

Media Access Control for LoRaWAN

BY

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TABLE OF CONTENTS

TABLE OF CONTENTS	V
LIST OF FIGURES	VIII
LIST OF ABBREVIATIONS	IX
ABSTRACT	X
الملخص	XI
CHAPTER 1 INTRODUCTION	1
1.1 Applications of IoT	2
1.2 Research Objectives	7
1.3 Problem Statement	8
1.4 Research Contribution	8
CHAPTER 2 BACKGROUND & RELATED WORK	9
2.1 LoRaWAN	9
2.1.1 LoRaWAN MAC Layer	12
2.2 ALOHA and Slotted ALOHA	12
2.2.1 Slotted ALOHA	14
2.3 Reinforcement Learning	15
2.4 Related Work	18

CHAPTER 3 METHODOLOGY	23
3.1 Reinforcement Learning-based Multi-Channel ALOHA	23
3.2 The Principal Idea.....	23
3.3 Notation and System Model	23
3.4 The Proposed Scheme	25
8 CHAPTER 4 PERFORMANCE EVALUATION.....	29
4.1 Choosing the Simulator	29
4.2 The Experimental Setup	31
4.3 Result and Discussions	35
CHAPTER 5 CONCLUSION.....	43
REFERENCES.....	44

LIST OF TABLES

Table 1 LoRa simulators comparison [36][37].....	30
Table 2 Hardware specifications used in the experiment.	33
Table 3 RL-MAC Simulator Configurations	33
Table 4 Q-Table of RL-MCA with One Gateway for 100 Nodes	34
Table 5 Experiment 1 for Single Gateway for RL-MCA	35
Table 6 Experiment 2 for Two Gateways for RL-MCA.....	36
Table 7 Experiment 3 for Four Gateways for RL-MCA.....	37
Table 8 ALOHA Parameters.....	37
Table 9 Experiment 1 for Single Gateway for ALOHA	38
Table 10 Experiment 2 for Two Gateways for ALOHA	38
Table 11 Experiment 3 for Four Gateways for ALOHA	39
Table 12 Comparative of RL-MCA and ALOHA for $N=600$ and $M=4$	42

LIST OF FIGURES

Figure 1 High-level Architecture of IoT Systems.....	2
Figure 2 Smart Home Application.....	3
Figure 3 IoT for Individuals with Physical Disabilities.....	4
Figure 4 IoT Technology for Mitigating Natural Disasters	4
Figure 5 Power Consumption and Coverage Area	5
Figure 6 Power consumption vs Range for BLE, Cellular, LoRAWAN, and Wi-Fi [20].....	6
Figure 7 Architecture of LoRaWAN System.....	10
Figure 8 Class A Window Time Frame.	11
Figure 9 Typical Model for ALOHA Network.....	13
Figure 10 Pure ALOHA.....	13
Figure 11 Collisions of Packets.	14
Figure 12 Slotted ALOHA.....	15
Figure 13 The Markov Decision Process (MDP) Framework.	16
Figure 14 System Model.....	24
Figure 15 Simulation Setup	32
Figure 16: Gateway placement for single, double, and four gateways.....	33
Figure 17 PDR vs Nodes.....	40
Figure 18 Average Transmitted Packets vs Nodes	40
Figure 19:Collision vs Nodes.....	41
Figure 20: Energy Consumption vs Nodes	41

LIST OF ABBREVIATIONS

IoT: Internet of Things

ICT: Information and Communication Technology

MAC: Media Access Control

LoRa: Long Range

ISM: Unlicensed Industrial, Scientific, and Medical

ADR: Adaptive Data Rate

LTE: Long Term Evaluation

LPWAN: Low-Power Wide Area Network

RL: Reinforcement Learning

SF: Spreading Factor

LoRaWAN: LoRa Wide Area Network

ABSTRACT

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Billions of devices are currently online, but most of them are computers, laptops, tablets, televisions, and smart phones. In the future, all things will be able to connect to the Internet through the Internet of Things (IoT) [1]. For example, various IoT devices are already being used to connect to the Internet. Wearables like the Google Glasses, Xiaomi MI Band Trackers, and smart jackets made by Levi's and Google's Jacquard are few examples of such technology [1]. LoRaWAN is an increasingly popular IoT wireless access technology that is characterized by low power and long range. In this thesis, we propose a novel Media Access Control (MAC) scheme for LoRaWAN. The new scheme enhances the multichannel ALOHA scheme used by LoRaWAN using Reinforcement Learning (RL). To our knowledge, this is the first study to propose such a scheme under LoRaWAN. The performance of the proposed scheme is evaluated via simulations and compared to the standard multichannel ALOHA in LoRaWAN. The experiments show the integrated approach demonstrates notable efficacy as substantiated by empirical data, indicating a remarkable throughput surpassing 82% within a network configuration featuring a singular gateway interfacing with 600 nodes. This attainment marks a substantial advancement compared to the maximum throughput of 60% achieved by the conventional ALOHA model operating under equivalent circumstances. Regarding collision dynamics, the amalgamation of ALOHA with reinforcement learning achieved an average collision rate of approximately 45, notably lower than the average collision rate of approximately 71 observed with ALOHA alone under comparable nodes and gateways configurations.

الملخص

الاسم: محمد عثمان عمر الاسم: محمد عثمان عمر

عنوان الدراسة: التحكم في الوصول لواجهة LoRaWAN

المجال الرئيسي: هندسة الحاسوب

تاريخ الحصول على الدرجة: يونيو، ٢٠٢٤

أصبحت تكنولوجيا المعلومات والاتصالات جزءاً لا يتجزأ من جميع الدول الصناعية والنامية تقريباً. يمكن لتكنولوجيا المعلومات والاتصالات تحسين جودة الحياة في مجموعة متنوعة من السياقات، بما في ذلك الرعاية الصحية والتعليم والزراعة والأمن. تمكن إنترنت الأشياء من توسيع خدمات تكنولوجيا المعلومات والاتصالات خارج نطاق الآلات العادية، مما يمنح الأشياء مرونة وإمكانية الوصول على مستوى العالم. تتمثل أربعة أركان لإنترنت الأشياء في الأشياء ذاتها والأشخاص والعمليات والبيانات. حالياً، هناك مليارات الأجهزة متصلة بالإنترنت، ولكن معظمها إما أجهزة كمبيوتر أو أجهزة لابتوب أو أجهزة لوحية أو تلفزيونات أو هواتف ذكية. بينما في المستقبل، ستمكن كل الأشياء من الاتصال بالإنترنت من خلال إنترنت الأشياء. علاوة على ذلك، يتم استخدام مجموعة متنوعة من أجهزة إنترنت الأشياء للاتصال بالإنترنت. ومن الأمثلة على هذه التكنولوجيا هي الأجهزة القابلة للارتداء مثل نظارات جوجل Google Glasses، متعقبات Xiaomi MI Band، والسترات الذكية التي أنتجتها Levi's بالتعاون مع Jacquard من جوجل. تعتبر LoRa تكنولوجيا لاسلكية لإنترنت الأشياء تحظى بشعبية متزايدة، وهي تتميز بالطاقة المنخفضة والنطاق الطويل. في هذه الرسالة، نقترح نظاماً جديداً للتحكم في الوصول إلى الوسائط (MAC) لـ LoRaWAN. يقوم النظام الجديد بتعزيز نظام ALOHA متعدد القنوات المستخدم في LoRaWAN باستخدام التعلم التعزيزي. وعلى حد علمنا، فإن هذه هي أول دراسة تقترح مثل هذا النظام في إطار LoRaWAN. تم تقييم أداء النظام المقترح من خلال المحاكاة ومقارنته بنظام ALOHA متعدد القنوات

القياسي في LoRaWAN. تظهر التجارب أن النهج المتكامل يظهر كفاءة ملحوظة كما يظهر البيانات التجريبية، مشيرة إلى قدرة تحمل ملحوظة تفوق 82% ضمن تكوين شبكي يضم بوابة واحدة تتفاعل مع 600 جهاز. هذا الإنجاز يمثل تقدماً كبيراً مقارنة بالنتائج الأقصى للنظام القياسي ALOHA والذي بلغ 60% في ظروف مماثلة. فيما يتعلق بديناميات التصادم، فإن دمج ALOHA مع التعلم التعزيزي باستخدام أربعة بوابات حقق معدل تصادم متوسط يبلغ حوالي ٤٥ ، وهو أقل بكثير من معدل التصادم الذي يبلغ حوالي ٧١ و الذي تمت ملاحظته مع نظام ALOHA تحت نفس الظروف

CHAPTER 1

INTRODUCTION

Information and Communication Technology (ICT) is now an integral aspect of nearly all industrialized and developing nations. ICT can enhance the quality of life in a variety of contexts, including healthcare, education, agriculture, and security. The Internet of Things (IoT) enables ICT to expand its services beyond ordinary machines, giving things worldwide accessibility and flexibility. The four pillars of IoT are objects, people, processes, and data.

The utilization of data is greatly improved by connectivity to the Internet. Instead of simply exchanging information, data can be collected, analyzed, and used to remotely control devices over the Internet. This has led to a new era termed the fourth industrial revolution that is spearheaded by IoT [1]. IoT exploits smart devices and the Internet to offer creative solutions to a wide range of problems and issues related to various sectors [2] [3]. Additionally, IoT can benefit many industries by enabling ideas like autonomous vehicles, smart transportation systems, smart homes, and smart grids, and more [4]. Today's networks, and especially 5G, have allowed IoT to become so popular and provide higher data rates, better coverage, and high throughput, which has enabled IoT to be used in mission critical applications such as drones and robotics [5]. IoT provides the ability to directly integrate various physical things with computer systems and allows remote control of devices. Figure 1 depicts a high-level architecture of IoT systems [6].

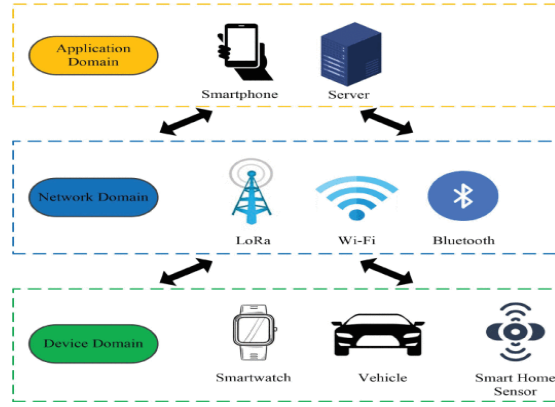


Figure 1 High-level Architecture of IoT Systems

The core principle of IoT revolves around the interconnection of diverse electronic devices, encompassing both digital and analog functionalities. These devices exhibit varying characteristics and operate within overlapping transmission ranges, facilitating seamless communication. This domain of technology is witnessing rapid expansion and is anticipated to burgeon significantly in the foreseeable future [8].

