LoRa Networking Techniques for Large-scale and Long-term IoT: A Down-to-top Survey

CHENNING LI and ZHICHAO CAO, Michigan State University

Low-Power Wide-Area Networks (LPWANs) are an emerging Internet-of-Things (IoT) paradigm, which caters to large-scale and long-term sensory data collection demand. Among the commercialized LPWAN technologies, LoRa (Long Range) attracts much interest from academia and industry due to its open-source physical (PHY) layer and standardized networking stack. In the flourishing LoRa community, many observations and countermeasures have been proposed to understand and improve the performance of LoRa networking in practice. From the perspective of the LoRa networking stack; however, we lack a whole picture to comprehensively understand what has been done or not and reveal what the future trends are.

This survey proposes a taxonomy of a two-dimensional (i.e., networking layers, performance metrics) to categorize and compare the cutting-edge LoRa networking techniques. One dimension is the layered structure of the LoRa networking stack. From down to the top, we have the PHY layer, Link layer, Media-access Control (MAC) layer, and Application (App) layer. In each layer, we focus on the three most representative layer-specific research issues for fine-grained categorizing. The other dimension is LoRa networking performance metrics, including range, throughput, energy, and security. We compare different techniques in terms of these metrics and further overview the open issues and challenges, followed by our observed future trends. According to our proposed taxonomy, we aim at clarifying several ways to achieve a more effective LoRa networking stack and find more LoRa applicable scenarios, leading to a brand-new step toward a large-scale and long-term IoT.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Networks** → **Network measurement**; **Network performance modeling;**

Additional Key Words and Phrases: LoRa, low powered wide area networking, taxonomy, Internet-of-Things

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1 INTRODUCTION

In recent years, **Low Power Wide Area Network** (**LPWAN**) has been proposed as a promising way to adapt to the increasing needs of connecting large numbers of low-complexity, low-cost **Internet-of-Things** (**IoT**) devices with long battery life and relatively low throughput in a

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Authors' addresses: C. Li and Z. Cao, Michigan State University, 426 Auditorium Road, East Lansing, Michigan 48824-2600; emails: {lichenni, caozc}@msu.edu.

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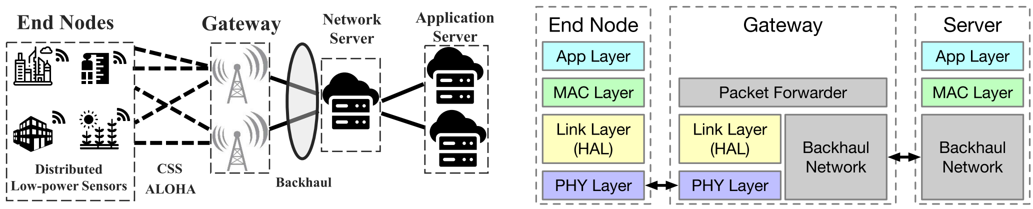
wide area. In comparison with similar approaches via short-range wireless techniques (e.g., Zigbee-based **wireless sensor network** (**WSN**), Bluetooth-based body-area network, Wi-Fi-based local-area network [59]), LPWAN is known for its better scalability, which is one of the most critical concerns in wide-area IoT (e.g., smart-industry [2, 130], smart-city, smart-agriculture [92, 106], and medical IoT [61, 91]). Commercialized LPWANs are developed with three mainstream threads characterized by different underline wireless communication techniques [102].

— As a part of 5G, several cellular IoT technologies (e.g., NB-IoT [95], LTE-M [80]) are developed. As a result, service providers can fully utilize the existing cellular infrastructures to lower the deployment cost. However, these techniques operate at licensed **Long-Term Evolution** (**LTE**) bands, bringing subscription fees to the uses' side.
— Some LPWANs use patented and proprietary wireless techniques like SIGFOX [13], INGENU [55, 83], and TELENSA [56]. Although they operate on free bands, users can only request services and build their applications through a service provider. SIGFOX is widely deployed in the European region, INGENU infrastructure is mainly deployed in the United States, and TELENSA focuses on smart city [32]. SIGFOX and TELENSA operate at unlicensed ISM Sub-GHz bands, while INGENU operates at unlicensed ISM 2.4 GHz bands.
— **Long Range** (**LoRa**) [4] is an open-source technique operating at the unlicensed ISM Sub-GHz bands. Specifically, LoRa uses **Chirp Spread Spectrum** (**CSS**) as a **physical** (**PHY**)-layer modulation scheme, which allows a LoRa radio to send a packet at various data rates (e.g., 0.018–37.5 kbps) to gateways several or even tens of kilometers away (5–15 km). Users and developers can follow the technical specification to customize their own LoRa networks for application demand and academic purposes in various ways.

Due to the open-source privilege, most existing research works focus on LoRa rather than other LPWAN techniques. LoRa networks have been deployed in various application scenarios like city/island environment monitoring [69], metering collection [18], campus vehicle tracking [128], golf cart monitoring [102], and so on. Although LoRa CSS-based PHY layer enables data symbol decoding at a low SNR level, even below the noise floor, the observed communication range varies due to the different land-covers in the deployed area [74]. Additionally, the standard ALOHA **media-access control** (**MAC**) is quite simple to avoid too much energy waste on network status maintenance, resulting in diverse network throughput and energy consumption in these deployments with different scales and configurations [69]. Many methods have been proposed to optimize LoRa performance in terms of communication range, transmission throughput, and energy consumption with these observations. These studies cover the whole LoRa networking stack, including SNR-enhanced PHY-layer encoder and decoder, fine-grained link estimation and configuration, low-cost collision avoidance, and recovery. Moreover, besides the traditional data collection enabled IoT applications, several new LoRa driven long-distance applications like human position/behavior sensing, backscatter communication, and cross-technology communication are proposed. A comprehensive survey is needed to understand the **state-of-the-art** (**SOTA**) development of the LoRa networking stack and new emerging LoRa driven applications.

Several LoRa related surveys summarized and reviewed LoRa from different aspects, including essential characteristics (e.g., standard specification, networking architecture, theoretical performance, and user cases) and advanced progress (e.g., real-environment measurements, research challenges, and designs). For example, U. Raza et al. [94], Q. Qadir et al. [92], and R. Sinha et al. [106] focus on comparing LoRa with other LPWAN techniques in terms of the essential characteristics. J. M. Erturk [27] and Sundaram et al. [102] show the advanced progress classified by various key performance issues (e.g., energy, coverage, security, throughput). Existing surveys cannot meet our goals for two reasons. First, the research designs are not fully aligned with the LoRa network



(a) LoRa Network Architecture [65] (b) LoRa Networking Stack

Fig. 1. The illustration of LoRa network architecture and the corresponding networking stack.

stack, making ambiguity to connect all the research efforts in a whole picture and obtain a clear future trend in LoRaWAN. Additionally, LoRa is a way to enable massive IoT and has great potential to facilitate other communication and sensing approaches on a large scale. Existing surveys, however, do not take into consideration the newly emerged LoRa driven applications. These two limitations motivate us to review existing LoRa research studies from a new angle.

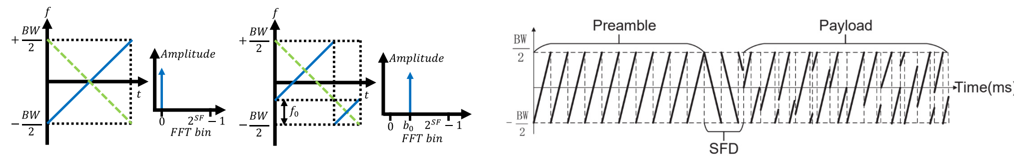
1.1 LoRa Background

Before introducing our taxonomy, we first illustrate the LoRa background from its network architecture to the layered techniques and protocols.

Network Architecture. As shown in Figure 1(a), a LoRa networking system comprises end nodes, gateways, network, and application servers, in which sensory data generated and transmitted by distributed LoRa end nodes through the wireless channel is relayed by gateways, then reaches network and application servers. For a LoRa packet, multiple gateways can simultaneously serve as the forwarders to the network servers, which suppress duplicate receptions, perform security checks, schedule acknowledgments, adjust the network configurations on end nodes, and gateways if needed. Eventually, the received data are forwarded to suitable application servers for further processing [20].

Networking Stack. Figure 1(b) illustrates a typical LoRa networking stack [3, 27] consisting of the PHY, link layer, MAC layer, and **application** (**App**) layer from bottom to top. The functionality of each layer is specified as follows:

- **PHY layer:** The functionality of the PHY layer is symbol modulation and demodulation. Taking the uplink data transmission as an example, an end node encodes its data as symbols that are modulated with baseband signals. Then, given the received symbols shadowed by the physical channels, gateways demodulate and decode them accordingly.
- **Link Layer:** The link layer is also known as **Hardware Abstraction Layer** (**HAL**), which is commonly used in low-power IoT (e.g., WSN) with dynamic links. We abstract several generic interfaces in the link layer to configure radio-specific PHY layer settings (e.g., **transmission power** (**TP**), **bandwidth** (**BW**), channel frequency). A high-level link model is developed to adaptively adjust PHY layer configurations when facing dynamic behaviors of low-power links.
- **MAC Layer:** In a large-scale LoRa deployment, a large number of end nodes have to share the same spectrum resource. In the MAC layer, we regulate the transmission of each end node to achieve efficient data delivery. For different duty-cycle modes, the common purpose of MAC layer protocols is power management and collision avoidance.
- **App Layer:** In the App layer, we use the under-layer transmission primitives to achieve application-specific and secure end-to-end data delivery.



(a) LoRa CSS (b) LoRa Packet

Fig. 2. LoRa PHY layer: (a) initial frequency shifting-based modulation and dechirp-based demodulation; (b) LoRa packet format with a preamble, SFD, and payload.

As shown in Figure 1(b), end nodes have a full networking stack, split into two parts at gateways and servers. The under-layer functions (e.g., PHY and link) are executed on gateways, while the other layers (e.g., MAC and App) are put at the network server-side.

