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A Comprehensive Survey of Data-Driven Solutions for LoRaWAN: Challenges & Future Directions

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***Abstract*—LoRaWAN is an innovative and prominent communication protocol in the domain of Low Power Wide Area Network (LPWAN), known for its ability to provide long-range communication with low energy consumption. However, the practical implementation of the LoRaWAN protocol, operating at the Medium Access Control (MAC) layer and built upon the LoRa physical (PHY) layer, presents numerous research challenges, including network congestion, interference, optimal resource allocation, collisions, scalability, and security. To mitigate these challenges effectively, the adoption of cutting-edge data-driven technologies such as Deep Learning (DL) and Machine Learning (ML) emerges as a promising approach. Interestingly, very few existing survey or tutorial has addressed the importance of ML or DL-based techniques for LoRaWAN in its current state. This article provides a comprehensive survey of current LoRaWAN challenges and recent solutions, particularly using DL and ML algorithms. The primary objective of this survey is to stimulate further research efforts to enhance the performance of LoRa networks and facilitate their practical deployments. We start by providing a technical background to LoRa alliances, LoRa, and LoRaWAN. Furthermore, we discuss an overview of the most utilized DL and ML algorithms for overcoming LoRaWAN challenges. We also present an interoperable reference architecture for LoRaWAN and validate its effectiveness using a wide range of applications. Additionally, we shed light on several evolving challenges of LoRa and LoRaWAN for the future digital network, along with possible solutions. Finally, we conclude our discussion by briefly summarizing our work.**

***Index Terms*—LoRa, LoRaWAN, PHY, MAC, Deep Learning, Machine Learning**

I. Introduction

In the era of the next wireless generation, the global connectivity of Internet of Things (IoT) applications is projected to exceed 45 billion devices by 2030 [1]. The successful implementation of IoT applications hinges on the choice of communication protocol. As the number of connected devices grows, the requirement for smooth and effective communication becomes crucial. Fortunately, numerous IoT communication protocols are available, each with distinct features suited for specific use cases. In this regard, Long Range Wide Area Network (LoRaWAN) has emerged as one of the promising Low Power Wide Area Network (LPWAN) communication protocols for IoT applications requiring long-range communication with low energy consumption [2]. However, within the domain of LPWAN technologies, there are competing alternatives to LoRaWAN, including Narrowband IoT (NB-IoT), Sigfox, and Random Phase Multiple Access (RPMA). This competition creates a diverse and vibrant landscape for IoT deployments seeking LPWAN solutions.

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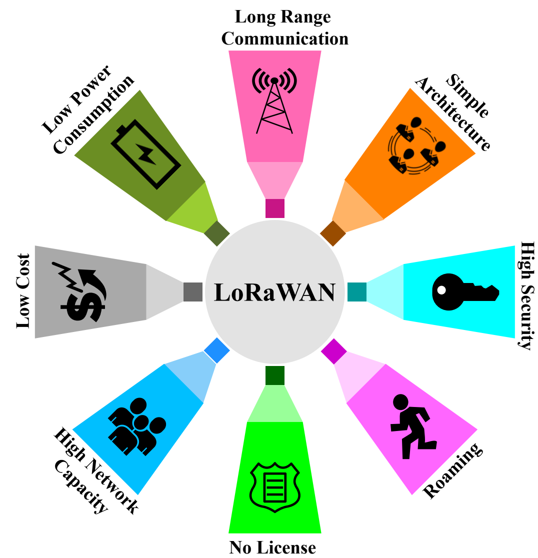


Fig. 1: Key features of LoRaWAN technology.

A. LPWAN Protocols: Why LoRaWAN?

LoRaWAN protocol offers several communication advantages that make it a preferable and prominent choice over the other LPWAN technologies. One of the key features of LoRaWAN is its ability to offer a long communication range of over 3 miles in urban areas and over 10+ miles in suburban areas (Line of Sight), outperforming other LPWAN technologies like SigFox [2]. LoRaWAN demonstrates remarkable energy efficiency, consuming almost 10 times less energy than NB-IoT for transmitting an equivalent payload [3]. This makes LoRaWAN a particularly promising choice for IoT applications, such as underground pipe monitoring, where battery replacement poses challenges. Additionally, LoRaWAN supports the connectivity of a large number of End Devices (EDs) in a network with efficient data management by utilizing a star-of-stars network topology while providing robust security through

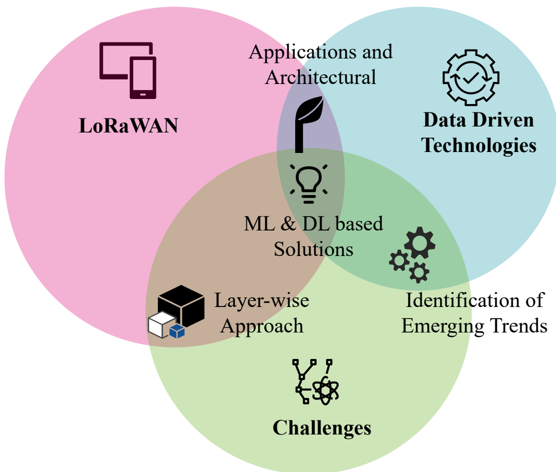


Fig. 2: Scope of the survey.

end-to-end encryption and device authentication. Furthermore, LoRaWAN offers better receiver sensitivity, approximately -140 dBm as compared to other IoT protocols like NB-IoT (-129 dBm), WiFi (-70 to -80 dBm), cellular technology (-110 to -120 dBm). Fig. 1 illustrates LoRaWAN features required for a range of IoT applications, encouraging widespread adoption and driving further technological advancements.

B. Potential of Machine Learning and Deep Learning

Data-driven technologies like Machine Learning (ML) and Deep Learning (DL) have a wide variety of applications in wireless communication, such as intelligent resource allocation, adaptive network optimization, and efficient spectrum management, enhancing network performance, reliability, and network scalability[4], [5]. LoRaWAN has seen a significant uptrend over the last few years, with a growing number of studies and publications exploring the integration of ML and DL techniques to mitigate LoRaWAN challenges like optimized energy consumption, security, collision etc. ML has potential to improve the effectiveness of networks by predicting traffic patterns, adjusting transmission parameters, identify and mitigate interference sources, resulting in more stable connections. Further, DL can enhance signal processing and decoding techniques, strengthening communication robustness. Moreover, beyond simulation studies, practical implementations of DL and ML techniques for LoRaWAN challenges demonstrate their effectiveness in addressing real-world issues. Emerging data-driven technologies offer the ability to identify the optimal network settings to maximize performance while minimizing costs and energy consumption, a crucial requirement for IoT applications. These comprehensive studies and practical applications provide compelling evidence of the viability and efficacy of data-driven methods for optimizing network performance in LoRaWAN.

C. State-of-the-Art Tutorials and Surveys

Over the years, several research efforts have been conducted on a variety of perspectives and dimensions [6], [7]. The researchers initially focused on LoRaWAN's specific features, particularly Adaptive Data Rate (ADR), in order to better understand the LoRaWAN technology. For example, Kufakunesu *et al.* [8] have presented a survey focusing on ADR challenges and highlighted recent solutions that have integrated ML and DL along with other approaches. Sundaram *et al.* [7] have conducted a study investigating LoRa networking open issues and discussing the existing solution with future opportunities. However, these surveys did not exclusively highlight current advancements in LoRaWAN technical specifications and newly released features. Some articles, such as [9]–[11] have partially explored ML and DL applications for LoRaWAN challenges. Recently, work [12] have provided a broad overview of the LoRaWAN challenges and discusses DL and ML-based solutions proposed by academia and industries.

Compared to previous studies, our survey adopted a protocol-layer-wise approach to examine the specific challenges and limitations of LoRaWAN. This approach offers novel dimensions for LoRaWAN analysis, facilitating a more comprehensive evaluation of protocol performance and potential enhancements. Furthermore, the present paper discusses recent advancements in LoRaWAN functionality and the revised technical specifications released to date. Moreover, this work introduces the LoRaWAN reference architecture, which provides a standardized framework to address LoRaWAN challenges with data-driven technologies. Table I presents a comparative assessment of our survey and highlights its unique features and contributions in relation to existing ones.

D. Survey Scope

With the evolution of the 21st century, IoT devices (*e.g.,* high-tech healthcare devices, autonomous robots, and transportation systems) continuously generate thousands of terabytes of data per second. However, these devices are not fully capable of processing these huge amounts of data. In order to manage these data smartly, we need standard and reliable communication technologies, and LoRaWAN has become the most popular communication technology for IoT applications on a large scale [13]. LoRaWAN uses a spread-spectrum technique and Frequency-Hopping Spread-Spectrum (FHSS) to reduce interference and maximize transmission range. It is a secure and low-cost communication technology suitable for large-scale latency-critical applications. However, only a few research initiatives have identified the importance of incorporating data-driven technologies in LoRaWAN protocol. Therefore in this survey, we will find the solution to the following questions:

1) *Why is LoRaWAN a crucial communication technology for IoT networks?*
2) *How do ML and DL-based solutions help to solve several LoRaWAN challenges?*
3) *Why do we need a standardized architecture to incorporate data-driven solutions?*

This study aims at enhancing the digitization and standardization of LoRaWAN IoT communication technology with ML and DL techniques. We discuss various LoRaWAN specifications or versions related to IoT application domains. Additionally, we discuss several LoRa modules, compatibility issues,

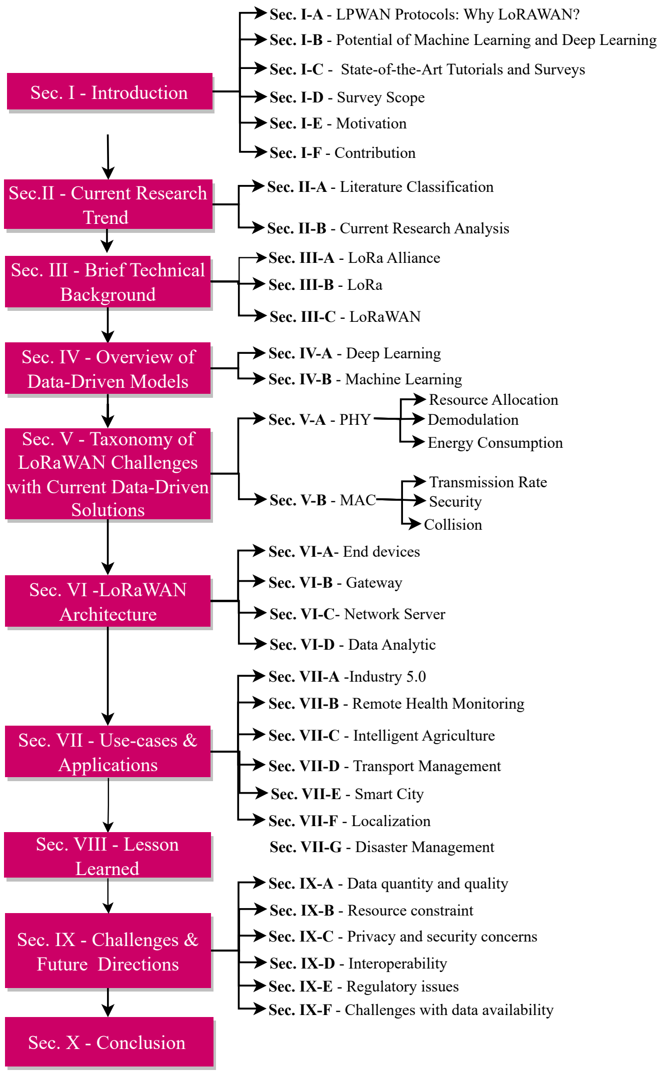


Fig. 3: Paper organization.

open research challenges, and a guide for handling those issues through the use of ML and DL. Specifically, this study conducts a comprehensive literature review on various aspects of LoRaWAN issues and state-of-the-art ML/DL solutions from four significant dimensions: protocol layer-wise analysis, recent advancements, data-driven technologies, and standard architecture. The scope of the present study is illustrated in Fig. 2.

E. Motivation

Noticeably, few review papers are devoted to ML and DL approaches for overcoming LoRaWAN challenges and discussing recent advancements in LoRaWAN protocols for IoT applications. An analysis of the available review articles is listed in Table I. It is evident that there are limited surveys specifically dedicated to ML and DL approaches in LoRaWAN. Hence, the primary motivation behind conducting this review is to fill this void. It will provide valuable insights into the state-of-the-art techniques employed in ML and DL for enhancing the performance and capabilities of LoRaWAN networks. Herein, we aim to identify research gaps, illuminate recent advancements, and outline future research directions in the rapidly evolving field of ML and DL. Our objective is to provide a comprehensive and up-to-date resource for researchers and practitioners, motivating them to explore and unleash the potential of ML and DL in this domain.

F. Contribution

Specifically, our survey provides a comprehensive overview of existing contributions, classifications of existing solutions, identification of gaps in the literature, identification of emerging trends, and discussion of key challenges and future directions. For reviewing and analyzing recent advances, methodologies, and utilization of ML and DL to address LoRaWAN challenges, such as network capacity, interference, and data management, we use a layer-wise protocol stack approach (PHY and MAC layer). The key contributions of this study are as follows:

1) *Comprehensive Coverage:* This survey aims to provide comprehensive coverage of the existing literature on LoRaWAN challenges. We particularly cover the most recent, relevant papers and research articles in this field and deliver an exhaustive analysis of state-of-the-art solutions based on data-driven technologies.
2) *Identification of Emerging Trends:* This survey identifies emerging trends in the field of data-driven technologies, especially various ML and DL algorithms for LoRAWAN-based applications and provides insights into the challenges and future directions for integrating DL and ML to meet evolving IoT requirements.
3) *Recent Advancement:* Our article highlights recent developments in the LoRaWAN protocol and LoRaWAN standardized bodies and provides a concise overview of the LoRaWAN technical specifications released to date.
4) *Data-driven Architectural Framework:* We discuss a high-level LoRaWAN architecture that demonstrates a framework for integrating data-driven solutions. With this in mind, we aim to direct researchers and practitioners to understand the current limitations and plan for future research and development.
5) *Classification of Existing Solutions:* This survey classifies existing ML & DL-based solutions for LoRAWAN challenges based on different criteria. This will provide precise and comprehensive knowledge of potential research directions, key challenges, and innovative solutions for LoRaWAN advancement.