1.1 Applications of IoT

IoT applications span all domains. Consider a smart home application as illustrated in Figure 2, where a person could place a water bottle to cool in the refrigerator. Instead of waiting, the person can go to do other thing while the bottle is cooling. Once ready, the refrigerator sensor can send out a broadcast message labeled ‘Search’ to all sensors placed throughout the house, including those in the living room, foyer, and dining room, to determine the person’s location, and alert him to go to the refrigerator to take the water bottle.

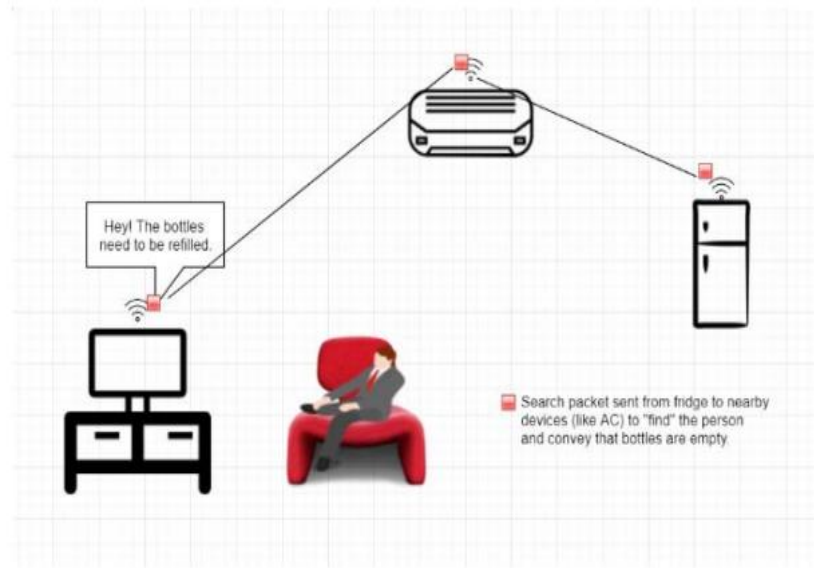


Figure 2 Smart Home Application

IoT has emerged as a powerful tool for addressing the unique challenges faced by individuals with disabilities or special needs in their daily lives. By leveraging IoT technologies, innovative solutions can be developed to enhance accessibility and improve the quality of life for such individuals. One example is the creation of a new web application that is accessible to all, ensuring compliance with the guidelines set forth by the Department of Empowerment of Persons with Disabilities (DEPwD) under the Ministry of Social Justice and Empowerment in India. This initiative aligns with the Access India campaign (Sugamya Bharat Abhiyan) [8], a global effort aimed at achieving universal accessibility for individuals with disabilities. Through the integration of IoT into various aspects of daily life, we can create inclusive environments and empower individuals with disabilities to participate more fully in society as we can see in Figure 3.

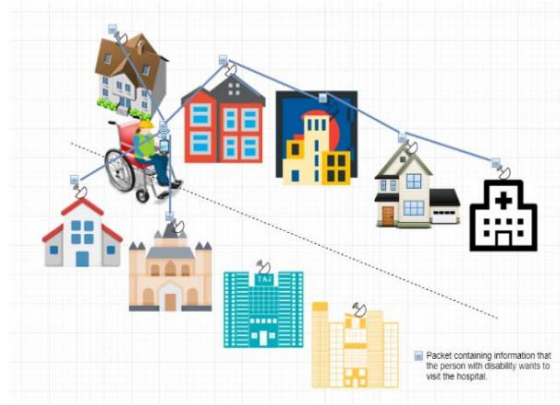


Figure 3 IoT for Individuals with Physical Disabilities

The Internet of Things (IoT) holds significant potential in forecasting and mitigating the impact of various natural calamities, including earthquakes, tsunamis, flash floods, thunderstorms, hailstorms, incessant rain, and high tides. By deploying sensor nodes in vulnerable regions and (SHIP) cluster-oriented network of IoT-compliant nodes, swift dissemination of critical information becomes feasible, even in remote and isolated areas. For instance, in regions encompassing disaster-prone areas, this network enables the prompt initiation of relief efforts, facilitating the timely rescue and relocation of affected individuals to secure locations [8], as illustrated Figure 4.

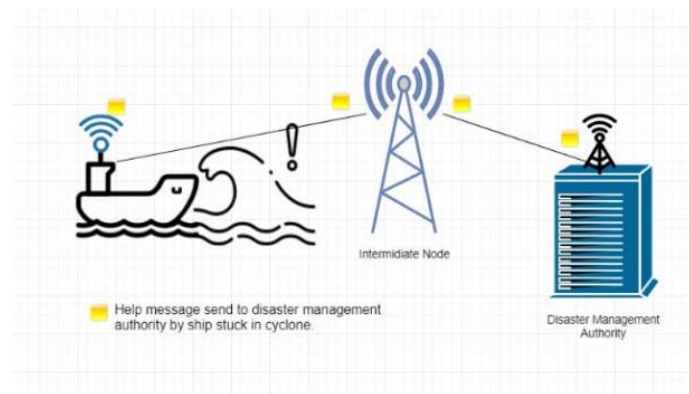


Figure 4 IoT Technology for Mitigating Natural Disasters

A key in any IoT system is its communication technology. Many technologies are being developed for various application scenarios. LoRaWAN has recently been introduced as a low-power, long-range wireless communications technology for IoT. Its extended range enables

sending data over several kilometers while consuming a small amount of power. The network protocol for LoRaWAN is maintained by the LoRa Alliance [9] which defines the network and medium access control (MAC) specifications. The protocol operates over the unlicensed Industrial, Scientific, and Medical (ISM) spectrum which enhances its flexibility and cost [10]. LoRaWAN also has an Adaptive Data Rate (ADR) mode, that uses different Spreading Factor (SF) configurations, that vary data rates depending on the distance of the device from the gateway [11].

While technologies like ZigBee and Bluetooth are popular, they are limited to short distances. The study in [12], includes three different comparative experiments (point to point, horizontal and vertical experiments) on the link performance between ZigBee and LoRa were test in an indoor campus in China, to test their effect on the performance. The building where the test was performed has 12 floors, each is 4-meter high. The study concluded that overall, LoRa offers better performance, making it a desirable option for network deployment over the whole campus especially when considering cost and energy consumption. For these reasons, LoRa has been used extensively in many sectors such as agriculture for applications like livestock monitoring, tractor communications, and location tracing [13] [14]. Figure 5 presents a summary of the power consumption profile and coverage area of different classes of technologies.

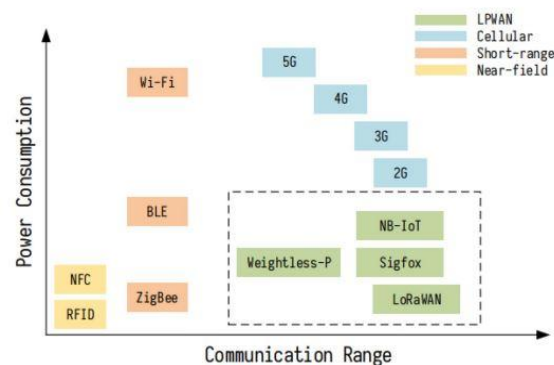


Figure 5 Power Consumption and Coverage Area

Figure 6 depicts the power consumption and communication range for some of the wireless communication technologies. It can be seen that LoRaWAN falls in the long range and lower power consumption when compared against with Bluetooth/LE, Wi-Fi and cellular network [20].

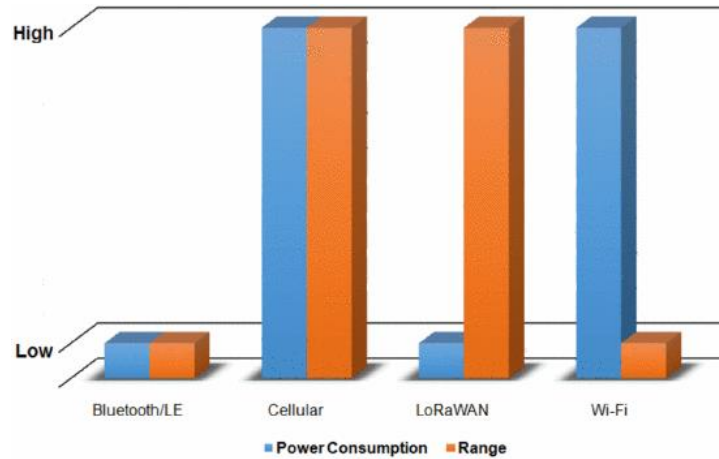


Figure 6 Power consumption vs Range for BLE, Cellular, LoRAWAN, and Wi-Fi [20]

Another competitor to LoRaWAN is NB-IoT which is developed by the 3GPP project. Its goal is to scale wireless sensor network nodes to be more dependable and usable, and it uses the licensed frequency bands for Long Term Evaluation (LTE). Another competitor is Sigfox, which is a public wireless sensor network deployment with large universal IoT network for connecting big number of things broadcasting data without setup and network connections [15].

MAC protocol design has historically been a field of research because of its significant impact on the overall system performance. LoRaWAN MAC is based on the ALOHA protocol, where nodes start sending packets without knowing the channel status [17]. ALOHA and its variants have the problem of low throughput and poor Packet Delivery Ratio (PDR) at high load [17]. Due to the ALOHA-based MAC that LoRaWAN uses for its uplink operation, it has been shown to have a low PDR, particularly when traffic load is high [18]. Such limitation is undesirable for many industrial applications, like predictive maintenance or critical health

applications [18][19], which require high reliability and low latency. To overcome this problem, network operators, solution providers and researchers started investigating LoRaWAN in recent years.

The main objective of the study is to propose a new MAC protocol for LoRaWAN using Reinforcement Learning and evaluate its performance compared to multichannel ALOHA. The main metrics used in the evaluation are collisions, PDR, and energy consumption.