Layered Technique and Protocol Specification. We further introduce the basic LoRa techniques and protocols from down to top in the LoRa networking stack.

—**PHY Layer:** LoRa PHY layer enables a bidirectional communication via CSS modulation using linear chirp signals. The frequency of a base up-chirp increases linearly at the rate of k over time from $-\frac{BW}{2}$ to $\frac{BW}{2}$, denoted as $C(t) = e^{j2\pi(-\frac{BW}{2}+\frac{kt}{2})t}$. Thus, encoded data bits can be modulated by *shifting the initial frequency* of a base up-chirp to f_0, rendering encoded chirp symbols as $y_e = C(t)e^{j2\pi f_0 t}$, as the solid blue lines in Figure 2(a). The standard demodulation, called *dechirp*, extracts encoded data bits by obtaining the shifted initial frequency f_0. Specifically, it multiplies a received chirp symbol with a base down-chirp (e.g., the green dash lines in Figure 2(a)), the conjugate of the base up-chirp. Then, with **Fast Fourier Transform** (**FFT**), the energy of a chirp symbol can be focused at a single tone at f_0 in the spectrum [114] (e.g., the blue arrows in Figure 2(a)). We further decode the data bits with the knowledge of f_0, SF, and BW. Figure 2(b) shows the structure of a LoRa packet, which consists of the preamble, **start frame delimiter** (**SFD**), and payload. Precisely, the preamble consists of multiple base up-chirps, followed by the SFD with 2.25 base down-chirps for packet detection and alignment [111, 112]. The payload contains multiple modulated chirps with different shifted initial frequencies for encoded data bits.

—**Link Layer:** In the link layer, four parameters are abstracted to balance the performance (e.g., range, energy efficiency, data rate) of a LoRa link.

(1) **Spreading Factor**,[1] (**SF**) ranging from 7 to 12, can be configured to balance communication range and energy consumption [111, 112]. And a symbol sent with higher SF takes more time on-air, thus reducing the data rate[2] but improves resilience to noise, signal fading, and interference [96].
(2) BW can be selected from 125 kHz, 250 kHz, and 500 kHz. The smaller the BW is, the lower the data rate is. However, it is much resilient to noise, thus can work at a lower SNR level.
(3) TP can be adjusted, but it is hardware-specific [66]. A larger TP enables a more extended communication range and increases energy consumption as well.
(4) Channel Frequency can be configured [1]. In North America, the frequency band from 902 MHz to 928 MHz is split into 64 125 kHz channels plus eight 500 kHz downlink channels and eight 500 kHz up-link channels. In Europe, ten 125 kHz channels spread on the frequency

[1]The SF denotes the number of bits that a chirp symbol can represent, determining the data rate of LoRa's CSS modulation.
[2]More precisely, decreasing SF from $n+1$ to n scales data rate by $2n/(n+1)$.

band 867 MHz to 869 MHz. Due to the multi-path effect in complex environments, frequency selective effect [24] incurs different communication range by selecting different channels.

In LoRaWAN, the default link model is a binary model, which utilizes RSSI to indicate whether a packet can be successfully transmitted over a link [19, 66]. Given a fixed BW and SF, an RSSI sensitivity is determined by PHY layer CSS modulation. Then, packets can be successfully transmitted over the link if the observed RSSI of a link is larger than the sensitivity. Otherwise, we fail to send any packet. Based on the binary link model, an intuitive ***adaptive data rate*** (**ADR**) strategy is adopted. With different SFs, we can have various sensitivity at different RSSI levels. End nodes use the smallest SF to ensure transmission reliability to keep energy efficiency as much as possible. Specifically, an end node asks the network server to adjust its SF by setting a request in a packet. After the network server gets the request, it returns the optimal SF setting by reviewing the historical RSSI records.

—**MAC Layer:** For power management, gateways and network servers always keep on. Therefore, an end node can send its data to gateways (i.e., uplink) at any time. However, end nodes are usually operating in duty-cycle mode to save energy. Therefore, gateways can only communicate with a duty-cycled end node (i.e., downlink) when it turns awake. Three duty-cycle modes (e.g., Class A, B, and C) are offered with different power consumption and down-link latency. Specifically, Class A is an event-driven duty cycle. An end node only wakes up when it has data to transmit. Class B is a periodic duty cycle. All end nodes periodically send a coordination beacon to the network server. In Class C, the radio of an end node is always on. Hence, Class A is the most energy-efficient with the highest downlink latency. Class C is the opposite, while Class B is the most balanced one. In all three duty-cycle modes, LoRaWAN adopts ALOHA as the default MAC protocol [36]. With ALOHA, end nodes transmit as soon as their packet is ready without synchronizing carrier sense and time slot. Due to the poor performance of ALOHA in collision avoidance, we need to regulate the duty cycle of an end node to 1% or less [23]. Besides widely adopted **Cyclic Redundancy Check** (**CRC**), LoRa adds **Forward Error Correction** (**FEC**) to protect against transmission interference. In FEC, we set the **Code Rate** (**CR**) to encode 4-bit data with 5–8-bit redundancies, increasing the collision resilience by detecting and correcting errors in a MAC frame.

—**App Layer:** LoRa's long-range communication capability inevitably renders itself susceptible to wireless attacks launched from remote and hidden sites. For the App layer, authentication, integrity, and encryption are achieved by using a couple of security keys pre-installed on end nodes or generated during the **over-the-air activation** (**OTAA**) registration mechanism [134].

1.2 Taxonomy Methodology and Overview

As shown in Figure 3, to provide a whole picture for building an efficient LoRa networking stack, we categorize research studies with a **two-dimensional** (**2D**) taxonomy. On the one hand, from the down-to-top view of the LoRa networking stack, we divide current solutions by matching their functionalities with those across PHY, link, MAC, and App layers. In each layer, techniques are organized according to three fine-grained and representative research issues. We briefly summarize the sub-branches of the specific research issues in each layer as follows:

- **PHY Layer** includes coding mechanisms, resolving collisions, and transmission security (Section 3). *Coding mechanisms* (PHY-1) refer to techniques supporting weak/biased signal decoding at both gateway and low-cost end node sides; *Resolving collisions* (PHY-2) contains the techniques enabling concurrent transmission; *Transmission security* (PHY-3) cares about device authentication and jamming defense via PHY layer signal features.

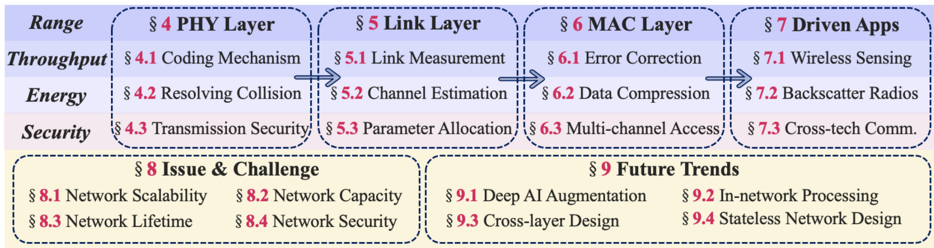


Fig. 3. Taxonomy overview of down-to-top layers and performance metrics, followed by issues and trends.

- **Link Layer** consists of link measurements, link estimations, and parameter allocation (Section 4). *Link measurements* (Link-1) focus on link behavior measurement in real deployment with **commercial-of-the-shelf** (**COTS**) hardware; *Link estimations* (Link-2) indicate the adaptive link models and corresponding estimation methods; *Parameter allocation* (Link-3) refers to the techniques to achieve optimal link performance by adaptively adjusting link layer parameters.
- **MAC Layer** considers the research issues of error correction, data compression, and multi-channel access. (Section 4). *Error correction* (MAC-1) refers to the coding techniques enabling data error detection and recovery; *Data compression* (MAC-2) includes techniques that locally or globally reduce the total amount of data transmissions to achieve efficient media access; *Multi-channel access* (MAC-3) focuses on collision avoidance among the huge amount of end nodes.
- **App Layer** considers some new emerging LoRa-driven applications, including wireless sensing, backscatter radios, and cross-technique communications (Section 6). *Wireless sensing* (App-1) contains the applications like gesture recognition, human localization and tracking, object imaging, and so on; *Backscatter radios* (App-2) refer to LoRa enabled backscatter hardware design for battery-less applications; *Cross-technique communication* (App-3) focuses on the direct communication between LoRa and other wireless techniques (e.g., Zigbee).

On the other hand, from a horizontal view, the motivations of existing studies emphasize improving several common **performance metrics**, including communication range, network throughput, energy consumption, and network security. And we wrap up existing studies with their concerned performance metrics as follows.

