Recent Advances in LoRa: A Comprehensive Survey

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The vast demand for diverse applications raises new networking challenges, which have encouraged the development of a new paradigm of Internet of Things (IoT), e.g., LoRa. LoRa is a proprietary spread spectrum modulation technique that provides a solution for long-range and ultra-low power-consumption transmission. Due to promising prospects of LoRa, significant effort has been made on this compelling technology since its emergence. In this article, we provide a comprehensive survey of LoRa from a systematic perspective: LoRa analysis, communication, security, and its enabled applications. First, we summarize works focusing on analyzing the performance of LoRa networks. Then, we review studies enhancing the performance of LoRa networks in communication. Afterward, we analyze the security vulnerabilities and countermeasures. Finally, we survey the various LoRa-enabled applications. We also present comparisons of existing methods, together with insightful observations and inspiring future research directions.

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CCS Concepts: • **Networks**; • **General and reference** → **Surveys and overviews**;;

Additional Key Words and Phrases: LoRa, Analysis, Communication, Security, Application

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1 INTRODUCTION

The rapid growth of IoT in past decades has witnessed the explosion of applications in a wide range of fields with respect to smart city [176], industry [34], agriculture [19], and so on. IoT thrives on a variety of wireless communication technologies, such as short-range wireless standards (e.g., Zigbee, Bluetooth) and cellular technologies (e.g., 4G, 5G). However, in the face of the future

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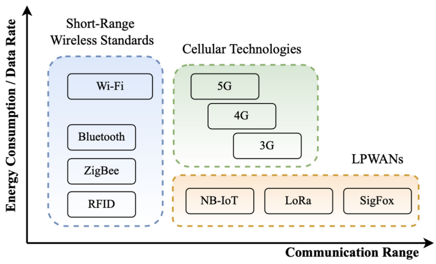

Fig. 1. Comparison with legacy wireless communication technologies.

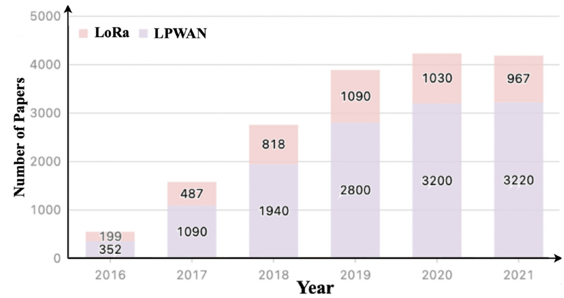

Fig. 2. Number of papers with years through Google Scholar hits for "LoRa" and "LPWAN" keywords.

demand for tens of billions of IoT access, these legacy wireless technologies are limited by communication range and energy consumption. In this context, such long-range and energy-efficient communication demands have inspired the emergence of **Low Power Wide Area Networks (LPWANs)** as a new IoT new paradigm, which fills the gap of legacy wireless communication technologies (see Figure 1). Among which, LoRa, due to its open-source privilege (operating in the unlicensed sub-GHz ISM band) and low-cost **Commercial Off-The-Shelf (COTS)** devices compared with other LPWAN technologies such as NB-IoT and SigFox, shows great potential in industry and research communities recently.

LoRa is a proprietary spread spectrum modulation technique on the basis of **Chirp Spread Spectrum (CSS)**, which is resilient and robust against interference and noise. Such modulation technique and a high sensitivity offered by LoRa enable receiving the potential weak signals at extremely low energy consumption, which provides significant link budget improvement to support a wide coverage [94]. LoRaWAN is a data link layer specification built on top of LoRa, defining the typical stat-topology network architecture and its bi-directional communication protocol. To date, LoRa networks have been deployed by 163 LoRaWAN network operators across 177 countries globally [76], widely distributed in various applications scenarios that require large-scale and delay-insensitive deployment [19, 21, 34, 176]. In the research community, an intuitive fact is that nearly 1,000 papers involving LoRa in their contents were published during 2021 through Google Scholar hits for the "LoRa" keyword (see Figure 2).[1]

Due to large-scale deployments and promising prospects of LoRa, extensive works on LoRa have been presented since its appearance. Accordingly, such fact motivated several survey papers [56, 85] on LoRa in the recent six years. In particular, some early surveys [22, 62, 146] gave an overview of LoRa with an emphasis of preliminary background and principle introduction, which laid a foundation for follow-up research. A small portion targeted specific areas such as testbed [103], simulator [32], security [114], and mesh topology [29]. Recently, several comprehensive surveys of LoRa [56, 85] were proposed. For example, Gkotsiopoulos et al. [56] focused on the network capacity from five main aspects, encompassing PHY layer characteristics, deployment and hardware features, transmission settings, MAC protocols, and application requirements. Li and Cao [85] gave a comprehensive and structured survey of LoRa from a two-dimensional taxonomy: networking layers (i.e., PHY, MAC, Link, and Application layer) and performance metrics (i.e., range, throughput, energy, and security). However, many LoRa methods typically do not show a clear boundary on the networking layer level but span multiple ones.

[1]Due to the huge number of references about LoRa, this survey only focuses on the papers published at top conferences or journals, coupled with highly influential ones.

Table 1. Summary and Comparison with Prior LoRa Surveys/reviews

Survey	Year	LoRa Analysis				LoRa Communication			LoRa Security		LoRa-Enabled Applications			
		Perf. Meas.	Anal. Models	Simulators	Testbeds	Modem	MAC Protocol	Config.	V. & C.	PLS	Backscatter	Sensing	WCE & CTC	Others
[22]	2016	◗	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
[103]	2017	●	❍	◗	●	❍	❍	❍	❍	❍	❍	❍	❍	❍
[62]	2018	●	●	●	◗	❍	◗	◗	◗	❍	❍	❍	❍	●
[146]	2019	●	◗	◗	◗	◗	●	●	●	❍	●	❍	❍	●
[114]	2020	❍	❍	◗	❍	❍	❍	❍	●	❍	❍	❍	❍	●
[81]	2020	❍	●	●	◗	❍	◗	●	❍	❍	❍	❍	❍	❍
[29]	2020	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	◗
[32]	2021	◗	❍	●	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
[56]	2021	●	◗	●	❍	❍	●	●	❍	❍	❍	❍	❍	●
[85]	2022	●	●	❍	◗	●	●	●	◗	❍	●	●	◗	●
Ours	2022	●	●	●	●	●	●	●	●	●	●	●	●	●

(❍–none, ◗–Moderate, ●–Comprehensive; Perf. Meas.: Performance Measurement, Anal.: Analytical, Config.: Configuration Setting, V. & S.: Vulnerabilities and Countermeasures, PLS: Physical Layer Security).

In comparison with prior works (see Table 1), our survey presents two novel contributions. First, our survey covers various efforts made to LoRa comprehensively and up to date, which complements the previously published ones. Second, our survey summarizes and compares LoRa works from a new perspective. Figure 3 gives a taxonomy of our survey. Specifically, our article provides a comprehensive survey on LoRa from four-fold: LoRa analysis works and tools, LoRa communication studies in terms of **Physical (PHY)** and **Media Access Control (MAC)** layer, LoRa security vulnerabilities and countermeasures, and LoRa-enabled applications. The rationale behind the organization is that, since the advent of LoRa, early-stage studies focus on understanding and analyzing LoRa performance through various field studies or simulation tools. Afterward, as a networking technology, a large quantity of research efforts have been made to improve the performance of LoRa networks in communication. Meanwhile, with massive deployments of LoRa networks, security is receiving much attention. As LoRa tends to mature in a variety of common IoT applications, many works contribute ones beyond the scope of LoRa radio. Thus, such taxonomy provides a good fit for the cognition of the evolution of LoRa technology, which provides an aggregation of LoRa methodologies in different aspects and a new perspective for the research community. In particular, the four parts are specified as follows:

- **LoRa Analysis.** LoRa performance analysis works aim to investigate and interpret LoRa network performance in various environments, which can also serve the further exploration in various LoRa communication, security, and its enabled applications works. Specifically, these works include early-stage performance measurements and three types of conducted tools: analytical models, simulators, and testbeds.
- **LoRa Communication.** Many efforts have been made to target improving the performance of LoRa networks in communication, in terms of throughput, communication range, scalability, and energy consumption. These works give a focus on LoRa PHY and MAC layer, which can be divided into three categories: LoRa (de)modulation techniques, MAC protocols, and configuration settings.
- **LoRa Security.** Security is fragile but critical for any wireless communication technologies, receiving significant attention in vulnerabilities and countermeasures, coupled with PHY layer security methods.
- **LoRa-enabled Applications.** The wide deployment of LoRa networks has inspired a wide range of applications, including backscatter, sensing, integration with heterogeneous wireless technologies, and other applications.

Based on that, comparisons of existing LoRa works (e.g., in Tables 6, 8, 11, 12, 13), with brief summaries and insightful discussions, are also given.

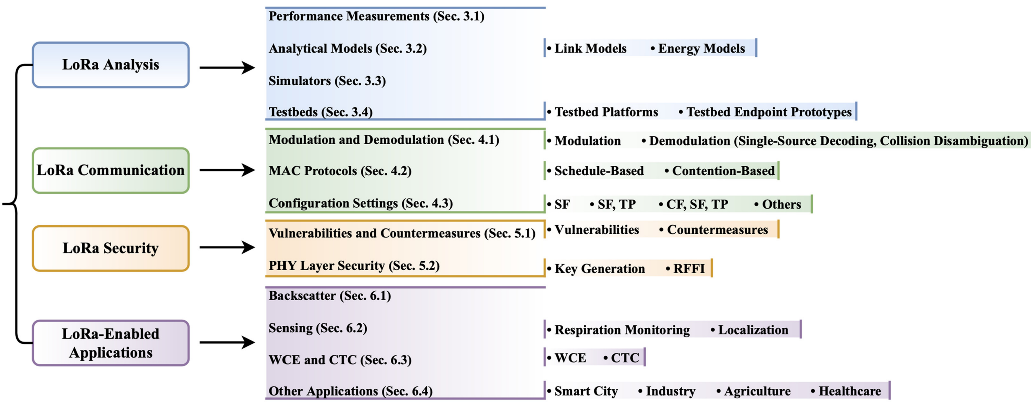

Fig. 3. Taxonomy of this survey.

The remainder of the survey is organized as follows: LoRa preliminary, inclusive of its PHY and MAC layer, is introduced in Section 2. LoRa analysis works and different types of tools are reviewed in Section 3. Various LoRa communication studies are surveyed and compared in Section 4. LoRa security vulnerabilities and countermeasures are discussed in Section 5. LoRa-enabled applications in different fields are reviewed in Section 6. The challenges and potential future development of LoRa are discussed in Section 7, followed by the Conclusion in Section 8.

2 LORA PRELIMINARY

Although LoRa has been extensively introduced in numerous papers, to make this article self-contained, we provide a brief preliminary of LoRa, together with LoRa PHY layer and LoRaWAN MAC layer.

2.1 LoRa Overview

LoRa, standing for "Long Range," is a proprietary spread spectrum modulation technique, while LoRaWAN is a data link layer specification built on top of LoRa. LoRa operates in the unlicensed sub-GHz ISM radio band, depending on the deployed regions (e.g., 863–870 MHz in Europe, 902–928 MHz in the USA), but also obliges to the duty cycle regulations (e.g., 1% in Europe). Compared with short-range wireless standards and cellular technologies, LoRa shows remarkable results in long-range transmission and ultra-low power consumption. Specifically, its coverage range is up to 15 km (rural areas) and 5 km (urban areas), its device battery life is up to 10 years, and its data rate ranges from 0.3 to 37.5 Kbps [22]. Some other properties, such as low cost of devices, concurrent reception capacity of gateways, and the resiliency of modulation attribute against fading, multipath, and Doppler effect compared to other wireless signals [89], also make LoRa compelling. It is noted that real-life deployed LoRa networks typically cannot obtain the optimal performance that LoRa promises, due to the deployment complexity and various interference.

2.2 LoRa PHY Layer

LoRa PHY layer adopts a proprietary spread spectrum modulation technique derived from CSS with an integrated **Forward Error Correction (FEC)** mechanism [128], which offers substantial processing gains for link budget improvements and resiliency to multipath and interference. Figure 4 shows a LoRa packet structure, which consists of a preamble with 8 base up-chirps, a

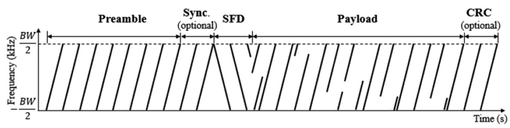

Fig. 4. LoRa PHY packet structure.

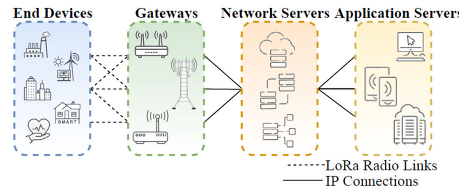

Fig. 5. LoRa network architecture.

synchronization word with 2 base up-chirps, a **Start of Frame Delimiter (SFD)** with 2.25 base down-chirps, and payload data followed by **Cyclic Redundancy Check (CRC)**.

In LoRa modulation, the frequency of chirps constantly varies linearly with time within the pre-defined available narrow bandwidth. Specifically, a base up-chirp is defined as one that linear sweeps from its initial frequency $-BW/2$ to $BW/2$, represented as $C(t) = e^{j2\pi(\frac{k}{2}t-\frac{BW}{2})t}$. LoRa modulation is performed by representing each bit of payload by multiple chirps with a shifted initial frequency f_{sym}, thus the signal of a symbol is denoted as $S(t, f_{sym}) = C(t) \cdot e^{j2\pi f_{sym}t}$ [68].

As for the demodulation, the receiver performs the "de-chirp" operation where each received symbol is multiplied with a base down-chirp (i.e., the conjugate of a base up-chirp), denoted as $S(t, f_{sym}) \cdot C^{-1}(t) = e^{j2\pi f_{sym}t}$ [68], resulting in a single frequency tone. Then the receiver applies the **Fast Fourier Transform (FFT)** on the multiplication result, where the resulted one FFT peak indicates the initial frequency f_{sym}.

The configuration for a LoRa device is mainly specified by such parameters: **Spreading Factor (SF), BandWidth (BW), Code Rate (CR), Carrier Frequency (CF)**, and **Transmission Power (TP)**. Specifically, SF, ranging from 7 to 12, represents the number of symbols per bit of payload. A higher applied SF incurs a lower data rate, longer propagation time, and more energy consumption, but provides better sensitivity and a wider transmission distance. Hence, devices located farther from the gateway require a higher SF due to the more link budget need, which provides increased processing gain but at the cost of a lower data rate. Besides, SFs are orthogonal (essentially quasi-orthogonal [128]), which allows transmission of signals modulated with different SF in the same channel. The BW is typically 125 kHz, 250 kHz, and 500 kHz. And the CR, denoting the rate of the FEC code, can be set to 4/5, 4/6, 4/7, or 4/8, where a higher one offers more protection at the cost of increasing the air time. Then, the LoRa modulation bit rate R_b can be calculated through $R_b = SF \times \frac{BW}{2^{SF}} \times CR$. Besides, LoRa band in distinct regions defines different multiple frequency channels, and CF is the center frequency of these channels. TP on a LoRa radio is restricted by the specific hardware, generally ranging from 2 to 20 dBm [14]. Tuning the parameters above can achieve a tradeoff between communication range, data rate, and power consumption, which inspires plenty of configuration setting methods (see Section 4.3).