The remaining of thesis are as follows: Chapter 2 provides background on LoRaWAN, ALOHA, and Reinforcement Learning (RL); and outlines a literature review of the most recent work relevant to the research topic. Chapter 3 presents the proposed media access scheme. Chapter 4 discusses the simulation setup and performance evaluation. Finally, Chapter 5 provides a conclusion to the study.

1.2 Research Objectives

The principal objective of this study is to enhance the performance of the MAC layer of LoRaWAN using RL.

To reach the main objective of this research, we can divide it into these sub-objectives:

- Developing an RL-based MAC scheme.
- Designing and performing representative experimental scenarios to evaluate the proposed scheme and compare it to the ALOHA-based MAC in LoRAWAN.
- Collecting the experimental data and analyzing results.
- Provide conclusion and recommendations to aid the design of future MAC layer for LoRaWAN.

1.3 Problem Statement

Studies have shown that the throughput of MAC in LoRAWAN has limitations when the number of end nodes increases, due to increased collisions [28]. In addition to limiting scalability, this results in higher latency and energy consumption. Many solutions have been proposed in the literature. In this research, we propose a novel multi-channel media access scheme using Reinforcement Learning. The proposed scheme is evaluated using simulations with respect to collisions, PDR, and energy consumption; and compared to the standard multichannel ALOHA scheme used in LoRAWAN. The study also provides an insight into how the MAC strategy used affects the scalability of the system and recommends ways to overcome such limitations.

1.4 Research Contribution

The main contribution of this research is designing a novel MAC scheme using RL to enhance multi-channel ALOHA protocol. Similar existing studies have proposed using RL but in a typical single-channel time-based access. Despite their proven improvements, time-based access ALOHA requires synchronization which diminishes LoRaWAN low-power claim. Furthermore, most schemes assume single-channel ALOHA which does not take advantage of the multi-channel nature of LoRaWAN.

CHAPTER 2

BACKGROUND & RELATED WORK

In this chapter, we will undertake an examination of the background information and related work.

2.1 LoRaWAN

LoRaWAN is one of the favorable technologies of LPWAN that achieves low power, long distance, and small data rate technology. A LoRaWAN network is comprised of gateways, end nodes, network server, and applications servers. End devices send their data over LoRaWAN links to gateways, and gateways forward these frames over an IP link to the network server which in turn forwards them to application servers, and vice versa [21]. The foundation of LoRaWAN technology lies in the LoRa radio technology developed by Semtech. LoRa employs a spread spectrum modulation technique, based on chirp modulation, to enable transmissions over extended distances at low rates. The LoRa Alliance standardizes the network architecture and MAC layer protocols for the LoRaWAN technology [23]. The main modulation parameter is the Spread Factor (SF) which affects the data rate and radio transmission range. Signals modulated with variety of SF parameters are orthogonal, therefore they can be decoded when transmitting at a similar time and on the same frequency. Alternatively, it is possible to decode signals using the same SF when their power levels differ by more than 6 dB [22].

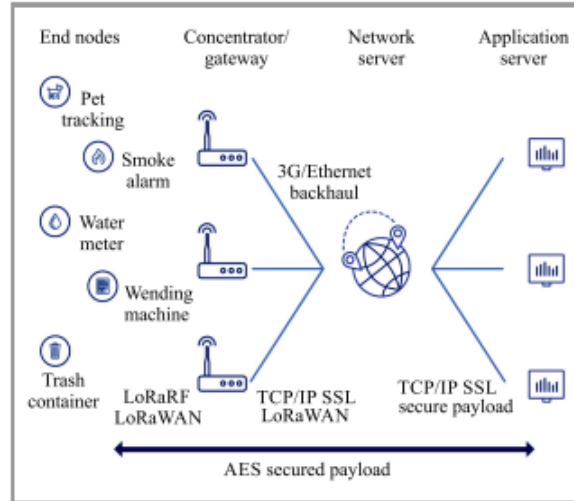


Figure 7 Architecture of LoRaWAN System

The LoRaWAN network utilizes a star topology architecture, while end device communicates with gateways in defined range. The gateways work as packet relays in connecting with network server by encapsulating data frames into IP packet using UDP/ TCP. The network server then sends those packets to the designated application server [22]. Application servers can also communicate with the end devices using the reverse path.

LoRaWAN offers three operational classes: Class A, tailored for energy-constrained devices; Class B, permitting synchronized network-initiated downlink frames to prompt additional receive windows for nodes, enhancing end-node predictability; and Class C, suitable for nodes with ample energy resources, enabling continuous listening for received data.

Low power nodes use Class A, as it uses low energy compared to the other two classes. The functionality of Class A must be included to all nodes on LoRaWAN. The transmit window is utilized in Class A implementation for up-link communication, while the two received windows RX1 and RX2 are used for downlink communication, as illustrated in Figure 8. The data rate for the transmitting window and RX1 is same, however the delay slot time varies depending on the area [21].

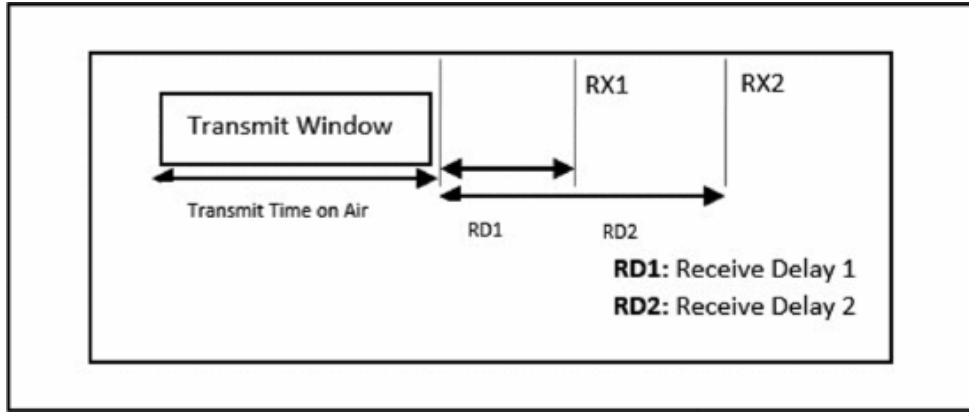


Figure 8 Class A Window Time Frame.

MAC Commands, which are included in the LoRaWAN specifications, can alter the transmission rate for RX2. After the RX2 window, the network server has to wait for the subsequent transmission call, that the end device shall begin. Class B is similar to Class A with the added feature that a node wakes up at regular intervals. This ensures the availability of nodes at predictable times. All nodes linked to the network are attached as Class A nodes initially, then the application decides if the nodes act as Class B or Class C. The state of Class B is swapped by setting the Class B bit that is present in the MAC's Frame Control field to format the class message. Class C devices are usually mains powered and consume more power than the rest of other classes. In addition, Class C are always ready to receive data. The idea behind a Class C node is to have the RX2 window continuously open until downlink communication takes place. Note class B cannot be implementable in Class C [21].

The LoRaWAN protocol features reliable and secure communication. Adaptive Data Rate (ADR) dynamically manages link parameters to increase packet delivery throughput. The link settings can be managed on both the terminal side and the network server side. According to the documentation of the standard [11], the terminal first tries to resolve the connection to increase its transmission capacity. If this is not enough, it will continue to reduce the data rate [22].

2.1.1 LoRaWAN MAC Layer

End-device access to LoRaWAN operates on a pure-ALOHA basis, which is a random-access protocol allowing multiple devices to transmit data across a shared channel without prior coordination. In simpler terms, when a node has data to send, it immediately transmits a packet without coordinating with other nodes or sensing/control mechanisms to check for ongoing transmissions. This lack of coordination results in more collisions, significantly elevating the likelihood of packet loss, particularly in large networks. To enhance transmission reliability, LoRaWAN incorporates acknowledgment messages to confirm data reception, thus introducing confirmed message transmission. This addition is crucial for improving downlink communication efficiency and scalability, as confirmed message delivery, especially for downlink traffic, imposes constraints on network capacity [24].

2.2 ALOHA and Slotted ALOHA

One of the primary hurdles faced by IoT technology is the limited capacity of the hardware employed. Consequently, the most apparent approach to implement media access control in IoT systems revolves around random access protocols. Due to its simplicity, ALOHA has emerged as the natural selection. The initial ALOHA setup encompassed two separate frequencies organized within a central hub. Previously, ALOHA channels were utilized for signaling and control objectives. With the advancement of technology and the widespread adoption of GPRS, ALOHA channels started being integrated into GPRS mediums within 3G-capable mobile devices. The framework of an ALOHA-based system is depicted in Figure 9, illustrating multiple nodes or stations connected to a central base station. The transmission spectrum is depicted as 407 MHz for uploading and 413 MHz for downloading [20]. ALOHA can be classified into two fundamental variants: Pure ALOHA and Slotted ALOHA.

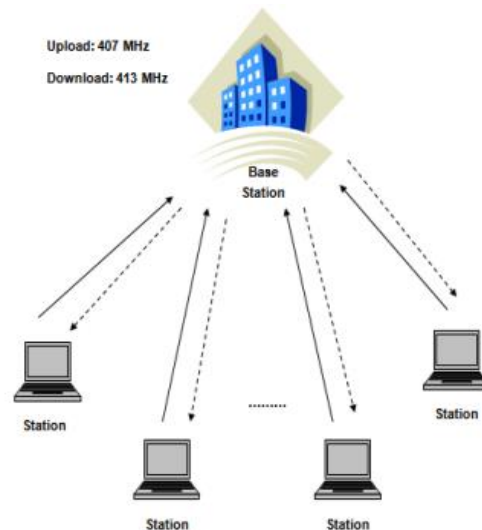


Figure 9 Typical Model for ALOHA Network

Pure ALOHA permits any station to send data whenever they have it. Every time a station transmits data without first ensuring that the channel is clear, there is a chance the data frames will collide. Figure 10 shows the principle of pure ALOHA.