The remainder of this paper is organized as follows. The analysis and significance of the current study are highlighted in *Section* II. *Section* III provides a technical overview of LoRa Alliances, LoRa and LoRaWAN. *Section* IV discusses the most utilized DL and ML models to overcome the challenges of LoRaWAN. *Section* V presents the literature on mitigating LoRaWAN challenges, particularly using DL and ML algorithms. The importance of the standard LoRaWAN architecture that integrates the data-analytic layer is highlighted in *Section* VI. The wide range of LoRaWAN use cases is discussed in *Section* VII, highlighting the potential of the LoRaWAN architecture.

TABLE I: A Comparison of the Current Surveys and Tutorials with Our LoRaWAN Survey.

Recent Works	Year	Summary	ML/DL	Architecture	LoRaWAN	LoRa	Layerwise Approach
Gambiroza *et al.* [14]	2019	A literature review for LoRaWAN network capacity is presented, with a focus on the ability of the network to handle traffic.	✗	✗	✗	✗	✗
Kufakunesu *et al.* [8]	2020	Existing ADR algorithms for LoRaWAN technology are examined in this comprehensive review, focusing on their strengths, drawbacks, and comparative analysis.	✓	✓	✗	✗	✗
Sundaram *et al.* [7]	2020	This article comprehensively surveys LoRa networks, discussing the technical challenges, recent solutions, and open issues in LoRaWAN deployment.	✗	✓	✗	✓	✗
Noura *et al.* [15]	2020	This article reviews the LoRaWAN architecture, applications, and security concerns and provides recommendations for countering vulnerabilities and preventing potential attacks.	✗	✓	✓	✓	✗
Ghazali *et al.* [16]	2021	This study reviews real-time deployments of UAV-based LoRa communication networks while focusing on their communication setup and performance analysis.	✗	✓	✗	✓	✗
Gkotsiopoulos *et al.* [17]	2021	An overview of LoRa-based networks is presented, focusing on physical layer characteristics, deployment features, end device settings, LoRa MAC protocols, and application requirements.	✓	✓	✗	✗	✗
Li *et al.* [9]	2022	An innovative two-dimensional taxonomy is presented to classify and assess the latest LoRa networking techniques. It also compares it based on networking layers and various performance metrics.	✓	✓	✗	✗	✓
Cheikh *et al.* [18]	2022	Several existing LoRaWAN solutions and future insights are discussed for enhancing energy efficiency across various layers.	✗	✓	✗	✗	✓
Jouhari *et al.* [11]	2023	At the physical and MAC layers, this paper examines the scalability challenges of LoRaWAN in detail. The pros and cons of existing solutions are also discussed.	✓	✓	✓	✗	✗
Milarokostas *et al.* [10]	2023	Analyzing the potential of LoRa modulation and LoRaWAN protocol for LPWAN applications in unlicensed spectrum bands, this paper explores cloud-based and open-source data management.	✓	✓	✓	✓	✗
Kamal *et al.* [6]	2023	This study thoroughly examines LoRa networking, addressing the technological complexities in setting up LoRa infrastructures and exploring current solutions.	✗	✓	✗	✗	✗
Paredes *et al.* [19]	2023	This paper presents both a technical overview and a systematic literature review of aspects of FANET (Flying Ad-Hoc Network) implementation related to LoRa technology.	✗	✓	✗	✓	✗
Our Survey	**2023**	**Our article discusses the challenges in LoRaWAN across different protocol layers, as well as recent solutions, particularly utilizing DL and ML**.	✓	✓	✓	✓	✓

"✓" Signifies that the features are fully or partially considered in the research work.
"✗" Signifies that the features are not considered in the research work.

Future developments, state-of-the-art challenges, and future directions of LoRaWAN technology are discussed in *Section* IX. The lessons learned from this survey and the authors' viewpoint are presented in *Section* VIII. Finally, we conclude this paper with a short summary in *Section* X. Additionally, the current study framework is illustrated in Fig. 3.

II. Current Research Trend

The LoRaWAN technology offers a range of research directions and scopes for next-generation IoT networks. However, our research primarily focuses on data-driven solutions, challenges, and applications. Additionally, a brief statistical analysis of LoRaWAN-related ongoing research is also presented in Fig. 4. The following subsections summarize current research issues for LoRaWAN targeting IoT networks.

A. Literature Classification

To examine current and future research opportunities around data-driven based solutions for LoRaWAN, we conducted an exhaustive literature review using four significant scholarly databases (ACM digital library, MDPI, IEEE Xplore, and Science Direct). Using our search keywords LoRaWAN, IoT, data-driven technology, DL, and ML, we found more than 100 research articles between 2017 and 2022, with more than 70 of these articles appearing between 2020 and 2023 in Elsevier and IEEE journals. Through these research efforts, we now have a better understanding of the literature study from different points of view. In particular, we intend to emphasize the changes that have occurred in the past five years (2019, 2020, 2021, 2022, and 2023) in terms of data-driven LoRaWAN-associated revolutions and the directions in which research should proceed.

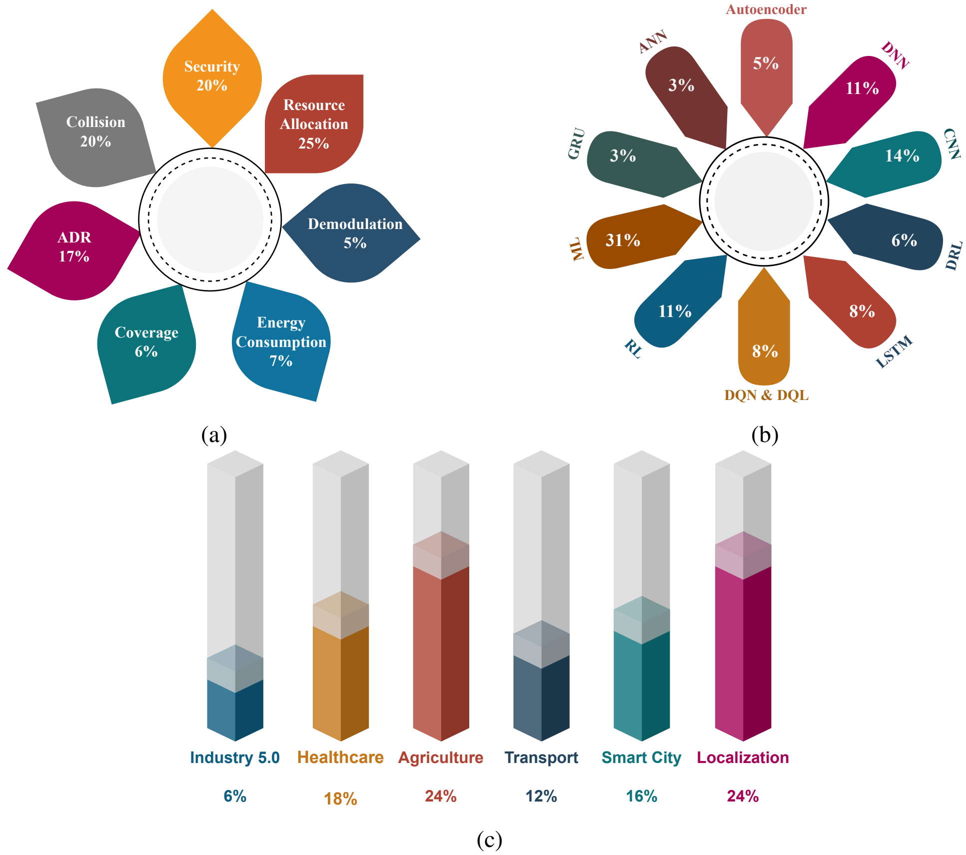


Fig. 4: Literature analysis on LoRaWAN with data-driven technologies. (a) Challenges-specific contributions, (b) Contributions of data-driven technologies, (c) Applications.

B. Current Research Analysis

It can be seen from Fig. 4a that research activities have been established for addressing LoRaWAN challenges and limitations. It is observed that resource allocation (25%) emerges as the foremost obstacle, demanding ingenious solutions to optimize resource distribution. In addition, security and collision (20%) rise as prominent challenges, emphasizing the necessity of strong data protection and effective network traffic management. Additionally, the challenge related to ADR (17%) requires dynamic data transmission methods to deal with communication conditions. However, Demodulation (5%) and communication range (6%) require more attention for seamless data retrieval and reliable connectivity. Consequently, researchers must delve more profoundly into emerging data-driven approaches to intelligent solutions.

Fig. 4b highlights the utilization of various data-driven technologies to overcome several potential challenges in LoRaWAN. For instance, Convolution Neural Network (CNN) (14%) and DNN (11%) are robust methods for tackling distinct aspects of LoRaWAN challenges, particularly in image understanding and pattern recognition tasks. On the other hand, techniques such as autoencoder (5%), DRL (6%), LSTM (8%), DQN & DQL (8%) indicate the diversity of approaches researchers employ to mitigate the signal strength and demodulation issues. Additionally, diverse ML algorithms (31%) are the most effective at tackling a wide range of problems such as QoS, optimization etc.

This paper examines the adoption of data-driven technologies across different applications and sheds light on their impact and their potential for future growth by providing insight into their use and impact, as shown in Fig. 4c. Research on LoRaWAN with data-driven solutions is active in both agriculture (24%) and remote patient monitoring (18%), while the research on Industry 5.0 (6%) is only in its infancy. The research also indicates that LoRaWAN has potential applications in the fields of Smart cities (16%) and localization (24%). There is no doubt that all of these areas have the potential to greatly benefit from the use of technology. Besides, transport management (12%) has the potential for further growth in the coming years. As expected, these data-driven tools will revolutionize industries, enhancing efficiency and shaping a more connected future.

III. Brief Technical Background

In this section, we discuss the importance of LoRa Alliances along with a discussion on LoRaWAN technical specifications. Basically, LoRa Alliance serves as an organization dedicated to ensuring interoperability between LoRa technology and its protocols. Then we briefly provide the technical background of LoRa and LoRaWAN connectivity technology.

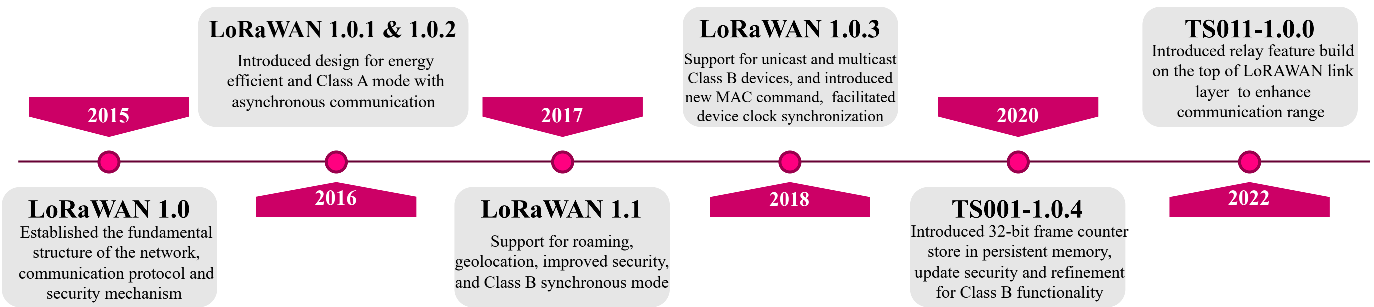
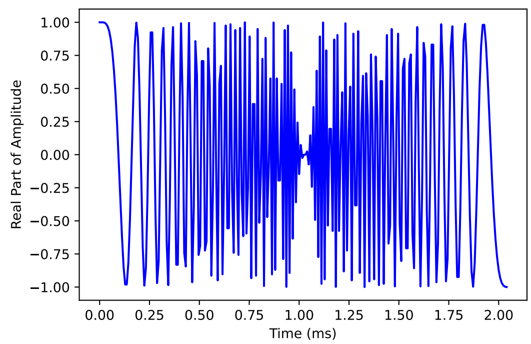
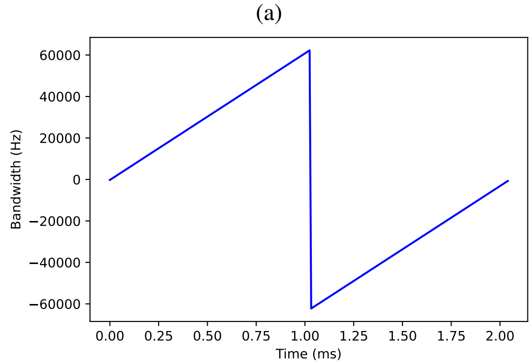


Fig. 5: Time evolution of the LoRaWAN technical specifications.



(a)



(b)

Fig. 6: LoRa symbol modulation with $SF = 8$, a) Time domain b) Frequency domain.