2.3 LoRaWAN MAC Layer

LoRa only defines the lower PHY layer in the communication stack, resulting in several available upper network protocols, among which LoRaWAN is the most popular networking protocol. It is noted that LoRaWAN is extensively regarded as a MAC protocol for LoRa; however, the LoRaWAN stack operates at the data link layer and does not define any channel access control scheme. LoRaWAN protocol mainly defines LoRa network architecture and its bi-directional communication protocol. As shown in Figure 5, the LoRaWAN network architecture is a typical star topology, mainly including end devices, gateways, network servers, and application servers. End devices (also called nodes, clients, points) equipped with various sensors are placed in the scenarios as data sources. Gateways (also called base stations) are the bridge between end devices and network servers. Network servers are the LoRa network controller taking charge of the management of devices and applications, while application servers provide the operation interface with users. Additionally, LoRaWAN defines three types of operation classes for end devices, i.e., class A(ll), B(eacon), and C(ontinue). Class A is the default one that all devices must implement, while B and C are the optional ones. Class A, where two receive downlink windows are created shortly after an uplink transmission from devices, is the most energy-efficient among these three ones. Apart from two receive slots, end devices add scheduled downlink ping slots in class B, triggered by synchronization beacons broadcasting from gateways. Class C, where end devices continuously keep listening when unless are transmitting (i.e., half-duplex), thereby is the most energy-consuming one. Choosing the optimal operation class can reduce energy consumption and meet the response time requirements of different application scenarios.

Additionally, LoRaWAN provides media access, **Adaptive Data Rate (ADR)**, and security services. LoRaWAN MAC layer employs a default primitive ALOHA MAC protocol [49] that allows end devices to transmit as soon as they wake up, without channel detection and time synchronization. Besides, ADR is a vital mechanism of LoRaWAN, allowing end devices to be configured with different data rates dynamically according to network conditions. However, LoRaWAN does not give a definition of the ADR algorithm, hence resulting in many studies [81]. LoRaWAN provides security functions by relying on **Advanced Encryption Standard (AES)** algorithms and two 128-bit unique session keys (i.e., NwkSKey and AppSKey) to complete data encryption, message integrity checking, and node authentication. The session keys can be obtained through two activation processes, i.e., **Activation By Personalization (ABP)** and **Over-The-Air Activation (OTAA)**.

3 LORA ANALYSIS

Since the advent of LoRa technology, various LoRa performance analysis works have been ongoing, aiming to investigate and interpret the performance of LoRa networks in terms of throughput, communication range, scalability, and energy consumption. Specifically, these works include early-stage performance measurements and three types of conducted tools (i.e., analytical models, simulators, and testbeds). Analytical models are designed to give a mathematical explanation process for some specific tasks, such as link and energy analysis. Simulators are popular in theoretical method evaluation due to their convenience and low cost. Testbeds are utilized for the performance evaluation of the real LoRa network under different scenarios to explore its capabilities and limitations to provide a benchmark standard. To this end, we first give a summary of performance measurement works, then review corresponding analysis tools in this section.

3.1 Performance Measurements

Some early performance measurement works conduct testbed experiments, perform simulations, build analytical models, or adopt their collaborations to explore LoRa-related performances in terms of LoRa radio [8], link condition [44], node energy consumption [89], network communication range [120], scalability [108], and so on. It is noted that analytical models are generally inevitable parts serving for testbed experiments and simulations, but testbed measurement is the most favored choice owing to its real and objective experimental results. Table 2 summarizes the classical performance measurement works, along with their corresponding conclusions.

Liando et al. [89] conducted various LoRa network performance measurements in a 3-gateway and over 50-node testbed. Specifically, they revealed: (1) the communication range in the **line-of-sight (LOS)** scenario is 10 km, while drops sharply to 2 km in obstacle blocking **non-line-of-sight (NLOS)** one under the settings of SF12 and PRR 70%; (2) the predicted node lifetime under different configuration settings ranges from 1.19 to 4.54 years; (3) multiple access performances in terms of

Table 2. Summary of LoRa Performance Measurement Works

Reference	Year	Experimental Setup	Performance Metric & Conclusion
Augustin et al. [8]	2016	Testbed and simulator	Modulation: resistance to interference Coverage: 2.8 km in an urban area
Bor et al. [15]	2016	LoRaSim simulator	Coverage: 120 nodes in the area of 3.8 ha in a city scenario
Petäjäjärvi et al. [120]	2017	1-node and 1-gateway testbed	Doppler robustness: getting worse when speed is greater than 40 km h^{-1} Range: 30 km on water with PPR 62%, SF12, and TP14 dBm
Feltrin et al. [44]	2018	2-node outdoor testbed	RSSI: decreases from −80 (2 km) to −100 dBm (10 km) Inter-SF: quasi-orthogonal, co-SF: SIR varies from 0.3 to 1.7 dB
Liando et al. [89]	2019	3-gateway and over 50-node testbed	Range: >10 km (LOS), <3 km (NLOS) Node lifetime: 1.19–4.54 years Multiple access: gateway capacity is 6,249 nodes with PRR 70% LoRa is resilient against Doppler effect, etc.
Xu et al. [177]	2019	10-node indoor testbed (4 types buildings)	Large-scale fading: influenced by many factors (e.g., materials, layout) Temporal fading: follows Rician distribution K-factors (12–18 dB)
Tian et al. [152]	2021	21-node outdoor testbed	High temperature gradient across nodes in different deployments Temperature and RSS: high correlation Impact of temperature is greater than weather conditions

(PRR: Packet Reception Ratio, RSSI: Received Signal Strength Indication, SIR: Signal-to-Interference Ratio, SNR: Signal-to-Noise Ratio).

SF and single-channel capacity, where the gateway capacity is 6,249 nodes with PRR 70%. Besides, they provided some insights on the enhancement of parameter optimization, MAC protocol, concurrent reception, and PHY layer based on their measurements. Xu et al. [177] investigated the LoRaWAN network performance in four types of multi-floor buildings, including LoRa large-scale and temporal fading characteristics, coverage, and energy consumption. They conclude that many factors, such as building materials and layout, influence the path loss greatly, and the temporal fading follows Rician distribution with its K-factors falls between 12 and 18 dB. Tian et al. [152] released a large-scale dataset focusing on the network and link-level performance in a 21-node outdoor LoRa network for over four months. Specifically, the data features with three types of attributes, i.e., basic (time, SF, TP, etc.), connectivity and link quality (PRR, RSS, SNR), and environmental (temperature measured by nodes, weather condition, etc.) attributes. Besides, they provided evaluation scripts for data analysis and visualization.

LoRa preliminary performance measurement works aim to understand the capabilities and limitations of LoRa networks, which have made a fundamental contribution to the follow-up research. Liando et al. [89] conducted large-scale deployment and measurement to comprehensively investigate the performance of LoRa networks in terms of range, energy, and capacity. Radio fading [177] and inter-SF transmission [44] also received considerable attention. Additionally, public datasets [152] provide a novel and labor-saving solution for research. However, the type of hardware and the diversity of deployment environments bring complexity to such measurement works. Furthermore, quantifying LoRa performance with the corresponding factors is a crucial and popular research trend.

3.2 Analytical Models

An analytical model, i.e., a mathematical model with closed-form solutions, quantitatively represents the interrelationship of a set of parameters to describe a specific problem. A large number of methods pursue capturing the complexity of real-world deployment of LoRa networks to derive an accurate, interpretative, and general analytical model before solving various research problems such as optimal parameter assignments [53]. The existing analytical models mainly concentrate on the link and energy models, where network deployment, device configuration, and environmental

Table 3. Summary of LoRa Analytical Models

	Reference	Year	Model	Features						
				Para. Config.	**Multiple Gateways**	**Channel Variation**	**Collision Probability**	**SF Quasi-orthogonality**	**Duty Cycle**	**Envir. Factor**
Link Model	Georgiou and Raza [55]	2017	SNR-based link-outage SF-based link-outage	✓	✗	✓	✓	✗	✓	✗
	Waret et al. [166]	2018	Throughput (bit-rate×success probability)	✓	✗	✓	✓	✓	✓	✗
	Mahmood et al. [102]	2018	SNR-based success probability	✓	✗	✓	✓	✓	✓	✗
	Chall et al. [40]	2019	Empirical measurement-based path loss	✗	✗	✓	✗	✗	✗	✓
	Demetri et al. [37]	2019	Learning-based path loss	✗	✓	✓	✗	✗	✗	✓
	Liu et al. [94]	2021	Learning-based path loss	✗	✓	✓	✗	✗	✗	✓
	Toro-Betancur et al. [157]	2021	Node-level delivery ratio	✓	✓	✓	✓	✓	✓	✗
				Para. Config.	**Multiple Chipsets**	**Inner Unit**	**Collision Probability**	**Multiple Modes**	**Duty Cycle**	**Envir. Factor**
Energy Model	Casals et al. [20]	2017	Current consumption, lifetime, and energy efficiency	✓	✗	✗	✓	✓	✓	✗
	Bouguera et al. [16]	2018	Node Energy Consumption	✓	✗	✓	✗	✓	✗	✗
	Liando et al. [89]	2019	Node lifetime	✓	✓	✓	✓	✓	✓	✗
	Delgado et al. [36]	2020	Battery-free LoRa node Markov-based uplink and downlink	✓	✗	✓	✓	✓	✗	✓
	Finnegan et al. [46]	2020	Ambient RF energy harvesting	✓	✗	✓	✗	✓	✓	✓

(Para.: Parameter, Envir.: Environment).

factors are integrated into these models for LoRa link and energy analysis. Table 3 summarizes current LoRa analytical models.

Link Models. A large body of work aims to understand the channel quality by analyzing the link conditions of LoRa networks, such as path loss [94], delivery ratio [157], and interference. In a single gateway scenario, Georgiou and Raza [55] leveraged a stochastic geometry framework to study link-outage conditions concerned with SNR and co-SF and revealed that the network scalability is susceptible to the latter one owing to the exponential degrading performance. Likewise, SNR threshold, co-, and inter-SF interference were studied in References [102, 166]. Several models [55, 166] only considered simple network topologies or make strict assumptions about the spatial network distribution, resulting in poor generality. Toro-Betancur et al. [157] proposed a general node-level delivery ratio model without any restrictions on network deployment or device configuration, which characterizes quasi-orthogonal transmission under many considerations such as capture effect, duty cycle, multiple gateways, and channel variation.

Besides, several methods [12, 40] focus on the path loss modeling of LoRa networks. The path loss (also called path attenuation) refers to the power attenuation during the transmission, varying along with different land-covers on the path due to the radio reflection, diffraction, and so on. Chall et al. [40] adapted the most widely used free-space, log-distance, and multiwall-and-floor path loss models based on the empirical measurement results to derive their models in indoor and outdoor environments, respectively. Remote sensing techniques are utilized for land-covers analysis in References [37, 94]. Demetri et al. [37] proposed an automated link quality estimation method without on-site measurements, which can also be used for gateway deployment planning. Specifically, they first proposed a toolchain to recognize seven types of land-covers based on freely multispectral images from satellites, and then they presented an Okumura-Hata [107] model-based framework for expected received power estimation. Rather than the physical path loss model [40], Liu et al. [94] proposed a deep learning-based long-distance path loss estimation framework termed DeepLoRa, with an emphasis on the types and order of land-covers. Specifically, DeepLoRa divides the link into an ordered sequence of micro links with equal length and utilizes remote sensing images to identify the detailed land-covers of each micro-link. Then, DeepLoRa adopts a **Bidirectional Long-Short-Term-Memory (Bi-LSTM)** network to learn the path loss model.

Energy Models. Energy consumption of LoRa nodes to complete routine data collection and transmission process is a key indicator for constrained LoRa networks. Thus, several studies

[20, 89] proposed models to characterize the energy consumption of transmission or the nodes' lifetime. Casals et al. [20] first defined the different states of the nodes from waking up to sleep in one transmission, then derived a series of energy models under various considerations concerning data rate, collision, un- and acknowledged transmission. Specifically, they modeled the node average current consumption of these different states, lifetime through the battery capacity divided by the current, and energy efficiency of data delivery through the real divided by the expected one. Bouguera et al. [16] deduced an energy model allowing for different settings of parameters and IoT scenarios by calculating and summing the energy consumption of inner sensor node elements in sleep and active operating modes. Liando et al. [89] modeled the energy consumption to quantify the lifetime of LoRa nodes via the testbed measurement across multiple chipsets. Specifically, they first captured the energy profile of the **microcontroller unit (MCU)** and LoRa transceiver using a monsoon power monitor under different parameter settings, then calculated the node lifetime by multiplying the single transmission cycle time duration and the supporting transmission cycle number of a specific battery.

Besides, several models [36, 96] explored the possibility of energy harvesting of LoRa. Delgado et al. [36] first derived a battery-free LoRa node model involving energy harvesting system, circuit, and load models, then proposed a Markov model to characterize the uplink **packet delivery ratio (PDR)** and probability of receiving downlink packets, defined by parameters with respect to device configuration, application behavior, and so on. Finnegan et al. [46] explored the boundaries of the feasibility of ambient **Radio Frequency (RF)** energy harvesting for LoRa devices. Specifically, they first recombined the energy model of nodes from the sensing, networking, data processing, and other system tasks parts, then deduced the aggregated energy model by quantifying ambient RF power level and integrating the impacts of harvesting components including rectenna, power management unit, and storage device.

In general, a reliable analytical model integrates principle characterization and interrelationship of parameters to reflect the internal law, which is significantly vital for further research in terms of quantitative analysis and performance evaluation. For link models, network configuration, SF quasi-orthogonality, and radio fading are typically common considerations. Remote sensing techniques [37, 94] provide a solution for measurement-free link modelling, which can be used for localization [91]. For energy models, the energy profiles under different inner units, states, and parameter settings are captured. Additionally, energy harvesting models shed light on some harvester designs [100]. However, strict assumptions, complex and long-term environmental variance will limit the deduction of general models.

3.3 Simulators

A network simulator is a virtual tool to explore the system-level or link-level performance through the reproduction of communication interactions in the networks. It is typically composed of network configuration definition (e.g., topology, parameter, and propagation model), event simulation (e.g., uplink and downlink), and performance evaluation. Simulators are widely used in theoretical model evaluation when large-scale testbeds are not deployed or inconvenient to operate. Therefore, several open-source LoRa simulators have been proposed in recent years, especially used for LoRa network scalability and throughput evaluation. Table 4 presents current popular simulators designed for LoRa networks, along with their included features.

Bor et al. [15] proposed a simulator termed LoRaSim based on their derived communication behavior model involving range and collision behavior considerations. Specifically, the range considers the configuration settings (i.e., received signal power, path loss, and sensitivity) to determine whether a packet is received or not, while the collision behavior determines the decoding under different conditions (i.e., CF, SF, timing, power). Magrin et al. [101] designed an ns-3 module for

Table 4. Summary of LoRa Network Simulators

Simulator	Year	Envir.	Features							
			Topol. & Para. Config.	Class C Support	MAC Command	Bi-directional Traffic	Propagation Model	SF Quasi-orthogonality	Duty Cycle	Node's Energy Consumption
LoRaSim [15]	2016	SimPy	✓	✗	✗	✗	✓	✗	✗	✗
Magrin et al. [101]	2017	ns-3	✓	✗	✓	✗	✓	✓	✓	✓
Abeele et al. [159]	2017	ns-3	✓	✗	✓	✓	✓	✗	✓	✓
Croce et al. [30]	2018	Matlab	✓	✗	✗	✗	✓	✓	✗	✗
FLoRa [140]	2018	OMNeT++	✓	✗	✓	✓	✓	✗	✓	✓
LoRaFREE [2]	2019	SimPy	✓	✗	✓	✓	✓	✓	✓	✓
Finnegan et al. [45]	2020	ns-3	✓	✗	✓	✓	✓	✓	✓	✓
LoRaWANSim [106]	2021	Matlab	✓	✓	✓	✓	✓	✓	✓	✓

(Topol.: Topology).

the LoRaWAN network performance simulation under the assumptions at both the link and the system level. Specifically, the link model contains a link measurement model abstracting the effect of such as propagation loss and fading, and a performance model determining transmission and interference. The system model includes SF and CF allocation tasks. Abeele et al. [159] built a physical error model through the baseband simulations over an **Additive White Gaussian Noise (AWGN)** channel, together with LoRaWAN MAC protocol, for the proposed ns-3 simulator. Croce et al. [30] focused on the superposition of multiple LoRa radios from different SFs. Besides, several proposed simulators were designed with an emphasis on specific methods, such as ADR [45, 140] and MAC protocol [2]. Marini et al. [106] proposed LoRaWANSim, a to-date simulator for the sake of completeness, which characterizes the LoRaWAN network behavior with respect to PHY, MAC, and network aspects.