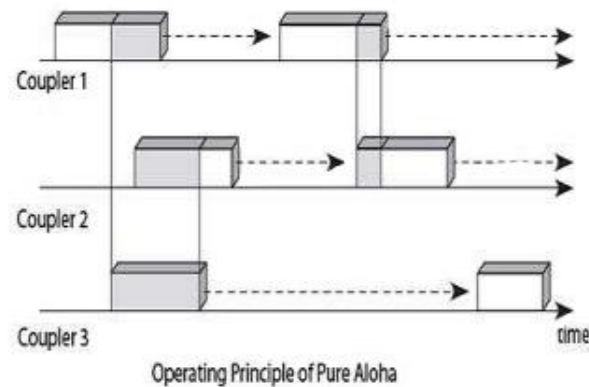


Figure 10 Pure ALOHA

If the received frame were acknowledged, everything would be good. Otherwise, the two frames clash and they are damaged. It simply considers that a node must send whatever data packet it wants to send, regardless of what any other nodes are doing. A collision occurs when a node transmits a data packet, and another node also happens to submit data at the same time. The data packets must be resent later in the event of a collision. The networking system's

overall throughput is decreased by the retransitions [20]. Figure 11 shows how a collision of packets looks like.

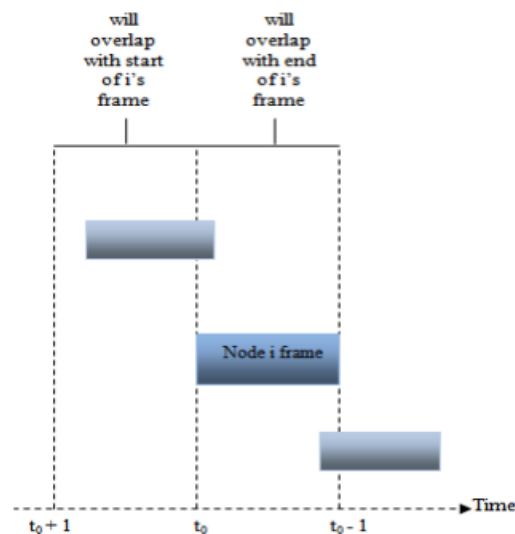


Figure 11 Collisions of Packets.

2.2.1 Slotted ALOHA

A refined version of the original ALOHA protocol is slotted ALOHA, which operates by initiating transmissions at predetermined intervals rather than immediately. Slotted ALOHA divides time into discrete periods, each consisting of frames with an equal number of bits, typically denoted as L . Time is then segmented into designated intervals of L/R seconds in duration. Nodes are only required to transmit data at the onset of these timed slots. The key feature of slotted ALOHA is its synchronization mechanism, which informs nodes of the precise timing for the beginning of each slot. This synchronization significantly contributes to enhancing throughput. Figure 12 illustrates the operational concept of slotted ALOHA.

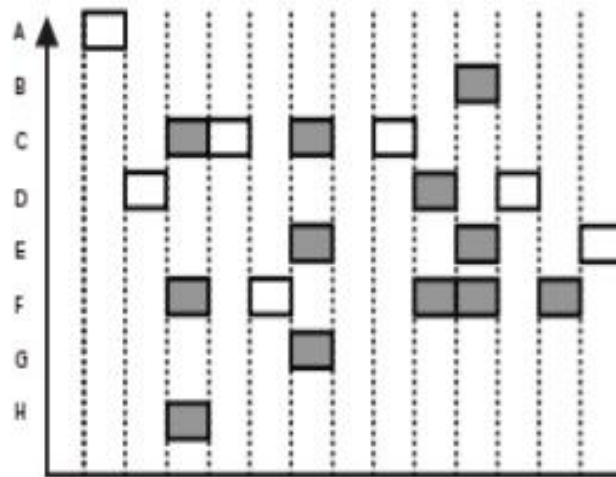


Figure 12 Slotted ALOHA

2.3 Reinforcement Learning

Reinforcement Learning (RL) is a popular unsupervised Machine Learning techniques which involves an agent engaging with its surroundings, acquiring knowledge through experimentation. This concept has been extensively discussed in works by Sutton and Barto (1998, 2018), Bertsekas and Tsitsiklis (1996), Bertsekas (2012), Szepesvari (2010), and Powell (2011) [25].

The illustration depicted in Figure 13 illustrates the RL paradigm, comprising two fundamental elements: the agent and the system. The agent, functioning as an ever-learning decision-maker, embodies the RL algorithm. It endeavors to acquire knowledge and mastery over the system through purposeful interactions. Conversely, the system encompasses all aspects beyond the agent's direct influence, remaining immutable to arbitrary alterations. In the context of process control, the agent corresponds to the controller logic, while the remainder constitutes the system. One of the most popular RL techniques is Q-Learning. The decision-making process of Q-learning is structured within the framework of the Markov Decision process (MDP) [26].

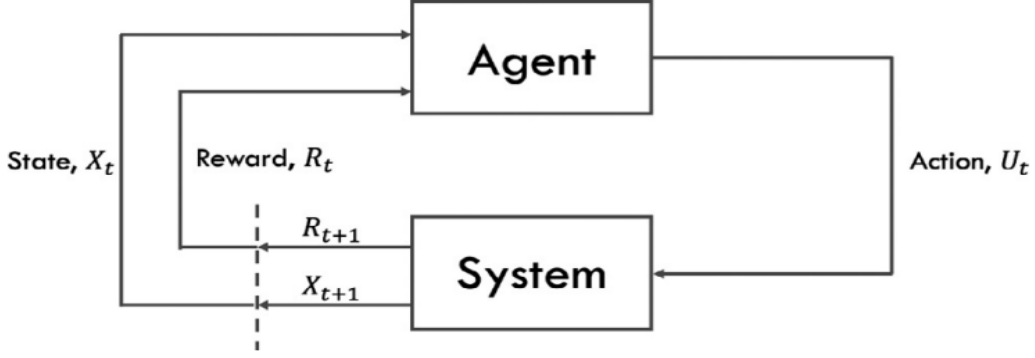


Figure 13 The Markov Decision Process (MDP) Framework.

In RL, MDPs offer a framework for modeling sequential decision-making challenges. An MDP is characterized by a tuple (S, A, p, r) , where S denotes the set of possible states and A represents the set of feasible actions. The function $S \times A \rightarrow [0, 1]$ defines a probabilistic transition model, where each entry $p(s_0 | s, a)$ indicates the probability of transitioning from state s to s_0 given action a . Similarly, the function $r: S \times A \times S \rightarrow \mathbb{R}$ represents the reward function.

During the agent-environment interaction at time t , the agent observes a state s_t from the environment and selects an action a_t . Consequently, the environment transitions to state s_{t+1} , and the agent receives a reward $r(s_t, a_t)$. The primary goal of the agent is to maximize the cumulative reward it accumulates through these interactions [27].

$$G_t = E[\sum_{k=0}^{\infty} \gamma^k r(s_t + k, a_t + k) | s_0 = s_t]$$

In the context of reinforcement learning, the discount factor γ plays a crucial role in determining the importance of future rewards. To assess the desirability of being in a particular state s , we rely on the value function, denoted as $V(s)$. This function encapsulates the expected cumulative reward that can be obtained starting from state s and following a given policy.

$$V(s) = E[G_t | S_t = s]$$

In evaluating the attractiveness of a particular state s and the action a taken within it, one commonly employs a quality metric referred to as Q , or the action-value function.

$$Q(s,a) = E [G_t \mid S_t = s, a_t = a]$$

The objective evolves into obtaining the optimal strategy from the action-value function $Q^*(s, a)$ by applying the Bellman optimality equation.

$$\pi^* = \arg \max_{a \in A} Q^*(s, a), \forall s \in S$$

One method for addressing this equation is through the utilization of the Q-learning algorithm [27]. In contrast to on-policy techniques like SARSA and actor-critic algorithms such as A2C, the method employed here is distinct for its off-policy nature and sole reliance on a critic. In this approach, the Q-value function is represented as a lookup table, which is initially filled with random estimates and subsequently refined iteratively through updates dictated by the Bellman Equation. [27].

$$Q(s, a) = Q(s, a) + \alpha [r(s, a) + \gamma \max_{a \in A} Q(s', a) - Q(s, a)]$$

At its core, the proposed algorithm relies on Q-Learning to develop a policy for selecting a channel and spread factor. In the context of Q-Learning, let the α , γ , ϵ , and $1 - \epsilon$ denote the learning rate, discount factor, exploitation rate, and exploration rate, respectively.

The *exploration rate* (ϵ) signifies the likelihood that an agent within a reinforcement learning framework opts to explore a new action instead of exploiting existing knowledge by selecting the action with the highest expected reward. It plays a crucial role in maintaining the equilibrium between exploration, aimed at gathering new information, and exploitation, focused on maximizing immediate rewards based on current knowledge. The *exploitation rate*

$(1-\epsilon)$ is the opposite of the exploration rate in reinforcement learning. It signifies the likelihood that an agent selects an action based on its current knowledge to maximize expected rewards. This rate demonstrates the agent's inclination to favor actions with historically high rewards, drawing upon its acquired knowledge. The learning rate (α) is a pivotal parameter in reinforcement learning algorithms, dictating the degree to which fresh information supersedes prior knowledge during the process of updating state or action value estimations. It governs the pace at which the agent adjusts its Q-values or policy in response to observed rewards and experiences [38].

2.4 Related Work

LoRaWAN has garnered considerable attention within the research community, with particular emphasis placed on the examination of its Medium Access Control (MAC) protocol. This protocol has been the subject of extensive investigation and analysis. The study in [29] examines six distinct backoff strategies implemented within a Slotted-ALOHA-based LoRaWAN network framework. A comprehensive suite of simulation results is utilized to assess their efficacy under diverse load scenarios, employing performance metrics including delay, throughput, and packet loss rate.

The results derived from the simulation of the EFB backoff algorithm suggest its efficacy in contexts characterized by elevated traffic volumes. Particularly, as evidenced by the data provided, wherein an approximate rate of 0.35 successful packets per time slot and a media access delay of 1000 units were observed, the application of the EFB algorithm manifests a discernible decrease in access delay as it attains its maximal operational effectiveness.

The algorithm under consideration employs a mechanism characterized by a progressive adjustment of the contention window (CW) size in response to collision events, wherein the CW is incrementally augmented following collisions and subsequently reduced following

successful transmissions by the node. This iterative process enables each node to adapt its CW more dynamically subsequent to a successful transmission, thereby enhancing its synchronization with the prevailing traffic conditions. Notably, a higher preceding CW value signifies a heightened frequency of collisions, indicative of heavier traffic loads. Nevertheless, the utilization of a Fibonacci-based methodology for CW adjustment introduces an inherent trade-off between throughput and delay, as it tends to elevate the average delay experienced within the system. Furthermore, the application of the aforementioned algorithm, denoted as the ASB algorithm, demonstrates its efficacy across a spectrum of traffic intensities, albeit with a marginal drawback discernible in the realm of network throughput observed under very specific (medium) traffic conditions where it was slightly outperformed by BEB, ECA, and EBEB. for λ in the range of $(1, 1.7) * 10^{-3}$, the delay for ASB exhibits a steeper increase compared to BEB, ECA, and EBEB. In scenarios of low and high traffic volumes, ASB achieves optimal throughput, equal to 0.35, when compared to other strategies, while also maintaining lower average access delay across each node equal to $3.5 * 10^{-3}$. Additionally, as traffic load escalates, the algorithm demonstrates efficient adaptation and reduction in access delay.