- **Range (RA):** enhancing communication and sensing distance for extensive network scalability.
- **Throughput (TP):** increasing network throughput and guaranteeing network reliability for low-cost network capacity.
- **Energy (EG):** reducing energy consumption for a long network lifetime.
- **Security (SE):** developing authentication, encryption, and integrity for network security

We fill the existing studies into our taxonomy. An overview in Table 1 demonstrates the current research focus in each layer. Based on the layers and performance of the existing works in our proposed taxonomy, we summarize some common open issues and challenges faced by the current LoRa community, covering the scalability, capacity, lifetime, and security of LoRa networking. Beyond reviewing the recent literature, we finally expound on our observed future trends for pervasive LoRa deployments, from the advanced processing techniques (e.g., deep AI augmentation, In-network processing) to sophisticated networking stack design (e.g., cross-layer design, stateless network design). Our ultimate prospect is to provide a structured review of current LoRa research

Table 1. The Overview of Existing Studies in the 2D Taxonomy

PHY Layer: (1) coding mechanisms; (2) resolving collisions; (3) transmission security
PHY-1: **RA** [24, 26, 110], **TP** [79], **EG** [122]
PHY-2: **TP** [17, 26, 52, 111, 112, 117, 119, 121, 125, 126]
PHY-3: **SE** [51, 104, 118]
Link Layer: (1) link measurements; (2) link estimations; (3) parameter allocation
Link-1: **RA** [9, 10, 14, 45, 69, 85, 90, 120, 124], **TP** [69, 89], **EG** [69]
Link-2: **RA** [22, 69, 74], **TP** [40, 113], **EG** [107], **SE** [50]
Link-3: **RA** [8], **TP** [33, 76, 82], **EG** [28, 33, 37, 38, 66]
MAC Layer: (1) error correction; (2) data compression; (3) multi-channel access;
MAC-1: **EG** [6, 20, 78]
MAC-2: **TP** [34], **EG** [73, 127]
MAC-3: **TP** [15, 21, 36, 46, 100, 116, 134], **EG** [36, 100, 116], **SE** [42]
App Layer: (1) wireless sensing; (2) backscatter radios; (3) cross-technique communications
App-1: **RA** [16, 34, 48, 49, 58, 71, 84, 93, 104, 123, 128, 131, 132], **EG** [47, 84], **SE** [25, 34, 70, 103]
App-2: **RA** [53, 88, 108, 109, 115, 115], **TP** [43, 46, 60, 108], **EG** [43, 88, 109]
App-3: **RA** [67, 68], **TP** [68, 75, 105]

Table 2. Summary of Related LoRa Surveys

Survey	Taxonomy	Topic focus
[94] [92] [106] [39]	standard goals and specifications	comparison and integration of LPWAN technologies
[27] [97]	networking layers	summary of existing LoRa research studies on networking
[44] [102]	performance metrics	summary of existing LoRa research studies on networking
[41] [64]	performance metrics	summary of LoRa sensing and localization methodologies
Ours	networking layers + performance metrics	summary of existing LoRa research studies on networking and sensing

advancements, inspiring researchers to resolve intractable open issues from new perspectives. **Survey Organization.** Related surveys are discussed in Section 2 to demonstrate the difference between ours and them. Then, based on our 2D taxonomy, we expound current research studies in a down-to-top manner from Section 3 to Section 6. Then, open issues and remaining challenges are demonstrated in Section 7, followed by Section 8 for future trends. We conclude our survey in Section 9.

2 RELATED WORK

To compare our survey with the existing LoRa related surveys, we summarize them with taxonomy and topic focus perspectives, as shown in Table 2.

Raza et al. [94] present the emerging LPWAN technologies and the standardization activities from the standards development organizations (e.g., IEEE, IETF, 3GPP, and ETSI) and the industrial consortia (e.g., LoRa Alliance, WEIGHTLESS-SIG, and DASH7 alliance). Besides the standard specifications, Qadir et al. [92] emphasize the need for horizontal integration of diverse LPWAN technologies. By focusing on the well-deployed LoRa and NB-IoT in LPWANs, Sinha et al. [106] compare their standard specified PHY features, network architecture, and MAC protocol, and the corresponding system goals like **Quality of Service** (**QoS**), latency, communication range, and deployment cost, in massive LPWAN application scenarios. Ghena et al. [39] observe that unlicensed LPWANs (e.g., LoRaWAN and SIGFOX) are not yet ready to connect massive IoT devices due to the limited capacity of the unlicensed LPWANs. For the research issues on capacity and coexistence for ubiquitous connectivity, potential network solutions are discussed from the design of PHY/MAC layers.

Beyond the standard specification-based surveys, Ertürk et al. [27] and Saari et al. [97] illustrate the techniques of LoRa networking stack, then show the effectiveness of LoRa research studies of different layers in a variety of application scenarios. Haxhibeqiri et al. [44] review the research progress of LoRa and LoRaWAN on technical algorithms, simulators&testbeds, evaluations&improvements, and feature extensions, from 2015 to 2018. Sundaram et al. [102] expound open issues in the LoRa community from power consumption, communication range, multiple access, error correction, and security. By focusing on the performance measurements and current solutions, recent studies are discussed on methodologies of link coordination, resource allocation, channel coding, interference cancellation, and secure authorization. Moreover, considering the research on LoRa driven applications, Gu et al. [41] and Li et al. [64] supplement recent studies on LoRa-based sensing and localization techniques. Specifically, Gu et al. [41] exploit the PHY layer features of LoRa to optimize the localization accuracy. Li et al. [64] propose a generic processing flowchart with diverse wireless signals and integrate deep AI techniques for ubiquitous sensing.

With more research opportunities and innovative advancements proposed since 2019, to the best of our knowledge, none of the existing surveys presents a uniform and comprehensive taxonomy from the LoRa networking stack to various performance metrics. Besides, it is different from existing ones in that we categorize and compare scattered open issues and current solutions for the LoRa-based communication and sensing completely in Table 1. In this way, we hope this survey can provide a comprehensive review of recent research studies on LoRa.

Remark. Overall, for the topic focus, some surveys [39, 92, 94, 106] focus on the performance comparison among various LPWANs, rather than the cutting-edge research progress on open issues in the LoRa community. Moreover, some surveys [27, 44, 97, 102] emphasize network research studies, while some others [41, 64] target on LoRa driven applications. None of them provides a full-stack view of the research studies. For taxonomy, none of the existing surveys demonstrates a 2D-structured taxonomy to categorize existing research studies. Instead, most taxonomies [39, 41, 44, 64, 102] contain only one storyline (e.g., networking layers, standard goals, and performance metrics), mixing each part. In contrast, we focus on the full-stack research studies on LoRa networks rather than the specification comparison among various LPWAN technologies or networking research without emerging applications. Additionally, we provide a 2D taxonomy, rendering more connections and comparisons among different research studies, a significant step toward achieving the whole picture of LoRa networking research.

3 PHY LAYER - EXPLORING CHIRP SIGNAL FEATURES

Research studies on the PHY layer rely on exploring chirp signal features in time, frequency, and energy domains. We summarize them with three main research sub-branches: coding mechanisms for decoding weak/biased signals at both gateway and low-cost end node sides, resolving collisions for concurrent transmission, and transmission security for device authentication and jamming defense. These studies are concluded in Table 3.

3.1 PHY-1: Coding Mechanism

Problem Statement. LoRa's PHY layer takes CSS modulation and dechirp demodulation to enable symbol decoding under low SNR levels. Some research studies have observed the following performance metric related problems:

Table 3. Summary of Research Advancements in PHY Layer

Reference	Research Issue	Performance Metric	Methodology and Algorithm
Charm [24]	**PHY-1:** Weak signal decoding	**RA:** 3× default dechirp	Geographical diversity combination among 2~8 GWs
Choir [26]	**PHY-1:** Weak signal decoding; **PHY-2:** Collision resolving	**RA:** 2.65×; **TP:** 6.84× default dechirp	Hardware diversity and constructive correlated transmission of co-located ENs
Falcon [110]	**PHY-1:** Weak signal decoding;	**RA:** 2.5× default dechirp	Data coding by selectively interfering LoRa transmissions
LiteNap [122]	**PHY-1:** Energy efficient coding	**EG:** Half default CSS	Timing of physical features (e.g., phase jitters and freq leakages) as fingerprints to identify modulated chirps
Marquet et al. [79]	**PHY-1:** Biased signal decoding	**TP:** reliable as ideal with a 0.4 dB SNR loss	Tracking slow varying timing and frequency offsets by symbols
AlignTrack [17]	**PHY-2:** Collision resolving	**TP:** 5.5× default dechirp	Window alignment and packet separation via the peak height
CoLoRa [112]	**PHY-2:** Collision resolving	**TP:** 14× default dechirp	Take spectral peak ratio as feature to separate collided packets
FlipLoRa [125]	**PHY-2:** Collision resolving	**TP:** 3.84× default dechirp	Interleaving quasi-orthogonal up-chirps and down-chirps
FTrack [121]	**PHY-2:** Collision resolving	**TP:** 3× default dechirp	Featuring continuity of frequency track and periodical symbol edges
mLoRa [117]	**PHY-2:** Collision resolving	**TP:** 3× default dechirp	Iteratively decoding with SIC
NScale [111]	**PHY-2:** Collision resolving	**TP:** 3.3× default dechirp at SNR loss < 1.7 dB	A noise-resistant iterative peak recovery for spectral ratio features
OCT [119]	**PHY-2:** Collision resolving	**TP:** 2~3× default dechirp	Preamble detection, SFD detection, and packet decoding
SCLoRa [52]	**PHY-2:** Collision resolving	**TP:** 3× default dechirp	Robust cumulative spectral coefficient with frequency and power features
Pyramid [126]	**PHY-2:** Collision resolving	**TP:** 2.11× default dechirp	Track the variation of peaks' height via a sliding demodulation window
Shen et al. [104]	**PHY-3:** Authentication ENs	**SE:** 97.61% accuracy with 20 ENs	Spectrogram-based features and adaptive CNN
SLoRa [118]	**PHY-3:** Authentication ENs	**SE:** 90% accuracy in 400 m distance	CFO and temporal-spatial link features
CloakLoRa [51]	**PHY-3:** PHY layer attack	**SE:** data leak over 250 m	Modulate amplitudes of LoRa chirps

—**RA - Weak Signal Decoding.** Though the CSS modulation enables a strong noise tolerance for long-distance LoRa transmissions, Charm [24] observes that Transmissions from end nodes located deep within buildings or in remote neighborhoods will suffer severe attenuation making the weak signal unable to reach the closest gateway. To demonstrate the noise resilience of the CSS modulation, as shown in Figure 5, we leverage the SX1278-based commodity devices and the USRP N210 platform as end nodes and the gateway to generate and capture OTA LoRa transmissions. In dechirp, by adopting FFT on the temporal LoRa signals, the energy of a chirp symbol can be focused at a single tone on the spectrum [114], as shown at the bottom of Figure 4(a). Thus, we can

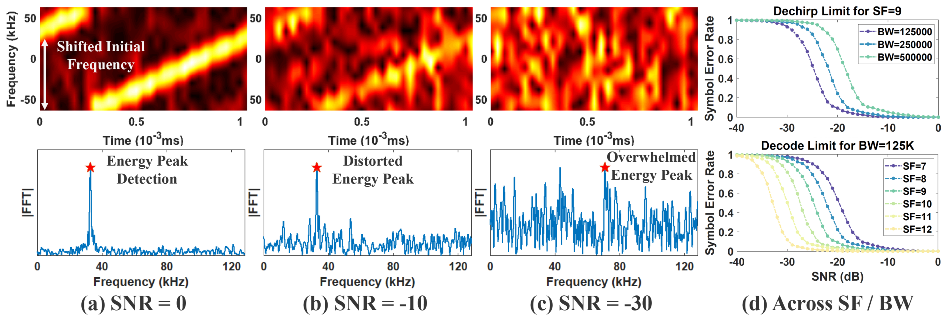


Fig. 4. (a)–(c): Dechirp suffers from the noise overwhelmed energy peak, rendering the increasing symbol error rate at low SNR levels. (d) SER v.s. SNR under various configurations of SF and BW [65].