In general, a simulator is an efficient, convenient, and low-cost tool to evaluate the performance of LoRa networks. Many classic simulators have been proposed so far, including References [15, 30, 101], and LoRaWANSim [106] is the most comprehensive one to date. However, current simulators are not full-featured enough, owing to the focus on some specific kinds of tasks. Hence, developing full-featured simulators still deserves further efforts. In addition, the characteristics of the simulator indicate that it is generally suitable for the theoretical method evaluation, so the testbed can make up for it with regard to the evaluation objectivity and reality.

3.4 Testbeds

A testbed is a real-life deployment platform containing complete network components, aiming at conducting controllable and reproducible experiments to obtain actual results via real-life deployments. Apart from private LoRa networks [49, 92], research communities have contributed to many public open-source testbeds for evaluation works. Current public open-source testbeds primarily include testbeds platforms [54] and endpoint prototypes [65]. Specifically, remotely accessible testbed platforms typically contain a complete network architecture for stand-alone instance spawning, including device management, programming, and web services. They enable researchers for remote application test and development, which resolve the problem of high-cost, time-consuming, and labor-consuming deployment and maintenance of a LoRaWAN testbed. Testbed endpoint prototypes provide a flexible and easily deployable solution in terms of heterogeneous networking protocol, inconvenient network (e.g., Ethernet, cellular), and power conditions. It is noted that both of them rely on a framework for device and service profiles management. Table 5 lists current LoRa public testbed platforms and endpoint prototypes.

Testbed Platforms. Dongare et al. [38] proposed an open-source LoRaWAN network testbed platform termed OpenChirp, built upon LoRaWAN with the user management framework, **application programming interfaces (APIs)**, and core services. In particular, OpenChirp is currently powering a hosted campus network, enabling users to spawn stand-alone instances with

Table 5. Summary of LoRa Public Testbed Platforms and Endpoint Prototypes

	Testbed	Year	Architecture	Networking	Node	Case Study
Platform	FIT IoT-Lab [3]	2015	Software (user, back-end), Hardware (open node, gateway, control node)	Wi-Fi, LoRa, BLE, etc.	2,728 IoT nodes, 117 mobile robots	Impact of Wi-Fi traffic visualizing, smart floor demonstration
	OpenChirp [38]	2017	LoRaWAN with user management, API, etc., LoRaBug hardware	LoRa	–	–
	FlockLab 2 [158]	2020	Testbed server (data services, web interface), observers, target devices	Wi-Fi, LoRa, etc.	15 observers	Synchronous transmission protocol, workflow testing, protocol debugging and analysis
	LinkLab [54]	2020	Web IDE, online compilers, device management components	Wi-Fi, LoRa, Bluetooth, Zigbee	156 IoT nodes	Indoor environment monitoring, IoT education
Prototype	WiSH-WalT [97]	2018	WiSHFUL unified interface, WalT single-board computer	LoRa	–	–
	TinySDR [65]	2020	Software radio, OTA programmer, power management system	900 MHz, 2.4 GHz	–	LoRa: modem, resource allocation, MAC BLE: transmission, latency
	ChirpBox [151]	2021	LoRaDisC protocol, target nodes, control nodes	LoRa	–	Benchmarking protocol performance, impact of temperature

various services concerning device registration, data serialization and storage, and web access. Gao et al. [54] proposed LinkLab, a scalable and heterogeneous testbed with support for multi-user and multi-site remotely experimenting and web-based developing. Specifically, LinkLab is composed of the WebIDE, online compilers featuring incremental compilation and multi-user caching, and device management components with a unified naming mechanism. Likewise, FIT IoT-Lab [3] and FlockLab 2 [158] large-scale testbeds also support heterogeneous wireless nodes including LoRa, but they possess a limited number of nodes and are deployed mainly in indoor environments [151].

Testbed Endpoint Prototypes. Lone et al. [97] presented a framework for controllable and reproducible LoRa testbeds termed WiSH-WalT, which consists of a WiSHFUL unified interface for flexible radio and network settings and a WalT single-board computer for easy device deployment and operation monitoring. Hessar et al. [65] proposed the first **Software-Defined Radio (SDR)** platform named TinySDR to enable large-scale deployment and over-the-air programming. Specifically, TinySDR is composed of software radio, OTA programmer, and a power management system, supporting various research of PHY/MAC protocols, IoT localization, backscatter readers, and so on. Besides, TinySDR outperforms existing SDR platforms in terms of low power consumption and cost. The complexity of assembling the backbone infrastructure limits the development and availability of existing LoRa outdoor testbeds. To this end, Tian et al. [151] proposed an infrastructure-less LoRa testbed termed ChirpBox, which could be deployed in areas without the need of cellular or backbone infrastructure providing communication and power conditions. Specifically, all LoRa target nodes are equipped with a daemon used for orchestrating the node's activities (e.g., execution of a test run, the collection of log trace) and a **Firmware Under Test (FUT)** for running tests. Target nodes are connected via a multi-hop network to the control node that serves as an interface with the user. Besides, they designed an efficient all-to-all multi-channel protocol-based concurrent transmission termed LoRaDisC to disseminate the FUT and test-run configurations.

In general, current public open-source LoRa testbeds provide a flexible and low-cost solution for researchers to conduct controllable and reproducible experiments for real-life evaluation, presenting significantly important to the research community. The existing testbed platforms [3, 38, 54, 158] all built a well-defined framework, among which LinkLab [54] can support multi-user remote development featuring Web-based development and incremental compilation. However, the existing testbed platforms only possess a limited number of LoRa nodes and type of sensors (mainly including temperature, humidity, sound, acceleration, and light sensors), whereas FlockLab 2 [158] is also capable of achieving high-dynamic range power and logic timing measurements for the debug and trace. FIT IoT-Lab [3], FlockLab 2 [158], and LinkLab [54] testbeds support various heterogeneous IoT nodes in various places, while OpenChirp [38] is a LoRa-specific testbed, but is deployed in restricted campus areas with an unknown number of LoRa nodes. Early testbed platforms [3, 158] are generally more popular than the emerging ones [38, 54], due to their stable and mature operations. Besides, as for the programmable endpoint prototypes, TinySDR [65] provides large-scale deployments with ultra-low energy consumption manner and OTA solutions, which is also satiable for research with respect to backscatter, PHY/MAC protocol, sensing, and so on. Likewise, ChirpBox [151] offers an infrastructure-less solution, featuring firmware dissemination and log trace, which is hence recommended to be deployed in remote areas without communication and power conditions. Additionally, both possess a low cost of construction and the capability of concurrent reception, but require a battery supply where energy harvesting can be further considered [151]. However, current testbeds have some limitations with regard to hardware (limited number of nodes and sensors, single network topology), framework (limited functionalities), and user experience (complex operation). Hence, providing a large-scale, comprehensive, and human-machine friendly testbed is in great need.

4 LORA COMMUNICATION

After fully understanding the performance of LoRa, a large number of studies have been devoted to enhancing its performance in communication. In this section, we review these studies from three aspects: modulation and demodulation schemes, MAC protocols, and configuration setting methods. Specifically, various LoRa modulation and demodulation schemes were proposed for the network throughput improvement on the basis of LoRa PHY layer CSS modulation and de-chirp demodulation. In addition, modified MAC protocols aim to handle multiple access problems without incurring collisions. Configuration settings refer to optimal determination of transmission parameter sets to rationalize the use of channel resources and achieve energy fairness across nodes.

4.1 Modulation & Demodulation

As stated in Section 2.2, LoRa PHY layer adopts a spread spectrum modulation technique derived from CSS, possessing substantial processing gains and link budget improvements. With considerable modulation benefits, LoRa demodulation based on the de-chirp operation enables low-SNR [86] and collision [167] signals decoding, which also receives great attention. Consequently, extensive methods [61, 167] were proposed to expand the benefits of LoRa PHY modulation technique.

4.1.1 Modulation. Recently, some modified modulation methods [27, 42] were proposed to leverage LoRa CSS properties or adopt a combination with other modulation techniques, aiming at increasing the modulation data rate without compromising its original performance.

Traditional digital modulation is primarily based on the amplitude, frequency, and phase information of the carrier to form these particular parameters shift keying, including conventional ASK, FSK, PSK, along with their improvements or combinations. The essence of LoRa modulation is the frequency shift of the chirp, thus some LoRa modified modulation methods [13, 112] mainly try to carry extra data information in the LoRa symbols by combining with other modulation techniques to increase the data rate. Bomfin et al. [13] proposed a modulation method termed PSK-LoRa, which adopts PSK modulation to embed additional data in the phase shift of the transmitted chirps. Specifically, the information bits are divided into two groups, which determine the initial frequency and the initial phase of the LoRa symbol, respectively. Similarly, in Reference [112], LoRa symbols can start from any phase value with the help of the pulse shaping filter, such that extra data information can be encoded to the initial stage of each symbol, which is then recovered using a coherent receiver. It is noted that PSK can only be decoded under coherent demodulation, as no carrier component is in the PSK signal's power spectrum. Such additional receiver design, along with timing and phase synchronization requirements, will increase the cost and degrade the battery life of nodes.

Besides, some methods [42, 61] focus on elaborate LoRa signal orthogonal sets. In LoRa conventional CSS modulation, the linearly varying-frequency up-chirp spans the entire bandwidth, whose cyclic shift serves as a multi-dimensional space for the orthogonal signals. Elshabrawy and Robert [42] proposed an **Interleaved Chirp Spreading LoRa (ICS-LoRa)** modulation method, which creates a new multi-dimensional space from the interleaved version of nominal LoRa signals. Specifically, the proposed ICS interleaver block subdivides the given signal containing 2^{SF} samples into four subintervals and simply swaps the samples of the two middle intervals of each signal. Such that ICS-LoRa can deploy all 2^{SF} possible cyclic shifts of the interleaved base chirp signal to achieve interleaved chirp signal that carries one extra bit within each symbol. In addition, ICS-LoRa demodulation can also share this ICS interleaver block for simplification without any coherent demodulation requirements. To reduce the cross-correlation between generated and base chirps in ICS-LoRa, Hanif et al. [61] proposed a **slope-shift-keying LoRa (SSK-LoRa)** modulation method, which utilizes the linearly varying-frequency down-chirp to generate the second orthogonal basis set to increase the data rate.

The improved modulation technique is promising, since it can carry more data in one transmitted symbol. Some studies [61, 112] have achieved the throughput gain from 11% to 33% of LoRa networks. However, the complexity of the transceiver design, the compatibility with COTS devices, and energy consumption issues still make this work challenging.

4.1.2 Demodulation. Recently, plenty of LoRa demodulation studies were proposed to push the limit of LoRa capabilities in terms of single-source decoding and collision disambiguation.

Single-source Decoding Methods. Single-source decoding methods aim to improve the performance of decoding signals from one specific source, mainly including low-SNR decoding [86], **Cloud Radio Access Network (C-RAN)** [39], error recovery methods [104], and so on.

Low-SNR decoding refers to the correct payload reduction of the received signals with an ultra-low SNR or RSSI. Such methods can break the decoding threshold of conventional LoRa and significantly improve the link budget to provide a wider coverage. The standard LoRa demodulation method performs the de-chirp operation to determine the SNR threshold, which is generally suboptimal. To this end, Li et al. [86] proposed NELoRa, a **Deep Neural Network (DNN)** demodulator to decode ultra-low SNR LoRa signals by extracting fine-grained information embedded in LoRa chirps. Specifically, NELoRa transforms the extracted chirp symbols to dual-channel spectrograms containing phase and amplitude, which are then fed into the dual-stream DNN for demodulation. The first DNN stream performs the noise filter operation to obtain a masked spectrogram, while the second one is used for packet decoding. Tong et al. [154] proposed Falcon, which provides an available link for unreachable LoRa devices via making them selectively interfering transmissions of other devices (base signals) on the same channel. Specifically, a Falcon device overhears the channel using a CAD-based detection approach and synchronizes its time and frequency offset by a reception-based algorithm, then maximizes the base signal deformation by an adaptive frequency adjusting strategy.

Additionally, several emerging methods [39, 93, 134] focused on the C-RAN design. Specifically, C-RAN is a centralized radio access network architecture based on cloud computing, whose core is to process the LPWAN PHY layer in the cloud. Hence, LoRa C-RAN architecture mainly transfers the incompetent PHY layer decoding tasks at the gateway to the cloud and exploits the spatial diversity gain for weak signal reconstruction. For example, Dongare et al. [39] proposed Charm, a LoRa C-RAN that pools and jointly decodes weak signals that cannot decode in any individual gateway into the cloud. In particular, the gateway introduces a hardware and software design to detect those signals much weaker than the noise floor by transforming the structure of the LoRa packet data symbol as resistant as the preamble. The cloud first adopts a phase-based time synchronization method, then exploits the timing and geographical location of the received signals to identify their sources (i.e., the combination of gateways) and collates such information to recover the transmitted data finally. Jointly decoding the multi-channel LoRa PHY layers in the cloud can improve the SNR of the radio signal but requires a higher bandwidth, which will then cause severe network congestion. To reduce the bandwidth, Liu et al. [93] proposed a compressive sensing-based C-RAN termed Nephalai, which leverages the sparsity of the PHY layer for signal compression and joint reconstruction. Specifically, Nephalai utilizes tailored dictionaries and measurement matrices for LoRa PHY layer compression, with which the adaptive compression ratios are chosen by considering SF and SNR.

In all, LoRa offers substantial processing gains and link budgets to decode low-SNR signals. Thus, many LoRa low-SNR signal decoding methods adopt different methodologies to expand these advantages and improve network throughput. Among these, learning methods [86] can achieve a high upper limit of the SNR gain based on the representation learning of data samples, but possess a poor generalization for distinct settings. Besides, C-RAN architectures [39, 93] mitigate the disadvantages of LPWAN in terms of narrow bandwidth and loose latency bounds. A full-scale distributed **multiple-input multiple-output (MIMO)** system embedded in C-RAN can provide a solution for handling collisions from a large number of nodes [39]. However, C-RAN architectures have a high operating cost, short transmission distance, and insufficient security, thus inspiring further developments.

Packets may be lost or destructed during transmission due to the varying channel and environment conditions. Thus, a payload recovery scheme [9, 104, 143] is hence considered to provide the increasing gain and enhance network throughput. Marcelis et al. [104] proposed a data recovery coding scheme at the application layer termed DaRe, which applies fountain codes on a sliding window with a finite window. DaRe extends the frame with the parity check of randomly selected previous frames as the redundancy data, such that the receiver can decode all payload data when only subsets are received. However, this comes at the cost of increased transmission time. Balanuta et al. [9] proposed an **Opportunistic Packet Recovery (OPR)** approach, which exploits gateway spatial diversity and tracks packet RSSI value for error detection and leverages the **Message Integrity Check (MIC)** field information for error correction. Specifically, OPR collects and groups the corrupt packets across gateways instead of discarding them, then generates a candidate set of corrupt bits based on the spatial diversity and reception time. The generated candidate set is leveraged by the cloud to search through the possible valid CRC combinations, which results in a few packets for final filtering via MIC check.

Additionally, decreasing clock rates can reduce the energy consumption of LoRa radio, but it is limited by the Nyquist sampling theorem that requires the clock rate to be at least twice the LoRa chirp bandwidth. To reliably decode packets sampled at the sub-Nyquist rate, Xia et al. [169] proposed LiteNap, which introduces downclocked operating mode for LoRa. They had two-fold observations: first, two under-sampled LoRa chirps suffer from frequency aliasing that causes demodulation ambiguity; second, radio hardware induces a constant phase shift to all modulated chirp after jitters, resulting in frequency leakage in the time domain. Based on these, LiteNap leverages such frequency leakage as a fingerprint to uniquely identify a LoRa chirp and extract the timing information. Besides, they proposed novel packet detection and synchronization strategies, along with the integration with LoRaWAN protocol.