The investigation conducted in reference [30] explores an LPWAN functioning within a licensed-exempt frequency band. LoRa, characterized by its low power consumption, facilitates extensive connectivity over significant distances for a multitude of devices. Regarding the link budget, devices situated far from the central gateway encounter interference stemming from nearby devices during data transmission. To mitigate collisions within the Long-Range network, Chirp Spread Spectrum (CSS) modulation employs a range of Spreading Factors (SF) assigned to active nodes. The proposed approach integrates a multi-agent Q-learning strategy to allocate control and range dynamically to LoRa uplink communications, aiming to enhance communication reliability and energy efficiency. The primary objectives

revolve around reducing the power consumption during uplink transmission while simultaneously enhancing network reliability. Through simulations, the study underscores the advantages of their Q-learning algorithm, showcasing improvements in Signal-to-Interference-plus-Noise Ratio (SINR), data transmission rates, and transmit power efficiency. Guidelines-based techniques for setting transmission parameters in the physical layer are a key contributor to packet collisions, leading to significant performance deterioration in densely populated LPWAN environments. LoRaWAN, a leading LPWAN technology, employs LoRa as its physical layer.

In this article [31], a reinforcement learning agent has been developed to compare with the central ADR module. This novel agent functions smoothly across all end nodes while maintaining rapid responsiveness to fluctuations. A comparative evaluation is conducted between the traditional ADR and the newly proposed RL-based ADR agent through discrete event simulation. Findings indicate that the novel ADR mechanism can identify optimal configurations, and the proposed reward function aligns well with the intended learning procedure.

With the objective of developing an adaptive LoRaWAN strategy suitable for industrial applications, this study [32] proposes utilizing Reinforcement Learning (RL) techniques. RL has gained traction across various domains due to its capacity to construct intelligent systems employing a stochastic discrete-time system methodology. The suggested approach has been integrated into a custom simulator, facilitating an initial evaluation of performance within a real-world setting. The assessment includes a consideration of a high density of independent nodes per square kilometer, demonstrating a notable enhancement (approximately 10%) in overall reliability concerning the data extraction rate (DER), while maintaining complete compatibility with standard specifications.

LoRa exclusively defines the physical layer protocol, while LoRaWAN operates as a medium access control (MAC) layer protocol built on top of it. However, utilizing ALOHA alone within LoRaWAN results in a high packet collision rate, especially when there is a large number of end-devices within the network, as numerous end-devices attempt to transmit packets to the gateway simultaneously. In order to address this issue, the authors propose [33] a reinforcement learning (RL)-based multi-access approach for LoRaWAN. This approach empowers end-devices to make informed decisions on when to transmit data based on the prevailing environment, thereby mitigating the packet collision rate. The paper also includes a comparison between the RL method and ALOHA, demonstrating that the RL method achieves a lower packet collision rate.

the authors utilize the PHC algorithm, a Q-learning-based approach, to educate the end-devices, enabling them to understand the channel conditions and make optimal decisions to maximize rewards, essentially transmitting data swiftly while minimizing collision occurrences. In comparison to slotted ALOHA, PHC algorithm demonstrates superior performance in collision reduction and convergence speed, especially in scenarios involving a large number of end-devices. Nonetheless, certain limitations persist with this method, notably instability observed when the number of end-devices approaches the total slots available in the superframe. Additionally, end-devices have the capability to employ a listening mechanism to ascertain channel availability, thereby conserving energy compared to direct data transmission.

This study [34] introduces a fresh Medium Access Control (MAC) protocol dubbed ALOHA and Q-Learning-based MAC featuring Informed Receiving (ALOHA-QIR) for Wireless Sensor Networks (WSNs). This approach melds frame-based Slotted ALOHA with Q-Learning. While ALOHA-based methods offer simplicity, minimal computational requirements, and low overheads, they are susceptible to collisions due to their blind transmission approach. Q-Learning, which takes into account past transmission experiences,

equips nodes with the ability to intelligently access slots with a reduced likelihood of collision. During data transmission, transmitters notify receivers about their forthcoming slot selections, enabling receivers to deactivate their radios in other slots to conserve energy. ALOHA-QIR demonstrates significant enhancements in throughput, delay, and energy efficiency compared to standard Slotted ALOHA.

The optimization of emergency data transmission is the central focus of the Q-Learning framework proposed in this paper [35]. However, given the multifaceted nature of real-world deployments, it may be necessary to further refine our Q-Learning approach to broaden its applicability.

During emergency data transmission, a comparative analysis of eOQ-MAC with CSMA/CA, S-MAC, and ALOHA-Q reveals significant performance improvements. Specifically, eOQ-MAC demonstrates substantial reductions in packet loss rates of 79.6%, 79.7%, and 48.9% compared to CSMA/CA, S-MAC, and ALOHA-Q, respectively. Moreover, the average delay experienced with eOQ-MAC decreases by 22.9%, 20.7%, and 9.1%, while the throughput increases by 28.1%, 34.3%, and 12.9%, respectively, in contrast to the aforementioned protocols. Furthermore, from the perspective of overall data transmission, eOQ-MAC showcases reductions in packet loss rates of 61.4%, 61.5%, and 7.9% compared to CSMA/CA, S-MAC, and ALOHA-Q, respectively. Correspondingly, the average delay is reduced by 19.1%, 18.2%, and 3.8%, while the throughput is enhanced by 24.8%, 27.3%, and 2.4%, respectively. Empirical findings confirm that eOQ-MAC significantly enhances the reliability of emergency data transmission across diverse scenarios, thereby optimizing the utilization of emergency time slots. Moreover, the utilization of enhancement objective Q-Learning underpins the efficacy of eOQ-MAC in improving performance metrics aligned with its enhancement objectives.

CHAPTER 3

METHODOLOGY

3.1 Reinforcement Learning-based Multi-Channel ALOHA

Within this chapter, we provide a detailed description of the proposed random media access scheme named Reinforcement Learning-based Multi-Channel ALOHA (RL-MCA). We start with a description of the central idea of the algorithm. Then, we introduce the notation and system model used. Finally, a formal description of the proposed scheme is presented.

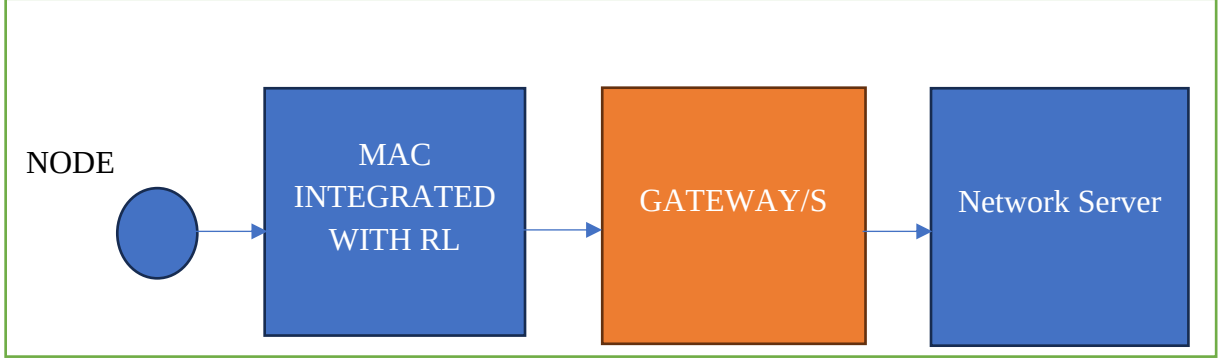
3.2 The Principal Idea

The choice of random media access in LoRaWAN is driven by the fact that IoT applications have low transmission rate and therefore it's more appealing to use random media access as it provides low complexity and satisfactory performance under low load.

In the realm of Internet of Things (IoT), data transmissions typically occur in response to either event-driven stimuli, where transmissions coincide with the detection of pertinent phenomena; or periodically, wherein transmissions are scheduled at regular intervals. In both scenarios, there exists a probability distribution governing the timing of device operations. Given this framework, the integration of random-access mechanisms with reinforcement learning techniques proves advantageous. Specifically, employing Q-learning facilitates the determination of such probability distributions. Moreover, preceding schemes lacked the benefit of multi-channel capabilities. In contrast, our proposed scheme capitalizes on multi-channel functionality, thereby enhancing efficiency and performance.

3.3 Notation and System Model

In our study, a LoRaWAN network comprising nodes, gateways, and a network server was posited as a foundational premise.



- Nodes: denote the peripheral devices or sensors positioned at the periphery of the network infrastructure, commonly tasked with the transmission of data to a centralized gateway.
- Gateway: In the LoRaWAN architecture, a gateway functions as an intermediary interface connecting end-node devices with the network server, thereby enabling bidirectional communication. This entails the reception of transmissions originating from end-nodes, forwarding of these transmissions to the server, and reciprocally relaying data from the server to the end-nodes.
- Network-Server: In LoRaWAN, a network server main role is data reception, encryption protocols, and routing data to application servers.

We assume a LoRaWAN network of N nodes and M Gateways. Also, time is assumed to be divided into equal intervals; in each interval t , a random number of nodes attempt to transmit their data to the gateways through the LoRaWAN network. In each attempt, a node selects a random channel and a spread factor pairs. Let

$$C = \{c1, c2, \dots, cl\}$$

be the set of channels and

$$SF = \{sf1, sf2, \dots, sfk\}$$

be the set of spread factors.

3.4 The Proposed Scheme

The algorithm RL-MCA was developed in this study, representing an amalgamation of ALOHA with Q-learning. This composite approach embodies a fusion of two distinct methodologies, namely, the random-access protocol ALOHA and the reinforcement learning technique Q-learning. In the ensuing discourse, the learning process of RL-MCA will be described initially, followed by an exposition on the utilization of the developed policy.