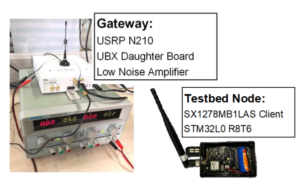


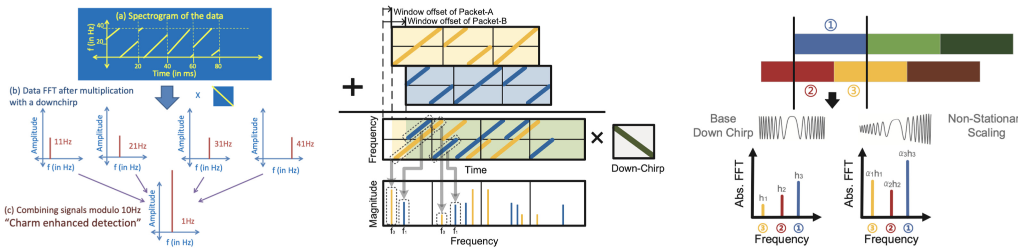
Fig. 5. LoRa experimental hardware.

decode the data bit by detecting the energy peak in the spectrum. As long as the communication distance increases or the **non-line-of-sight** (**NLoS**) link appears, Figure 4(b) and (c) illustrates the noisy chirp symbols by decreasing the **Signal-to-Noise Ratio** (**SNR**) gradually, where the energy peak can be distorted, or even overwhelmed by nearby noise energy. To validate the SNR limit for a successful dechirp, we add Gaussian white noise with controlled amplitudes to the I and Q traces of the collected 4 million chirp symbols [111, 112] for a fine-grained SNR control. Figure 4(d) then shows an increasing **symbol error rate** (**SER**) of dechirp as SNR goes down and renders the SNR limit for configurations across SFs and BWs, under which the dechirp cannot guarantee a robust transmission. Some research studies propose new coding mechanisms on weak signal decoding under low SNR levels to improve the communication range.

—**TP - Biased Signal Decoding.** The low-cost oscillators may bring time and frequency jitters at end nodes during their long-term and unattended deployment. At gateways, the jitters converted to **sampling frequency offset** (**SFO**) and **carrier frequency offset** (**CFO**) cause unreliable demodulation. While we use a preamble to compensate initial SFO and CFO, oscillator offset tracking is necessary to prohibit demodulation failure from oscillator fluctuation.

—**EG - Decoding with low-cost end nodes.** Since energy is a precious resource on low-cost LoRa end nodes, which are usually powered by non-rechargeable batteries. PHY layer consumes considerable energy during down-link packet reception. For end nodes, it is a fundamental way to save energy consumption with an energy-efficient decoding scheme.

Current Approaches.—RA: Inspired by using multiple antennas (e.g., MIMO) to improve SNR in Wi-Fi and cellular communication, recent studies [24, 26] bring the diversity gains of distributed MIMO on the uplinks in LoRa. Charm [24] proposes the idea of coherent combining decoding, which coordinates multiple gateways to decode weak signals that are undecodable at any individual gateway with the combined energy peak in the spectrum. Figure 6(a) illustrates how Charm enhances the packet detection process, in which windows of the resulting peak



(a) Coherent Combining [24] (b) Peak Ratio on the Spectrum [112] (c) Non-stationary scaling [111]

Fig. 6. PHY Layer: Processing on radio frequency signals by designed coding mechanism and physical features.

ratio in the spectrum are then combined for further threshold detection. Due to the extra signal gains of the geographical diversity, it achieves up to 3× in range by capturing additional 1-3 dB SNR gains with 2–8 gateways. Choir [26] exploits the constructive signal correlation among 30 end nodes to make them simultaneously transmit the same data packets to a faraway gateway, achieving a communication range expansion by 2.65× than each one. The most recent work is Falcon [110], which leverages the fact that low-SNR LoRa signals can introduce interference to other LoRa transmissions via destructive signal overlapping. Thus, it provides emergency links for unreachable LoRa clients by selectively interfering with other LoRa transmissions on the same channel, achieving 2.5× increment on communication range.

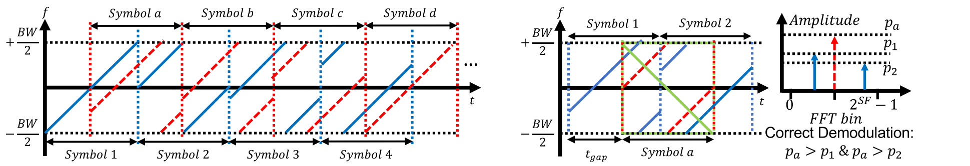
—**TP:** Marquet et al. [79] design an offset tracking loop with two symbol-by-symbol estimators for offset correction to avoid the impact of timing and frequency offsets on CSS modulation. The simulation results show that the offset tracking loop can provide the same demodulation reliability as the ideal case with a 0.4 dB per-bit signal-to-noise ratio sacrifice.

—**EG:** Observing that the power consumption of core LoRa radio components (e.g., MCU, ADC) is generally proportional to the operating clock rates [133], LiteNap [122] proposes a decoding method for down-clocked LoRa symbol demodulation. By exploiting the timing information of phase jitters and frequency leakages as physical fingerprints, it can uniquely identify an under-sampled chirp and resolve ambiguities in symbol demodulation. LiteNap can downclock LoRa end nodes to 1/8 of Nyquist rate, reducing the half energy consumption without affecting packet reception performance (e.g., >95% packet reception rate).

Remark and Limitations. At the gateway side, existing demodulation methods [24, 26] can provide 1–3 dB SNR gains with multiple gateways or end nodes rather than applying dechirp on an end node's signals received by a single gateway. Thus 2.65×–3× communication distance can be enlarged. The extra cost is the demand for deploying multiple gateways and co-located end nodes. Additionally, biased signals' time and frequency offset can be tracked and compensated in a symbol-to-symbol manner [79] to guarantee transmission reliability. The limitation is to keep the accuracy of the existing tracking method, and we need a little higher SNR than the ideal cases without any offset. On the end node side, the energy consumption can be halved by downclocking [122]. However, the downclocking works efficiently when the SNR is higher than 5 dB; thus, sacrificing symbol reception's sensitivity, leading to a trade-off between energy consumption and communication distance.

3.2 PHY-2: Resolving Collisions

Problem Statement. In LoRa networks, a star-of-stars topology is conventionally implemented with thousands of nodes connected to a single gateway, resulting in a severe collision with the



(a) Two packets collide at the receiver side (b) Multiple spectral energy peaks in collisions

Fig. 7. Collisions prohibit weak signals from being decoded with dechirp, limiting the network throughput.

overlapped transmissions [72, 117], especially in dense networks. Figure 7(a) gives an example to illustrate the collided symbols from two end nodes (e.g., different colors and line types) on the spectrogram. After dechirp, as shown in Figure 7(b), multiple spectral energy peaks can be observed, in which target peak (e.g., p_a has to be larger than the other two interfered peaks). However, the weak symbols can be buried by the strongest ones, leading to packet loss, which impairs the network throughput.

Current Approaches.—TP: The basic idea of current approaches is to disentangle the overlapping symbols via their unique hardware, time domain, or frequency domain features. Choir [26] extracts the frequency offset related to the **hardware imperfections** of LoRa end nodes to represent the symbols from different end nodes, improving network throughput by 6.84×. However, recent studies [111, 112, 121] observe that it is difficult to extract the hardware frequency offset accurately due to noises. Besides, the frequency offset of LoRa end nodes may be similar in a dense LoRa network, rendering inevitable decoding failure. To recover collided LoRa packets with low SER under diverse SNR levels, **time-domain features** [117, 119, 121] are extracted from periodical chirp symbols to separate collisions. mLoRa [117] detects the collision-free symbols from the beginning and decodes them iteratively via **successive interference cancellation** (**SIC**), achieving 3× network throughput improvement with up to three concurrent transmissions. Observing that mLoRa [117] incurs significant latency for collided packets, OCT [119] achieves the online concurrent transmissions with three steps (i.e., preamble detection, **Start-of-Frame-Delimiter** (**SFD**) detection, and packet decoding), enabling the comparable concurrency while reducing 67% time delay. FTrack [121] jointly exploits the distinct *frequency tracks* with *misaligned edges* of periodical LoRa symbols to separate collided symbols, boosting the network throughput by up to 3×.

To combat packet collisions by exploiting the intrinsic CSS modulation by concentrating energy in the frequency spectrum, CoLoRa [112] translates the time offsets of the collided packets into spectral peak ratio to concentrate energy as unique features, enabling extended communication range under low SNR levels. Figure 6(b) gives an example of decomposing a two-packet collision into packet time offset. When choosing a misaligned window, each chirp is divided into two segments by two consecutive windows, delivering the frequency peak of incomplete chirp segments for each window. Since the height of the peak is proportional to the length of the segment [111, 112], the peak ratio between two peaks belonging to the same chirp with the same frequency is identical for chirps of the same packet, while it is distinct for chirps different packets. Thus, by grouping chirps with the same peak ratio, CoLoRa [112] can finally disentangle the collided packets. Illustrated in Figure [111] with the incomplete chirp segments, NScale [111] further designs a non-stationary scaling function to amplify the time domain signal within two consecutive windows, rendering the controlled frequency peak with different peak scaling factors. Thus, it can improve the extra noise resistance in the following iterative peak recovery algorithm, which only incurs SNR loss <1.7 dB to original LoRa theoretically, but improves the network throughput by 3.3× for low SNR LoRa signals compared with other methods [26, 117, 121].