Collision Disambiguation Methods. The LoRa gateway has an extremely wide coverage of nodes, thus LoRa networks may be subject to pervasive and severe intra- and inter-network interference, especially when in a dense deployment scenario. Interference adversely affects the signal reception, coupled with the capture effect, which is a waste of air time and spectrum. This problem results in the demand to support concurrent transmissions or avoid collisions. Consequently,

Table 6. Summary of LoRa Disambiguation Decoding Methods

Method	Year	Methodology	Performance			
			Low-SNR	Real-time	#Collision	Throughput
Choir [41]	2017	Hardware imperfection-induced offset	✗	✗	10	6.84× the conventional LoRa
mLoRa [162]	2019	Successive interference cancellation	✗	✗	3	3× conventional LoRa
CoLoRa [156]	2020	Identical peak ratio of chirps in the same packet	✓	✗	20	3.4× Choir [41]
FlipLoRa [180]	2020	Encoding with interleaved up-down chirp	✓	✗	18	3.84× conventional LoRa
Ftrack [168]	2020	Time-domain misaligned edges and signal frequency continuity	✗	✗	10	3× conventional LoRa
Nscale [155]	2020	Non-stationary amplitude scaling down-chirp	✓	✗	30	3.3× Choir [41]
OCT [165]	2020	Decoding with time and power offsets	✗	✓	3	3× conventional LoRa
SCLoRa [71]	2020	Multi-dimensional cumulative spectral coefficient	✓	✗	20	3× Ftrack [168]
Temim et al. [150]	2020	Successive interference cancellation	✗	✗	3	-
AlignTrack [26]	2021	Collided chirps alignment	✓	✗	12	1.68× Nscale [155] 3× CoLoRa [156]
Pcube [167]	2021	Reception diversities of MIMO and air-channel phase difference measurement	✗	✗	40	4.9× Ftrack [168]
Pyramid [181]	2021	Variation of FFT peak heights in multiple windows	✓	✓	6	2.11× conventional LoRa
Shahid et al. [135]	2021	Concurrent Interference cancellation	✓	✗	20	4× Ftrack [168]

plenty of interference solutions were proposed, including PHY layer collision disambiguation algorithms [167, 168] to recover packet information and MAC protocols [49, 173] (reviewed in Section 4.2) to maximize the use of channel resources, which both do not conflict but collaborate with each other.

Collision disambiguation refers to the separation and correct decoding of multiple collided signals at the receive side. As stated in Section 2.2, in demodulation, the LoRa receiver detects the packet preamble and SFD and divides the received signals into a series of windows. Then it performs the de-chirp operation in each window, where each symbol is multiplied with a base down-chirp. The resulted single frequency tone (i.e., an FFT peak in FFT bins) indicates the initial frequency. While in the case of collisions, signals from multiple nodes are superimposed at the gateway, which induces a distorted one, i.e., multiple peaks are obtained in FFT bins. To this end, the existing collision disambiguation methods mainly separate and divide the collided symbols to the transmitters based on the unique features (in time [162, 168], frequency [41], phase [167], and power [68, 165] domains) of each transmitter symbol and decode them individually. Table 6 summarizes the existing LoRa collision disambiguation methods.

As the transmitted signal has a shift in time, frequency, and phase resulting from natural hardware offsets, Eletreby et al. [41] proposed Choir, which exploits such subtle frequency shifts to separate different signals, then tracks users to decode data finally. However, such hardware-induced frequency offset is hard to capture due to the background noise and frequency leakage. Hu et al. [71] proposed SCLoRa with adaptation to the dynamic environment, which exploits cumulative spectral coefficient integrating multi-dimensional information (frequency and power) under the considerations of channel fading and spectrum leakage. Xia et al. [168] revealed that the frequency of the LoRa symbol increases periodically, while the symbol edges of different interference transmissions are misaligned in the time domain. They presented FTrack, which separates collisions and recovers frames by leveraging such time-domain misaligned edges and signal frequency continuity. FTrack requires a sliding window per sample, resulting in a large computational overhead. In their follow-up work [167], besides using time and frequency features, they designed a Phase-based Parallel Packet decoder termed PCube for concurrent transmissions by leveraging the reception diversities of MIMO hardware. Specifically, Pcube first calibrates the frequency offset of the received signal to extract the correct frame timing of each packet based on the frame structure of the LoRa preamble and SFD. Then it measures the phases of all concurrent symbols and mitigates the impact of hardware-induced phase variance. Furthermore, Pcube extracts the air-channel phase of each symbol and groups symbols to corresponding packets.

Some collision disambiguation methods [156, 180] are designed for low SNR situations. For example, Chen and Wang [26] proposed AlignTrack for low-SNR collision decoding, which aligns a moving window with different collided chirps to find the peak of the aligned chirps, and thus separates these frequency peaks to their belonging packets. Instead of chirp partition in References [155, 156], AlignTrack leverages the entire chirps, such that the aligned chirp can induce the highest peak in the frequency and lowest SNR loss. Some methods [162, 168] focused on the time-domain feature that is vulnerable to noise, falling short of decoding low SNR signals. To this end, more robust frequency features [155, 156, 181] were utilized. Tong et al. [156] proposed CoLoRa for collision decoding based on the peak ratio of chirps. Specifically, CoLoRa first demodulates the collided chirps in multiple (usually misaligned) reception windows, thus each chirp can result in two peaks in two windows. Then CoLoRa leverages the finding that the peak ratio of chirps (the height of the latter divided by that of the former) in the same packet is identical to disentangle collided signals. To relax the restrictions of the reception window, Tong et al. [155] proposed NScale. Specifically, NScale leverages the non-stationary amplitude scaling down-chirp to translate the packet time misalignment into frequency features, thus can determine the distribution characteristics of the symbol segments in the window according to the peak height variation before and after scaling. Besides, they proposed an iterative peak recovery algorithm to resolve peak distortion. With the reception window shifting, the FFT peak heights of one chirp in multiple windows will be presented in a pyramid shape. So, Xu et al. [181] proposed Pyramid to achieve low-overhead real-time collision decoding, which separates packets via exploiting each "top" of the pyramid.

Rather than matching symbols to transmitters, interference cancellation algorithms [135, 150, 162] are also applied. Wang et al. [162] proposed mLoRa, which iteratively decodes and then cancels part of the collision-free symbols. Similarly, Temim et al. [150] identified and decoded the strongest received signal, then reproduced its complex envelope and removed it from the received signal utilizing a conventional **Successive Interference Cancellation (SIC)** algorithm. Shahid et al. [135] proposed a **Concurrent Interference Cancellation (CIC)** method. In particular, CIC first determines these symbol boundaries via preamble detection, then selects an **Interference Cancelling Sub-Symbols Set (ICSS)** with no common interfering symbol across all symbols. Finally, CIC adopts a spectral intersection operation to demodulate symbols via canceling out all interfering symbols.

Current collision disambiguation methods have significantly ameliorated the concurrent transmission capability of LoRa gateways and alleviated serious collisions. Most of these methods [41, 156] achieve more than 3× increment in throughput, and some [155, 156] give a focus on weak decoding of signals below −5 dB. Fundamentally different with collided signals separation methods by leveraging signal features, SIC algorithms provide a novel solution. However, devising an effective and energy-efficient collision decoding method remains challenging in terms of accurate packet detection, optimal peak height search, and algorithm complexity. Specifically, the **Carrier Frequency Offset (CFO)** and inter-packet interference need to be combated first to avoid the wrong packet estimation [26]. Demodulating a low-SNR signal results in a poor peak height, coupled with accompanied sidelobes around. Besides, the reception windows (e.g., alignment, length) also affect the peak height. Heavy algorithm complexity is impractical for resource-constrained LoRa networks, as a semi- or off-line decoding way will cause great delay, memory cost, and computational overhead at the gateway side.

Overall, various demodulation methods leveraging LoRa PHY CSS properties and adopting advanced techniques have improved the network throughput and scalability to a large extent, which is a primary research focus in the research community. Irrespective of the remarkable results achieved, the complexity of the algorithm, cost of hardware and actual deployment, and the

Table 7. Summary of LoRa MAC Protocols

	Method	Year	Methodology	Performance
Contention-based	Ihirri et al. [72]	2019	Slotted-ALOHA with synchronization leveraging FM-RDS broadcasting	–
	Polonelli et al. [122]	2019	Slotted-ALOHA with synchronization relying on the timestamp and offset	Throughput: 5.8× conventional LoRaWAN
	LMAC [49]	2020	Three LMAC versions based on CAD: LMAC-1 using DIFS with BO, LMAC-2 by indirect channel probing, LMAC-3 relying on beacon broadcasting	Throughput: 2.2× conventional LoRaWAN Energy efficiency: 2.4× conventional LoRaWAN
	p-CARMA [80]	2020	p persistent-CAD multiple access	Throughput: 3–20× conventional LoRaWAN Energy efficiency: 1.42–1.63× conventional LoRaWAN
	Xu and Zhao [173]	2020	Residual energy-based CAD, CSMA-CA, or dynamic adjustment duty cycle according to traffic load	Latency: 0.79× conventional LoRaWAN Energy efficiency: 1.19× conventional LoRaWAN
	Beltramelli et al. [11]	2021	Scalable Slotted-ALOHA based on the divided contention sequence code from LoRa frame	Throughput: 2× conventional LoRaWAN Energy efficiency: 2× conventional LoRaWAN
Schedule-based	Rizzi et al. [131]	2017	Integration with TSCH and TDMA	–
	Haxhibeqiri et al. [63]	2018	Centralized scheduling	Throughput: 1.3× conventional LoRaWAN
	Piyare et al. [121]	2018	On-demand TDMA using wake-up radios	PDR: almost 100%
	RS-LoRa [129]	2018	Two-step lightweight MAC scheduling	Throughput: 1.2× conventional LoRaWAN
	EF-LoRa [52]	2019	Energy fairness-enabled FDMA	Energy fairness: 177.8%
	FREE [2]	2019	Bulk transmission and parameter assignment	PDR: almost 100%
	LoRaCP [58]	2019	TDMA featuring an urgent ALOHA channel and negative ACK	Throughput: 65% → 90%
	RT-LoRa [84]	2019	Novel MAC layer design	–
	S-MAC [179]	2020	Sending time prediction and frequency channel assignment	Throughput: 4.01× conventional LoRaWAN
	TS-LoRa [190]	2020	Distributed time-slotted approach	PDR: >99%
	PolarTracker [164]	2021	Node attitude tracking and transmission scheduling	Throughput: 1.49× conventional LoRaWAN

influence of multiple external factors (e.g., dynamic channel conditions, various environments) still require further study.

4.2 MAC Protocols

MAC protocols refer to the methodology that allows multiple nodes in the networks to access a shared transmission medium. LoRaWAN employs a default pure ALOHA MAC protocol, whose basic idea is to send data without detection. It is simple and has no time synchronization requirements, making it suitable for resource-constrained LoRa networks. However, the network performance will degrade dramatically due to the inevitable interference restrictions when the number of transmissions increases greatly, thereby suffering limited scalability. To avoid severe collisions, plenty of MAC protocols were proposed recently, which can be divided into two classes: the contention [49] and schedule-based [2] ones. The contention-based MAC protocols are mainly those random access protocols such as Slotted-ALOHA and **Carrier Sense Multiple Access (CSMA)**, where all nodes keep listening to and compete for the shared medium for transmission. In the schedule-based ones, multiple nodes access the predetermined collision-free medium that is divided according to time (TDMA) or frequency (FDMA). Table 7 summarizes the existing MAC protocols.

4.2.1 Contention-based MAC Protocols. Recently, plenty of LoRa contention-based MAC protocols were proposed, where the sender listens to the shared medium before transmission and transmits until the medium is free. The existing methods mainly include Slotted-ALOHA and CSMA ones.

Slotted-ALOHA Methods. Slotted-ALOHA, a variant of ALOHA, aligns the transmissions to slot boundaries relying on the relative synchronization of nodes, which can reduce the interference and increase channel capacity. The general process is to divide the time into several identical time slices, where all senders access the channel synchronously at the beginning of the time slice and have to wait until the beginning of the next time slice before transmission in the case of an occurring conflict. As **Real-Time Clocks (RTCs)** have significant clock drift problems over time, Polonelli et al. [122] introduced a lightweight time synchronization method based on the timestamp and offset during one transmission and achieved a Slotted-ALOHA mechanism with random backoff to increase the channel capacity. Ihirri et al. [72] proposed a scalable Slotted-Aloha method by introducing a contention sequence code in the option field of the LoRa frame. Such code determines the priority of transmission and decreases iteratively. Beltramelli et al. [11] proposed a Slotted-ALOHA MAC protocol using an out-of-band synchronization based on **FM-radio data system (FM-RDS)** broadcasting, which could save energy and improve the capacity unlike an in-band synchronization strategy.

Carrier Sense Multiple Access Methods. Slotted-ALOHA and TDMA protocols require clock synchronization that brings a burden to LoRa networks, while CSMA protocols provide an alternative solution without synchronization operation. Several studies [49, 173] have exploited CSMA or its variants (i.e., Listen-Before-Talk mechanism [116]) on LoRa networks based on the **Channel Activity Detection (CAD)** feature. To address the issue of false negatives introduced by CAD during the transmission of the payload, Kouvelas et al. [80] proposed a CSMA variant termed p-CARMA, where nodes adaptively select an appropriate probability value of p for transmission using a heuristic approach when the channel is idle. In the system proposed by Xu et al. [173], the LoRa nodes exploit the residual energy to determine the effective preamble from the noise to avoid false awakening, and access to the channel via selecting CSMA-CA or dynamic adjustment duty cycle mechanism in the case of low or high traffic load, respectively. Gamage et al. [49] designed three modified LMAC versions to enable CSMA for LoRa networks based on the CAD feature. Specifically, LMAC-1 achieves the basic functionality of CSMA based on a **Distributed Inter-Frame Space (DIFS)** mechanism with a fixed number of CADs and a random **back-off (BO)** strategy. LMAC-2 achieves a balanced resource load through an indirect channel probing approach, which updates the knowledge regarding the channels' crowdedness based on the CAD results during DIFS and BO processes. LMAC-3 receives a global view of channel loads via broadcasting periodic beacons by gateways.

4.2.2 Schedule-based MAC Protocols. Recently, LoRa schedule-based MAC protocols are also popular, where the sender transmits according to pre-assigned link resources. The existing schedule-based ones mainly focus on **Time Division Multiple Access (TDMA)** along with time slot scheduling strategies, and **Frequency Division Multiple Access (FDMA)** methods.

Time Division Multiple Access Methods. TDMA protocols allow multiple nodes to use the same frequency for transmission in different time slots, thereby sharing the same transmission medium without incurring collisions. They also avoid the energy waste of over-listening and idle-listening to the channel, hence receiving much popularity. For example, Rizzi et al. [131] integrated **Time Slotted Channel Hopping (TSCH)** strategy with TDMA to enhance the network throughput and reliability. However, the synchronization strategy is missing. Piyare et al. [121] proposed an on-demand TDMA approach using low-energy wake-up radios, which, respectively, provides unicast and broadcast modes for node triggering and time slots allocation. Gu et al. [58] designed a TDMA-based LoRa multi-channel transmission control featuring an urgent ALOHA channel and negative **acknowledgment (ACK)**, to achieve the one-hop out-of-band control plane for wireless sensor networks.