The proposed approach consists of two primary components. The first component utilizes the Q-Learning algorithm to construct an estimate of the probability distribution of access collisions across various nodes, considering different channel and SF configurations.

The algorithm considers two states represented by 0 or 1. State 0 represents a transmission where the previous attempt was successful. On the other hand, State 1 represents a state where the previous attempt was a collision. Moreover, the policy is represented by a matrix comprising two rows and six columns. Initially, this matrix assumes a null state, with all elements set to zero. Following this initial learning stage, successive iterations occur, where the matrix evolves into a complete policy.

The study explores a system encompassing eight distinct channels and six spread factors, delineated by their respective combinations. Initially, channel and SF selections are randomized, followed by subsequent selections informed by a learning algorithm. Within this framework, a binary matrix emerges, characterized by two states: 0 or 1. Initially set to zero, this matrix evolves through iterative engagement with the learning process, gradually acquiring non-zero values. This iterative evolution persists until the prescribed process is completed.

Let $Q_{\square}$ be a $2 \times |SF| \times |C|$ probability matrix, where $|SF|$ is the magnitude of the SF vector and $|C|$ is the magnitude of the C vector. We define state $\in \{0,1\}$ to be current state of the system.

Also, let α , γ , ϵ , and $1 - \epsilon$, defines the learning rate, discount factor, exploration rate, and exploitation rate, respectively.

Algorithm 1

Input: *state*

// Selecting the action for the given state

Define Function (*state*)

If `random.random() <  $\epsilon$` :

// Explor: choose a random action

action = random integer between 0 and $|SF| \times |C| - 1$

Else:

// Exploit: choose action with maximum Q-value

action = index of maximum Q – value in $q_table[state]$

// Converting the action to SF and CH

Calculate $sf = action / |SF|$

Freq = action mod $|C|$

Return *sf, freq*

Updating *q_table*

Define Function (*state, action, next_state, reward*)

Best_next_action = index of maximum Q – value in q_table [next_state]

q_value = q_table [state, action]

Next_q_value = q_table[next_state, best_next_action]

*New_q_value = q_value + α (reward + γ * next_q_value – q_value)*

Update q_table [state, action] to new_q_value

The listing above shows the proposed algorithm. In the learning phase, the algorithm explores and develops the policy using the Q-Learning algorithm. After learning converges, the q_table contains the policy of assigning SF and CH. After this, the policy is utilized by selecting the SF and CH based on the highest q-value.

Part 1

The algorithm receives as input the current state of the last transmission. It commences its operation by initiating a random selection process based on a predefined exploration rate, whereby actions are chosen probabilistically. Alternatively, in the absence of a random selection, the algorithm elects to pursue the action associated with the highest *q_value* stored within the *q_table* pertinent to the current state under consideration.

Part 2

The algorithm operates on the current matrix, wherein it associates a given action with a pair comprising a SF and a frequency index. This association is established through a process involving the determination of the SF, which is computed by performing integer division on

the action by the total count of spread factors. Subsequently, the algorithm proceeds to ascertain the frequency channel index before ultimately returning both the computed SF and the corresponding frequency index.

Part 3

1. The function ``update_q_table`` is defined to update Q-values based on state, action, reward, and next_state.
2. It calculates the *best_next_action* as the index of the maximum Q-value in the *q_table* for the *next_state*.
3. *q_value* is obtained from the *q_table* for the given state and action.
4. *Next_q_value* is retrieved from the *q_table* for the *next_state* and the *best_next_action*.
5. The Q-value is updated using the formula: $New_q_value = q_value + \alpha (reward + \gamma * next_q_value - q_value)$, and the *q_table* entry for the state-action pair is updated to *new_q_value*.

CHAPTER 4

PERFORMANCE EVALUATION

Computer modeling and simulation plays a crucial role in exploring the performance of computing systems and assessing its operation in cost effective and timely manners. Particularly, simulation in the context of LoRa networks holds significant importance as it allows for exploration without the need for costly implementation prior to actual deployment, facilitating the design and evaluation of LoRa-based applications [36].

In this chapter, we evaluate the proposed scheme against the standard LoRaWAN MAC. In what follows, we discuss the selection criteria for the simulator, the experimental setup, and the findings derived from the experimentations. The aim of this study is to assess the improvements in Packet Delivery Ratio (PDR), collision occurrences, and energy consumption of the proposed scheme compared to the standard LoRaWAN MAC.

4.1 The Simulator

In the realm of LoRaWAN, there exists a variety of specialized simulation tools that are freely available. These tools have been developed and utilized in the literature to investigate various LoRaWAN aspects. Despite the abundance of these simulation tools, previous review studies have not conducted a comprehensive comparison among them. Thus, there is a need to provide an overview of the commonly used simulators for examining LoRa/LoRaWAN performance. This overview aims to bridge the gap in understanding by presenting a detailed comparison of these simulation tools.

Table 1 LoRa simulators comparison [36][37]

Features	LoRaSim	NS-3	FLoRa	CupCarbon	PHY Simulator
License type	Source is open	Source is open	Source is open	Free (education)	Free
Operating system	macOS, Linux, Windows	Linux, Windows	Linux, Windows, macOS	macOS	MacOS, Windows
Installation requirements	SimPy, NumPy, matplotlib	Import all libraries online	OMNeT++ 6 and INET 4.3.1	Java	Matlab
Type language	Python	C++, Python	C++	Java	MATLAB
GUI	Only plot	Yes	Yes	2D or 3D with OSM	Only plot
Community support	Limited	Very Good	Limited	Good	Good
Last update	2020	October 2020	November 2020	2020	2020
Last version	n/a	ns-3.32	6.0	3.8	n/a
Popularity	High	High	Medium	Little	High

Table 1 shows five simulation tools for simulating LoRaWAN, where each of the five simulators operate on discrete events, specifically tailored to support the LoRaWAN protocol while modeling network dynamics through sequential events in discrete time intervals. This architecture enables the simulators to automatically transition to the next event in the absence of changes between consecutive events, eliminating the need for continuous monitoring. Moreover, all the simulators are built on widely recognized and community-supported programming frameworks. This aspect is crucial as it facilitates rapid extension of the simulators' functionalities by specialists through the development of new modules or integration of supplementary tools within the existing environment, thereby enhancing support for new network protocols or incorporating additional functionalities seamlessly.

The research undertaken in this investigation encompassed simulations executed utilizing the LoRaSIM platform integrated with RL-MCA. This amalgamation enabled the examination of diverse metrics including PDF, collision rates, and energy consumption. Furthermore, the

adoption of a widely recognized programming language resulted in expedited computational processes, enhanced efficacy, and streamlined integration protocols.

4.2 The Experimental Setup

The study plans included conducting three separate simulations, each with unique sets of parameters, to evaluate their individual performances comprehensively. Following the completion of these simulations, an in-depth analysis of the results was conducted to demonstrate the effectiveness of each simulation configuration.

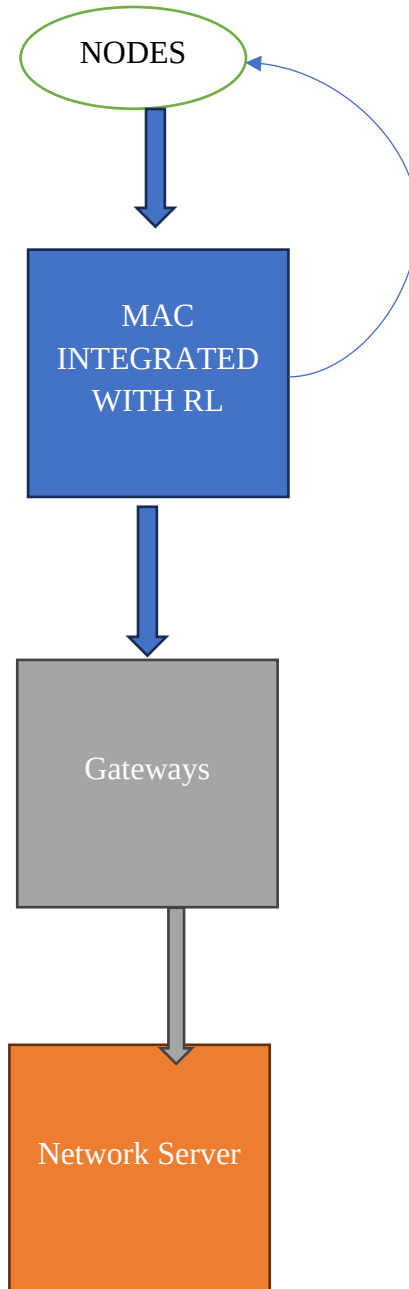


Figure 15 Simulation Setup

As mentioned before, the developed simulator is based on LoRaSIM [29] which is written in Python. The simulator enables simulation on LoRaWAN network with multiple gateways. For the physical layer, the log-distance path loss model with a minimum sensitivity of -132 dBm is used. The simulation allows generating different networks with different number of nodes and gateways. The following figures show the topology and gateway placement for single, double and quadric gateways. The nodes are uniformly distributed over the network area. The

arrow shows the maximum distance between a node and the given gateway. Table 3 shows the input parameters of the simulator. As seen in Figure 16, the network area is assumed to contain as many squares as there are gateways. Each square has a diagonal equals to the maximum transmission range of the gateways.

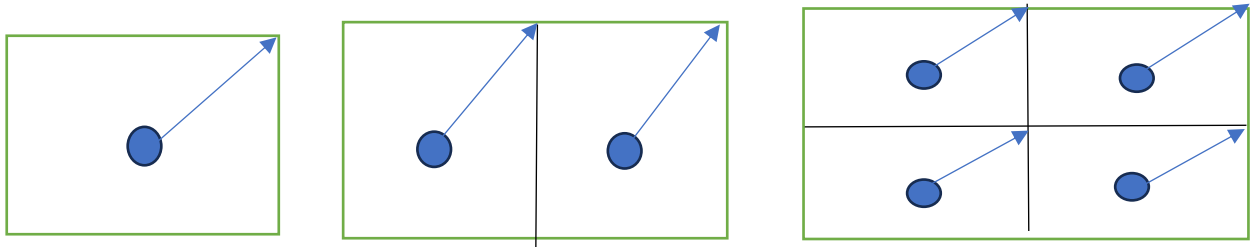


Figure 16: Gateway placement for single, double, and four gateways

Table 2 Hardware specifications used in the experiment.