A. *LoRa Alliance*

The LoRa Alliance was formed in January 2015 as a non-profit organization consisting of various companies and organizations dedicated to advancing and establishing the LoRaWAN protocol as a standard for LPWAN. Semtech Corporation is a major contributor to the advancement of LoRa technology. It actively participates in the LoRa Alliance and has played a substantial role in enhancing the LoRaWAN ecosystem. Recently, LoRaWAN has been formally recognized as the international standard for LPWAN by the International Telecommunication Union (ITU) [20]. The first LoRaWAN technical specification, *i.e., LoRaWAN 1.0* was released in 2015, which demonstrates the fundamental structure of LoRaWAN protocols for communication [21]. The LoRa Alliance periodically updates the released technical specifications to ensure that the LoRaWAN protocol is aligned with the current development requirements of IoT solutions. Subsequent versions, such as *LoRaWAN 1.0.1* [22] and *LoRaWAN 1.0.2* [23] in 2016, focused on energy-efficient end-devices and introduced a Class A communication mode with asynchronous uplink transmissions. *LoRaWAN 1.1* [24] enhances the network functionality with roaming support, improved security, and compatibility across Class B devices and introduces Class C device support. There have been further updates and revisions within *1.0.X* series, providing features such as support for unicast and multicast Class B devices, improved device claims using QR codes, and enhanced security. The latest version, *TS011-1.0.0* [25] in 2022, provides a relay feature to extend the communication range without hardware replacement in existing applications. Knowledge of LoRaWAN specifications is crucial for a comprehensive understanding of the technology. Fig. 5 shows the chronological progress and evolution of LoRaWAN technical specifications and advancements over time.

B. *LoRa*

LoRa is a proprietary physical layer (PHY) modulation technique that depends on a few configurable parameters like the spreading factor SF $\in \{7, 8, 9, 10, 11, 12\}$, the available bandwidth BW $\in \{125, 250, 500\}$ kHz, and code rate CR $= \frac{4}{4+n}$, where $n \in \{1, 2, 3, 4\}$. LoRa utilizes the Chirp Spread Spectrum (CSS) technique [2] where a signal is spread over the available bandwidth and uses continuous frequency-varying modulated chirps (up-chirp and down-chirp) to encode the information as shown in Fig. 6.

Up-chirp is a sinusoidal signal with increasing frequency, whereas down-chirp is a decreasing frequency sinusoidal signal. The starting frequency of a chirp is used to encode a LoRa symbol which is encoded with SF number of bits. The available two-sided baseband bandwidth ($-\frac{BW}{2}$ to $\frac{BW}{2}$) is divided into 2^{SF} frequency bins of length $\frac{BW}{2^{SF}}$ as shown in Fig. 6(b). The modulator starts chirp transmission with a frequency bin representing the decimal of SF bits. The starting and end of the chirp frequency are the same (except for the pure chirp). The mathematical expression of the LoRa modulated signal can be expressed as $e^{j\phi(t)}$, where $\phi(t)$ is

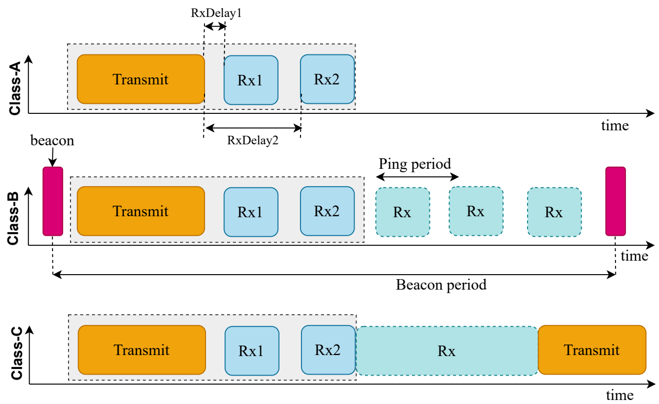


Fig. 7: LoRaWAN classes.

either an up-chirp or down-chirp and in general, $\phi(t)$ can be defined as [26],

$$\phi(t) = \begin{cases} \frac{BW}{2T_s}t^2 + (f(s) - \frac{BW}{2})t, & 0 \le t < t_{fold} \\ \frac{BW}{2T_s}t^2 + (f(s) - \frac{3BW}{2})t, & t_{fold} \le t < T_s \end{cases} \quad (1)$$

where $f(S)$ indicates the initial baseband frequency of a chirp, which depends on the LoRa symbol $S \in \{0, 1, \cdots, 2^{SF} - 1\}$, defined as $f(S) = S\frac{BW}{2^{SF}}$ and $t_{fold} = \frac{2^{SF}-S}{BW}$. T_s indicates a LoRa symbol duration expressed as,

$$T_s = \frac{2^{SF}}{BW}. \quad (2)$$

Using the transmission parameters like SF, BW, and CR, LoRa modulation defines the bit rate as,

$$R_b = SF * \frac{BW}{2^{SF}} * CR. \quad (3)$$

LoRa has predefined Signal-to-Noise-Ratio (SNR) threshold values, i.e. SNR_{th} used to determine the minimum signal quality required for successful reception, referred to as Receiver sensitivity (S). By establishing a specific SNR_{th}, the system sets a criterion for accepting or rejecting received signals based on their quality. LoRa technology can successfully demodulate signals below the noise floor, even with a negative SNR (-7.5 dB to -20 dB). This capability enables reliable communication in challenging environments with weak signals and high background noise levels. The receiver sensitivity in LoRa systems is influenced by several factors, including the SF, BW and noise figure (NF) and is defined as.

$$S = -174 + 10 \times \log(BW) + NF + SNR_{th} \quad (4)$$

LoRa receivers typically have $NF = 6$ dB depending on hardware implementation, while -174 dBm indicates thermal noise. BW is the bandwidth in kHz.

C. LoRaWAN

LoRaWAN is an open Medium Access Control (MAC) layer protocol specifically designed to operate using LoRa modulation. LoRaWAN supports bidirectional (uplink and downlink) communication and utilizes a star-of-stars topology. LoRaWAN protocol deals with two modes of messages: *1)* unconfirmed and *2)* confirmed messages. The network server does not need to send an acknowledgement in unconfirmed message mode. However, it requires sending an acknowledgement for successful uplink reception in a confirmed mode.

Prior to establishing communication in a LoRa network, an ED must undergo the activation process. There are two methods of activating an ED: Over-The-Air Activation (OTAA) and Activation-By-Personalization (ABP). OTAA utilizes a join request and join acceptance process, where session keys for secure communication are generated dynamically. On the other hand, ABP relies on preconfigured keys for communicating with the network server and is simple to implement. Both methods ensure confidentiality and integrity of communication between the ED and NS.

LoRaWAN standard specifies three separate categories of EDs *1)* Class-A, *2)* Class-B, and *3)* Class-C, to cater to the diverse needs of emerging IoT applications. By default, all LoRa EDs support Class-A characteristics [27]. Class-A communication is asynchronous, and each uplink frame is accompanied by two brief downlink windows Rx1 and Rx2 as shown in Fig. 7. Class-B communication is synchronized with the network through regular beacons transmitted from the gateway. Class-B devices periodically open extra receiving windows Rx compared to Class-A devices to receive downlink messages transmitted from the gateway (see Class B functionality in Fig. 7). Class-C extends Class-A functionality by keeping the receiving window open except for uplink transmission as shown in Fig. 7. As a result, Class-C devices have more power than Class-A and Class-B devices.

LoRa operates in unlicensed spectra (sub-GHz) depending on the regional parameters of the countries. For instance - LoRaWAN operates at the frequency of around 865 MHz to 867 MHz in India, 470 MHz to 510 MHz in China and 868 MHz in Europe [28]. The LoRaWAN standard architecture consists of end devices, gateways, network servers, and application servers as shown in Fig. 8. End devices communicate with gateways using the LoRa protocol, while gateways connect with the network and application servers using Ethernet/WiFI/ or other wireless technologies. To ensure secure communication, 128-bit AES encryption is employed for all connections between end devices and both the network and application servers.

IV. Overview of Data-Driven Models

Data-driven techniques cover a broad range of methodologies that encompass intelligent systems development. ML is a popular data-driven technique that emphasizes using data to make predictions or decisions. On the other hand, DL is a subfield of ML that utilizes deep neural networks to learn and interpret complex patterns. DL is particularly useful in tasks like image and speech recognition, where traditional algorithms and models fail. DL can also be used to automate decisions in a wide range of applications, such as medical diagnosis and autonomous vehicle navigation. This section discusses the potential of DL and ML algorithms to mitigate LoRaWAN performance challenges as illustrated in Table II. Widely adopted data-driven technologies to overcome LoRaWAN challenges in the literature are shown in Fig. 9.

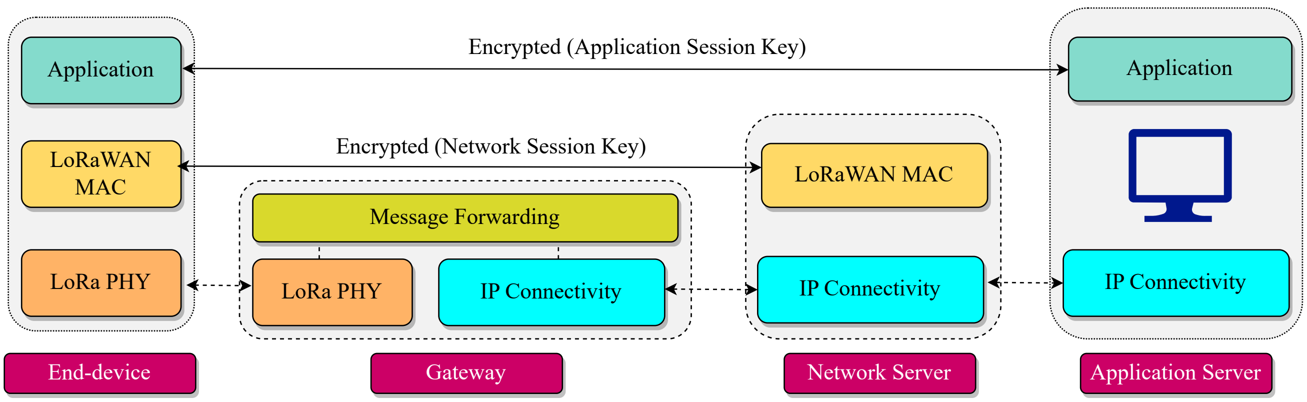


Fig. 8: LoRaWAN protocol stack.

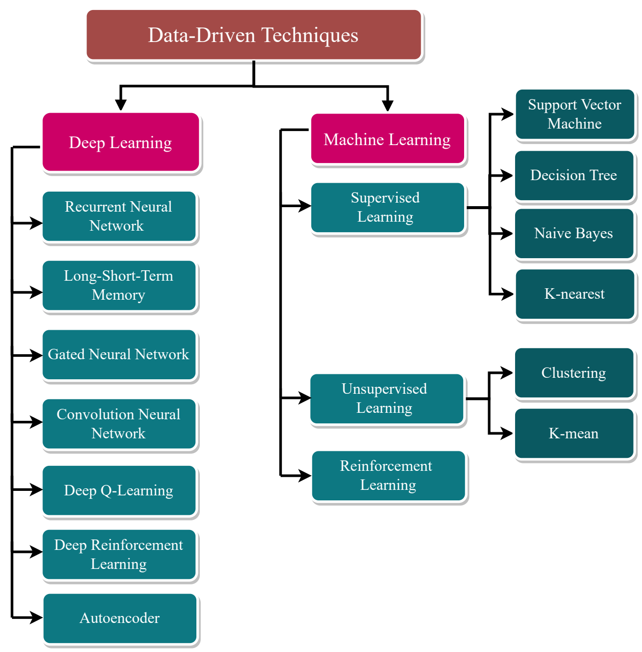


Fig. 9: Explored data driven technologies for LoRaWAN challenges.

A. Machine Learning

ML can be utilized to forecast the performance of LoRaWAN networks, particularly in analyzing EDs through their transmission patterns. By training machine learning algorithms using diverse network parameters such as Spreading Factor (SF), Signal-to-Noise Ratio (SNR), Received Signal Strength Indicator (RSSI), and packet size, it becomes possible to predict the behavior of individual EDs. In addition to profiling and predicting ED behavior, machine learning can also be applied to forecast the overall behavior of the entire LoRaWAN network. This can include predicting the network's state at a future time based on its present condition and historical data. There are three main types of learning approaches in machine learning: supervised learning, unsupervised learning, and reinforcement learning.

1) Unsupervised Learning: LoRaWAN networks can employ unsupervised learning techniques, such as clustering, to create profiles of EDs based on their transmission patterns. This approach can be useful in detecting anomalies in the network and improving the network's efficiency and scalability. Other algorithms, like k-means, can be used to group LoRaWAN transmissions based on their radio and network characteristics. This method allows for the monitoring of system behavior, optimization of network planning, and the development of a labeling system for identifying connected EDs. Additionally, it can aid in the allocation of radio resources, configuration of appropriate parameters, and the planning of diverse IoT ED and service configurations. For instance, the k-mean method can be employed to categorize packets into clusters based on their attributes, such as signal intensity, error rate, and transmission frequency. These clusters represent groups of packets exhibiting similar behavior, enabling the identification of common patterns or irregularities through analysis. The findings from clustering may provide valuable insights into the behavior of the LoRaWAN network. For example, it may reveal the clusters that contain the largest portion of data, the clusters that show normal or abnormal activity, and the evolution of EDs' behavior over time. However, it is important to recognize that the effectiveness of these unsupervised learning methods depends on the quality and relevance of the data used for clustering. If the data used is inaccurate or irrelevant, the clustering results may be misleading. Thus, it is crucial to carefully preprocess and sanitize the data before using these techniques.

2) Supervised Learning: The use of supervised learning methods, such as Support Vector Machine (SVM), can be applied to predict essential parameters in LoRaWAN networks. The predictions rely on labeled data that may include information such as RSSI and SNR, the distance between ED and Gateways, and the acknowledgment status of Uplink (UL) packets. The SVM method can be trained using a dataset that includes packets sent in a LoRaWAN network during a specific timeframe in a real-world scenario. The packets are organized based on their transmitting ED, and characteristics are computed for each ED. The SVM method employs the feature data to categorize the EDs, aiming to maximize the margin, which refers to the gap between the hyperplane and the nearest data points from each class. The performance of the algorithm can be evaluated using metrics such as accuracy, F1-score, and average precision. The effectiveness of supervised learning techniques is highly contingent upon the availability and quality of annotated data. Inaccurate or insufficient labeling of data may lead to compromised forecast accuracy. Future advancements may give rise to semi-supervised learning algorithms that increase the reliability of labeling. These algorithms would utilize both labeled and unlabeled data during training, with the unsupervised component continually updating labels which are then provided to the supervised learning component. This approach has the potential to improve prediction precision and optimize resource allocation in LoRaWAN networks.