Besides the time-domain and frequency-domain features, SCLoRa [52] leverages multi-dimensional information (e.g., amplitude and frequency offset) of chirps for symbol separation, rendering the robust feature *cumulative spectral coefficient*. Besides, the channel fading, similar symbol boundary, and spectrum leakage are also considered for accurate feature extraction, achieving a 3× network throughput. Additionally, observing the *quasi-orthogonality between up-chirp and down-chirp* in LoRa, FlipLoRa [125] encodes information with interleaved up-chirps and down-chirps instead of only using up-chirps. Algorithms on chirp cancellation are further designed to reduce cross chirp interference and decode packets iteratively, improving the throughput by 3.84× over LoRa PHY layer. Pyramid [126] tracks the variation of peak height for each chirp via a sliding demodulation window, achieving a 2.11× throughput improvement over the dechirp approach. Similarly, AlignTrack [17] also relies on the window alignment and energy peak height across all demodulation windows for resolving collisions. Specifically, it decodes LoRa collisions with the least SNR loss as a chirp is transformed to the highest peak with the aligned window. As a result, it improves the throughput by 5.5× over the standard LoRa.

Remark and Limitations. Prior works on resolving LoRa collisions have followed a central scheme: exploring the unique features of collided LoRa symbols in time domain [117, 119, 121], frequency domain [26, 111, 112, 125], or both [52], achieve 2∼14× network throughput improvement with different SNR requirements. However, all of these approaches do not scale to the *near-far deployment* where the distance from the transmitters to the receiver differs significantly from each other. This is because, after dechirp, the weak reception from a remote transmitter produces a tiny FFT peak that is likely to be buried by strong FFT peaks from LoRa nodes that are closer to the receiver. Although SIC can be leveraged to deal with this near−far issue [26, 117], it functions only in high SNR conditions (e.g., mLoRa [117] requires $SNR > 5$dB) to ensure strong transmissions can be successfully recovered and then canceled out. This, however, sacrifices the noise resilience of chirp signals and thus deviates the design principle of LoRa for long-range communication.

3.3 PHY-3: Security

Problem Statement. PHY layer attacks: Current LoRa networking mainly adopts message encryption to ensure the security of end-to-end communication. For example, symmetric key algorithms (e.g., AES-128) are adopted and implemented at MAC and App layers, rendering some risky attacks from the PHY layer, such as the information leak of illegal LoRa end nodes and jamming attack. Moreover, PHY layer features can benefit the end node authentication process. Observing that the CSS modulation ignores the changes of other RF parameters (e.g., amplitude and phase), CloakLoRa [51] builds a covert channel over LoRa PHY by modulating amplitudes of LoRa chirps for sensitive information leakage, which is orthogonal to CSS modulation and transparent to all encryption at upper layers. Evaluations with COTS LoRa end nodes show that the covert information can be transmitted over 250 m.

Current Approaches. EN authentication with PHY layer features: To secure the LoRa communication by determining whether the received signal is conveyed from a legitimate LoRa node, SLoRa [118] proposes two physical features, hardware-related CFO and multi-path based spatial-temporal link signature, for LoRa node authentication. Experiments show a high authentication accuracy for legitimate nodes by SLoRa, around 97% indoors (5∼25 m) and 90% outdoors (400 m). Additionally, Shen et al. [104] explore fine-grained time-frequency spectrogram of LoRa signals for LoRa end node authentication. By compensating the estimated CFO to maintain the stability of the extracted feature, an adaptive **convolutional neural network (CNN)** is designed for predictions as the classifier, achieving the best authentication accuracy of 97.61% for 20 LoRa end nodes.

Remark and Limitations. With the abundant features of chirp signals, new side-channel attacks [51] and authentication systems [104, 118] are proposed in LoRa networks. However, the efficient range is relatively short in comparison with the communication range of LoRa links.

4 LINK LAYER - REAL DEPLOYMENTS AND ADAPTIVE CONTROL

LoRa promises a communication coverage spanning tens of kilometers. And a potentially large number of unattended IoT devices can be covered by a single gateway with a simple star topology, simplifying deployment, operation, and management cost of the communication infrastructure. However, due to the low-power nature of LoRa transmissions, the performance of a LoRa link is intrinsically dependent on the environment it traverses. So, how is the LoRa link performance in a real deployment, and how to adaptively set link configuration are critical problems to guarantee the delivery reliability and energy efficiency of LoRa end nodes? This section includes the literature that focuses on three research sub-branches, including measurements, estimations, and configurations of LoRa links. The existing research studies are summarized in Table 4.

4.1 Link-1: Link Measurements in Real Deployments

Problem Statement. Although LoRa standard [4] specifies the theoretical link performance in terms of its range, reliability, and energy efficiency. To empirically understand the capability of LoRa links, some real systems are deployed in different environments. According to our performance metrics, real deployment-based link measurements cover the communication range in outdoor and indoor environments, link reliability in the mobile scenarios, and energy consumption.

Current Approaches.—RA: Petajajarvi et al. [90] report that the maximum ranges can reach 15–30 km on ground and water by setting LoRa to end nodes on the roof-rack of cars or radio mast of the boat and a gateway on a 24 m tower. Liando et al. [69] show that the LoS and NLoS communication ranges are 9.08 km and 2 km, respectively, in a campus environment. Centenaro et al. [14] observe a communication range of 2 km in an area of high-buildings. Wixted et al. [120] observe the communication range varies from 1.6 km to 2.2 km in different directions in the central business district. Bor et al. [9, 10] observe 100 m–2.6 km communication range in built-up environments and rural areas, respectively. Focusing on the indoor environments (e.g., office building, residential building, car park, and warehouse), Xu et al. [124], Navarro et al. [85] and Haxhibeqiri et al. [45] verify that the communication range can reach over 100 m.

—**TP:** Petajajarvi et al. [89] show that the packet delivery ratio is above 96.7% and 95% when the end nodes are static and mobile in a campus environment. Liando et al. [69] observe the packet delivery ratio is higher than 85% when the speed of end nodes is between 50–80 kmph.

—**EG:** Liando et al. [69] provide energy profiling of end nodes. Under the experimental setting (e.g., 6 bytes payload, CR = 4/8, BW = 125 kHz, and battery capacity 3.7 V 2Ah), the measured lifetime is 4.6 and 1.37 years with different SFs and TPs.

Remark and Limitations. LoRa link can provide more than 10 km communication under LoS environments (e.g., rural area, deploy gateway as high as possible). In contrast, the communication range dramatically decreases to 100 m under NLoS scenarios (e.g., urban area, high buildings, and indoor environment). However, the only communication range is not accurate enough to understand the fine-grained coverage performance of the LoRa network due to the expensive cost of dense and large-scale deployments. LoRa links are resilient to Doppler Effect. The end nodes' lifetime is deeply coupled with link configuration.

Table 4. Summary of Research Advancements in Link Layer

Reference	Research Issue	Performance Metric	Methodology and Algorithm
Petajajarvi et al. [90]	**Link-1:** Link measurement	**RA:** 15 and 30 km on ground and water	ENs: car and boat; GW: 24 m tower
Bor et al. [9, 10]	**Link-1:** Link measurement	**RA:** 100 m built-up and 2.6km rural area	ENs: 1.5 m above floor; GW: 3 floor windowsill in built-up
[85], [124], [45]	**Link-1:** Link measurement	**RA:** about 100 m indoor communication	Static ENs deployments at different distance with different obstacles
Petajajarvi et al. [89]	**Link-1:** Link measurement	**TP:** 95% PRR of mobile ENs	Compare the PRR of static and mobile ENs.
Liando et al. [69]	**Link-1:** Link measurement	**RA:** 2–9.08 km; **TP:** 85% PRR; **EG:** 1.37–4.6 yrs	50 ENs and 3 GWs on 3 building roofs
Centenaro et al. [14]	**Link-1:** Link measurement	**RA:** 2 km in high buildings	GW: two storey building roof
Wixted et al. [120]	**Link-1:** Link measurement	**RA:** 1.6–2.2 km in CBD area	ENs: mobile on foot; GWs: 7-floor roof
DeepLoRa [74]	**Link-2:** Long link estimation	**RA:** Estimation error of < 4 dB	Bi-LSTM model for path loss estimation of long links in the wild
Demetri et al. [22]	**Link-2:** Auto. link estimation	**RA:** ∼10 dB error with 20∼40 dB of others	Toolchain on landscape based link modeling from remote sensing images
N. Hou et al. [50]	**Link-2:** LoRa Jamming and defences	**SE:** Synchronized jamming chirps jam all previous solutions	Separate LoRa chirps from jamming ones by the difference in the received signal strength in the power domain
ToroBetancur et al. [113]	**Link-2:** Link estimation	**TP:** device-level packet delivery ratio modeling	Quantify the capture effect, duty cycling, multiple GWs, and shadow fading on performance
AdapLoRa [38]	**Link-3:** Parameter adaptation	**EG:** 123.7% lifetime over EF-LoRa [37]	Periodically estimate lifetime via a linear regression for energy fairness
Angrisani et al. [5]	**Link-3:** Parameter allocation	**RA:** Packet loss in larger BWs, lower SFs	The distance, payload, and preamble are set to 10 m, 1 byte, and 8 symbols.
Cattani et al. [12]	**Link-3:** Parameter allocation	**RA:** 10% variance on packet reception ratio for parameters	Conclude selecting high data rate and TP for ENs far away from GWs in diverse environments
Chime[33]	**Link-3:** Freq. adaptation	**EG:** 230%(1.4∼5.7 yrs); **TP:** 3.3×/3.4 dB gains	Coherently combine phase info at multi-GWs for multi-path estimations
DyLoRa [66]	**Link-3:** Parameter adaption	**EG:** 41.2% improvement over ADR [107]	Model energy efficiency by SER/PDR with transmission parameters
EF-LoRa [37]	**Link-3:** Parameter allocation	**EG:** 177.8% of the legacy LoRa on energy fairness	Allocate network resources, (e.g., freq channels, SFs and TP) via greedy resource allocation
Fahmida et al.[28]	**Link-3:** Parameter allocation	**EG:** 4× lifetime over legacy LoRa with the same throughput	Peer-to-peer communication for packet offloading and a heuristic method for parameter allocation
Flauzaci et al. [31]	**Link-3:** Parameter allocation	**RA:** A relay protocol on out-of-range ENs	A LoRa-LoRaWAN relay protocol with synchronization

