augmenting LoRaWAN performance with listen before talk. *IEEE Transactions on Wireless Communications*, *18*(6), 3113-3128.

[101] Polonelli, T., Brunelli, D., Marzocchi, A., & Benini, L. (2019). Slotted aloha on lorawan-design, analysis, and deployment. *Sensors*, *19*(4), 838.

[102] El Rachkidy, N., Guitton, A., & Kaneko, M. (2019). Collision resolution protocol for delay and energy efficient LoRa networks. *IEEE Transactions on Green Communications and Networking*, *3*(2), 535-551.

[103] Torroglosa-Garcia, E. M., Calero, J. M. A., Bernabe, J. B., & Skarmeta, A. (2020).

Enabling roaming across heterogeneous IoT wireless networks: LoRaWAN MEETS 5G. *IEEE Access*, *8*, 103164-103180.

[104] Yousuf, A. M., Rochester, E. M., & Ghaderi, M. (2018, February). A low-cost LoRaWAN testbed for IoT: Implementation and measurements. In *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)* (pp. 361-366). IEEE.

[105] Agarwal, V., Sharma, S., & Agarwal, P. (2021). IoT based smart transport management and vehicle-to-vehicle communication system. In *Computer Networks, Big Data and IoT: Proceedings of ICCBI 2020* (pp. 709-716). Springer Singapore.

[106] Sandoval, R. M., Garcia-Sanchez, A. J., & Garcia-Haro, J. (2019). Optimizing and updating lora communication parameters: A machine learning approach. *IEEE Transactions on Network and Service Management*, *16*(3), 884-895.

[107] Mekki, K., Bajic, E., Chaxel, F., & Meyer, F. (2019). A comparative study of LPWAN technologies for large-scale IoT deployment. *ICT express*, *5*(1), 1-7.

[108] Liando, J. C., Gamage, A., Tengourtius, A. W., & Li, M. (2019). Known and unknown facts of LoRa: Experiences from a large-scale measurement study. *ACM Transactions on Sensor Networks (TOSN)*, *15*(2), 1-35.

[109] Voigt, T., Bor, M., Roedig, U., & Alonso, J. (2016). Mitigating inter-network interference in LoRa networks. *arXiv preprint arXiv:1611.00688*.

[110] Duncombe, J. U. (1959). Infrared navigation—Part I: An assessment of feasibility. *IEEE Trans. Electron Devices*, *11*(1), 34-39.

[111] Adame Vázquez, T., Barrachina-Muñoz, S., Bellalta, B., & Bel, A. (2018). HARE: Supporting efficient uplink multi-hop communications in self-organizing LPWANs. *Sensors*, *18*(1), 115.

[112] Zhu, G., Liao, C. H., Sakdejayont, T., Lai, I. W., Narusue, Y., & Morikawa, H. (2019). Improving the capacity of a mesh LoRa network by spreading-factor-based network clustering. *IEEE Access*, *7*, 21584-21596.

[113] Aihara, N., Adachi, K., Takyu, O., Ohta, M., & Fujii, T. (2019). Q-learning aided resource allocation and environment recognition in LoRaWAN with CSMA/CA. *IEEE Access*, *7*, 152126-152137.

[114] Adi, E., Anwar, A., Baig, Z., & Zeadally, S. (2020). Machine learning and data analytics for the IoT. *Neural Computing and Applications*, *32*(20), 16205-16233.

[115] El-Aasser, M., Elshabrawy, T., & Ashour, M. (2018, December). Joint spreading factor

and coding rate assignment in LoRaWAN networks. In *2018 IEEE global conference on internet of things (GCIoT)* (pp. 1-7). IEEE.

[116] Alam, A. S., Hu, Y. F., Pillai, P., Xu, K., & Baddoo, J. (2017). Optimal datalink selection for future aeronautical telecommunication networks. *IEEE Transactions on Aerospace and Electronic Systems*, *53*(5), 2502-2515.

[117] Yu, H. W., & Zhang, B. (2018). A heterogeneous network selection algorithm based on network attribute and user preference. *AD hoc Networks*, *72*, 68-80.

[118] Alenezi, M., Chai, K. K., Chen, Y., & Jimaa, S. (2020). Ultra-dense LoRaWAN: Reviews and challenges. *IET Communications*, *14*(9), 1361-1371.

[119] Farhad, A., Kim, D. H., & Pyun, J. Y. (2020). Resource allocation to massive internet of things in lorawans. *Sensors*, *20*(9), 2645.

[120] Bankov, D., Khorov, E., & Lyakhov, A. (2020, July). An Algorithm to Satisfy the QoS Requirements in a Heterogeneous LoRaWAN Network. In *2020 IEEE Symposium on Computers and Communications (ISCC)* (pp. 1-6). IEEE.

[121] Kwasme, H., & Ekin, S. (2019). RSSI-based localization using LoRaWAN technology. *IEEE Access*, *7*, 99856-99866.

[122] Coutaud, U., Heusse, M., & Tourancheau, B. (2020). High reliability in LoRaWAN. In *2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications* (pp. 1-7). IEEE.

[123] Sanz, J. M., Delgado, C., Blondia, C., & Famaey, J. (2021). Batteryless LoRaWAN Communications Using Energy Harvesting: Modeling and Characterization.

[124] Witayarat, A., Jansang, A., & Phonphoem, A. (2019, July). The Effects of Duty Cycle Limit to Small Single Gateway LoRaWAN Protocol Network. In *2019 16th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)* (pp. 701-704). IEEE.