3) Reinforcement Learning: LoRaWAN networks can enhance their use of network and radio resources by applying reinforcement learning, a subset of machine learning. Reinforcement learning involves an agent improving a cumulative reward through its decisions and actions, adjusting its behavior to achieve the best outcome, and learning from the consequences of its actions. Implementing a reinforcement learning agent within the network server of LoRaWAN networks is possible. This agent takes into account the network conditions of all EDs and is responsible for finding the optimal network parameters, such as the SF, transmission capacity, and channel allocation. The objective of the reinforcement learning agent's reward function is to maximize the overall number of packets transmitted while minimizing the energy consumption of the LoRa end nodes. The agent selects an action from the possible combinations of the available parameters. As energy consumption increases, the reward decreases, while it rises in proportion to the total number of packets received. However, this strategy is not without its challenges. Reinforcement learning requires a gateway device with enhanced computational capabilities, as the learning process can be time-consuming. Despite these obstacles, reinforcement learning presents a promising approach for improving network resource utilization in LoRaWAN networks. Future research may focus on finding ways to reduce the computational requirements and learning period associated with this method, thereby enhancing its feasibility and effectiveness.

B. Deep Learning

Deep learning, which is a subset of machine learning, has shown promise in optimizing LoRaWAN networks. By employing artificial neural networks with multiple layers, known as deep structures, it can analyze complex data patterns. One example of deep learning in LoRaWAN is its use in managing transmission intervals for IoT devices, which improves the scalability of LoRa networks. This method utilizes a deep learning-based scheme to dynamically adjust IoT device transmission intervals, reducing collisions and enhancing scalability. Additionally, deep learning can be applied to uplink LoRa networks to detect and remove noise from signals, improving the reliability and performance of uplink communications. A Bayesian-optimized deep neural network (DNN) can significantly reduce the signal-to-noise ratio. Furthermore, deep learning can be used to locate objects both indoors and outdoors using LoRa. By analyzing received signal strength and other parameters, the model can accurately predict the location of devices, which is crucial for many IoT applications.

The LoRaWAN framework has witnessed a groundbreaking application of deep learning through the implementation of a comprehensive communication system that utilizes an autoencoder architecture. This model optimizes the utilization of scarce spectrum resources in LoRaWAN, and it comprises several components, including a sender net, which simulates the modulation of data and functions as a LoRa transmitter, a channel net, which represents impairments in the channel, and a receiver net, which demodulates the transmitted data and retrieves the original. The model has been trained and evaluated using simulation-generated LoRa samples and has demonstrated excellent performance as measured by Packet Success Rate (PSR) and Bit Error Rate (BER). While deep learning has proven to be effective in optimizing LoRaWAN networks, it is heavily dependent on the availability of ample and precisely annotated data, which can be challenging to obtain in an IoT environment with limited resources. Despite these challenges, deep learning presents a promising strategy for improving the scalability and performance of LoRaWAN networks, and further research and development in this domain may lead to significant enhancements.

V. Taxonomy of LoRaWAN Challenges with Current Data-Driven Solutions

The LoRaWAN protocol stack consists of four layer (namely, Regional ISM Band, LoRa Modulation, LoRaWAN MAC, Application), where the combination of bottom two layer i.e., ISM Band and LoRa Modulation is referred as LoRa or PHY and top two layers i.e., LoRaWAN MAC and Application is know as LoRaWAN or MAC. In this section, we adopt a protocol layer-wise approach to provide a background for LoRaWAN challenges, limitations and examine the proposed solutions in the literature that utilize DL and ML techniques to address these challenges. It also gives us a framework to better understand the impact of DL and ML techniques on LoRaWAN networks.

A. Physical Layer

The physical layer of the LoRaWAN protocol refers to LoRa modulation that depends on various radio parameters. A key focal point of ongoing research involves effectively managing the allocation of network resources, such as Spreading Factor (SF), Bandwidth (BW), and Transmit Power (TP), among the devices connected to the network. Failure to optimize the utilization of these parameters can lead to inefficiencies within the network. Additionally, the LoRaWAN receiver is required to meet the target SNR for demodulating a received transmission from an ED. Since there is a significant path loss between the transmitting device and the gateway, demodulation processes cannot occur successfully. Consequently, EDs are required to initiate multiple re-transmissions due to transmission or acknowledgement failures. This re-transmission cycle substantially increases energy consumption, making the system more costly in terms of energy.

1) Resource Allocation: Choosing the appropriate radio resource, especially SF involves a trade-off between data rate, communication range and energy consumption. Higher SF

TABLE II: Summary of the Data-Driven approaches utilized to overcome LoRaWAN Challenges.

Data Driven Techniques	Overview	Strength	Weakness	Related Work
Supervised Learning	It is capable of forecasting the SF and TP using factors such as RSSI, SNR, the distance between the ED and the Gateway, and the acknowledgement status of every Uplink (UL) packet transmitted	• Provide accurate predictions if the data is well-labeled. • Used to predict SF and TP, which are crucial parameters in LoRaWAN for efficient resource management	• Requires a large amount of labeled data to train the model • If the data is not well-labeled, the model may not make accurate predictions	[29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43]
Unsupervised Learning	The model is trained on an unlabeled dataset with the aim of identifying patterns or structures within the data. In the context of LoRaWAN, it can be utilized to detect anomalies or unusual behavior within the network	• Identify patterns and structures in the data that might not be apparent to a human observer • Useful in LoRaWAN for detecting anomalies or unusual behavior in the network.	• May not be able to detect anomalies or unusual behavior if they are not part of the patterns it has learned to recognize	[32] [44], [45] [46]
Reinforcement Learning	Herein, an agent can learn to make decisions by interacting with its environment, and in LoRaWAN, it can be utilized to intelligently manage network resources such as BW, SF, and TP to optimize efficiency and achieve optimal results	• Intelligently manage network resources to maximize efficiency • Used to enhance the overall performance of LoRaWAN networks	• Can be slow to converge to an optimal solution • Requires careful design of the reward function to guide the learning process	[47] [48] [49] [50] [51] [52] [53]
Deep Learning	LoRaWAN utilizes artificial neural networks with numerous layers, which possess the ability to learn and make decisions based on the data they have been trained on.	• Learn complex patterns and make accurate predictions • To enhance the data transmission over the network in LoRaWAN.	• Models can be complex and computationally expensive to train • May be prone to over-fitting, where the model performs well on the training data but poorly on new, unseen data.	[54] [55] [56] [57] [30] [48] [35] [36] [37] [38] [39] [40] [41] [42] [51] [58] [59] [60] [46] [61] [62] [43] [52] [53]

values provide a longer range but lower data rates and energy consumption, while lower SF values offer higher data rates but a shorter range [63]. In addition, LoRaWAN networks experience dynamic changes in device density, traffic patterns, and environmental factors due to many factors like urbanization [64]. In order to optimize network performance, adaptive resource allocation mechanisms are required to account for these dynamic conditions in real time. Addressing these challenges requires intelligent algorithms and mechanisms for SF allocation that consider factors such as network congestion, battery life, signal conditions, QoS requirements, and adaptability to dynamic network conditions [65]–[68].

The literature presents a wide range of approaches and techniques for overcoming LoRa challenges. These studies aim to enhance various aspects of network performance, such as Packet Success Ratio (PSR), convergence period, collision rate, energy consumption, and coverage. Some authors like Farhad and Pyun [54] have introduced an AI-ERA framework, which utilizes an AI model for allocating suitable SFs to static and mobile EDs. This approach showed significant PSR improvements compared to the standard LoRaWAN ADR scheme. Similarly, Li *et al.* [55] presented a Deep Q Learning-based resource allocation, where a DNN trained by the gateway helps EDs make optimal channel selection and SF decisions. Both works [54], [55] leverage AI and ML techniques to optimize resource allocation and enhance network performance. RL algorithms were also explored for resource allocation in LoRaWAN networks [47]. Ilahi *et al.* [56] have proposed a DRL-based algorithm to assign PHY layer parameters, reducing collisions and increasing Packet Delivery Ratio (PDR). The MIX-MAB algorithm in [57] employs RL to allocate transmission parameters to EDs in a distributed manner, achieving improved performance. In addition, the authors in [29] have discussed ML models, namely SVM and Decision Tree Classifier (DTC), with the aim of improving collisions in the network.

Detection of inter-spreading factor and intra-spreading factor interference and reducing collision probability were addressed by Elkarim *et al.* [30] using DL architectures such as Fully Connected Neural Networks (FCNN) and CNN. The proposed Artificial Neural Network (ANN) estimates optimal SFs for EDs, reducing collisions and optimizing energy consumption. Similarly, in [48], a DRL approach was developed to minimize collision rates in LoRa dense networks. Furthermore, few researchers introduced novel approaches to specific challenges in the LoRaWAN standard. Finnegan *et al.* [69] have proposed an enhanced ADR (EADR) scheme that improves the convergence period of the standard ADR by estimating PSR and analyzing received packets' SNR standard deviation. In addition, Sandoval *et al.* [31] have adopted RL, specifically evolution strategies, to derive optimal transmission configurations for EDs. Also, a K-means clustering approach presented in [32], [33] assigned SFs to spatially distributed EDs, resulting in improved coverage probability. The literature demonstrates the potential of AI, ML, and RL techniques for optimizing resource allocation, reducing collisions, improving PDR, and enhancing coverage.

Aihara *et al.* [70] have proposed an efficient Q-learning model for assigning orthogonal channels in LoRaWAN networks with CSMA/CA to avoid interference and collisions.

This work complements the use of RL techniques in resource allocation, showcasing the potential of intelligent algorithms in optimizing transmission resources. In line with the same objective, Mu *et al.* [49] have introduced a runtime SF allocation scheme that leverages the K-Nearest Neighbors (KNN) algorithm. This work provides further evidence of the importance of considering link characteristics when assigning optimal SFs. By utilizing empirical studies conducted over a considerable time span, this approach offers valuable insights into the impact of different SF configurations on network performance. Furthermore, the authors of [34] have presented a lightweight learning algorithm, specifically a multi-armed bandit approach, for optimizing communication parameters in LoRaWAN networks. Some researchers also emphasized the importance of accurate path loss estimation. Liu *et al.* [35] have introduced the DeepLoRa algorithm, which utilizes DL, specifically the Bidirectional Long Short-Term Memory (Bi-LSTM) model, to estimate path loss accurately. By considering land cover characteristics, DeepLoRa enhances the reliability of LoRa gateways' coverage.

2) Demodulation: The LoRaWAN protocol utilizes sub-gigahertz frequencies to facilitate long-range communication. However, these frequencies experience significant deterioration in signal strength when obstructed by buildings or other barriers. Moreover, sometimes the gateway and EDs cannot capture the preamble, essential for demodulating the packet, due to a lack of synchronization between the EDs and the gateway. Additionally, the preamble is extremely short, approximately equivalent to 12.25 LoRa symbols and can be easily missed if there is inadequate synchronization between the device and the gateway. Researchers like Li *et al.* [36] have proposed an approach for a more efficient way of demodulating the LoRa symbol using DL named NELoRa (neural-enhanced LoRa). NELoRa extracts multi-dimensional features from the amplitude and phase spectrum using the designed mask-enabled DNN filter and decodes the LoRa chirps using the spectrogram-based DNN decoder. NELoRa evaluation results show not only SNR improvement but also an extended battery life of the LoRa EDs.

To mitigate inter-network and intra-network interference among various LoRa networks causing high symbol error rates, Tesfay *et al.* [37] have proposed a DL-based receiver decoder to decode the LoRa uplink transmission in LoRaWAN. Deep Feedforward Neural Network (DFNN) and CNN methods were used to detect the transmitted LoRa symbol at the receiver. In addition to signal interference, the characteristics of the wireless propagation channel, such as path loss, multipath fading, and interference, can significantly impact the received signal quality and introduce challenges in demodulating the transmitted symbols. Dakic [38] has presented a CNN to demodulate the LoRa symbols, where the CNN network is trained with various channel impairments like noise, carrier offset, and time offset. Furthermore, to enhance LoRa network scalability, authors like Tesfay *et al.* [39] have proposed an approach to LoRa uplink transmission detection using DL models. Herein, deep feedforward neural networks and CNN were used for bit and LoRa symbol detection, respectively, in overlapped transmissions. Some researchers like Shilpa *et al.* [62] have focused on a DL autoencoder architecture to optimize the transmitter and receiver operations with efficient consideration of channel impairments. The autoencoder was trained and assessed using generated LoRa samples through the simulation, and the results outperformed LoRaWAN with default settings in terms of error and delivery success rate.

3) Energy Consumption: LoRaWAN stands out among LPWAN technologies due to its remarkable energy efficiency, making it a preferred choice [71]. LoRaWAN EDs are typically battery-powered and expected to operate reliably for at least 6+ years after deployment [72], which is particularly relevant in applications where battery replacement is not feasible, such as underground communication. Hence, power consumption in LoRaWAN is one of the major challenges. In certain scenarios, such as harsh environments, EDs may need to transmit higher power to overcome path loss and interference [73]. Additionally, adopting network topologies like mesh topologies to improve scalability, throughput, reliability, coverage, and synchronization can introduce protocol overhead and increase energy consumption. Balancing the desired functionality of the LoRaWAN network with energy consumption is crucial. Optimizing the protocol design and data packet size can help mitigate energy consumption challenges to some extent [74]. However, to make an impact on energy consumption, the underlying hardware also needs to be optimized. This includes radio transceiver design, antennas, and power management circuitry. Furthermore, energy harvesting may also reduce overall energy consumption. To reduce energy consumption even further, the adoption of data driven-based solutions can be crucial. These approaches may encompass energy-efficient algorithms and models that leverage data to optimize various aspects of sensor systems, such as radio transceiver design, antennas, power management circuitry, and energy harvesting techniques.