(Continued)

Table 4. Continued

Reference	Research Issue	Performance Metric	Methodology and Algorithm
FLoRa [107]	**Link-3:** Adaptive configuration	**EG:** Increase reliability/energy efficiency against legacy ADR	Implement the ADR on LoRa to dynamically manage link parameters for efficient network operations
Mahmood et al. [76]	**Link-3:** SFs' orthogonality	**TP:** 15% drop for 1500 devices in a channel	Inference modeling and measurements on co-SFs and inter-SFs
ShuttleNet [82]	**Link-3:** SF configuration	**TP:** 1.58× against existing SF selection algorithms [8, 107]	K-Nearest Neighbors algorithm to adapt the SF configuration based on the current link condition

4.2 Link-2: Link Estimation Models and Methodologies

Problem Statement. Facing the dynamic PHY-layer communication observed with the link measurement studies, link estimation plays an essential role in guiding the link configuration and upper-layer MAC protocol designs. We summarize the existing link estimation studies from two aspects, link model and estimation methodology. We can utilize an accurate link model to estimate the coverage of LoRa gateways before deployment and achieve reliable link communication by adaptively adjusting link configuration. Meanwhile, an efficient estimation methodology can reduce the overhead of on-site measurements for the model establishment and local computation at an end node.

Current Approaches. Link Model: Existing studies focus on establishing a path loss model to depict link behavior. Then, we can use the model to predict whether a packet can be receipted by taking TP, antenna amplification, radio receiver sensitivity, and link distance as input. Bor et al. [8], Losee [128], Toro-Betancur et al. [113], and Xu et al. [124] adopt the log-distance path loss model, which uses a reference path loss at d_0 a loss coefficient to calculate the path loss. Demetri et al. [22] utilize the Okumura–Hata empirical model, which uses different empirical functions for urban and rural areas. DeepLoRa [74] utilizes **Bidirectional Long Short Term Memory** (**Bi-LSTM**) to develop a land-cover aware path loss model.

Link Estimation Method: With a log-distance path loss model, for a different environment, we need to collect measurements of the path loss at different distances to determine d_0 and the loss coefficient with data regression. The more data we collect, the more accurate the model is. The loss coefficient is hard to be reused in a different environment, even with the same land-cover type. An end node needs to know the distance between it and the gateway to estimate its link path loss with the model. With the Okumura–Hata model, Demetri et al. [22] use the multi-spectral images from remote sensing to classify the landscape along with a link, then determine which empirical function should be adopted. There is no site survey cost, but we need to label the land cover in the interested area and train a land-cover classifier. A validation on 8,000+ samples from a real dataset shows that this automated approach predicts the expected signal power within a ∼10 dBm error. DeepLoRa [74] needs to collect more training data (e.g., 30,000 packet records) to train the DNN model. A land-cover classifier is required as well. Then, when we move to a new gateway, the original trained model can be fine-tuned with a relatively small data set the estimation error to less than 4 dBm. With the latter two models, we need a specific position of an end node beyond the distance since the land cover along the link should be known in advance. The link estimation can also be used for security protection, such as the undecodable collided packets with synchronized jamming chirps at high power [50]. To separate LoRa chirps from jamming chirps, Hou et al. [50] leverage their difference on the received signal strength in the power domain, effectively protecting LoRa gateways from the jamming attacks.

Remark and Limitations. Log-distance path loss model, Okumura–Hata model, and DNN-based model are adopted to depict the link path loss. We need different methodologies to establish and utilize these models for link estimation. The most accurate path loss estimation error can reach 4 dB, achieved by DeepLoRa [74]. In Demetri et al. [22], the site survey is not needed anymore if we have the relatively low overhead remote sensing image to achieve a lightweight estimation method. Besides these centralization link estimations, how to enable a distributed link estimation on the end node is a challenging and untouched research issue due to the balance between model accuracy and methodology cost facing the long-term deployment requirement of LoRa end nodes.

4.3 Link3: Adaptive Link Parameter Allocation

Problem Statements. Given the direct link between the LoRa nodes and gateways, various transmission parameters can be allocated to ensure efficient and reliable communication (Section 4.1). For example, a LoRa device can be configured with different SFs, BWs, CRs, and TP from 0 dBm to 14 dBm [20], resulting in over 6,720 possible settings [8]. Mahmood et al. [76] further analyze the scalability issue of a LoRa network under the imperfect orthogonality of SFs, quantifying the interference by co-SF and inter-SF with 1,500 devices. This section discusses how to adapt the link parameter allocation to minimize transmission energy cost while meeting the required communication performance.

Current Approaches. The impact of link parameter allocation. Recent advancements for adaptive parameter allocation start from the link measurements evaluation on the impact of various transmission parameters and environmental factors for the optimal parameter allocation. For example, Angrisani et al. [5] evaluate the coverage and throughput with varying SF, BW, and CR and expound the relationship and trade-off. Meanwhile, five performance measurements in the wild [12, 57, 62, 81, 86] further investigate the performance with different parameter allocations in various environments (e.g., mountain regions) and emphasize the necessity of adapting transmission parameters with the deployed environment. For example, Cattani et al. [12] focus on communication reliability and energy efficiency and conclude that the packet reception ratio of the fastest parameter allocation is only 10% lower than the slowest one for LoRa end nodes far away from the gateway. And the received signal strength is decreased by 6 dBm at 60°.
Adaptive parameter allocation mechanism. To adapt the link parameter allocation for optimal performance, Bor et al. [8] develop a link probing regime for quick parameter allocation, which uses only 44% more energy than the SOTA to balance the network performance and energy consumption. FLoRa [107] further develops an open-source framework for end-to-end LoRa simulations. It implements and optimizes the **Adaptive Data Rate** (**ADR**) mechanism to dynamically manage link parameters for scalable and efficient network operations on LoRa. Besides, several adaptation mechanisms are inspired from observations on specific parameters and problems as follows. (1). Observing the critical confliction induced by SF,[3] ShuttleNet [82] employs the K-Nearest Neighbors algorithm to adapt the SF configuration based on the current link condition, achieving 1.58× throughput improvement against existing SF selection algorithms [8, 107]. (2). Given hundreds of operating frequencies to choose from for LoRa transmissions, Chime [33] identifies an optimal operating frequency for LoRa radios by coherently combining phase measurements from multiple gateways. A wide-area deployment at CMU (0.7×0.5 km^2) shows a net increase in battery-life of

[3] A larger SF provides higher network reliability at the cost of lower throughput.

1.4–5.7 years (230%) and network throughput by 3.3× compared to commodity LoRa. (3). Observing the unfair energy consumption across end nodes with various parameters, EF-LoRa [37] further formulates the parameter allocation as a max–min optimization problem for energy efficiency's fairness. As a result, it carefully allocates different network resources (e.g., frequency channels, SFs, and TP) and improves the energy fairness of legacy LoRa networks by 177.8%. (4) Beyond the designed parameter selections via a heuristic method, Fahmida et al. [28] enable a low-cost offloading with a lightweight MAC protocol for peer-to-peer communication, in which LoRa nodes with depleting batteries offload packets to the neighboring nodes with affluent energy. As such, it increases the network lifetime up to 4× while maintaining the same throughput as the traditional LoRa network. (5) To further extend the communication range of LoRa, Flauzac et al. [31] propose a new LoRa to LoRaWAN relay protocol for data collection from isolated end nodes which cannot join a LoRaWAN gateway.

Remark and Limitations. The link parameters can be configured based on the global knowledge of the network (e.g., the location of the devices) [107]. Though LoRa links are robust and resilient by design, it varies significantly while deploying in real environments. The dynamic link channel brings new challenges and potential improvements for parameter allocation in real-life applications [38, 66]. To adapt the dynamic link quality of end nodes, AdapLoRa [38] first periodically adjusts the resource allocation by estimating the corresponding network life, improving the lifetime by 23.7% against the SOTA works [37]. We believe its performance can be further improved with a detailed measurement of the dynamic LoRa links to understand the relationship between the parameter allocation and performance.

5 MAC LAYER: DATA TRANSMISSION CONTROL AT SCALE

LoRa networking is specially designed and well-suited to support low data rates, delay tolerance, and battery-powered IoT devices, which excludes LoRaWAN from using the **Listen-Before-Talk** (**LBT**) mechanisms commonly used in wireless communication technologies, such as WiFi and ZigBee [119]. Thus, current LoRaWAN uses the ALOHA mechanism with the duty-cycle setting for MAC. As the LoRa network scales up, we review several core research problems induced by the increasing number of end nodes and unscheduled radio transmissions, including error correction, data compression, and multi-channel access. And recent solutions are expounded aiming for optimal throughput and energy efficiency by focusing on the massive data transmission incurred channel contention in the MAC layer, illustrated in Table 5.

5.1 MAC-1: Error Correction for Corrupted Packets

Problem Statements. Conventional wireless communication systems are typically designed for a single transmitter-receiver pair in each link, which is often overly pessimistic for LPWANs in terms of link budget as the network scales up [6]. And multiple co-located networks will cause interference in unlicensed spectrum, requiring extra re-transmissions for those corrupted or lost packets. Beyond exploiting physical features of LoRa packets in the PHY layer for collision resolving [46, 111, 112, 121], another way to avoid the re-transmissions is to recover those corrupted packets from being discarded for energy efficiency.