For TDMA MAC studies, the critical problem is time slot scheduling/allocation. Haxhibeqiri et al. [63] relied on the **network synchronization and scheduling entity (NSSE)** as the central scheduler for the LoRaWAN network to schedule transmissions. Specifically, the node sends a request containing the traffic periodicity to the NSSE and receives a reply about the allocated time slots encoded in a probabilistic space-efficient data structure. However, some nodes may share the same slot with a certain probability, incurring collisions. Abdelfadeel et al. [2] proposed a fine-grained scheduling scheme termed FREE. Specifically, nodes are assigned with corresponding transmission parameters inclusive of SF, TP, and time slot, then perform bulk data transmission in the predetermined time slot. However, FREE resolves the collision problem but falls short of real-time transmission. Leonardi et al. [84] proposed RT-LoRa, a novel LoRa MAC protocol as an alternative of LoRaWAN, which can support real-time flow transmission. In RT-LoRa, the time slot duration is limited by minimal packet size as a lower bound and varies according to different SFs. Rather than relying on the centralized scheduler to allocate separate time slots for all nodes, Zorbas et al. [190] proposed TS-LoRa, a self-organizing time-slotted communication approach based on computing a hash algorithm mapping the nodes' assigned addresses into unique slot numbers. Additionally, the dynamic attitude of floating nodes incurs signal strength losses and packet errors compared with those deployed statically on the ground due to the polarization and directivity of the antenna. To this end, Wang et al. [164] proposed an attitude-aware link model along with a channel access method termed PolarTracker, which leverages the attitude alignment state of the node, then schedules the transmissions into best-aligned periods for better link quality.

Frequency Division Multiple Access Methods. Similarly, FDMA protocols allow multiple nodes to transmit in different frequency channels of the shared medium simultaneously. As LoRa band in distinct regions defines different multiple frequency channels, FDMA-based studies are CF allocation methods in essence. Plenty of CF parameter allocation methods [52, 129] were proposed recently. For example, Reynders [129] proposed a MAC layer protocol termed RS-LoRa, which employs a two-step lightweight scheduling based on the RSS at both nodes and gateways. Specifically, the gateway specifies the allowed TPs and SFs for each frequency channel via beacon broadcasting, while nodes specify their own ones. Gao et al. [52] proposed EF-LoRa to allocate frequency channels under the consideration of the randomness of LoRa MAC protocol. Xu et al. [179] proposed an adaptive MAC layer scheduler termed S-MAC, which predicts the sending times based on the periodic transmission characteristics of nodes and allocates frequency channels according to the SF parameter of the packet.

In general, the existing MAC protocols have significantly ameliorated the severe occurrence of collisions to improve the network performance in capacity and scalability. However, it is also challenging to devise adaptive, effective, and energy-efficient MAC protocols. Classic Slotted-ALOHA methods adopt synchronization strategies mainly based on timestamp [122] and out-of-band radio. Nevertheless, the number of time slots required is fixed and cannot be adjusted arbitrarily, which can induce collisions (too many) or time slot waste (too few). The synchronization and slot scheduling will bring the cost of calculation and propagation transmission time. The CAD features of LoRa facilitate the CSMA-based methods, among which LMAC [49] achieves communication fairness across nodes on the basis a 2.2× and 2.4× improvement in throughput and energy efficiency, respectively. CSMA-based methods have no requirements for synchronization, but impose additional energy for the over-listening and long-time continuous transmission detection operation. TDMA-based methods mainly focus on the efficient time slot allocation in centralized [2] and distributed [190] manners. They are inflexible, especially when the data packet size varies and network topology changes dynamically. Energy-efficient synchronization and feedback ACK problems require to be tackled. FDMA-based methods are CF allocation methods in essence, along with other parameters together. They lower the interference and are easy to implement, but may cause spectrum waste due to the existence of the guard-band.

4.3 Configuration Settings

Configuration settings typically refer to the optimal determination of transmission parameter sets in terms of SF, TP, CF, and CR assigned to LoRa nodes or networks. Different transmission parameter sets resulting in different data rates and air time have a distinct effect over the network performance or functionality, such as throughput and energy consumption unfairness across nodes. For example, nodes far away from the gateway are tuned to use a larger SF to trade low data rate for

Table 8. Summary of LoRa Configuration Setting Methods

Method	Year	Parameter	Problem Formulation	Methodology	Real-time	Dynamic	Evaluation
EXPLoRA [31]	2017		Data extraction rate optimization	Heuristic algorithm	✗	✗	S
CA-ADR [105]	2020		Minimizing the collision probability	Choosing the smallest SF based on the power	✗	✓	T, S
Loubany et al. [98]	2020	SF	Throughput optimization (traffic load×probability of success)	Adjusting SNR thresholds	✗	✗	S
Mu et al. [109]	2020		Maximizing throughput based on the dataset containing RSS, SNR, SF, etc.	K-Nearest Neighbors	✓	✓	T
FADR [1]	2018		Fair data rate distribution based on DER	Allocation based on the average RSSI values	✗	✗	S
Liando et al. [89]	2019		Node lifetime model	Allocation based on the distance and lifetime threshold	✗	✓	T
Amichi et al. [5]	2020	SF, TP	Short-term average rate modeling	Matching theory for SF, constrain approximation for TP	✗	✗	S
DyLoRa [87]	2020		Symbol error and energy efficiency model	Traversing and comparing all combinations in the prediction model for optimal settings	✓	✓	T
Reynders et al. [127]	2017		Packet error rate fairness	Allocation based on path loss values and SF distribution under TP	✗	✗	S
RS-LoRa [129]	2018		RSS value restriction and packet error rate fairness	Two-step lightweight MAC scheduling	✗	✗	S
EF-LoRa [52]	2019	CF, SF, TP	Max-min energy fairness optimization	Greedy heuristics algorithm	✗	✗	S
Su et al. [142]	2020		Maximizing system and node energy efficiency	Matching theory for channel, heuristic algorithm for SF, and optimization algorithm for TP	✗	✗	S
Bor et al. [14]	2017	SF, BW, CR, TP	PRR measurement	Traversing and comparing all combinations	✗	✓	T
Liu et al. [96]	2019	CF, TP	MDP model characterizing harvested energy and channel conditions	ECAA for channel, dynamic programming for TP	✓	✓	S
AdapLoRa [53]	2020	CF, SF, CR, TP	Symbol-level network model for network lifetime optimization	Allocation adaption acceptance depending on the comparison with the lifetime threshold	✗	✓	T
Chime [47]	2020	CF	Optimal frequency estimation across base stations collaboratively	Multipath signal disentangling and recombination	✗	✓	T
EARN [117]	2020	SF, TP, CR	Tradeoff between the delivery ratio and energy consumption	Allocation based on the aggregated load status for SF and SNR	✗	✓	S

(S: Simulation, T: Testbed).

long range, but resulting in longer transmission time and higher energy consumption. Hence, an effective network configuration setting method is crucial for the appropriate division of channel resources and enhancing the throughput and energy efficiency of LoRa networks.

Specifically, the existing configuration settings methods [52, 87] mainly achieve the optimal parameter sets determination of LoRa nodes according to the deployment topology, communication behavior, and channel conditions. The main process consists of three steps: first, taking the throughput and energy consumption/fairness as the optimization goal; second, formulating a system or link model based on the optimization problem; third, adopting specific optimization methods based on current system model. It is noted that the data rate of LoRa radio is defined by the combination of SF, BW, and CR, thus the ADR method is also regarded as the configuration setting category. Table 8 summarizes the existing LoRa configuration setting methods.

SF Allocation Methods. Loubany et al. [98] formulated the throughput optimization problem under consideration of the capture effect and proposed an adaptive SF allocation algorithm via adjusting the SNR thresholds. Mu et al. [109] proposed a **K-Nearest Neighbors (KNN)**-based SF allocation method, containing an initialization and operation period. In the initialization period, nodes are set to utilize all SF configurations in a round-robin fashion, and the gateway creates a dataset containing link characteristics (i.e., RSS, SNR), SF configurations, and packet reception results. In the operation one, a KNN algorithm is adopted to select optimal SF under the given link conditions or to meet the application reliability requirements via voting threshold adjustment. Cuomo et al. [31] proposed a heuristic SF allocation algorithm termed EXPLoRA to improve the **Data Extraction Rate (DER)** and achieve air time fairness. Specifically, EXPLoRA first calculates the available SF list of each node based on the RSSI and the sensitivity of each SF and then utilizes an "ordered waterfilling" strategy to allocate the SF to balance the air time. Marini et al. [105] proposed a **collision-aware ADR (CA-ADR)** algorithm. CA-ADR first calculates the maximum number of nodes under specific allocated SFs based on the given packet success probability that considers the link-level performance and the collision probability and then determines the smallest available SF for each node based on the average received power.

SF and TP Allocation Methods. Liando et al. [89] modeled the energy consumption of LoRa nodes for SF and TP allocation. Amichi et al. [5] formulated a joint SF and power allocation problem as the uplink short-term average rate modeling featuring SF quasi-orthogonality. Specifically, they achieved SF assignment sub-question under fixed TP via a low-complexity many-to-one matching algorithm and TP allocation under fixed SF via two types of constraints' approximation. Abdelfadeel et al. [1] proposed a **Fair Adaptive Data Rate (FADR)** algorithm. Specifically, FADR derives a fair data rate distribution on the basis of DER across nodes, then adopts a genetic algorithm for the optimal SF distribution and adjusted TP within a safe margin. Li et al. [87] proposed a Dynamic LoRa transmission control system termed DyLoRa, which derives an energy efficiency characterization model based on transmission parameters including TP, SF, and SNR. In particular, DyLoRa gateway first extracts the average SNR of the last pre-defined number of data packets as an indicator of link quality, then traverses and inputs all combinations SF and TP with this average SNR to the prediction model for the optimal setting.

CF, SF, and TP Allocation Methods. Reynders et al. [127] derived the optimal SF distribution under the constrained TP to minimize collision probability and also assigned nodes from long distances that possess large path loss values to different frequency channels to avoid near-far problems for fairness. In their further work [129], they proposed RS-LoRa, which employs a two-step lightweight scheduling. Specifically, the gateway specifies the allowed TPs and SFs for each channel, which are restricted by the RSS value and collision probability, respectively. Then, the nodes traverse to find a proper channel, among which nodes divided into one group choose similar parameters to alleviate the capture effect. Gao et al. [52] proposed EF-LoRa, formulating energy fairness issues as a max-min optimization problem and utilizing a greedy heuristics algorithm to allocate frequency channel, SF, and TP parameters. Specifically, EF-LoRa adopts a multiple-gateway system model considering various LoRa network features such as interference, the randomness of MAC protocol, and capacity limitation of gateways, to serve energy fairness optimization. However, EF-LoRa runs only once at the first time of network deployment. In Reference [142], they formulated user scheduling as a two-sided many-to-one matching problem with peer effects to achieve channel allocation and allocated SF via a heuristic algorithm. Then, they performed TP allocations under maximizing system and nodes' minimal energy efficiency via lower bound approximation and sequential convex programming, respectively.

Other Parameters Allocation Methods. Gadre et al. [47] proposed Chime, where the node sends one packet across multiple base stations at one frequency, and the stations can collaboratively determine the optimal frequency. Specifically, Chime first requires synchronizing distributed base stations to avoid the time-varying and long-lasting phase errors, then models the signals and disentangles different signal multipath. Finally, Chime recombines these separated signal components to estimate the optimal one. Bor et al. [14] proposed a simple link probing regime that traverses and approaches the optimal parameter configuration based on the measured PRR. Liu et al. [96] adopted a **Markov Decision Process (MDP)** model to formulate the harvested energy and channel conditions for energy harvesting-based LoRa networks. Besides, they proposed an **efficient channel allocation algorithm (ECAA)** based on a many-to-one matching game by enabling users to self-match properest ones and perform optimal TP allocation via solving the dynamic programming problem. Current methods mainly focus on static resource allocation, Gao et al. [53] proposed AdapLoRa, an adaptive allocation system for CF, SF, TP, and CR parameters based on the dynamic link conditions on the contrary. Specifically, AdapLoRa adopts a symbol-level fine-grained network model featuring the properties of enhanced error correction scheme and packet reception by multiple gateways to periodically estimate the network lifetime under different resource allocations and determines whether to perform this adaption through comparison with the threshold rather than always seeking the optimal setting. Park et al. [117] formulated the link performance as an **energy per packet (EPP)** model and then proposed an enhanced greedy ADR mechanism with CR adaptation termed EARN based on the aggregated load status for each SF and SNR. Besides, EARN exploits adaptive SNR margin to withstand the dynamic link changes.

Apart from the aforementioned configuration setting studies at the node level, several methods aim at the network topologies and deployments at the network level, such as gateway planning [123, 144] and packet offloading [43]. Rady et al. [123] first adopted a K-means clustering-like method or a grid and spatial method to determine the optimal gateway location under the network-aware or network-agnostic gateway deployment, respectively. Then, they performed link allocation tasks, i.e., many-to-one mappings between node and gateway. Specifically, such tasks are conducted based on the minimal distance or the corresponding RSSI value under the unconstrained gateway capacity while using the integer linear programming (NP-complete) approach under the constrained one. Sun et al. [144] proposed a deleted greedy algorithm for optimal gateway number and location search for heterogeneous LoRa nodes and also considered SF allocations.

In general, the existing configuration setting methods utilize network resources to the greatest extent based on the link conditions and network deployments, which greatly improved the network throughput, energy efficiency, and fairness. Such methods generally take the throughput and energy performance indicator as a starting point for problem formulation and modeling. Then, comprehensive and careful considerations of various effect factors are required, such as dynamic link characteristics and signal interference, along with their representation margin. Among these methods, SF, TP, and CF are the most-chosen parameters, which are mainly allocated based on the packet SNR and node distance information. However, the algorithm complexity, convergence time, and dynamic adaption deserve to be tackled for further improvements.

Apart from the aforementioned methods on LoRa communication, other works have made contributions with respect to the network synchronization strategies [124], data forwarding schemes [25], different network topologies such as mesh [83, 115] and tree [149].

5 LORA SECURITY

With massive deployments of LoRa networks recently, the security and privacy issues are receiving great attention. Security requires the hardware, software, and data flow in LoRa networks are protected, and the whole system can operate regularly and continually. However, maintaining the **confidentiality, integrity, and availability (CIA)** of LoRa networks faces severe challenges due to the openness of the transmission medium and the instability of the network structure. To this end, we survey LoRa security-related works, including vulnerability analysis and corresponding countermeasures, coupled with the emerging PHY layer security methods.

5.1 Vulnerabilities and Countermeasures

The vulnerability is the weakness that an attacker can exploit to perform unauthorized actions, modify data, or make a system unavailable, while the countermeasure is the defense taken against such attacks. The self-explanatory importance of cyber security and the wide popularity of LoRa networks have stimulated the rapid development of the attacks and defenses designed for LoRa networks. The first step in conducting LoRa security is to understand the network security requirements. CIA Triad is typically used to describe the security of IoT applications:

- **Confidentiality.** Data is only authorized to legitimate parties, while not leaked to others.
- **Integrity.** Data is ensured not to be tampered or destructed during the period of transmission and storage, or can be discovered quickly after malicious use.
- **Availability.** Data can meet the standards for use when needed.