Recent advancement in data-driven technologies have shown promising results in overcoming the challenges and limitations of LoRaWAN related to energy optimization. Researchers like Lu *et al.* have successfully employed DL models, specifically ANN, to maximize energy efficiency by optimizing transmit power [40]. Another study proposed by Bernard *et al.* have utilized the Support Vector Regression (SVR) and DNN models to reduce power consumption in LoRa devices [41]. Additionally, ML techniques have been applied to enhance data transmission through lossy compression methods, thereby reducing channel traffic from LoRa EDs. Furthermore, Yazid *et al.* [75] have proposed a Markov Decision Process to estimate the batter life of Class A LoRaWAN devices by optimizing the transmission parameters settings. Through the incorporation of link quality and collision considerations, a multi-agent reinforcement learning technique have introduced by Zhao *et al.* to optimize energy consumption within the constraints of limited battery energy [52]. Continuing in alignment with the objective of energy optimization, Mhatre and Lee [53] have introduced a scheduling algorithm based on Deep Deterministic Policy Gradient reinforcement learning through collision avoidance in a densely populated LoRaWAN network. These findings emphasize the potential of data-driven technologies and stochastic models to enhance the energy performance of LoRa technology.

B. MAC Layer

The MAC layer of LoRaWAN defines the protocol to efficiently communicate between the EDs and the gateways. However, implementing it effectively presents challenges such as managing interference, collision, optimizing data rates (DR), ensuring network scalability and security. The LoRaWAN protocol, based on ALOHA, permits EDs to transmit without sensing channel availability, which can lead to collisions in the network. This collision issue needs to be managed to maintain communication efficiency. Further, during the activation process, where EDs share security keys with the network server, there is a potential vulnerability to security breaches and attacks. Ensuring the integrity of this process is crucial for maintaining the overall security of the LoRaWAN network and the data transmitted through it.

1) Transmission Rate: The optimization of transmission rate in LoRaWAN can be achieved using the ADR feature. However, ADR faces a significant challenge due the lack of a standardized specification explaining how NS commands ED regarding the optimized parameters [8]. The unavailability of clear guidelines poses several challenges in coordinating optimal rate adaptation strategies across LoRaWAN networks. As a consequence, many versions of ADR schemes are proposed to overcome the standard ADR limitations [76]. Additionally, the support for ADR is currently limited to static devices only. The standard ADR scheme in LoRaWAN faces challenges in accurately estimating link margin [77], delayed response, adaptability to changing conditions, balancing power consumption, network capacity, and managing interference [76]. Many frameworks and approaches have been proposed to address ADR limitations [78]–[83]. However, many of these frameworks require modifications to the LoRaWAN architecture and may not be applicable to all use cases. Therefore research is needed to develop a reliable and efficient ADR scheme which can be integrated with the existing LoRaWAN protocol. Utilizing ML algorithms and AI techniques can be one approach to enhance the prediction of network behaviour and optimization of ADR parameters by analyzing data patterns.

Data-driven techniques have the potential to be utilized in resource management in LoRaWAN, enabling intelligent capabilities directly in the devices themselves. Authors like Carvalho *et al.* [50] have proposed an RL-based ADR scheme that estimates the best transmission configuration compared to standard ADR. The ADR scheme in LoRaWAN may not be appropriate for certain situations, such as when dealing with mobile EDs or in the presence of abrupt channel changes. To address these issues, Farhas *et al.* [42] have proposed a DL-based transmission resource allocation (similar to ADR) that utilizes GRU to reduce packet loss in harsh environments. Network slicing in LoRaWAN is a trending area of research. Efficient resource allocation to meet Quality of Service (QoS) requirements for each slice is a challenge, particularly in dense networks where the standard ADR scheme is inadequate. Tellache *et al.* [51] have proposed a DRL-based strategy for the effective allocation of TP and SF to EDs in an intra-slicing dense LoRaWAN network. The conventional ADR scheme was replaced with the proposed multi-agent DQN. The experimental results demonstrated that the proposed approach outperforms the existing ADR scheme for all slices.

2) Security: Security is one of the major concerns for IoT applications. One challenge is ensuring secure authentication and authorization of the devices joining the network [84]. Another concern is the confidentiality of data during transmission. LoRaWAN employs AES-128 encryption algorithms, but proper key management is vital for maintaining data integrity. Managing the security of numerous devices is also a challenge that requires secure provisioning, firmware updates, and monitoring. The current LoRaWAN protocol has room to build physical layer-based attacks, such as building a covert channel over LoRa PHY [85], [86]. LoRaWAN vulnerabilities, such as replay attack [87], sniffers [88]–[90], jamming [91]–[95], key extraction [58], [96], [97], and energy attacks [98] must be addressed. Such attacks can lead to data breaches, financial losses, and even the interruption of critical services. Security measures must be taken to protect against these attacks and ensure the safety of networks and users. Integrating cloud computing and fog computing with LoRaWAN security, along with leveraging blockchain, holds promising research directions. Cloud computing can provide the computational power and processing required memory for robust key management processes, while fog computing can bring security closer to the edge devices, reducing latency and enhancing real-time threat detection. Further enhancing security and resilience against attacks, blockchain technology ensures tamper-proof records, secure key management, etc. These technologies can be integrated together to create an end-to-end secure system with multiple layers of protection. This can provide greater security and trust in the system, making it suitable for handling sensitive data.

The work [58] has demonstrated a possible channel attack in the LoRaWAN communication protocol by using DL to recover an AES key used for payload encryption. The proposed CNN model was trained with less than hundred LoRa communication packets and demonstrated the ability to fully recover the AES encryption key. Anomaly detection enhances communication protocol security by identifying and mitigating abnormal activities. Kurniawan *et al.* [59] have demonstrated the implementation of an anomaly detection mechanism using ML models to enhance the security of the LoRaWAN gateway. An analytic server is positioned between the LoRaWAN gateway and the network server to collect and evaluate data for detecting anomalous data behaviours. A total of 11 ML algorithms were employed for training purposes to achieve the highest level of performance.

3) Collision: The occurrence of collisions in LoRaWAN networks is primarily attributed to blind transmissions from EDs [99]. In addition, LoRaWAN is designed to support highly scalable networks with numerous end devices connected per gateway, this scalability can unintentionally lead to collisions, resulting in a substantial impact on throughput and overall performance. Optimal resource allocation can play a crucial role in mitigating collision. Other IoT technologies like SigFox

TABLE III: Summary of The Related Work Section Presented in The Paper

Ref.	Objective	Algorithm	Platform	Performance Matric
[54]	Resource allocation assignment issue in static and mobile devices.	DNN	Simulation	Packet Success Ratio
[55]	Resource allocation to avoid the collision among low-powered end devices.	DQN	Simulation	Frame Success Rate
[47]	To optimize the transmit power corresponds to maximum data rate.	RL	Simulation	Energy Efficiency
[56]	PHY-based transmission parameter assignment to reduce the collision in dense network.	DRL	Simulation	Packet Delivery Ratio
[57]	Improving resource allocation to enhance the transmission success rate.	RL	Simulation	Packet Delivery Ratio
[29]	Smart SF allocation scheme to mitigate the collision in the network.	SVM, DTC	Simulation	Packet Delivery Ratio
[30]	Addressing inter-SF and intra-SF interference and reducing collision probability.	FCNN, CNN	Simulation	Packet Delivery Ratio, Total Energy Consumption
[48]	Minimizing the collision rate without any additional resource or infrastructure.	RL	Simulation	Data Reception Rate, Total Energy Consumption
[31]	Maximize the throughput per node by optimal dissemination policies.	RL	Simulation	Throughput
[32]	Optimal SF allocation scheme to enhance the network coverage.	K-mean	Simulation	Success Probability, Network Coverage
[33]	Fair SF allocation scheme to enhance the scalability and performance.	K-mean	Simulation	Data Extraction Rate
[70]	Resource allocation to avoid collision due to blind transmission.	Q-learning	Simulation	Packet Delivery Rate
[49]	Optimal selection of SF to maximize the network throughput.	K-NN	Realtime data	Packet Delivery Rate
[34]	Optimize the SF and emission to improve the network performance.	Multi-armed bandit	Simulation	Energy Consumption, Cost, Failure Rate
[35]	Estimate the accurate LoRa link path loss in a complex environment.	B-LSTM	Experimental	Pathloss Estimation
[36]	Proposed an efficient way of LoRa demodulation for improving SNR and extending battery life.	DNN	Experimental	Symbol Error Rate, SNR Threshold
[37]	To improve LoRa demodulation performance.	DFNN, CNN	Experimental	Symbol Error Rate
[38]	To improve the LoRa symbols demodulation for enhancing performance compared to standard demodulator.	CNN	Simulation	Bit Error Rate
[39]	Enhance LoRa signal detection to address the network scalability.	DFNN, CNN	Simulation	Symbol Error Rate
[40]	Enhance the energy efficiency of the network.	ANN	Simulation	Transmit Power
[41]	Improve the data transmission efficiency.	DL	Experimental	Energy Consumption, Error Rate
[50]	Optimise the transmission parameter for a dynamic environment.	Q-learning	Simulation	Energy Consumption, Success Rate
[42]	Improve transmission parameter assignment for real scenario.	GRU	Simulation	Packet Success Ratio
[51]	Enhance ADR functionality to meet QoS requirements in dense sliced network.	DRL	Experimental	Packet Delivery Ratio
[58]	Investigate the possible channel attack in LoRaWAN communication protocol.	CNN	Experimental	Correlation Coefficient, Ranking
[59]	Examine the anomaly detection in LoRaWAN communication protocol.	KNN, SVM, etc	Experimental	Accuracy
[60]	Mitigate LoRaWAN collisions by optimising channel access and collision avoidance strategies.	LSTM	Experimental	Collision Rate
[44], [45]	Optimize the collision and delay in the dense network	K-mean	Simulation	Collision Rate, Transmission Delay
[46]	Mitigating LoRaWAN challenges.	K-mean, DT, LSTM	Simulation	Inter-Arrival Time
[61]	Determine transmission channel conditions and predict PDR.	RF, SVM, etc	Simulation	Inter-Arrival Time
[62]	Optimize the transmitter and receiver operation.	Autoencoder	Simulation	Error Rate, Delivery Success Rate
[43]	Predicting network behaviour to optimize performance.	Fusion Transformer, SVM	Simulation	Traffic Loss Prediction, Traffic Received Prediction, QoS
[52]	Energy Optimization for LoRaWAN underground sensors.	RL	Simulation	Energy Per Packet, Data Extraction Rate
[53]	Scheduling algorithm for energy efficient performance.	RL	Simulation	Energy Consumed

coexisting within the same unlicensed frequency band as LoRa can introduce substantial interference, potentially resulting in transmission failures [100] [101]. Few researchers explore the possibility of introducing intelligent channel access scheduling [102], [103], collision avoidance scheme [104], algorithm to extract the information from the collided frame [105]–[111] and novel network topology to overcome collision challenges in LoRaWAN. Future initiatives to improve collision management in LoRaWAN can utilise sophisticated MAC protocols and ML-based collision prediction to optimise channel access and reduce interference for enhanced network reliability and performance.

Research has shown that ML and DL offer promising potential for mitigating LoRaWAN collisions through optimized channel access and collision avoidance strategies. Cui and Joe [60] have proposed a DL model, Long Short-Term Memory Extended Kalman Filter (LSTM-EKF), for accurately forecasting collisions in LPWANs with high scalability (number of EDs connected to the gateway). Based on the proposed prediction models, pre-judgments can be made, and allocation management problems can be addressed in advance. Additionally, the work [44], [45] has investigated the issues with highly dense LoRaWAN applications, such as collision and delay. To overcome these issues, Alenezi *et al.* [44], [45] have proposed an approach of a priority transmission scheduling based on an unsupervised learning clustering algorithm, K-Means. The proposed approach not only reduces collisions ($\approx$56%) and delays but also enhances network throughput. The study conducted in [46] has also shared a similar objective of mitigating LoRaWAN challenges using ML models. Herein, Cuomo *et al.* have investigated how ML models can be utilized to enhance LoRaWAN performance. The k-means algorithm was utilized to categorize network EDs, grouping them based on similar behaviour, low and high error rates. Further, DT and LSTM have been proposed and tested on real LoRa networks to forecast the behavior of the EDs.

Furthermore, Guerrero *et al.* [61] have focused on estimating transmission channel conditions and predicting Packet Delivery Ratio (PDR) using ML. To accomplish this, a comprehensive data-gathering initiative was carried out. The authors established relationships between connectivity metrics at the EDs and the occurrence of a packet being received at the gateway to predict PDR. Another research group, like Elbsir *et al.* [43], has also focused on optimizing network performance by predicting the network behaviour and using classification mechanism-based temporal fusion transformer and SVM models. Closely aligned with a similar objective, Bhat *et al.* [112] have demonstrated the correlation between ambient weather conditions and estimated channel performance indicators (RSSI and SNR) using the LSTM-based stacked autoencoder model.

Table III illustrates the data-driven technologies to address a variety of LoRaWAN issues. These solutions demonstrate the ability to provide approaches for enhancing productivity, scalability, and overall performance. However, it is essential to recognise that regardless of these data-driven advancements, there remain several challenges within these techniques that require comprehensive solutions. Further research and refinement are essential for achieving more complete and robust solutions.