Current Approaches.—EG: Recent works mainly utilize the data redundancy for error correction in corrupted packets. For example, DaRe [78] combines the convolutional and fountain codes to explore the spatial (i.e., frame loss over distance) and temporal (i.e., burstiness of frame loss) information of LoRa communication channels. As such, it exploits the redundant data from the other received frames for data recovery. Compared with a naive repetition coding method of LoRa, DaRe reduces up to 42% of energy consumption, with a significant recovery rate of 99% at a CR = 1/2

Table 5. Summary of Research Advancements in LoRa on Data Transmission Control in the MAC Layer

Reference	Down-to-top	Performance Metrics	Methodologies and Algorithms
DaRe [78]	**MAC-1:** Lost frame recovery	**EG:** Save 42% of consuming energy	Explore spatial and temporal features of frames via convolutional and fountain codes
LoRaFFEC [20]	**MAC-1:** Error correction	**EG:** Data delivery rate>98%	Combine error correction with the fragmentation for data redundancy
OPR [6]	**MAC-1:** Recovery on corrupted bits	**EG:** Correct 72% packets in failed CRCs	Detect error bits via RSSI and combine multiple GWs coherently
Joltik [127]	**MAC-2:** Universal sketching for data compression	**EG:** 24.6× reduction in energy against raw data transmission	Sensor nodes report compact data for massive statistical summaries to reduce memory and computation
Nephalai [73]	**MAC-2:** Compressive sensing based cloud radio access	**EG:** 1.7× battery life with 87.5% PHY samples compressed	Customized dictionary to exploit the structure of LPWAN packets and sparse approximation for PHY samples
QuAiL [34]	**MAC-2:** Compression for fast information retrieval	**TP:** 4× faster information retrieval from 30k unique locations	Enable base stations to simultaneously find approximate responses to types of queries on aggregate sensed data
DeepSense [15]	**MAC-3:** DL carrier sense	**TP:** 4× data-rate in 21 LoRa configurations	Transform processing function; spectrogram+CNN/dilated CNN + RNN
D. Zorbas et al. [134]	**MAC-3:** Time-slotted protocols for access	**TP:** Parameters from the Aloha to a time-slotted protocol	All parameters of LoRaWAN to be considered and a frame structure for the time-slotted LoRa(WAN) protocol
FLIP[21]	**MAC-3:** Contention management for access	**TP:** Improved contention management with 20% more ENs	Transforms LoRa GWs into a federated network for inherent support roaming by consensus-driven load balancing.
LMAC [36]	**MAC-3:** Efficient carrier-sense multiple access	**TP:** 2.2×;**EG:** 2.4× per successfully delivered frame against ALOHA	CAD feature to detect payload chirps and LoRa CSMA to balance communication loads among multiple channels
LoRaTS [42]	**MAC-3:** Frame delay attack and the defense	**SE:** Efficient awareness of attack over 50, 000 m^2	Track the inherent freq biases of the ENs for the detection of the frame delay attack which induces extra freq bias
NetScatter [46]	**MAC-3:** Distributed CSS	**TP:** 14∼62× with concurrent 256 ENs	Combining coding of CSS and ON-OFF keying for concurrent transmissions
WiChronos [100]	**MAC-3:** Time-interval modulation for access	**TP/EG:** 60% battery life improvement at distance of 800 m	Improve spectral efficiency by minimizing symbols per message/bound timing induced bit errors with correction
p-CARMA [116]	**MAC-3:** Channel activity recognition	**TP:** 5.25× scaling up; **EG:** 37.31%∼58.17% less than LoRaWAN	Combine CAD with persistent-CDMA to evade collisions across ENs via p-value opportunistic estimation

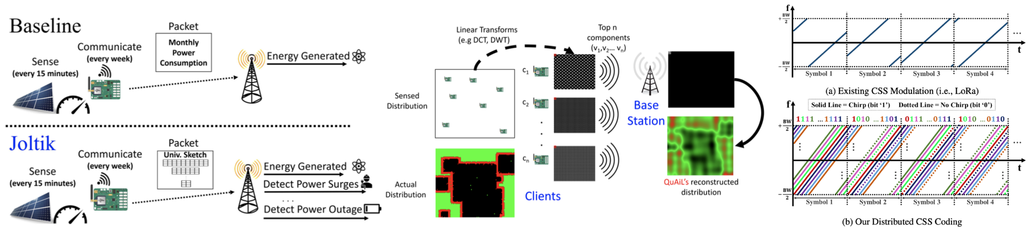
when the frame loss is up to 40%. Observing the correlations of packets across multiple gateways, OPR [6] collects those corrupt packets that suffered failed CRCs in the network service and groups them based on geographic proximity and reception time for efficient recovery. The rationale is that even though these packets may fail integrity checks, they often fail in a disjoint manner due to the spatial diversity in the receivers, which can be recovered opportunistically by collaborating multiple gateways. Wide-deployed evaluations at CMU over a 10 km^2 area demonstrate that up to 72% of packets can be corrected that usually would be dropped (when received by multiple gateways), improving the battery life by removing the need for costly re-transmissions. LoRaFFEC [20] combines the error correction with a fragmentation mechanism using **Low-Density Parity-Check** (**LDPC**) by incorporating a new coding mechanism[35]. By exploiting the **Forward Error Correction** (**FEC**) redundancy at the cross-packet level, it obtains a better application **Data Delivery Rate** (**DDR**) of >98% for energy efficiency. WiChronos [100] further proposes the error detection and correction mechanisms for timing-induced bit errors (e.g., anchor symbol loss, processing time error, clock skew error, and propagation error). Thus, it achieves 100% accuracy of received data even in the presence of timing error.

Remark and Limitations. While exploiting the data redundancy, the processing latency and security issues can be induced without appropriate system designs. For example, Sandell et al. [99] prove a limit to what can be recovered by introducing the redundancy for DaRe [78]. Besides, OPR also analyzes its compatibility with LoRaWAN's security model. By only intercepting traffic between the gateways and the network server, the newly recovered payloads can then be validated on the network server without further security issues. Meanwhile, OPR does not assume knowledge of the device-specific root keys (NtwKey and AppKey) for its system design. Diving into the lower layer from the MAC, future studies can study the impact of how the underlying structure of CSS coding could be used to search the possible error codes efficiently [6]. For example, those particular symbols are much more likely to fail in a specific manner. Another direction for error correction in the MAC layer is to explore the trade-off of how much information is indeed gained from the redundant data by additional frames [78] or receivers [6]. Thus, a system should expand or refine the number of bits it can error-correct based on the number of redundant data sources, which could be beneficial in systems with extremely low SNR ratios like what one might expect with backscatter LoRa devices [6].

5.2 MAC-2: Data Compression for Efficient Transmissions

Problem Statements. The core of LoRa networking is to connect massive low-cost devices widely to conduct an in-depth analysis of the collected data. Given the densely deployed IoT devices and correspondingly massive data, it expects flexible connection, real-time control, and data optimization, especially for the transmission and integration with the cloud enormously [2]. Multiple communication channels are required with high BW of network infrastructure between gateways and the cloud server for the cloud radio access, rendering potential network congestion, and increased cost due to the Internet data usage.

Current Approaches.—EG: The data compression is a well-used method for efficient transmissions. For example, Nephalai [73] proposes a compressive sensing-based LPWAN packet acquisition mechanism by designing a customized design dictionary to demodulate compressed PHY samples in the cloud with (joint) sparse approximation. Experiments with four gateways show up to 93.7% of PHY samples can be reduced, extending the battery lifetime of embedded LoRa nodes to 1.7. To reduce data transmissions between sensor nodes and gateways, Joltik [127] applies recent theoretical advances in **universal sketching** [11] to induce nodes to report a compact summary of sensed data for a variety of statistical summaries. Figure 8(a) shows the difference between the traditional data collection and Joltik. By completing the aggregation over significantly more sensed samples, Joltik compresses them within a single packet transmission and can further compute a wide range of unforeseen metrics without additional energy overhead at the sensor.



(a) Transmission Compression [127] (b) Heatmap of Sensing Data [34] (c) Distributed CSS [46]

Fig. 8. Network-level data transmission control in the MAC layer.

Such an energy-efficient analytic provides up to a 24.6× reduction in energy cost compared to transmitting raw data. Analogous to Joltik on the sensor data compression, QuAiL [34] exploits the coherent construction of concurrent transmissions from multiple sensor nodes. Thus it can quickly estimate the spatial distribution of sensed data across sensor nodes at the base station. Figure 8(b) gives an illustrative example for the distribution construction of sensor data, in which massive temperature sensors are supposed to be queried to obtain a spatial heatmap of the current impact of the forest fire quickly. QuAiL first relies on the high degree of spatial correlation of sensor heatmaps, which is sparse in linear domains such as the Discrete Cosine Transform. Then, by recovering the top-n most significant non-zero terms (e.g., $v_1, \ldots, v_n$) of this linear domain quickly from distributed low-power sensor nodes, the contribution of each sensor node can be computed locally to each of these n terms. For quick estimation at the base station, each sensor node can concurrently transmit n orthogonal codes at powers weighted precisely by the n terms efficiently, which can be coherently constructed at the base station. Evaluations in a wide-area area of 3 km^2 show QuAiL [34] achieves 4× faster aggregation of representation of forest fire maps from over 30,000 unique locations when the same number of queries are used over individual sparse sampling.

Remark and Limitations. Inspired by the compression-based transmission in LPWANs, the massive data from densely deployed IoT devices also presents a promising opportunity for highly data-intensive machine learning algorithms, including deep learning. This will allow the vast computation resources at the edge and cloud to leverage rich sensed information for various applications while maintaining the energy efficiency of individual sensors [127].

5.3 MAC-3: Enable Multi-channel Access

Problem Statements. Though the adopted primitive ALOHA mechanism guarantees the deployment simplicity and the battery longevity, it inevitably disables the channel sensing, which suffers from massive collisions when LoRa end nodes grow sharply in this era of IoT. And a growing body of researches [7, 94] shows that the scalability of LoRaWAN does not live up to the marketing claim that a single gateway can handle many thousands of end nodes [21].