Name	Description
CPU	Intel Core I7
OS	Windows 11
MEMORY	16 GB

Table 3 RL-MAC Simulator Configurations

Number of Gateways	1,2 or 4
Number of Nodes	100-600
GENERATION_PERIOD	500 ms
NO_GENERATION	1000
AVG_TRANS_TIME	2000 ms
LEARNING_RATE	0.7
DISCOUNT_FACTOR	0.9
EXPLORATION_RATE	0.1
Frequency channels	8

The simulator runs as follows:

- Generate a network based on the number of gateways as seen above. Generate a random topology by distributing the nodes uniformly at random over the area.
- The simulation processed in generations where in each generation a random number of nodes attempt to transmit. The simulation duration is determined as the number of

generations times the duration of each generation. The inter-transmission for each node is exponentially distributed with a mean equal $1/AVG_TRANS_TIME$.

- Each node includes a q_table that stores the q_values for each state/action combination.
- When a node is to transmit, the SF and CH are selected using the Q-Learning algorithm, the packet is forwarded to all gateways that are in the range of the node, and we test for collision. The q_table is then updated based on the result of the attempt.
- The simulator records the required performance measures including, PDR, collisions, and energy consumption.

Table 4 Q-Table of RL-MCA with One Gateway for 100 Nodes

[[137.88307265	0.	0.	177.41888852	175.9974799	194.39836564	118.4100518	0.	98.51366563	194.24737852	181.63661626	194.21873986	134.562145	121.32685381	139.95137952	0.	39.96362935	134.94279485	0.	104.11846941	60.86232614	138.03125756	134.562145	0.	0.	101.41770904	185.09619212	169.4540858	0.	119.50219164	0.	181.52636879	199.94226881	137.55240218	139.42667744	139.23357929	136.95707526	139.88384875	0.	139.88384875	181.44119994	45.74544674	197.97044175	0.	127.91865772	139.82047448	0.	139.74194548]
[	0.	0.	0.	0.	0.	0.	0.	0.	0.	-14.	0.	0.	0.	0.	0.	-14.	0.	0.	0.	0.	-18.2	0.	-14.	0.	-18.2	0.	0.	0.	0.	0.	0.	-14.	0.	0.	0.	0.	-14.	-18.2	]]								

The above tables show the structure of q_table of the combination of SF and Channels. The values shown corresponds to one node after completing the training phase.

Within the simulator, each node has a 2×48 q_table corresponding to two states and 48 actions. Initially, this matrix is empty, representing a MAC that learns over time and subsequently determines the optimal action.

4.3 Result and Discussions

Before discussing the results, it is useful to define the performance criteria used:

Packet Delivery Rate (PDR): refers to the percentage of successfully delivered packets out of the total sent.

Average Transmitted Packets per Generation refer to the average number of packets transmitted per generation simultaneously.

Average Collisions per Generation: refers to the average number of collided packets per generation. Note that a single collision may lead to multiple packets lost. Also, a single packet may encounter multiple collisions seen at different multiple gateways.

Average Energy per Packet: is defined as the total energy over the course of the simulation over the number of successfully received packets.

EXPERIMENT 1:

In this experiment, we examine the performance of the proposed scheme under different network sizes. We tested different networks with different number of nodes, denoted as N , ranging from 100 to 600, alongside a single gateway, represented by $M=1$. The subsequent table and graph present data regarding Packet Delivery Ratio (PDR), Energy Consumption, and collisions. Table 5 shows the outcome of nodes starting from 100 to 600 with single gateway.

Table 5 Experiment 1 for Single Gateway for RL-MCA

Nodes	Average Collision	Average Transmitted Packets	PDR	Energy Consumption [mJ]
100	1.5865	21.808	0.859	16.30
200	3.47	43.908	0.844	16.58
300	5.6295	65.946	0.831	16.867

400	8.6695	87.615	0.823	17.008
500	8.715	109.717	0.811	17.26
600	10.907	132.282	0.802	17.43

EXPERIMENT 2:

A scenario with a variable number of nodes, denoted as N, ranging from 100 to 600, alongside a double gateway, represented by M=2. The subsequent table and graph present data regarding Packet Delivery Ratio (PDR), Average Transmitted Packets, Energy Consumption, and other relevant metrics. In this experimental observation, a discernible increment of 10% is evident in comparison to the outcomes observed in the initial experiment. Table 6 shows the outcome of nodes starting from 100 to 600 with double gateway.

Table 6 Experiment 2 for Two Gateways for RL-MCA

Nodes	Average Collision	Average Transmitted Packets	PDR	Energy Consumption [mJ]
100	2.014	21.823	0.9071	15.435
200	5.886	43.951	0.8596	16.2866
300	11.872	65.786	0.84770	16.5167
400	14.0385	88.055	0.84298	16.72
500	20.6925	110.12	0.82104	17.05
600	24.486	132.039	0.81580	17.161

EXPERIMENT 3:

In this case examines a scenario with a variable number of nodes, denoted as N, ranging from 100 to 600, alongside a quadric gateway, represented by M equaling 4. The subsequent table and graph present data regarding Packet Delivery Ratio (PDR), Average Transmitted Packets,

Energy Consumption, and other relevant metrics. Table 7 shows the outcome of nodes starting from 100 to 600 with four gateways.

Table 7 Experiment 3 for Four Gateways for RL-MCA

Nodes	Average Collision	Average Transmitted Packets	PDR	Energy Consumption [mJ]
100	2.465	21.862	0.934	14.977
200	9.885	43.804	0.887	15.78
300	17.284	65.438	0.8580	16.317
400	26.139	88.071	0.8483	16.509
500	35.751	109.831	0.8320	16.83
600	45.088	131.758	0.8221	17.03

In the subsequent table, we delineate the network parameters. The number of nodes (N) is presumed to fluctuate between 100 and 600, as depicted in the accompanying graphical representation. These nodes are dispersed randomly across the network, interspersed with M gateways where M spans from 1 to 4. The propagation of path loss is characterized by employing the log-distance model. The ensuing table provides an overview of the configuration pertaining to ALOHA.

Table 8 ALOHA Parameters

Parameter	Value
GENERATION_PERIOD	500 ms
NO_GENERATION	1000
AVG_TRANS_TIME	2000

The first experiment investigates a scenario characterized by a variable number of nodes, denoted as N, spanning from 100 to 600, in conjunction with a single gateway denoted by M,

which equals 1. The ensuing table and graph depict pertinent data pertaining to Packet Delivery Ratio (PDR), Average Transmitted Packets, Energy Consumption, and additional relevant metrics. Table 9 shows the outcome of nodes starting from 100 to 600 with single gateway.

Table 9 Experiment 1 for Single Gateway for ALOHA

Nodes	Average Collision	Average Transmitted Packets	PDR	Energy Consumption [mJ]
100	4.016	21.822	0.809	17.29
200	8.3785	43.845	0.629	22.23
300	15.4865	65.65	0.516	27.13
400	23.2245	87.044	0.466	30.04
500	31.654	108.701	0.415	33.73
600	40.8095	130.759	0.362	38.67

The second experiment investigates a scenario characterized by a variable number of nodes, denoted as N, spanning from 100 to 600, in conjunction with a double gateway denoted by M, which equals 2. The ensuing table and graph depict pertinent data pertaining to Packet Delivery Ratio (PDR), Average Transmitted Packets, Energy Consumption, and additional relevant metrics. Table 10 shows the outcome of nodes starting from 100 to 600 with two gateways.

Table 10 Experiment 2 for Two Gateways for ALOHA

Nodes	Average Collision	Average Transmitted Packets	PDR	Energy Consumption [mJ]
100	0.923	21.681	0.82998	16.88
200	11.148	43.029	0.70607	19.81
300	20.321	65.584	0.62518	22.401

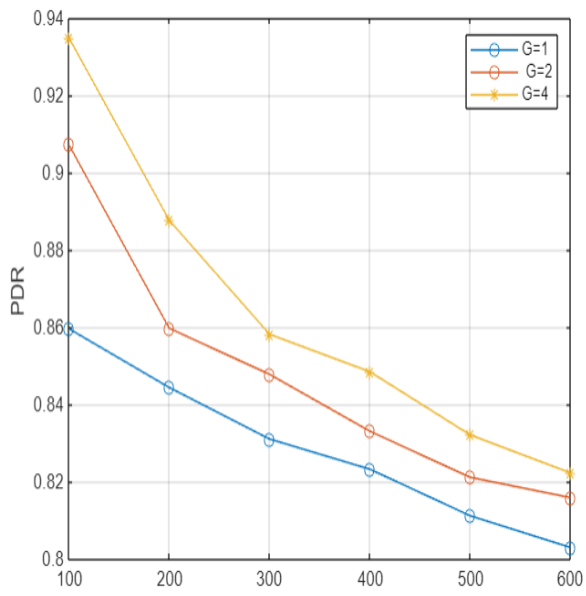
400	31.8395	86.769	0.57843	24.2
500	43.1665	108.618	0.51695	27.13
600	55.21	131.276	0.47834	29.3

The third experiment investigates a scenario characterized by a variable number of nodes, denoted as N, spanning from 100 to 600, in conjunction with four gateways denoted by M, which equals 4. The ensuing table and graph depict pertinent data pertaining to Packet Delivery Ratio (PDR), Average Transmitted Packets, Energy Consumption, and additional relevant metrics. Table 11 shows the outcome of nodes starting from 100 to 600 with four gateways.