VI. LoRaWAN Architecture

LoRaWAN has a vital role in IoT when a standardised architecture is established, which can ensure uniformity in deployment, facilitating communication between diverse IoT devices and facilitating interoperability. Besides, designing a standard LoRaWAN architecture not only reduces conflicts arising from proprietary implementations but also facilitates efficient network management, scalability, and cross-platform integration, making LoRaWAN-based IoT ecosystems more reliable and effective. Herein, we take the initiative to introduce an architecture with slight modifications in standard LoRaWAN architecture to provide a standardized platform for incorporating data-driven solutions. The LoRaWAN architecture mainly comprises four components: *i)* End Device (ED), *ii)* Gateway (GW), *iii)* Network Server (NS), and *iv)* data analytics, as shown in Fig. 10. The importance of data-driven techniques at each layer of the LoRaWAN architecture can be incorporated to improve its efficiency and robustness, ultimately enabling insightful analysis and optimization for exceptional performance. With the addition of data-driven techniques, it can make a huge difference over the existing network in terms of making it more intelligent and allowing it to self-learn.

A. End Devices

LoRa EDs are generally battery-operated sensors that utilize the LoRa RF modulation technique to wirelessly transmit data to LoRaWAN gateways. These gateways connect to the internet, allowing the data to be accessed via the cloud or other networks. The key component enabling LoRaWAN connectivity in IoT applications is the LoRa chipset. These chipsets are specifically designed to incorporate the LoRa modulation scheme and provide essential functionalities for LoRaWAN-based communication. Generally, LoRa chipsets are available through LoRa Alliances. Each chipset offers specific features and advantages, enabling developers to choose the chipset that ideally suits their IoT application requirements and regional radio dependency. Table IV briefly summarises various LoRa chipsets. A LoRaWAN hardware chipset as shown in Fig. 11 comprises several key components like transceiver, Micro-Controller Unit (MCU), antenna, Power Management Unit (PMU), memory, interfaces port, clock and timer that enables long-range, low-power communication for various IoT applications. The transceiver integrated in LoRa modem handles the LoRa physical layer and manages RF transmission and reception for maintaining the connectivity between the EDs and the gateways. MCU (like STM32, nRF52, ATmega, STM8 and STM32L0) manages the data processing, controlling the transceiver and application logic executions. PMU optimizes energy consumption and enhances battery life. Additionally, the interfaces, such as UART, I2C, SPI, and GPIOs, provide smooth integration with external peripheral devices. On the other hand, data-driven technology can optimize operation and security, resulting in enhanced efficiency and improved decision-making. However, incorporating data analytics at the device level can be challenging due to limitations in processing power and battery life. Therefore, it is essential to develop efficient algorithms that can extract valuable insights from the data without depleting excessive resources.

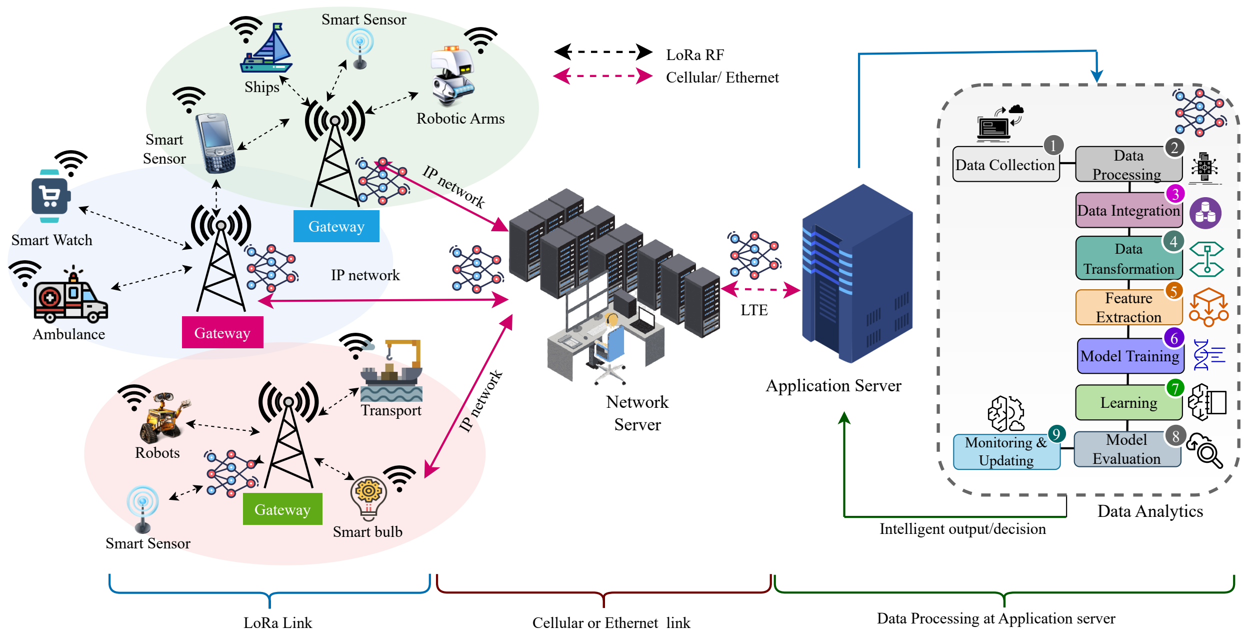


Fig. 10: Architecture for incorporating the data driven solutions in classical LoRaWAN architecture.

TABLE IV: LoRaWAN Chipsets

Chipset	Brief Summary
Semtech SX127x	Semtech's SX127x series, including SX1272 and SX1276, are popular LoRa transceiver chipsets widely used in LoRaWAN applications. They offer long-range communication, low power consumption, and high sensitivity.
Semtech SX126x	Semtech's SX126x series, including SX1261 and SX1262, provide improved features compared to the SX127x series. They offer a longer range, higher output power, and lower power consumption, making them suitable for various IoT applications.
Semtech SX130x	Semtech's SX130x series, including SX1301 and SX1308, are LoRaWAN baseband transceiver chipsets. They are designed to handle gateway functionalities and communicate simultaneously with multiple end devices.
Microchip RN2483	The Microchip RN2483 is a low-power, highly integrated LoRaWAN module that includes a LoRa transceiver and a microcontroller. It provides a simple, cost-effective solution for implementing LoRaWAN connectivity in IoT devices.
Microchip SAM R34	The Microchip SAM R34 is a system-in-package (SiP) module that combines an ultra-low-power microcontroller with a LoRa transceiver. It offers a compact and efficient solution for battery-powered IoT applications with LoRaWAN connectivity.
STMicroelectronics STM32WL	The STMicroelectronics STM32WL is a System-on-Chip (SoC) that integrates an Arm Cortex-M4 microcontroller and a LoRa transceiver. It combines low power consumption, high performance, and extensive peripheral support for LoRaWAN applications.
Murata CMWX1ZZABZ	The Murata CMWX1ZZABZ is a compact LoRaWAN module that combines a Semtech LoRa transceiver and an STM32 microcontroller. It provides a ready-to-use solution for adding LoRaWAN connectivity to IoT devices.

B. Gateway

Gateways function as intermediaries connecting EDs to the network server. Their primary purpose is to collect LoRa messages from multiple end devices and forward them to the network server for further analysis and handling. Generally, gateways communicate with the network server using high-bandwidth protocols such as WiFi, Ethernet, fibre-optic, or cellular. Based on software, LoRaWAN gateways can be classified into Minimal Firmware and Operating System. Minimal Firmware gateways have essential packet-forwarding software for communication, offering cost-effectiveness and user-friendliness. Operating System gateways utilize an operating system, enabling background packet forwarding software and providing flexibility for additional device functionalities alongside LoRaWAN capabilities. LoRaWAN gateways rely on protocols such as Semtech UDP Packet Forwarder or MQTT to receive and transmit LoRa packets from EDs to the network server.

Furthermore, the gateways can also be categorized as inside and outdoor based on application. Indoor gateways are cost-effective and suitable for deep-indoor locations, utilizing internal or external antennas. Outdoor gateways offer wider coverage, are mounted on towers or rooftops, feature external antennas and have higher receiver sensitivity than indoor gateways. LoRaWAN gateways have unique identifiers like the GatewayEUI for configuration and identification, enabling connectivity with LoRaWAN cloud platforms while supporting MQTT-based forwarders with user-selected Gateway IDs. Further, the benefits can be improved by incorporating data-driven technologies in the gateway devices. This allows for improved

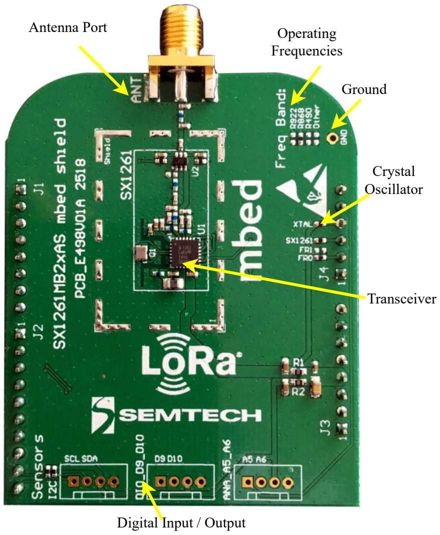


Fig. 11: LoRaWAN hardware chipset.

data collection, better decision-making, and improved network performance. Additionally, outdoor gateways offer improved security and reliability as they are not exposed to the same risks as indoor gateways. These features make the gateways more flexible and cost-effective, allowing them to be deployed in a wide variety of situations. This makes them ideal for large-scale IoT applications.

TABLE V: LoRaWAN Network Servers

Server	Country	Brief Summary
The Things Network (TTN)	Global	TTN is a globally used, open, and decentralized LoRaWAN network server that operates on a star-of-stars topology.
ChirpStack	UK, Germany, and France	It is a customizable and open-source LoRaWAN Network Server that provides a scalable and robust solution for managing networks.
Loriot	Switzerland, Germany	Loriot is a cloud-based LoRaWAN network server with many management features.
Actility ThingPark	France, Spain, Belgium	Actility ThingPark is a robust commercial LoRaWAN network server that provides comprehensive management for large-scale deployments.
OrbiWise	Switzerland, Spain	OrbiWise offers reliable and scalable LoRaWAN network servers with diverse features to efficiently manage networks.

C. Network Server & Application Server

The LoRaWAN network server is responsible for managing gateways, EDs, and application servers. Simultaneously, the application server processes application-specific data, generates downlink payloads and integrates with various systems. It securely handles and analyses sensor data received from EDs and facilitates the implementation of various services and applications on top of LoRaWAN infrastructure. Meanwhile, the network server secures end-to-end communication between EDs and the application server using 128-bit AES encryption. Moreover, the network server ensures the integrity of messages and validates the authenticity of EDs to prevent unauthorized access. It also enables secure, efficient, and reliable communication between devices and applications, providing necessary tools for maintaining the network and managing connected devices. The network server efficiently handles messages by discarding duplicate copies received from multiple gateways, reducing network congestion and optimizing processing. In addition to receiving and forwarding uplink messages, it manages downlink messages and routes them to available gateways. It processes join-request and join-accept messages between EDs and the join server.

Numerous LoRaWAN network servers are widely utilized worldwide for implementing LoRaWAN-based applications. These network servers also help manage the end devices' data rate and transmission power, providing an interface for network operators and application developers to efficiently manage their LoRaWAN networks. Table V briefly summarizes a few LoRaWAN network servers where TTN stands out as a widely embraced network server choice for deploying LoRaWAN applications. Further, the benefits can be improved by incorporating data-driven technologies in the network servers. For instance, predictive analytics can help identify network performance issues, such as traffic congestion and data saturation, which can be quickly addressed before they cause any disruptions. Additionally, AI-driven optimization engines can improve the network's energy efficiency and performance. AI-driven optimization engines can help identify the most efficient routes for data packets to travel and the best placement of routers for better performance.

D. Data Analytics

Data analytics is an essential part of any IoT network as it helps to understand hidden patterns and dynamic changes in the environment. It can identify trends and opportunities by detecting anomalies and correlations in the data, leading to improved decision-making through predictive analytics and maintenance. Similarly, integrating a data analytics layer in LoRaWAN can provide more functionality and control to the network. Analyzing data collected from sensors in an IoT network using data analytics can reveal valuable patterns and trends for predictions. This, in turn, helps develop better resource management strategies and enhances network performance. Moreover, data analytics plays a crucial role in identifying potential problems before they escalate, facilitating smooth network maintenance. Scientists and researchers widely employ data mining and ML models to understand dynamic changes in networks based on available data. By tracking network changes and evaluating their effects, they can develop more efficient resource management techniques and optimize network performance. In addition, data analytics enables predictive capabilities to anticipate potential issues, enabling proactive measures to ensure network smooth and efficient operation. As shown in Fig. 10, the data analytic module encompasses the process of gathering data from diverse sources, preparing and organizing it through preprocessing, integrating data from multiple origins, and converting it into a suitable format for analysis. Additionally, they involve feature selection or extraction, training and evaluating models, optimizing for enhanced accuracy, deploying models for real-world applications, and continually monitoring and updating to adapt to evolving data patterns.

VII. Use-cases & Applications

LoRaWAN has several potential applications in diverse domains as shown in Fig. 12. These application domains include industrial applications, health applications, agriculture-based applications, transportation, smart city and several other domains. However, the LoRaWAN protocol must be standardized in a way that ensures interoperability, efficiency, and robustness at the same time. Consequently, in this section, we will demonstrate the importance of maintaining a standard reference architecture and how we can continue to improve the capabilities of LoRaWAN applications through the continued use of standard reference architectures.