Table 9. Summary of LoRa Vulnerabilities and Countermeasures

	Vulnerability	Operation	Countermeasure
Confidentiality	Eavesdropping	Retrieving private information stealthily	Key generation [50]
	MITM Attack	Creating separate links to both legitimate parties	Authentication [163]
	Replay Attack	Sending a former eavesdropped packet	Key-related solution [79, 147, 153], random token [110], authentication [163]
	Side-channel Attack	Recovering secret key information from additional signal features (e.g., power, electromagnetic leaks)	Key management [60, 78]
	Spoofing Attack	Impersonating legitimate parties to access and tamper data	Authentication [163], RFFI [132]
Integrity	Covert Channel (e.g., CloakLoRa [69], EMLoRa [137])	Embedding hidden information into the covert channel	Demodulation examination, gateway collaboration [68]
	Wormhole Attack	Creating a high-speed link tunnel between two malicious parties	Beating jammer reaction time [7], message relation [66]
Availability	Beacon Synchronization Attack	Sending fake beacons	Beacon authentication key [17], cryptographic signature [184]
	Delay Attack	Malicious frame collision and delayed replay	RFFI [57]
	(Distributed) DoS Attack	Causing the link overload or triggering network crash (from multiple sources)	Blockchain [67, 90]
	Jamming Attack	Disrupting the legitimate communication using powerful interference radio	Traffic analysis [7], intrusion detection [33], collision decoding [68], passive packet sniffing (LoRadar) [28]

Table 9 lists the common attacks to LoRa networks from the perspective of the violation of the CIA Triad, along with the proposed corresponding countermeasures.

5.1.1 Vulnerabilities. Studying network vulnerabilities shows significant importance, which can better serve the corresponding defenses. Thus, plenty of studies [6, 17, 18, 66, 184] have investigated the common attacks of networks, inclusive of replay, jamming, spoofing attacks, and so on. Besides, some vulnerabilities specific to LoRa networks [69, 137] are discovered. Hou et al. [69] revealed the existence of a covert channel using a modulation scheme orthogonal to CSS over LoRa PHY layer, which is transparent and covert to current security mechanisms. Specifically, they proposed CloakLoRa to embed hidden information into the covert channel utilizing **Amplitude Modulation (AM)**, where the malicious attacker could decode the hidden data based on the RSS while the transmission between legitimate parties is not affected. There is a common belief that **electromagnetic (EMG)** covert channel is a common short-range attack, as EMG radiation is easily attenuated. However, Shen et al. [137] proposed a resilient EMG covert channel termed EMLoRa, which reshapes EMG radiation into LoRa-like chirps through AM, hence the receiver can decode and steal the sensitive data from a long distance. Specifically, EMLoRa enables three attacks in terms of wide-area data exfiltration, penetrating Faraday cage, and localization of air-gapped devices.

5.1.2 Countermeasures. LoRa networks are vulnerable to kinds of attacks as investigated in References [6, 184], hence plenty of attack defense and prevention methods are proposed accordingly.

Countermeasures against Replay Attacks. The replay attack refers to when the attacker sends a former eavesdropped packet intact (the receiver node has received before) to deceive the receiver. The attacker does not need to obtain the explicit raw data but replays some data packets to destroy the correctness of authentication, which burdens the link load and induces some specific former-packet effects. Traditional solutions include adding nounces, timestamps, session ID [178]. For LoRa, replay attack defense methods mainly focus on DevNonce and NwkSKey of the LoRaWAN packet header in the OTAA join procedure. DevNonce is a random number generated from nodes, while NwkSKey is the session key that changes every time the joining process is completed. Na et al. [110] proposed a replay attack scenario occurring in the join request transfer process and a token-based countermeasure against it accordingly. The random token is the first six bits of NwkSkey, which is used to be XOR-ed with the DevNonce and MIC fields of the join request packet. However, the problem of missing NwkSkey is ignored when the device resets. The network server needs to store all DevNonce values used in the previous joining process, such that requests from benign nodes will not be mistaken as replay attacks [153]. To this end, Kim and Song [79] defined the initial and non-initial join requests and checked the validity of NwkSKey of non-initial join requests and DevNonce of initial ones to prevent replay attacks. Since checking the DevNonce value only is not reliable [153], Sung et al. [147] also utilized RSSI and a hand-shaking technique to protect networks.

Countermeasures against Jamming Attacks. Jamming attack, a subset of **Denial of Service (DoS)** attack, refers to deliberately disrupting or preventing legitimate communication based on malicious interference. Such attacks can be addressed by efficient intrusion detection/filtering, traffic analysis, and verification. Several methods [28, 68] were proposed for anti-jamming attacks for LoRa networks. Aras et al. [7] proposed three jamming attack techniques and a series of complementary countermeasures such as maximum use of channel hopping and real-time traffic analysis. Danish et al. [33] proposed a novel **LoRaWAN-based Intrusion Detection System (LIDS)** involving two LIDS algorithms, namely, Kullback Leibler Divergence and Hamming Distance, deployed on gateways to monitor the real-time traffic distribution for the comparison with those from baseline to prevent from jamming attacks. Synchronized jamming chirps will make packets not be decoded in the time domain, hence Hou et al. [68] proposed a prevention and error recovery method by leveraging the signal strength difference. With massive deployments of LoRa networks, Choi et al. [28] proposed a passive packet sniffing framework for MAC layer termed LoRadar. LoRadar cannot decode payload data but extracts a large number of parameter information and deployment statistics related to the link quality, which is utilized for jamming detection, RSSI-based device localization, and so on.

Countermeasures against Other Attacks. Apart from the aforementioned studies, several other attack defense methods [57, 163] were proposed. Wang et al. [163] proposed a lightweight node authentication method termed SLoRa, using fine-grained CFO resulting from hardware imperfections and spatial-temporal link signature relying on positions of nodes, to prevent from various attacks such as spoofing, MITM, DoS attacks. Specifically, they proposed a CFO compensation algorithm adopting linear fitting for received up-chirps to mitigate the noise's randomness and derived a conventional de-convolution operation-less link signature extraction scheme. However, SLoRa is insensitive to drift caused by weather and environmental conditions. Gu et al. [57] proposed a synchronization-free data timestamping approach based on the signal arrival time at the gateway due to the star topology of LoRa networks rather than multi-hop and high time accuracy requirements (μs level). This approach is vulnerable to the frame delay attack, so they designed a LoRaTS gateway to track the natural frequency deviation of the nodes based on the linear regression and least-squares methods. Further, they proposed a Pseudorandom Interval Hopping scheme to prevent from zero frequency bias attacks to maintain security. Besides, several key management schemes [60, 78] focus on the LoRaWAN key derivation, distribution, update, and destruction process to prevent from side-channel attacks.

Overall, the existing vulnerabilities and countermeasures complement each other to make a significant contribution to the security of LoRa networks. In addition to attacks common to networks, attacks specific to LoRa specific networks are an open and trending research area, coupled with the combination with cross-technology. Covert channels [69, 137] have been proven as threatening attacks to LoRa networks, where there are no effective countermeasures against EMLoRa [137]. The existing countermeasures mainly focus on the packet header information [79, 110, 153], passive traffic analysis [7, 28], or authentication system [57, 163] to improve the safety of LoRa networks. However, the effectiveness and energy efficiency of such security defense mechanisms are key factors that need attention.

5.2 PHY Layer Security

PHY layer security methods essentially exploit the physical characteristics of the wireless channel to achieve secure transmission. The traditional secure key establishment between two parties can

Table 10. Summary of LoRa PHY Layer Security Methods

	Method	Year	Methodology				Performance	
			Feature	Quantization	Reconciliation	Privacy Amplification	KGR (bit/s)	KAR(%)
Key Generation	LoRa-Key [175]	2018	RSSI	Multilevel	Compressive sensing	SHA	18–31	98–100
	Zhang et al. [187]	2018	RSSI	Differential	Secure sketch	Hash function	-	95–96
	Ruotsalainen et al. [133]	2019	RSSI	Threshold	Secure sketch with BCH code	SHA-256	-	71–85
	Gao et al. [50]	2021	$RSSI_r$	Multilevel	Compressive sensing	SHA-256	13.8	86
	LoRa-LiSK [76]	2021	RSSI	Multilevel	BCH code	SHA-256	-	80–90
	Vehicle-Key [182]	2022	arRSSI	Multilevel	Autoencoder	SHA-256	14–16	98–99
			Input		Learning Model	Supervision Manner	Accuracy(%)	
RFFI	Robyns et al. [132]	2017	Signal sample		MLP, CNN	Supervised, zero-shot	59–99 (identical vendors), 99–100 (distinct vendors)	
	Jiang et al. [75]	2019	Differential constellation trace		Clustering of Euclidean distance	Unsupervised	63–99	
	SLoRa [163]	2020	CFO and spatial-temporal link signature		SVM	Supervised	97 (indoor), 90(outdoor)	
	DeepLoRa [4]	2021	IQ, amplitude-phase, and spectrogram		CNN, RNN-LSTM	Supervised	89(RNN), 99 (2D CNN)	
	Shen et al. [138]	2021	IQ, amplitude-phase, and spectrogram		CNN	Supervised	98	

(BCH: Bose–Chaudhuri–Hocquenghem, SHA: Secure Hash Algorithm).

be completed by **Public Key Cryptography (PKC)**, but PKC schemes require a **Public Key Infrastructure (PKI)** and are computationally expensive. Another solution is the **Pre-Shared Key (PSK)** scheme, but it lacks scalability [178]. Thus, plenty of methods [50, 138] consider PHY layer features as a supplement or replacement of the upper-layer cryptography method for the consideration of network security. We divided them into two categories: PHY layer key generation and **Radio Frequency Fingerprinting Identification (RFFI)** methods. Table 10 summarizes the existing LoRa PHY layer security methods.

5.2.1 Key Generation Methods. Key generation, also called key agreement or establishment, refers to the process of generating the same cryptographic key based on the PHY layer characteristic parameters (e.g., RSSI, CSI, phase) of the wireless channel through common channels between two legitimate parties that have no prior secret. Its feasibility is mainly due to the characteristics of channel reciprocity, spatial variation, and temporal variation, which ensure the uniqueness and randomness of the generating keys. Channel reciprocity means that the channel characteristics between two communication nodes are almost identical. Spatial and temporal variation mean that the radio channels between two nodes vary with the location and the environment across time.

Key generation is a promising technique to maintain secure communications for LoRa nodes recently [76, 133]. It generally includes the following four stages: channel probing, quantization, reconciliation, and privacy amplification. Two legitimate nodes send messages end-to-end and measure some kinds of channel features, mainly RSSI information for LoRa. The measured value is then converted into a string of key bits using different quantization methods. Reconciliation is for discarding or correcting the bit differences, and privacy amplification is designed for handling information leakage issues to the attacker. The feasibility of key generation of LoRa was first verified in Reference [174]. Zhang et al. [187] proposed a differential quantization method, which discards the RSSI value whose variation with the adjacent value is smaller than the set RSSI resolution against the measurement imperfection. LoRa-Key [175] is the first RSSI-based key generation method for LoRa, which employs several signal processing techniques (e.g., outlier detection, linear interpolation) to improve the key generation rate and a novel compressive sensing-based reconciliation approach to reduce the key disagreement rate. Rather than RSSI, Gao et al. [50] employed **RegRssiValue (**$RSSI_r$**)** provided by LoRa transceivers for LoRa key generation. Specifically, $RSSI_r$ is the raw instantaneous strength estimation, which provides better channel estimation compared with RSSI and whose distributions produced by the legitimate parties are extremely similar. Furthermore, they adopted a random waypoint model to derive an optimal window size, which can balance the channel reciprocity and entropy. To further improve the correlation of channel measurements, Yang et al. [182] exploited the mean value of **adjacent** $RSSI_r$ **(arRSSI)** as a novel feature for key generation in **Internet of Vehicles (IoV)** scenarios. They also proposed a Bi-LSTM model for prediction and an autoencoder-based reconciliation method for mismatch correction.

PHY layer key generation for LoRa could maintain the network security without the need for fixed infrastructure or secure communication channels. Also, it requires less storage and computing power compared to asymmetric cryptographic solutions. However, due to the characteristics of the low data rate and high energy efficiency of LoRa technology, the issues of low channel reciprocity and probe packet exchanging make key generation for LoRa challenging. Besides, spatial and temporal variations of the radio channel require multiple key establishment times for the LoRa nodes, which is not a long-term security mechanism. Additionally, current key generation methods are almost designed for two legitimate parties [50, 175]; group key generation among a large number of nodes is still an open problem [178].

5.2.2 Radio Frequency Fingerprinting Identification Methods. Device identification is essential for IoT security to allow legitimate users to access the network while preventing malicious users. Recently, the emerging PHY layer RFFI technique uses features extracted from radio signals to uniquely identify devices. Its essence is to use the inherent tiny defects (e.g., inphase and quadrature imbalance, frequency/sampling offset) in the analog circuit of radio device hardware to generate a unique fingerprint of this device, which is impossible to imitate by adversarial devices. As hardware defects are interrelated and complex, hand-crafted low-dimensional features are often unable to generate distinguishable and high-level fingerprints effectively, machine learning algorithms are utilized to make up for this issue. RFFI generally includes two stages, namely, training and classification. In the training stage, the trainer performs feature extraction (e.g., IQ, CFO, spectrogram) after collecting enough data packets. Then, these features are fed into the classifier for training. While in classification one, after receiving the data packet and feature extraction, the classifier infers the identity of the device.

As the pioneering work of LoRa PHY layer fingerprinting, Robyns et al. [132] proposed two per-symbol supervised machine learning models, i.e., a **Multilayer Perceptron (MLP)** and a **Convolutional Neural Network (CNN)**. These models process the entire signal instead of low-dimensional features of the local one to distinguish devices from different manufacturers. Besides, a zero-shot learning model was proposed to consider the unknown device cases. Differently, Jiang et al. [75] adopt the differential constellation trace figure as the feature and utilize an unsupervised method based on the Euclidean distance comparison. Gu et al. [57] designed a LoRaTS gateway to track the radio frequency biases of the nodes based on the linear regression and least-squares methods. Wang et al. [163] proposed SLoRa, an authentication method using fine-grained CFO and spatial-temporal link signature of different nodes' positions. SLoRa collects and inputs CFO and signature features into an SVM model for training in the offline stage. Then, such features from the new node are inputted into the model for authentication in the online one. Al-Shawabka et al. [4] first collected a dataset containing LoRa waveform data from 100 bit-similar devices and then proposed a deep learning-based data augmentation technique termed DeepLoRa. Specifically, DeepLoRa focuses on three different representations, i.e., IQ, amplitude-phase, and spectrogram of the signal preamble or payload, as the input of the deep learning models. Besides, DeepLoRa generated and applied **finite input response (FIR)** filter taps to transform the original dataset, which acts as a data augmentation technique and increases channel diversity. Shen et al. [138] proposed a CNN taking the IQ, amplitude-phase, and spectrogram of LoRa signal as input, among which spectrogram achieves the best performance. Besides, they revealed that the drift of the instantaneous CFO will affect the classification results and degrade system stability. To this end, they proposed a CFO estimation and compensation algorithm, where a CFO database was generated to help the hybrid classifier use the estimated CFO to calibrate CNN's softmax output.

In general, RFFI methods rely on the hardware imperfection, where the derived fingerprint is unique to maintain the network security preventing from spoofing or counterfeiting attacks. Compared with traditional cryptography-based security solutions, RFFI methods do not impose additional computational burdens on devices for authentication. The existing RFFI methods [75, 138, 163] have achieved more than 90% identification accuracy due to the representation learning capability of deep learning models. However, they are not friendly to newly join-request legitimate devices, resulting in poor scalability. In addition, since most RFFI methods seek stable and discriminative features from the entire LoRa signal samples, using instantaneous features is still challenging.

Apart from the aforementioned studies, several other studies [67, 90, 113] focused on blockchain-enabled LoRa networks for trust verification and security issues. Blockchain is a **Peer-to-Peer (P2P)** distributed and decentralized ledger technology. Its essence is a shared database that contains specific and verifiable records of each transaction, possessing the characteristics of non-counterfeiting, traceable, and transparent. Lin et al. [90] proposed the first conceptual blockchain-enabled LoRaWAN infrastructure design, which is built upon many LoRaWAN network servers that communicate with each other via P2P. Each network server is added the blockchain management components of packaging transaction, hashing broadcasting, verification, making and storing blocks to perform the message flow process. Niya et al. [113] proposed a blockchain-enabled LoRaWAN network based on Ethereum, an open-source, public blockchain platform supporting smart contracts to store data. Specifically, **Ethereum Light Clients (ELCs)** were deployed in the LoRa nodes or gateways for the data transmission to the application server. Hou et al. [67] proposed HyperLoRa, a blockchain-enabled LoRa system with edge computing ability. In particular, HyperLoRa possesses two ledgers in the central could and getaway to process the delay-tolerant application data with large size and the time-critical network data with small size, respectively. Besides, HyperLoRa utilizes edge computing technology to migrate the works of the join procedure and application packages processing from the network servers. Blockchain-enabled LoRa methods mitigate security risks and solve authentication problems, but are still immature.