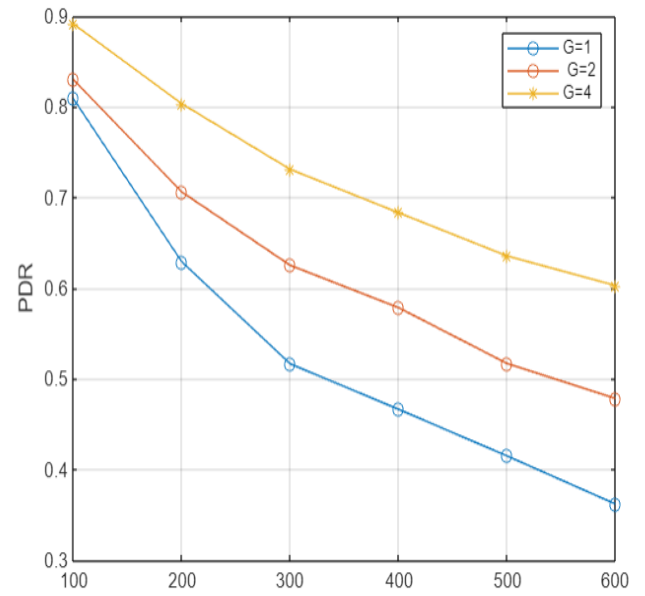
Table 11 Experiment 3 for Four Gateways for ALOHA

Nodes	Average Collision	Average Transmitted Packets	PDR	Energy Consumption [mJ]
100	3.902	22.002	0.89125	15.73
200	13.403	43.884	0.80331	17.4
300	26.345	65.522	0.73099	19.17
400	40.8935	87.35	0.68311	20.6
500	57.206	108.604	0.63548	22.04
600	71.576	130.704	0.60282	23.25

The below Figure 18 shows a comparison of PDR for both RL-MCA and ALOHA. As shown in the figure, RL-MCA can reach a PDR of 82% when it uses four gateways while ALOHA drops to around 60% for a network of 600 nodes.

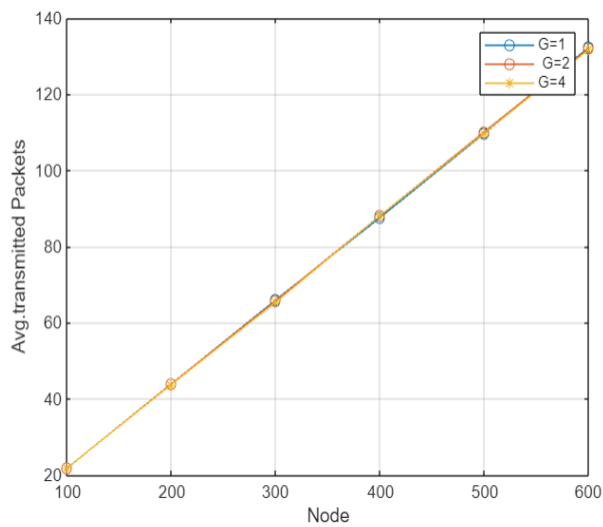


RL-MCA

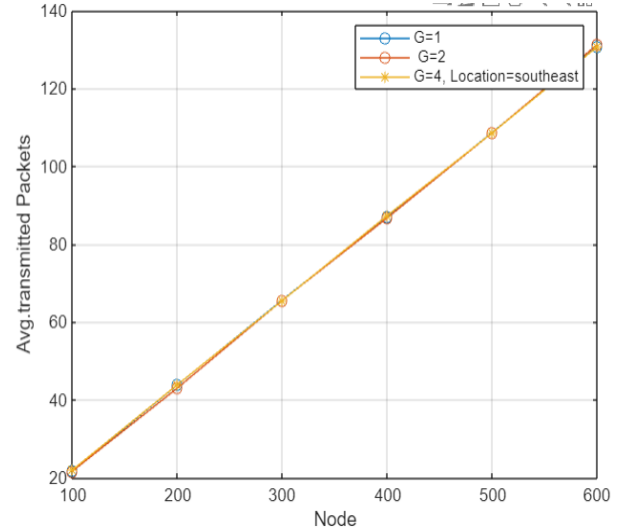


ALOHA

Figure 17 PDR vs Nodes



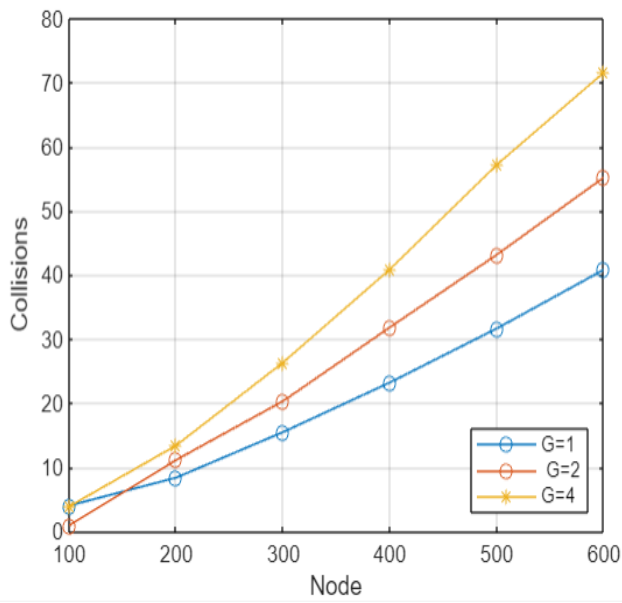
RL-MCA



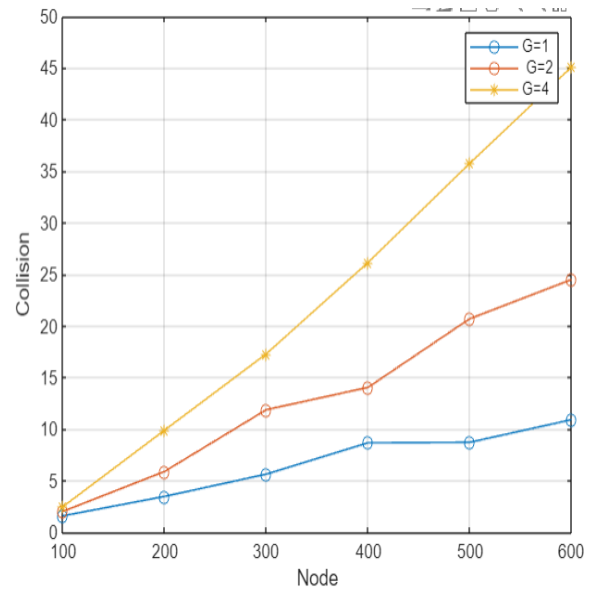
ALOHA

Figure 18 Average Transmitted Packets vs Nodes

Figure 19 compares the average collisions for both RL-MCA and ALOHA. It can clearly be seen that ALOHA results in higher collisions than RL-MCA for all values of N and M .



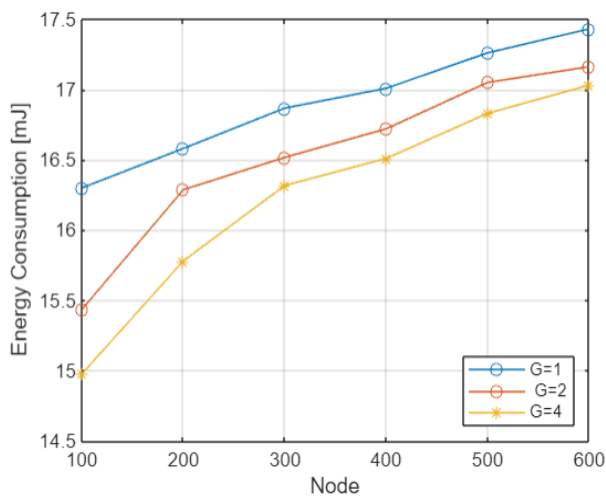
ALOHA



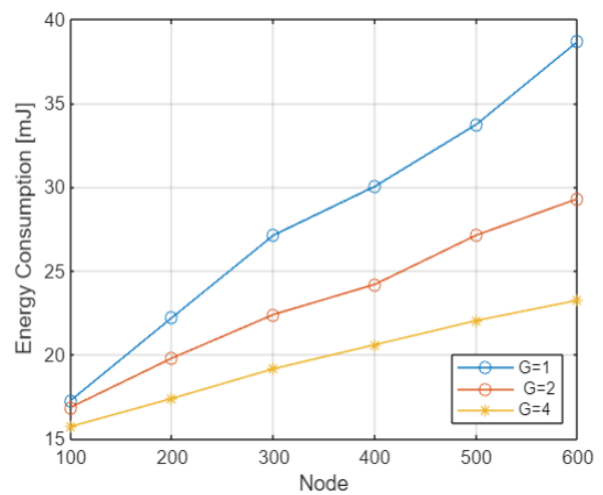
RL-MCA

Figure 19: Collision vs Nodes

When it comes to energy consumption, collisions result in retransmissions which yields extra energy consumption. This can be seen in Figure 20 where the average energy per packet for ALOHA is more than double that of RL-MAC.



RL-MCA



ALOHA

Figure 20: Energy Consumption vs Nodes

In conclusion the incorporation of Reinforcement Learning with the ALOHA protocol not only showcases a marked improvement in throughput but also underscores the substantial progress achieved over traditional ALOHA methodology. Empirical evidence underscores the effectiveness of this integrated approach, revealing that it yields a remarkable throughput exceeding 82% for a network setup comprising four gateways interfacing with 600 nodes. This achievement signifies a significant leap forward when juxtaposed with the maximum throughput of 60% attained by the conventional ALOHA model under identical conditions. The utilization of Reinforcement Learning within the ALOHA framework thus emerges as a pivotal catalyst driving substantial advancements in network performance, affirming its efficacy in enhancing throughput and mitigating potential bottlenecks, thereby underlining its potential for optimizing network operations and fostering efficient data transmission in diverse networking environments.

Table 12 Comparative of RL-MCA and ALOHA for N=600 and M=4.

	RL-MCA	ALOHA
Experiment	PDR	
	82%	60%

CHAPTER 5

CONCLUSION

In the initial chapters of this dissertation, we provided a comprehensive overview of the Internet of Things (IoT) and delved specifically into LoRaWAN, elucidating its constituent components including the end-nodes, gateways, and servers. Through textual explanations and visual aids presented in the third chapter, we elucidated the intricate interconnections among these components. Subsequently, we conducted three distinct experiments aimed at evaluating the efficacy of integrating ALOHA protocol with Reinforcement Learning (RL) techniques in comparison to the performance of ALOHA alone. A key focus of this investigation was the enhancement of the average delivery ratio within wireless communication networks. Our findings revealed notable advancements in this regard, with the integrated RL-MCA approach achieving average delivery ratios of 82% across the conducted experiments. By contrast, the performance of the traditional ALOHA protocol yielded average delivery ratios of 60% in ALOHA Experiment. Based on this empirical observation, we arrived at the conclusion that the integration of ALOHA with reinforcement learning techniques constitutes a superior approach compared to the standalone implementation of ALOHA.

The cost of this scheme demands additional memory and computation for the extra processing required for Q-Learning. Further, the scheme assumes a stationary transmission distribution which can be found in many IoT applications such as traffic monitoring. One possible extension of this work is the applicability to situations with non-stationary distribution.

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