A. Industry 5.0

Leveraging LoRaWAN in Industry 5.0 offers a multitude of benefits, empowering industries to attain enhanced connectivity, data-driven insights, energy efficiency, and improved safety and security [113]. LoRaWAN features enable industries to connect devices cost-effectively and allow remote monitoring and control. Additionally, LoRaWAN can be used to create real-time intelligence and analytics for improved decision-making as well as better energy efficiency, safety, and security [114]. The long-range communication and low power consumption features of LoRaWAN align perfectly with the goals of Industry 5.0 for enabling the development of intelligent, autonomous, and interconnected manufacturing systems. The architecture of LoRaWAN opens up innovative opportunities for industrial use cases. It can detect anomalies using data-driven technologies like ML and DL, preventing breakdowns and safeguarding workers in hazardous environments. By integrating data-driven layers into standard LoRaWAN architecture, autonomous robots can collaborate intelligently with humans for better productivity and quality. LoRaWAN can also be used to monitor industrial processes in real time, improving operational efficiency. Furthermore, it can be used to collect and analyze valuable data to help industries make better decisions.

B. Remote Health Monitoring

LoRaWAN architecture has immense remote health monitoring potential. A lot of applications based on healthcare can benefit greatly from technologies such as LoRaWAN and the corresponding reference architectures. For example, works [115], [116] have demonstrated the significance of intelligence algorithms like ML to enhance the performance of remote health monitoring systems. Remote health monitoring relies on wearable devices with sensors that capture vital health parameters such as heart rate, blood pressure, temperature, and activity levels. Using the standard architecture, AI models can analyze the data received from connected devices in real time, detect anomalies, identify patterns, and provide predictive insights related to the patient's health condition. Moreover, data-driven technologies like ML and DL can provide personalized suggestions and treatment plans using patients' health history data and improving care quality. In this regard, Hossain *et al.* [117] have demonstrated a patient activity recognition framework based on the LoRaWAN sensor. ML techniques were used to analyze continuous sensing data to identify in-person patient activity. Additionally, the use of ML and DL algorithms can reduce the amount of time required to develop a treatment plan, as well as the cost associated with the development of such plans. This is because ML and DL algorithms can quickly process large amounts of data and generate accurate predictions and recommendations.

C. Smart Agriculture

The LoRaWAN protocol in agriculture has become more popular due to its cost-effective deployment, long-range connectivity, and low-power requirements [118]–[120]. However, the standard LoRaWAN faces several challenges, such as establishing reliable communication with underground sensors under adverse environmental conditions. Additionally, there is sometimes ambiguity in making smart decisions about crop yield. Therefore, an extension to the LoRaWAN architecture by incorporating a data analytic layer is beneficial, which can utilize data-driven technologies for crop yield prediction and other tasks. Recent advancements show that researchers have developed underground communication systems that are more resilient to extreme environmental conditions. These developments have improved the efficacy and reliability of the LoRaWAN protocol in the agriculture sector. Furthermore, the LoRaWAN architecture can incorporate DL and ML models to analyze sensor data, remove noise and interference, and establish reliable sensor-to-gateway connectivity even in challenging weather conditions and varying soil properties. This allows farmers to decide how much water to use, how healthy their crops are, and where to allocate their resources, even in harsh environments. With a similar objective, Chang *et al.* [121] have proposed a smart irrigation system based on LoRa, utilizing an ML algorithm to improve greenhouse irrigation efficiency and precision. The real implementation of a smart irrigation system utilizing data-driven technologies offers a cost-effective, accurate, and intelligent greenhouse irrigation system.

D. Transportation Management

The LoRaWAN architecture with a data analytical layer can significantly improve the safety and sustainability of transportation systems. Data on traffic flow, vehicle speed, and road conditions can be collected by connecting sensors and devices to the infrastructure. The data analytics layer processes this information. ML and DL models can also be used to predict congestion and accident situations, optimize vehicle routes, and reduce traffic jams. The implementation of this LoRaWAN system can improve road safety, reduce traffic congestion, and increase the efficiency of transportation

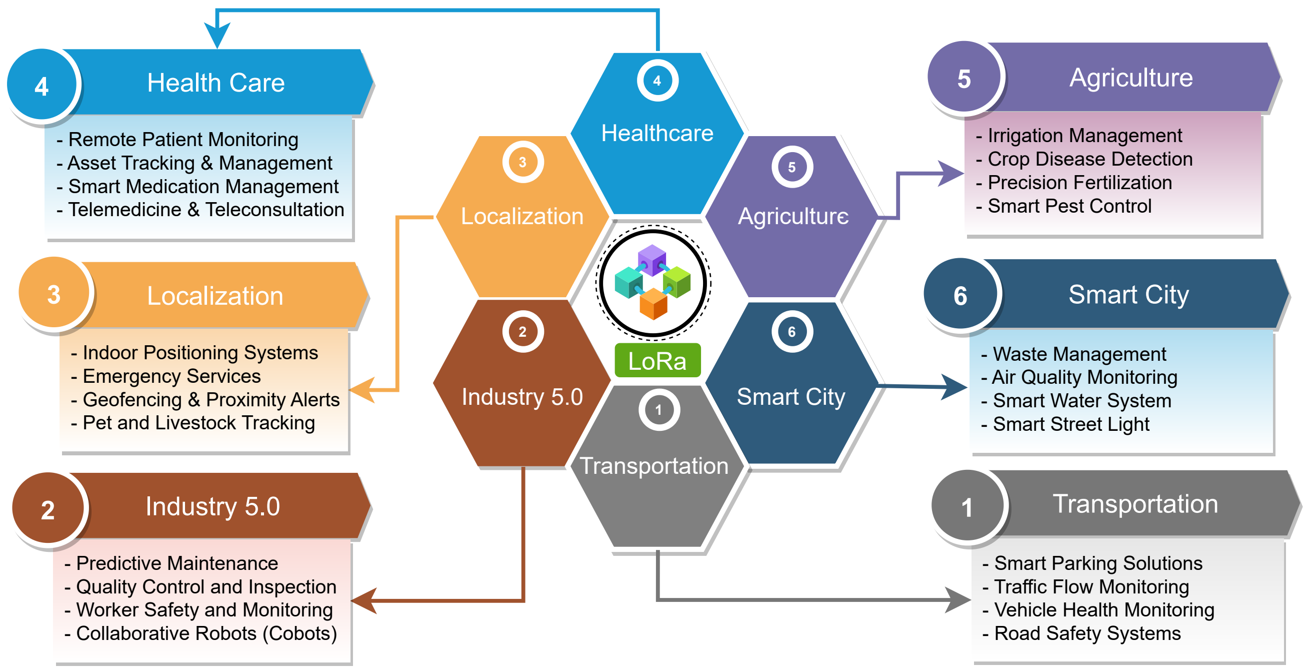


Fig. 12: Various applications of LoRaWAN use cases.

systems. Moreover, it can reduce overall environmental pollution by providing insight into the most efficient routes and speeds to reduce fuel consumption [122]. Seid *et al.* [123] have demonstrated a smart camera-based Intelligent Transportation System (ITS) prototype, utilizing LoRaWAN edge computing and ML to monitor real-time traffic. It emphasizes the system's effectiveness in detecting risky scenarios, including instances like pedestrians crossing roads, sudden braking, and reckless driving. In the upcoming developments, the LoRaWAN architecture has the potential to guide drivers to available parking spots, reducing traffic congestion and lowering carbon emissions. This initiative contributes to creating a healthier and more sustainable environment.

E. Smart City

LoRaWAN substantially transforms connectivity and revolutionizes smart city deployment by establishing intelligent, interconnected ecosystems [124]. Smart cities have a wide range of applications, such as smart energy management, environmental monitoring, public safety and security, and efficient water management, effectively utilizing advanced technologies such as LoRaWAN. LoRaWAN solutions, based on a data-driven approach, increase sustainability, services, and quality of life. Some research groups like Ali *et al.* [125] have developed a low-cost sensor based on the LoRaWAN technique integrated with ML to measure air pollution. Furthermore, Thu *et al.* [126] have presented a scalable and smart air-quality calibration system implemented by low-cost sensors using the LoRaWAN protocol. The ML model was trained over two months and collected air quality data to predict air pollution mitigation parameters. As seen in the designed architecture, the integration of LoRaWAN and the data analytical module empowers smart cities to optimize resource use, make better-informed decisions, and protect the environment. It also presents significant opportunities to explore innovative applications and solutions that enhance environmental preservation, energy efficiency, and public safety. This will undoubtedly drive smart cities towards a brighter and more sustainable future.

F. Localization

Localization and positioning have emerged as important applications of LoRaWAN technology [127]. The advanced integration of ML and DL has taken these applications to another level of development. Traditional localization techniques based on Received Signal Strength (RSSI) and Time-of-Flight (ToF) measurements can be improved further using the LoRaWAN architecture. Moreover, it can automatically extract complex features from data and enhance localization and positioning capabilities. Perkovic *et al.* have introduced an ML model based on a Neural Network (NN) for accurate indoor localization of EDs using beacon signals received by multiple gateways. Building on this, Anjum *et al.* [128] have investigated ML techniques for RSSI-driven ranging in LoRaWAN, whereas another study proposed an approach called DeeoFi-LoRaIN [129] for LoRa indoor localization through DL-based fingerprint data. In addition, Carrino *et al.* [130] have proposed a fingerprinting approach for outdoor geolocation, and another work addressed TDoA positioning errors with a DNN model [131]. Data-driven solutions have shown substantial promise in localization and positioning. Further advancements in multimodal sensing and edge computing will drive the growth of ML and DL in localization, enabling more accurate, reliable, and versatile solutions.

G. Disaster Management

LoRaWAN proves indispensable in disaster management, thanks to its robust, rapid, and resilient connectivity that withstands harsh conditions like extreme weather and seismic activities. This dependability ensures uninterrupted operations, facilitating swift and precise outcomes during emergency situations. In disaster management, flood monitoring and warning emerge as a key application of LoRaWAN. However, challenges exist when using LoRaWAN for disaster management, such as scalability issues that arise as the number of devices and sensors increases. Handling data from these devices becomes more intricate. Moreover, data quality and security concerns emerge. Variations in data quality from different sensors can compromise decision-making accuracy, demanding measures to maintain data confidentiality and integrity. To tackle these challenges, a data-driven solution can be implemented. Machine learning algorithms offer a feasible approach to analyze collected data, identifying patterns that contribute to disaster prediction. This proves particularly valuable in the prevention phase of disaster management, aiming to mitigate potential impacts through informed decision-making.

VIII. Lesson Learned

This research takes a step-by-step approach by establishing a technical grasp of LoRa and LoRaWAN. While both LoRaRF technology and the open medium access control LoRaWAN protocol are at a revolutionary stage, they offer a range of unexplored dimensions that require rigorous investigation [132], [133]. Therefore, we begin our discussion by identifying LoRaWAN requirements and analysing why ML and DL can be the most appropriate solutions for making LoRaWAN smarter (Section I). This section also describes the scope of the research, and we aim to answer some unanswered research questions about LoRaWAN. Additionally, we have discussed state-of-the-art surveys and tutorials in LoRaWAN and highlighted how our survey differs from other survey articles. This will help readers better understand the purpose and direction of the paper.

The study in Section II presents a comprehensive literature review, encompassing major databases, has revealed a significant increase in research articles from 2020 to 2023, which underscores the growing interest in data-driven approaches. Furthermore, the diverse application of data-driven technologies, including CNN, DNN, and various ML algorithms, demonstrates the strategies employed by researchers to address the network challenges. The study also highlights active applications in agriculture, remote patient monitoring, smart cities, localization, and transport management, which are expected to have transformative impacts on these sectors.

In Section III, we provide a technical foundation for a better understanding of LoRa and LoRaWAN. Beyond their protocol mechanisms, these technologies are crucial to the integrated vision of IoT. Their capacity for long-range, energy-efficient communication has broad uses, from smart cities to farming. The significance of LoRaWAN Alliances is also highlighted in this section. The paper thoroughly discusses adopting prevalent DL and ML models for overcoming LoRaWAN challenges. This examination illuminates the promising potential of DL and ML models for enhancing the efficiency and reliability of LoRaWAN networks. However, numerous unexplored possibilities remain, inviting further investigation and innovation. One approach to this involves the integration of edge computing with LoRaWAN, promising improved data processing efficiency and reduced latency. Furthermore, the fusion of blockchain and federated learning stands to elevate data security and network privacy measures.

Section IV thoroughly discusses adopting prevalent DL and ML models for overcoming LoRaWAN challenges and then Section V emphasizes the landscape of challenges and the subsequent literature on data-driven-based solutions, focusing on integrating Deep DL and ML techniques. We extend our study by focusing on the opportunities ahead and glimpsing into the potential future these advancements might create. A comprehensive review of the existing literature identified a notable absence of a standardized framework for implementing data-centric solutions to mitigate LoRaWAN challenges and limitations. As a result, we propose a LoRaWAN architecture integrating the data-analytic layer derived from literature on various domains to bridge the identified research gap in section VI. This study establishes a significant foundation for future research and lays the groundwork for more in-depth exploration. Additionally, the future outlook embraces the evolution of IoT applications autonomously, promoting highly efficient systems and real-time monitoring.

Noticing the emerging and growing applications and use cases of LoRaWAN [134] as discussed in Section VII, it becomes evident that LoRaWAN is positioned to emerge as the dominant and favoured choice amidst the landscape of LPWAN technologies in the era of digitized IoT. This trend shows how significant LoRaWAN is now and how it will change.

Although ML and DL models offer potential solutions for overcoming LoRaWAN performance issues, they confront challenges such as such as limited training data and dynamically changing communication channels. The availability of representative datasets is crucial for accurate generalization and effective decision-making. However, the dynamic channel conditions in LoRaWAN networks make it challenging for models trained on static datasets to adapt to real-time changes in the network conditions. Energy efficiency is one of the critical aspects of LoRaWAN networks. However, some ML and DL models may be computationally intensive and energy-demanding, potentially conflicting with the energy-saving goals of LoRaWAN. Therefore, a balance must be struck between radio resource allocation to optimize network performance and energy efficiency. One approach to address this problem is to explore hybrid models that combine data-driven technologies with standard rule-based or analytical approaches. Developing lightweight versions of DL and ML models can also mitigate computational overhead, making them more suitable for resource-constrained LoRaWAN devices. These approaches can improve network performance and resource utilization in LoRaWAN systems.