6 LORA-ENABLED APPLICATIONS

The wide deployment of LoRa has inspired a wide range of applications. In this section, we review these applications from four categories: backscatter, sensing, integration with heterogeneous wireless technologies, and other applications.[2] Specifically, backscatter refers to the passive reflection and modulation of incident RF signals for transmission. LoRa sensing captures the LoRa signal variance during propagation to achieve specific kinds of task sensing, such as respiration monitoring and localization. The integration with heterogeneous wireless technologies aims to explore their interoperability, which involves **wireless co-existence (WCE)** and **cross-technology communication (CTC)**. Other applications, such as smart city, industry, agriculture, and healthcare, are reviewed at the end of this section.

6.1 Backscatter

Backscatter has been widely used in long-distance, low-cost communication systems such as **Radio Frequency Identification (RFID)** tags and commodity Wi-Fi access points. As the representative example, a RFID system typically relies on readers and tags, where the reader transmits high-power RF signals as queries and the tag responds by changing the antennas' impedance. Another typical backscatter communication system is the ambient one, which does not require a

[2] Inspired by the LoRa survey [85], we continuously adopt "application" as the classification criterion of the references about backscatter, sensing, and integration with heterogeneous wireless technologies.

Table 11. Summary of LoRa Backscatters

Method	Year	Excitation Signal	Range	Consumption	Parallel Decoding	COTS Tag Compatibility
LoRa Backscatter [148]	2017	Dedicated	2,800 m	9.25 μW	✗	✗
LoR$_{EA}$ [160]	2017	Dedicated	3,400 m	70 μW	✗	✓
PLoRa [119]	2018	Ambient	1,100 m	220 μW	✗	✗
NetScatter [64]	2019	Dedicated	-	45.2 μW	✓	✗
Aloba [59]	2020	Ambient	250 m	0.3 mW	✓	✓
PolarScatter [141]	2020	Dedicated	1,500 m	71 μW	✗	✗
FD LoRa Backscatter [77]	2021	Dedicated	300 ft (LOS), 4,000 ft (NLOS)	3.04 W	✗	✓
P^{2}LoRa [74]	2021	Ambient	2,200 m	320 μW	✓	✓

dedicated signal source but explores the available RF signals nearby (e.g., RF or LoRa signals from active nodes), thus becoming the most energy-efficient and the lowest cost solution among them.

LoRa backscatter [73, 141, 160] is becoming a promising technology recently, due to its high sensitivity and resilience against both in-band and out-of-band interference, Typically, a LoRa backscatter system consists of three parts: transmitters, receivers, and backscatter tags. When the transmitter sends excitation LoRa signals, a backscatter tag uses the on-board circuit (e.g., programmable logic units) to modulate RF signal (e.g., amplitude, frequency, phase) under a modulation mechanism (e.g., OOK), and then reflects the signal. The receiver captures the reflected backscatter signal and decodes the information. Table 11 summarizes the existing LoRa backscatters.

As the pioneering work, Talla et al. [148] proposed LoRa Backscatter, which receives and utilizes the single tone transmitted by a single RF source to synthesize the CSS signal for decoding of the receiver. Specifically, LoRa Backscatter adopts a hybrid digital-analog backscatter design that uses the digital domain to create a frequency plan of a **Voltage-Controlled Oscillator (VCO)** for the continuously varying CSS signal and then map it to the analog domain via a converter. In addition, a harmonic cancellation mechanism was proposed to improve spectral efficiency. Hessar et al. [64] proposed Netscatter to decode large-scale concurrent backscatter transmissions by using only one single FFT operation. In particular, they introduced a distributed CSS coding mechanism, where each concurrent node is assigned to a different chirp cyclic shift and utilizes OOK to transmit bits. They also considered the Near-far problem using power-aware and power-adaption methods and leaves gaps in cyclic shifts to be more robust in time synchronization among nodes. Instead of using dedicated single-tone RF as external excitation signals in References [64, 148], Peng et al. [119] proposed **Passive LoRa (PLoRa)**, which modulates an ambient LoRa signal into a new chirp signal and shifts it into a different channel. Specifically, PLoRa is composed of a low-power packet detection circuit, a blind chirp modulation algorithm, and an energy management component. The packet detection circuit aims to reduce the sampling rate of the input signal and perform cross-correlation operation between input signals and the pre-stored preambles. The modulation algorithm is to generate FSK modulated baseband signal and multiply it with incoming LoRa chirp. To disentangle and demodulate the weak backscatter signal from the strong excitation signal, Guo et al. [59] proposed Aloba, which first detects ambient LoRa excitation signal using unique RSS pattern from other irrelevant signals or noise, then utilizes OOK to modulate the data and reflects to the receiver. The receiver decodes the carrier signal by leveraging the capture effect and transforms it into a constant sinusoidal tone, so the backscatter signal can be demodulated via tracking the amplitude and phase variation. To achieve ubiquitous backscatter connectivity, Katanbaf et al. [77] designed the first **Full-Duplex (FD)** LoRa backscatter reader. FD LoRa Backscatter consists of a single antenna hybrid coupler along with a two-stage tunable impedance network for carrier and offset cancellation, and a microcontroller for implementing the adaptive tuning algorithm. Since PLoRa and Aloba can decode a small number of concurrent backsacatter

Table 12. Summary of LoRa Respiration Monitoring Methods

Method	Year	Sensing Model	Methodology	Antenna Array	Through-wall	#target	Range	Metric
Zhang et al. [185]	2020	Phase difference of signal ratio of received signals at two antennas	Modeling and quantifying	2 directional	✓	1	25 m	Mean absolute error: 0.1–0.37 RPM (5–25 m)
Sen-fence [170]	2020	Phase difference of signal ratio of received signals at two antennas	Virtual fence, search algorithm	2 directional	✓	1–3	50 m	Average error: 0.2–0.7 RPM (1–3 interferer)
Xie et al. [171]	2021	Phase difference of signal ratio of received signals at two antennas	Search algorithm, time-domain beamforming	3 directional	✓	1	75 m	Average absolute error: 0.1–0.6 RPM (1–7 wall)
Palantir [73]	2021	Phase difference of backscatter and direct path signal	OOK-based modulated LoRa backscatter (signal shaping, clustering)	1 omni-directional	✗	1	100 m	Median deviation: 4.39–11.65% (10–100 m)
Zhang et al. [186]	2021	Dividing beamforming signal by beam-nulled one, phase of dynamic path signal mapping distance	Beamforming, direction-frequency spectrogram pre-processing, multi-target detection	4 directional	✓	2–5	24 m	Accuracy: 98.12–99.75% (1–5 targets, 10 m), 96.46–99.62% (8–24 m, 2 targets)

(RPM: Respiration Per Minute).

packets, Jiang et al. [74] proposed an ambient Passive and Parallel LoRa backscatter design termed P^{2}LoRa. Specifically, P^{2}LoRa shifts the ambient LoRa signal at a small certain frequency to modulate the data in the backscatter signal and concentrates the leaked energy in the frequency and time domain to improve its SNR. Then it utilizes a two-level parameter estimation method to reconstruct and eliminate the in-band excitation signal accurately and adopts a window-based method to eliminate the interference to perform parallel decoding.

So far, current LoRa backscatter systems have significantly improved the communication range and throughput of LoRa networks at a low energy cost. Ambient excitation signals [59, 74, 119] get rid of the limitation of dedicated excitation signal source, low-power packet detection approaches [74, 119] achieve long-term deployment, parallel decoding [59, 64, 74] enables simultaneous communications among multiple nodes. However, the existing LoRa backscatter designs still face some challenges in terms of high-range packet detection, simple backscatter modulation mechanism at the tag side, out-of-band LoRa signal interference, and compatibility with COTS devices.

6.2 Sensing

Wireless sensing is an emerging technology of acquiring information about a remote object and its characteristics using ambient wireless signals. The rationale behind wireless sensing is to capture the signal variance (e.g., phase, RSSI) of the wireless signal itself (e.g., RFID, Wi-Fi, LoRa) reflected from the targets with some specific movements. Compared with transitional wireless signals, LoRa possesses strong penetration capability to perform through-wall sensing tasks and long sensing range to fill the gap of Wi-Fi (3–6 m), RF (3–6 m), and acoustic (less than 1 m) signals [185]. Thus, a large number of LoRa sensing methods [92, 185] were proposed recently. We review the existing LoRa sensing works, including respiration monitoring and localization.

6.2.1 Respiration Monitoring. Studies on LoRa-based respiration monitoring generally model the propagation and reflection of the LoRa signal, then adopt a series of signal processing techniques to quantify a mapping between specific signal variation (e.g., phase, amplitude) and the sensing goal (e.g., distance). Table 12 summarizes the existing LoRa respiration monitoring methods.

Zhang et al. [185] achieved real-time LoRa sensing for the first time, including through-wall fine-grained respiration and coarse-grained walking monitoring in the range of 25 m. Specifically, they first derived a basic LoRa signal propagation model and utilized the ratio of received signals at two antennas to cancel out noise and eliminate the random signal phase shift. They further quantified the phase change of the signal ratio to capture the relationship with distances corresponding to target movements for sensing. Besides, they have conducted a comprehensive experiment concerning the impacts of the target, distance, and environment. LoRa radio suffers surrounding interference along with its long-distance communication, Xie et al. [170] proposed Sen-fence, which restricts interference from outside the created virtual fence to mitigate it. In particular, Sen-fence first forms a beam-shaped or spot-shaped virtual fence depending on the number of receiver, then maximizes the movement-induced phase variation by adding a newly static signal purely in software. Such static signal needs to meet the requirements of tuning the phase difference between the static and dynamic vectors to 180° and minimizing the amplitude of the composite signal. Finally, Sen-fence confines the phase within the virtual fence based on the search algorithm of the optimal static signal. However, Sen-fence requires the sensing area as prior knowledge and multiple receivers, which limits sensing in mobile scenarios. In their further study [171], they increased the respiration sensing range to 75 m, resulting from enlarging the target-induced phase variation and adopting a time-domain beamforming method combining signals with different timestamps to increase SNR.

Jiang et al. [73] provided a cyclist respiration sensing method relying on OOK modulated LoRa backscatter signal termed Palantir, which consists of four stages of preprocessing, signal shaping, clustering, and sensing. Specifically, Palantir first demodulated the received direct path signal and backscatter one by exploiting the capture effect. Then, Palantir performed signal shaping to obtain the stable state samples, including amplitude shaping by leveraging a low-pass filter to resolve the problem of amplitude instability and baseband removal by conjugate demodulation and curve fitting to eliminate offset and drift. Then, Palantir adopts the dual clustering method to transfer the state samples from the I-Q coordinate system to the logarithm of the amplitude-phase coordinate system and performs cluster identification enabling consistent identification even if there is a global mismatch, which resolves the challenge of spectrum leakage. Finally, Palantir achieves sensing based on the derived phase difference between the vectors of the direct path signal and the backscatter one. To enable multi-target sensing, Zhang et al. [186] proposed a LoRa multi-antenna beamforming technology to separate the signals in the space domain. In particular, they constructed a "beam nulling" signal as a reference and divided beamforming signal of different directions with this beam-nulled signal, which can eliminate impacts of CFO and **Sampling Frequency Offset (SFO)** for synchronization-free between transceivers and not corrupt the signal amplitude or phase variation information. Moreover, they utilized the amount of phase rotation of the location-independent dynamic path signal rather than the composite signal to determine the chest displacement, thereby solving the location-dependent issue of the composite signal for respiration monitoring. Apart from respiration monitoring, the aforementioned methods also achieved walking [171, 185, 186] and gesture tracking [170].

In general, LoRa has greatly compensated for the short sensing range of conventional wireless signals and achieved great improvements. The existing methods [170, 185] mainly focus on the signal modeling and processing to capture the phase difference among multiple antennas to achieve fine-grained respiration monitoring sensing. Although backscatter signal [73] and beamforming technique [171, 186] provide new possibilities on range expansion and multi-target sensing, there still remain some challenges:

- **Range.** Sensing is more susceptible to channel quality compared with communication [73]. With range expansion, LoRa sensing systems will inevitably suffer from various and complex interference, remaining challenging to be resolved.
- **Multi-target.** Signals from multiple targets will be interleaved and superposed, so a higher complexity of the receiving antenna array and a more robust sensing model are required for sensing. Besides, target mobility will bring additional challenges.

6.2.2 Localization. Target localization and tracking techniques primarily focus on four categories of information: **Angle of Arrival (AoA)** [92], **Time Difference of Arrival (TDoA)** [10], RSSI [91], and amplitude [24]. AoA-based methods leverage the phase difference of a signal arriving at multiple antennas for localization. The multipath can be effectively separated, but good resolution and accuracy require large-scale antenna arrays at the receiver side. TDoA-based methods achieved localization using the time difference of the same signal arriving at multiple gateways. High resolution can be achieved, but suffers from the measurement error and the limited

Table 13. Summary of LoRa Localization Methods

Method	Year	Technique	Antenna Array	Synchronization	Latency	Range	Error	COTS Compatibility
μLocate [111]	2018	Backscatter	3 chip antennas	Access Points	25–70 ms	60 m	1.5 m (outdoor), 0.3 m (indoor)	✗
WIDESEE [24]	2019	Amplitude-based	1 reconfigurable directional	–	–	53 m (outdoor), $20 \times 42 \times 85\,m^3$ (indoor)	4.6 m	✗
SateLoc [91]	2021	RSSI-based	1 omnidirectional	–	3 s	$350 \times 650\,m^2$	47.1 m	✓
OwLL [10]	2021	TDoA-based	Virtual multi-antenna arrays	Base stations	20.97 s	>500 m	9 m	✗
Seirios [92]	2021	AoA-based	2×2 MIMO	Multiple Channels	0.24 s	100 m (outdoor), 25 m (indoor)	4.6 m (outdoor), 2.4 m (indoor)	✓

bandwidth. AoA and TDoA methods generally require clock synchronization between transceivers. RSSI-based methods can be further divided into fingerprinting-based methods [91] and model-based methods [12, 82]. They are generally effective, but have poor resolution. Besides, the amplitude is utilized to deal with the multipath effect, which is simple and low-cost, but has poor accuracy due to signal attenuation. Table 13 summarizes the existing LoRa localization methods.

Chen et al. [24] proposed a localization prototype termed WIDESEE, which consists of a reconfigurable antenna system, a data collection and antenna control system, and a target detection and localization system. Specifically, the antenna system integrates horn directional antennas and phased arrays for fast radiation mode switching and narrower beamwidth offering to further reduce interference. The data collection and antenna control system is built on single LoRa transceiver pair carried by a flying drone. WIDESEE exploits the **power spectrum density (PSD)** for target detection after vibration noise elimination using a low-pass filter, then extracts direction-related information from amplitude and isolates the target path from the interfering multipath to achieve localization sensing. Lin et al. [91] proposed SateLoc, a LoRa localization system based on the virtual fingerprints extracted from satellite images. Specifically, in the offline stage, SateLoc trains a **Random Forest (RF)** using satellite images associated with labeled land-cover types to generate an **Expected Signal Power (ESP)** map as a virtual fingerprinting for each gateway. In the online one, SateLoc produces a location likelihood distribution for each gateway based on its ESP map using the extracted RSSI and SNR from the received packets and adopts a weighted combination strategy for joint localization. Besides, μLocate [111] designed a sub-centimeter sized multi-band backscatter system, together with the extracted phase information for microwatt-level localization.

As the narrow bandwidth of LoRa incurs low-range localization resolution, several methods [10, 92] focused on the bandwidth expansion. Bansal et al. [10] proposed an **Outdoor whitespace-band LoRa Localization (OwLL)** method based on the TDoA transformed by the measured phase difference across antennas. Specifically, OwLL emulates wide bandwidth in a low-cost manner by frequency hopping over wireless spectrum in TV whitespace and ISM frequency bands, where an iterative maximum-likelihood algorithm is adopted to determine a small set of optimal frequencies hopped rather than all possible ones. After ensuring phase synchronization with reference to Chime [47], OwLL treats diverse spatial base stations as a virtual distributed array to mitigate the impact of signal multipath and utilizes a particle filter as well as the prior measured phase and TDoA to trilaterate LoRa clients. Liu et al. [92] proposed a super-resolution localization algorithm termed Seirios. In particular, Seirios utilizes a novel interchannel synchronization algorithm to increase the bandwidth, where ToneTrack [172] technique is for overlapped channels while a virtual intermediate channel response is generated as a bridge is for non-overlapped channels. Then, Seirios exploits both the original and the conjugate of the CSI measurements for AoA estimation based on the ES-PRIT algorithm [70] to further increase the capacities for multipath resolution, where the synchronized LoRa CSI value of multiple channels is obtained through the amplitude and phase comparison between the received symbols with the pre-defined training ones.

Table 14. Summary of LoRa WCE and CTC Methods

	Method	Year	Heterogeneous Technology	Methodology	Performance	Hardware Design	COTS Compatibility
WCE	Zhang et al. [188]	2018	LoRa & NB-IoT	Multi-module node design	Range: 1.6 km	✓	✗
	Gao et al. [51]	2019	LoRa & NB-IoT	Multi-module node design	-	✓	✗
	LoFi [23]	2021	LoRa & Wi-Fi	Spectrum reservation	PRR: 98%	✗	✓
	PSR [143]	2021	LoRa & CT interference	Symbol recovery	PRR: 45.2% → 82.2%	✗	✓
CTC	Symphony [88]	2019	BLE and ZigBee → LoRa	GFSK and OQPSK modulation	Range: >500 m	✗	✓
	XFi [95]	2020	ZigBee, LoRa → Wi-Fi	Signal hitchhiking	Accuracy: >97% under 8 parallel devices	✗	✓
	EMLoRa [137]	2021	EMG → LoRa	AM modulation	Range: 130 m	✗	✓
	LoRaBee [139]	2021	LoRa → ZigBee	Correlation with payload data and RSS value	Throughput: 281.61 bps	✗	✓

In general, LoRa localization methods have achieved promising accuracy and resolution results and greatly expanded the range compared with Wi-Fi and RFID signals. The existing localization methods have attempted various features, such as amplitude [24], RSSI [91], angle [92], and time [10]. Among which, RSSI can achieve the longest range, but amplitude, time, and angle information can obtain higher resolution. Apart from attempting various features to expand the range, several studies [10, 92] focus on the bandwidth expansion of LoRa to improve the resolution. However, some possible challenges may include:

- **Synchronization-free and Multipath Disambiguation.** The synchronization between transceivers guarantees the accuracy of AoA and TDoA-based methods, resulting in additional energy consumption. Multipath disambiguation addresses the problem of signal change in terms of the polarization mode, phase, and Doppler shift for better accuracy.
- **Multi-target Sensing.** Multi-target reflected signals will be inter-weaved, thus separating these signals under a limited channel bandwidth is challenging. Besides, concurrent transmission for multi-target localization deserves further exploration.
- **Mobile Localization.** Moving targets or gateways induce the complex multipath effect and signal attenuation, which deserves further study.

6.3 Wireless Co-existence & Cross-technology Communication

The emerging paradigm of IoT has inspired the exploration of interoperability between LoRa and other heterogeneous wireless technologies. These works can be divided into two categories: **Wireless Co-Existence (WCE)** and **Cross-Technology Communication (CTC)**. Table 14 summarizes the existing LoRa WCE and CTC methods.

Wireless Co-existence Methods. WCE methods mainly rely on interference avoidance, detection, and cancellation to achieve the co-existence of different technologies. Recently, a new LoRa chip called SX1280 was proposed by Semtech that provides a possibility of LoRa radio operating at 2.4 GHz frequency, resulting in a larger available bandwidth (from 500 to 1,600 kHz) and a faster data rate (from 21 to 70 kbps). In this context, LoRa packets may be severely damaged by Wi-Fi interference, so Chen et al. [23] proposed a weak signal detection method termed LoFi to achieve the co-existence of LoRa and Wi-Fi. Inspired by the physical phenomenon named **Stochastic Resonance (SR)**, LoFi adds appropriate white noise that is capable of enhancing weak LoRa signals at specific frequencies. Specifically, LoFi first selectively transforms the frequency of a LoRa chirp into one particular small frequency and separates Wi-Fi signal to another frequency range to detect LoRa signals. Then, LoFi adopts a bandwidth-aware spectrum reservation method to adaptively reserve the spectrum for LoRa collision-free transmission according to the spectrum occupancy. Sun et al. [143] proposed a **Partial Symbol Recovery (PSR)** scheme to combat CT interference, including Wi-Fi, ZigBee, and Bluetooth. In the coarse-grained localization stage, PSR performs the maximum pooling and calculates the ratio between the dominant frequency component and the average after **Short Time Fourier Transform (STFT)** operation. PSR identifies and recovers LoRa symbols based on this ratio in the fine-grained detection one. Besides, several methods [51, 188] paid attention to the combination of NB-IoT and LoRa technology. Zhang et al. [188] proposed an information monitoring system integrating NB-IoT and LoRa, which mainly relies on the designed main-nodes equipped with both radio modules to receive messages from LoRa sub-nodes and transmit them to the cloud server.

Cross-technology Communication Methods. CTC mainly refers to exchanging instructions and data flow across two or more different technologies (i.e., the carrier and target ones), which exploits both (or all) of their advantages. Shi et al. [139] proposed LoRaBee to support CTC from LoRa to ZigBee unidirectional. In LoRaBee, the LoRa signal is adopted as the carrier with elaborate frequency tuning and payload encoding, and Zigbee can decode the packet by sampling the RSS value. Specifically, the main idea is to correlate (i.e., map) the data bytes in the LoRa payload with the generated RSS signature between the LoRa transmitter and ZigBee receiver and make both sides store this mapping. However, it is computation-inefficient and lacks scalability. Li et al. [88] proposed Symphony to support the CTC from **Bluetooth Low Energy (BLE)** and ZigBee to LoRa, along with a parallel decoding method. Specifically, BLE, ZigBee, and LoRa signals are modulated by **Gaussian Frequency Shift Keying (GFSK), Offset Quadrature Phase Shift Keying (OQPSK)**, and CSS to generate single-tone sinusoidal signals, respectively. The received samples are split, multiplied with correlation templates, then disentangled and decoded via performing FFT operation at the LoRa receiver side in turn. Shen et al. [137] proposed EMLoRa, which reshapes EMG radiation into LoRa-like chirps through AM. Liu et al. [95] presented XFi based on signal hitchhiking. Low-speed IoT (ZigBee, LoRa) data packets collide with (hitchhike) high-speed Wi-Fi ones in the overlapped spectrum, which can then be decoded by commodity Wi-Fi receivers. Specifically, XFi first reconstructs the IoT waveform with erased segments by analyzing the Wi-Fi payload and then utilizes the enhanced IoT decoder to reliably decode the reconstructed waveform through incorporating the signal erasure pattern with the IoT signal redundancy information.

Current emerging WCE and CTC methods adapt to the unprecedented proliferation of heterogeneous wireless devices and make up for the shortcomings of another single technology by exploiting the advantages of the considerable communication range of LoRa. The existing WCE [23, 143] and CTC [88, 137] methods mainly focus on interference avoidance and signal approximation to the receiver waveform methodologies. Additionally, RSS mapping [139] and signal hitchhiking [95] provide novel solutions. However, these methods still leave room for improvement in terms of hardware design, network deployment, generality for other technologies, and security issues.

Apart from the aforementioned LoRa-enabled applications, several methods focus on others, such as network aggregation [48, 183], C-RAN [39, 93]. For example, LoRa network aggregation [48, 183], information retrieving on the basis of the selection and analysis of data in the network, receives popularity recently. Yang et al. [183] proposed an accurate, general, future-proof, and energy-efficient analytic framework for LPWAN termed Joltik. Joltik can calculate sensor data aggregation, utilize universal sketching for transmission, and support unforeseen metrics without additional energy overhead. Specifically, Joltik is built on universal sketching, which discreetly provides a smaller number of counters at the lower level for efficient storage, employs a compression scheme for reducing the communication cost, and eliminates updates of redundant counters for reducing the computational cost. Gadre et al. [48] proposed QuAiL, which enables coarse aggregation queries of sensing data across LPWAN (LoRa, NB-IoT) clients within one packet timespan, inducing spatial distribution, statistics, and machine learning types. QuAiL mainly relies on encoding the information in the energy of concurrent transmissions across clients and leverages this linear addition of powers of phase-asynchronous channels for different types of queries. Besides, QuAiL requires wireless impairment tackling (e.g., timing and frequency offsets, noise) for synchronization and involves security and privacy considerations using random power weights of clients.

6.4 Other Applications

As LoRa networks possess the advantages of low power consumption and wide coverage, they have been widely used in various real-world IoT applications, summarized below:

- **Smart City.** Smart building and lighting [118, 176], public assets tracking [35], surveillance system [136], are deployed to better serve the city life.
- **Smart Industry.** Industry applications, such as smart grids [34], smart metering [161], and distributed measurement system [130], also receive much popularity.
- **Smart Agriculture.** LoRa is widely used in agriculture area, such as soil health monitoring [125], smart irrigation system [189], and precision agriculture [19].
- **Smart Healthcare.** Besides, LoRa is utilized for healthcare monitoring [21] and against COVID-19 pandemic [126].

7 CHALLENGES AND FUTURE DIRECTIONS

In previous sections, we have reviewed extensive works developed for LoRa networks. Below, we provide researchers with challenges of existing works and potential future research directions in this domain.

7.1 Challenges

LoRa Analysis. Extensive analysis of LoRa performance can help understand the capabilities and limitations of LoRa. Quantifying LoRa performance with the corresponding factors becomes an early and crucial work for further study. LoRa analysis tools also leave room for further improvements. The existing analytical models are mostly derived under strict assumptions. The major influencing factors need to be explicitly represented before combating various interference for devising accurate and general analytical models. Simulators offer a convenient way for experiment test and validation, but they are not full-featured enough. Developing large-scale public testbeds is challenging concerning network deployment, numbers of LoRa devices, types of sensors, remote development, and user experience.

LoRa Communication. The performance of LoRa communication primarily relies on its PHY layer modulation and demodulation, MAC protocol, and configuration settings of nodes. The effectiveness and efficiency are of primary concern for LoRa communication studies. In particular, the transceiver modification, the compatibility with COTS devices, and additional energy consumption issues make improvements on LoRa modulation challenging. For demodulation, the complexity of the algorithm, synchronization requirement, and the impact of CFO, SFO, and inter-packet interference still require further study. It is also challenging to devise adaptive and effective MAC protocols, due to the inflexibility of contention-based and energy waste of schedule-based ones. Besides, different network deployment, various intra- and inter-network interference, dynamic link quality, and algorithm complexity are challenging for configuration settings methods.

LoRa Security. Security and privacy are vital with the surging growth of LoRa networks, on the premise that LoRa is susceptible to various vulnerabilities. LoRa PHY properties have shed light on novel and powerful attacks that are difficult to combat, while the high power efficiency requirement also makes its countermeasures challenging. Additionally, although PHY layer security methods can maintain theoretically absolute security, non-robust characteristics limit the practicality. For example, the existing key generation methods generally allow occurring only two legitimate parties in a long-term probing period but not group ones. Discriminative instantaneous features and suitability for newly join-request legitimate devices are challenging for RFFI methods.

LoRa-enabled Applications. Beyond the scope of LoRa networks, plenty of works have attempted various LoRa-enabled application designs inclusive of backscatter, sensing, heterogeneous technologies, and so on. These works have made promising progress and shown great potential in the research community, but also deserve further much-room exploration. For backscatter, ambient excitation signals, concurrent transmission capability, and demodulating weak backscatter signals from the strong superposed excitation signal are valuable and challenging factors. The major challenges of wireless sensing lie in effective feature extraction, robust signal model derivation, and comprehensive data collection. The generality is a long-term challenge for integration with heterogeneous wireless technologies.

7.2 Future Directions

LoRa Protocol Stack. As an emerging LPWAN technology, various efforts have been made on the protocol stack of LoRa, especially its PHY/MAC layers. The unique characteristics of LoRa PHY signals have been leveraged for collision disambiguation [167], sensing [186], and backscatter [74], which undoubtedly demonstrates the capability and potential of LoRa PHY layer. For further directions, novel modulation technology is a new way to break through the conventional theory for transmission performance optimization. Apart from leveraging LoRa PHY packet structure and chirp features in time and frequency domains, exploiting spatial [93] and reception [167] diversity gain, adopting deep learning networks [86] can break through some inherent limitations of LoRa conventional PHY decoding while ensuring the advantages of its weak and collision decoding ability. Cross-layer, cross-device, and cross-sensor sensing can provide multi-domain knowledge fusion for better sensing [99]. **Integrated Sensing and Communication (ISAC)**, focusing on joint-protocol design and time-frequency resource reuse, has been a hot research topic recently. Additionally, as LoRa only defines the lower PHY layer in the communication stack, upper network protocols can refine LoRa protocol stack with respect to MAC protocol, data/control plane, and so on.

LoRa Network. In essence, LoRa is a communication technology to form wireless sensor networks featuring low energy consumption and long transmission distance. However, many network performance indicators, such as throughput, communication range, energy consumption, capacity, scalability, and security, deserve further consideration and enhancement. Apart from LoRa networking protocols, the aforementioned ones can be improved via link coordination and adaptability, network management, and so on. Link quality dramatically affects the extent of signal propagation's attenuation (e.g., fading, path loss). Hence, channel diversity, adaptive transmission strategies, and opportunistic spectrum access deserve further improvements. The real-life deployed LoRa networks often present a large-scale complex architecture, which could be multi-topology, multi-hop, or heterogeneous networks. Therefore, network management can achieve resource allocation, load balance, device configuration, accounting, and security services. Among these, network aggregation [48, 183] on LoRa networks is an emerging way for information retrieving and accounting. Besides general security mechanisms, regular firmware updating via over-the-air for remotely deployed LoRa devices sheds light on network security.

AI-empowered LoRa. Artificial Intelligence (AI) plays a significant role in a wide range of research and industry fields [145]. The mainstream deep learning methods can learn implicit and fine-grained feature representations from the sample instances, render high accuracy and acceptable generalization, and avoid complex feature engineering. Data-driven deep learning methods on LoRa signals have achieved remarkable results and incredible purposes in signal demodulating [86], RFFI [138], and sensing [91]. Additionally, few-shot learning, un-/semi-supervised learning [145], federal learning, and embedded AI can be applied to LoRa technology to achieve different tasks. Thus, LoRa technology integration with AI is a worthy and broad future direction.

8 CONCLUSION

LoRa is a crucial and promising LPWAN technology that gains significant research momentum over the past decades, thus inspiring extensive works. In this article, we give a comprehensive review of LoRa from four aspects, i.e., analysis, communication, security, and applications. Besides, several challenges and potential research directions have also been discussed. Although we have reviewed nearly 200 articles in this survey, the list of studies is far from exhaustive. Nevertheless, it covers the majority of recent achievements and directions. We hope that this survey will make it easier for researchers to identify research gaps and discover answers. Additionally, we would like to welcome all researchers to contribute to this intriguing field by expanding it and providing fresh insights.

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