The increasing deployment of edge computing can enable the integration of DL and ML models within LoRaWAN gateways and edge devices. This brings processing closer to the data source, reducing latency and enabling real-time analytics, predictive maintenance, and autonomous decision-making at the network edge for efficient and intelligent LoRaWAN deployments. Furthermore, standardization is crucial for the broad adoption of DL and ML in LoRaWANs. Common frameworks, protocols, and interfaces are required to integrate intelligent applications across diverse LoRaWAN networks, encouraging collaboration and innovation. The LoRaWAN Alliance regularly updates technical specifications to align with evolving IoT requirements. Moreover, there is a need for standardized protocols to facilitate the widespread adoption of DL and ML, which can enable the seamless integration of intelligent applications across diverse LoRaWAN networks. The integration of DL and ML algorithms presents a promising path to enhancing the performance of LoRa networks and facilitating their deployment.

IX. Challenges and Future Directions

There are several new challenges that LoRaWAN faces alongside the advancements it has made in recent years. Among these challenges, one needs to consider data quantity and quality, resource constraints, privacy and security concerns, interoperability, regulatory issues, and issues related to the availability of data. There are also issues around scalability, latency, and reliability. Furthermore, LoRaWAN needs to be able to handle large amounts of data and complex applications. Besides, LoRaWAN needs to be secure and reliable in order to protect the data that is being transmitted.

A. Data Quantity and Quality

The significance of data quantity and quality in the domain of data-driven technologies cannot be overstated. These aspects directly influence the operation of ML and DL algorithms and the accuracy of the predictions made by these models. Data quantity refers to the sheer volume or size of the dataset used to train and test ML/DL models whereas data quality is a measure of how well information can be used for a certain purpose. When data is of high quality, it means it is correct, complete, consistent, and useful for the job at hand. Achieving enhanced data quantity and quality in a LoRaWAN network involves strategic considerations to optimize the volume and reliability of collected data.

To augment data quantity, one can strategically increase sensor density across the deployment area, capturing a more extensive and detailed dataset [135]. Fine-tuning the transmission rates of sensors based on application requirements is essential, balancing high-frequency transmissions with considerations of energy consumption and network capacity [136]. Aggregating data from multiple sensors provides a holistic view, enriching the dataset [137]. While LoRaWAN excels in low-power, long-range applications, the incorporation of 5G and 6G technology facilitates significantly increased data transfer speeds, catering to applications demanding real-time communication and higher bandwidth [138]. On the front of data quality, regular calibration and maintenance of sensors are crucial to ensure accuracy and reliability. Implementation of error-checking mechanisms within communication protocols helps identify and rectify data transmission errors, maintaining data integrity [139]. Prioritizing the quality of service, securing against unauthorized access, and filtering out noise contribute to the overall quality of the collected data [140]. This comprehensive approach, integrating considerations for both quantity and quality, is vital for optimizing LoRaWAN-based IoT systems effectively.

B. Resource Constraint

Data-driven technologies require the transmission of substantial amounts of data to the application server for effective decision-making. However, this process demands extensive communication resources, posing a challenge for LoRa devices that operate within constrained resource environments. The conventional approach of transmitting data to the server for decision-making also introduces a time-consuming element. To address this issue and optimize resource utilization for extensive data transmission and analysis, the integration of edge computing techniques has proven to be effective [141]. In this paradigm, LoRa devices process tasks locally and transmit refined parameters to the server. This approach not only mitigates the demand for communication resources but also significantly reduces the time required for data analysis. Embracing distributed data processing methodologies, such as MapReduce [142], can further alleviate bottlenecks during the transfer of these refined parameters to the server. Adding to the complexity, LoRa devices are low-powered, posing a challenge in deploying large and complex ML and DL models. To overcome this challenge, the implementation of advanced techniques like knowledge distillation [143], TinyML [144], and compressed models [145] are required. These techniques enable the deployment of smaller models onto low-powered devices, ensuring enhanced accuracy despite the limitations in processing capacity. In essence, the combination of edge computing and model optimization techniques helps to achieve the seamless integration of data-driven technologies with LoRa devices.

C. Privacy and Security Concerns

The complexity of privacy and security challenges in LoRaWAN is increasing, driven by the dependence of data-driven technologies on information flow for analytics and decision-making. The key challenge lies in ensuring robust protection for the data transmitted over LoRaWAN networks, containing sensitive details, against unauthorized access and malicious use. Moreover, as data-driven insights derived from IoT devices become more integral to various sectors, including healthcare, smart cities, and industrial applications, it becomes crucial to address concerns related to data integrity and confidentiality within the LoRaWAN framework. Therefore, ensuring a smooth integration of data-driven technologies with the necessity to maintain privacy and security standards is important for the development of LoRaWAN amid the age of data-centric innovations.

Ensuring privacy and security in LoRaWAN requires a multifaceted approach. Robust end-to-end encryption for pay-

TABLE VI: Summary of Research Challenges and Future Scope in LoRaWAN with Data-Driven Technologies

Challenges	Description	Objective	Possible Solutions and Research Opportunities
Data quantity and quality	• Data quantity and quality are paramount in data-driven technologies. • Efficient method to optimize volume and reliability of collected data.	• Increase data quantity. • Correct, complete, and consistent data collection. • Noise-free data collection.	• 5G and 6G technology [138]. • Aggregating data from multiple sensors [137]. • Error-checking mechanism [139]. • Prioritizing the QoS [140].
Resource constraint	• LoRaWAN is low powered device, not suitable for large ML/DL models. • Resource-aware deployment of data-driven technology.	• Low powered device processing. • Resource-aware model deployment. • Compressed data communication.	• Integration of edge computing [141]. • Distributed data processing [142]. • Knowledge distillation [143], TinyML [144], and compressed models [145].
Privacy and security concerns	• Data exchange for analysis and decision making in data-driven technology. • Secure data transmission in LoRaWAN network.	• Authorized access. • Data integrity and confidentiality. • Secure data communication.	• Blockchain technology [146]. • Third-party key management [147]. • Proxy-based key establishment [148]. • Application specific security.
Interoperability	• Multiple platforms, data from separate subsystems. • Interoperable protocol for connecting all devices into the network.	• Hybrid communication protocol. • Barrier-free communication. • Cross-platform IoT device connectivity.	• Design a new standardized protocol [149]. • Mesh network based on LoRa. • Interoperable platform.
Regulatory issues	• LoRaWAN uses unlicensed ISM bands which faces regional regulatory constraints. • An efficient solution to give more flexibility.	• Real-time data transmission. • Enhance spectral efficiency. • Reduce interference.	• Dynamic frequency hopping mechanisms [150]. • Technological flexibility.
Challenges with data availability	• LoRa parameters data are very limited. • Enhancing dataset collection in the LoRaWAN network.	• Augments the dataset. • Empowering network operators. • Optimizing LoRaWAN networks.	• Dataset collection within the LoRaWAN network. • Fast data collection techniques [151], [152].

load data is pivotal for safeguarding information confidentiality. Establishing secure key management practices, including blockchain [146], third-party key management [147], and proxy-based key establishment [148], is crucial to prevent unauthorized access and system compromise. Moreover, adopting privacy-preserving measures, such as anonymization of sensitive metadata, helps protect user identities and maintain a level of data anonymity. Continuous monitoring and auditing of the LoRaWAN infrastructure swiftly detects and responds to potential security threats. Additionally, collaborating industry-wide and ensuring compliance with data protection regulations contribute to a comprehensive security posture. While current techniques contribute to strengthening LoRa security, there exists a gap in addressing application-specific security requirements. Future efforts must prioritize understanding diverse requirements. For example, certain applications may require independent Network and Application Session keys, to ensure confidentiality. Investigating distinct security needs for each scenario is crucial to mitigate vulnerabilities in varying contexts.

D. Interoperability

The wide range of sensor types used in IoT applications frequently calls for the integration of numerous communication methods, especially when there are many platforms and data coming from separate subsystems. Hybrid communications are implemented using LoRa platforms in conjunction with ZigBee to manage diverse sensor clusters. Alternatively, a mesh networking architecture is constructed using the IEEE 802.11s-based system. A mesh network based on LoRa can send fewer data packets, yet IEEE 802.11s can handle huge dataset transfers efficiently in a condensed amount of time. The integration pathway for diverse technologies, including cloud, IoT, and software-defined networking, along with data-driven technologies, is outlined in [149], encompassing associated challenges and opportunities. Some platforms such as FIWARE [153], Cayenne [154], and mySense [155] help make smart IoT applications interoperable. These solutions fit into the ”industry 4.0” paradigm, in which several protocols are integrated and work together to suit the needs of automating technical and computer activities [149].

E. Regulatory Issues

Many LPWAN technologies that rely on unlicensed ISM radio bands, which are free to use, are subject to regional or country-specific regulatory restrictions. While parameters like bandwidth and spreading factor can be adjusted for different modulations, LoRaWAN faces the constraint of operating on a single carrier frequency for a given transmission. The ETSI EN300.220 standard outlines specific limitations for unlicensed frequency bands, including maximum radiated power, channel spacing, spectrum access, and mitigation requirements [28]. In Europe, LoRa commonly uses the 868.0 MHz frequency, with the 868.0 MHz to 868.6 MHz band having a maximum radiated power limit of 25 mW and a maximum duty cycle of 1%. This limitation significantly restricts the real-time transferable amount of data, ensuring fair network usage. Consequently, a large number of devices can connect to a single access point. The modulation directly influences the range, thereby imposing constraints on the maximum attainable data rate for the distance to the access point. Implementing dynamic frequency hopping mechanisms within LoRaWAN networks can enhance spectral efficiency and reduce interference, addressing issues associated with unlicensed spectrum use [150]. There is a need to skillfully manage the complex challenges of unlicensed ISM radio bands through a combination of technological flexibility, collaborative initiatives, and a strong commitment to following regional regulations. This approach ensures a responsible and compliant deployment of IoT solutions.

F. Challenges with Data Availability

In a LoRaWAN network, data comes in two main forms: LoRa parameters data and sensory data. The LoRa parameters data encompasses transmission timestamp, channel information, device extended unique identifier, SNR, port for message differentiation, binary RF chain value, RSSI, and frame counter. The significance of LoRa parameters, specifically SNR and RSSI, in the collected data is pivotal. SNR evaluates signal strength relative to background noise, offering insights into communication reliability, while RSSI provides a comprehensive measure of overall signal strength. These parameters play crucial roles in optimizing LoRaWAN networks by assessing link quality, optimizing spreading factors and transmission power, estimating communication range, identifying interference, and ensuring QoS. Continuous monitoring aids in fault detection, troubleshooting, and improving battery life for LoRa devices. In essence, meticulous analysis of SNR and RSSI details enriches the dataset, empowering network operators to make informed decisions for a robust and efficient LoRaWAN ecosystem. While some datasets are available, such as those referenced in [156], [157], [158], [159], their availability is limited. There is a need to encourage more extensive dataset collection within the LoRaWAN network. Some of the methods for fast data collection may help to create a comprehensive LoRaWAN dataset, as illustrated in the papers [151], [152].

X. Conclusion

In this study, a literature review was conducted to explore how DL and ML have been employed to overcome the challenges and limitations of LoRaWAN. State-of-the-art DL and ML algorithms offer a promising and innovative approach to effectively address the major challenges of LoRaWAN, including collisions, scalability, and communication range. The analysis began with a thorough technical background on LoRa and LoRaWAN, and then utilized a layer-by-layer protocol approach to discuss the LoRaWAN challenges and proposed solutions in the literature, with a specific focus on DL and ML algorithms. Furthermore, a four-layered LoRaWAN architecture was introduced to enhance the efficiency of the IoT ecosystem, highlighting the aforementioned challenges. Despite their significant potential, the implementation of DL and ML models in real-world applications poses several challenges, such as data quantity and quality, interoperability, energy efficiency and others. Our extensive review aims to highlights the significant transformation that can be achieved by utilizing advanced DL and ML algorithms to tackle critical issues within the LoRaWAN network.

Appendix

The abbreviations used in this article are listed in Table VII.

TABLE VII: Nomenclature

Acronym	Abbreviation
ABP	Activation By Personalization
ADR	Adaptive Data Rate
ANN	Artificial Neural Network
BW	Bandwidth
CNN	Convolution Neural Network
CSS	Chirp Spread Spectrum
DNN	Deep Neural Network
DL	Deep Learning
DR	Data Rate
DER	Data Extraction Rate
DQL	Deep Q-Learning
DRL	Deep Reinforcement Learning
DTR	Decision Tree Regression
ED	End Device
FHHS	Frequency Hopping Spread Spectrum
FCNN	Fully Connected Neural Networks
GRU	Gated Recurrent Unit
IoAT	Internet of Agriculture-Things
IoT	Internet of Things
ITU	International Telecommunication Union
ITS	Intelligent Transportation System
K-NN	K-Nearest Neighbors
LSTM	Long Short-Term Memory
LPWAN	Low Power Wide Area Network
LoRaWAN	Long Range Wide Area Network
MAC	Medium Access Control
MDP	Markov Decision Process
ML	Machine Learning
OTAA	Over The Air Activation
PHY	Physical Layer
PDR	Packet Delivery Ratio
PSR	Packet Success Ratio
QoS	Quality of Service
RL	Reinforcement Learning
RNN	Recurrent Neural Networks
RSSI	Received Signal Strength Indicator
SF	Spreading Factor
SER	Symbol Error Rate
SINR	Signal to Interference plus Noise Ratio
SNR	Signal to Noise Ratio
SVM	Support Vector Machines
TOF	Time of Flight
TP	Transmit Power

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