Current Approaches. Specially designed carrier sense mechanism: To improve the network throughput and energy efficiency by exploiting the disabled **Carrier-Sense Multiple Access** (**CSMA**) scheme from ALOHA in LoRaWAN, LMAC [36] explores the channel-selective carrier sense capability of the PHY feature called **Channel Activity Detection** (**CAD**), designed for energy-efficient preamble detection. An extensive measurement study shows that CAD can detect the occupancy of a logic channel due to an ongoing frame transmission, with more than 95% accuracy. By balancing the communication loads among channels defined by frequencies and SFs, LMAC [36] designs an efficient CSMA-based **LoRa MAC** (**LMAC**), achieving 2.2× goodput and

2.4× reduction of radio energy per successfully delivered frame on a 50-node lab test-bed and a 16-node university deployment. However, CAD can introduce false negatives for medium sense via direct preamble detection [116], as packets can take a long to transmit. p-CARMA [116] combines CAD with principles of persistent-CSMA (p-CSMA) [63] to evade collisions with neighboring end nodes via a p-value-based probability estimation. As such, it reduces 37.31%–58.17% of energy consumption against the LoRaWAN. By exploiting the data features with deep learning, DeepSense [15] designs two tailored DNNs for carrier sense and configuration recognition. A comprehensive evaluation at the campus-scale deployment achieves a 1.7× of the number of locations connecting to the campus-wide network.

Specially designed coding mechanism: We can also design unique coding mechanisms for collision avoidance from multiple sensor nodes. Illustrated in Figure 8(c), NetScatter [46] presents a distributed CSS coding by assigning a different cyclic shift of the chirp to each concurrent device. In comparison with the traditional CSS systems, which use various cyclic shifts to convey bits, NetScatter uses **ON-OFF keying** over these cyclically shifted chirps to convey bits. For example, the presence and absence of the corresponding cyclic shifted chirp correspond to a 1 and 0 bit, respectively. Incorporating the CSS and ON-OFF keying enables hundreds of end nodes to concurrently transmit on the same frequency band, achieving throughput and latency improvements of 14~62× and 15~67× over existing approaches. A similar ON–OFF keying-based coding mechanism is also adopted in the battery-free backscatter radios [43, 88], achieving a low data rate but extremely LoRa communication (Section 6.2). Different from NetScatter's ON–OFF keying-based coding, WiChronos [100] encodes information in the **time interval between two narrow-band symbols**, in which two anchor symbols are transmitted for per message, and the data modulates the duration between them. To further alleviate issues on scalability and reliability of ALOHA-based MAC layer, On the one hand, Zorbas [134] combines time division protocols with efficient slot allocation mechanisms, rendering a LoRa (WAN)-based time-slotted protocol as alternatives to ALOHA. Multiple parameters and characteristics of LoRa can be considered (e.g., the radio duty cycle, transmit power restrictions, scheduling, battery lifetime, and security), and a time-slotted frame structure is proposed based on the experimental time-slotted LoRa platform. On the other hand, FLIP [21] proposes the first fully distributed and open architecture for LoRaWAN gateways. By transforming LoRa gateways into a federated network that provides inherent support for roaming while tackling contention using consensus-driven load balancing, FLIP [21] decreases channel utilization by 45% against independent gateways while allowing 20% more devices to join.

Remark and Limitations. The security issues are still a challenge for multi-channel access. Given the LoRaWAN's delay-inherent, low duty cycle, scarce BW, and wide-area star topology, it prefers the sync-free approach for up-link data timestamping, which can suffer from the frame delay attack consisting of malicious frame collision and delayed replay. As such, the multi-channel access cannot be coordinated as scheduled. To secure such a sync-free approach, LoRaTS [42] estimates the inherent frequency biases of the end nodes for the awareness of the frame delay attack and securing multiple timestamp-sensitive applications. However, how to recover the timestamp under attack is challenging and needs further study. Meanwhile, DeepSense [15] verifies the feasibility of adopting deep learning techniques in LoRa networking (e.g., carrier sense and configuration recognition). Unfortunately, the borrowed WaveNet [87] of DeepSense from speech synthesis lacks prior knowledge of CSS modulation, making it ineffective to deal with more complicated tasks (e.g., the demodulation of LoRa at extremely low SNRs). We believe it is promising to incorporate the data-hungry deep learning techniques with the data-abundant LoRa deployments (Section 8.1).

Table 6. Summary of Methodologies on LoRa Driven Applications

Wireless Sensing: Activity Recognition (e.g., drone state, human recognition) [48, 49, 123, 131], Target Localization (e.g., human, gesture, bike) [16, 41, 58, 84, 128, 131, 132], Sensing Heatmap [34]
Backscatter Radios: CSS Coding Mechanism [46, 109, 115, 115], Ambient LoRa Transmissions as the Excitation Signals [43, 53, 60, 84, 88, 108]
Cross-tech Communication: BLE to LoRa [67, 68], ZigBee to LoRa [67, 105], LoRa to WiFi [75]

6 APP LAYER: ENABLING LOW-POWER AND LORA APPLICATIONS

Given the uniquely low-power LoRa, several research problems and solutions are inspired by applications and deployments to integrate and tailor the LoRa techniques. And we expound on the mainstream LoRa-driven applications in Table 7, such as the LoRa wireless sensing, low-power backscatter radios, and cross-technology communication, with sub-branches on methodologies in Table 6.

6.1 Wide-range Wireless Sensing Augmented via LoRa Techniques

Problem Statement. Recently, wireless sensing has been well studied due to its promising progress in human-machine interaction, enabling various smart applications, such as gesture recognition, human localization, and pose estimation [64]. However, current wireless systems (e.g., WiFi, acoustics, and UWB) are restricted by their sensing range and power consumption, hindering their wide-area deployment in the wild. For example, the maximum localization range can be 10–35 m for WiFi and UWB, while it only reaches a couple of meters for acoustics and ultrasound [129]. Therefore, LoRa-based sensing attracts many research interests. And the main problem is to enlarge the sensing range while guaranteeing decent accuracy and security for the applications.

Current Approaches.—RA: As the first localization system that consumes microwatts of power at a mobile device, μLocate [84] achieves a LoRa low-power 3D localization by extracting the phase information from the weak backscattered signals via commercial LoRa devices. Real-world deployments show that μLocate achieves an accuracy of 2, 12, 50, and 145 cm at ranges of 1, 5, 30, and 60 m, respectively, with a sub-centimeter-sized IoT platform. Observing the Doppler frequency shift distortion from moving targets on the LoRa-based localization, Marvel et al. [132] fuse the backscatter-based sensing estimation with the IMU measurements, achieving a mean error of 0.8 m against 2.45 m for μLocate [84].

To further broaden the LoRa sensing area actively, on the one hand, WIDESEE [16] incorporates drone's mobility with the LoRa propagation characteristic of LoRa for wide-area human detection and localization, with the localization error of 4.6 m at a building with the size of $20 \times 42 \times 85\,\text{m}^3$. On the other hand, to alleviate the noise of long-distance transmission, Zhang et al. [131] extract the noise-resilient and offset-free ratio of signals to model the fine-grained target movements (e.g., a subtle 5 mm chest displacement for human respiration). Thus, it achieves accurate respiration sensing and human tracking with a distance of 25 and 30 m, respectively. Following Zhang et al. [131] on noise reduction, Sen-fence [123] creates a virtual fence to constrain sensing area to mitigate the interference of multi-path and shadowing effect, which maximizes the movement-induced signal variation for analysis and achieves a 50 m sensing range for fine-grained respiration monitoring. Note that Sen-fence can even detect human respiration even through five concrete walls at a distance of 9.3 m due to the strong penetration capability of LoRa.

Beyond human-centered sensing, LoSee [128] delivers the LoRa-based LoRa tracking system for the shared bike's route by quantifying the relationship between the **Packet Delivery Rate** (**PDR**) and **Signal to Noise Ratio** (**SNR**). A campus-scale experiment shows that LoSee achieves the tracking range radius of 1,031 m with up to 423 bike nodes. Furthermore, SateLoc [71] applies

Table 7. Summary of Research Advancements in LoRa on LoRa-driven Applications

Reference	Down-to-top	Performance Metrics	Methodologies and Algorithms
F. Zhang et al. [131]	**App-1:** Respiration recognition	**RA:** 15∼25 m, even with walls	Model the target movement with signal variation via the noise-resilient chirps
G. Shen et al. [103]	**App-1:** EM covert channel attack	**RA/SE:** Info disclosure with a 20× range	Encode sensitive data into chirps to be received by long-range LoRa radios
LoSee [128]	**App-1:** Bike route tracking	**RA:** Radius of 1,031 m for 423 bike nodes	Adaptive transmission parameter/link estimation with LDPL for higher PDRs
Marvel [132]	**App-1:** State estimation for MAV	**RA:** 50 m with an error of 34 cm	Attach backscatter tags to MAV for CSS decoding and phase extraction
SateLoc [71]	**APP-1:** Wide-area Localization	**RA:** 227,500 m^2 in locating error of 47.1 m	ML virtual fingerprinting map via satellite images by multi-GW combination
Sen-fence[123]	**App-1:** Respiration recognition	**RA:**2× (50 m), even by 5 walls of 9.3 m	Virtual fence to constrain signals, optimize movement-induced variations
TinySDR [47]	**App-1:** SDR platform	**EG:** 10,000× lower-power sleep mode	Design of hardware/protocol for over-the-Air programmable IoT endpoints
WIDESEE [16]	**App-1:** Detection/localization	**RA:** Locating error of 4.6 m at building scale	Combine the agility of drone and long-range LoRa, by a single transceiver pair
μLocate [84]	**App-1:** 3D wide-area localization	**RA:** Up to 60m away; **EG:** 93μW/5∼15 years	Phase analysis from weak backscattered signals of sub-cm sized platform
COOK [53]	**App-2:** Chirp coding backscatter	**RA:** ES-tag distance from 1 m [88] to 27 m	Backscatter tags change the ON-OFF key unit length to adapt bitrate
Aloba [43]	**App-2:** Ambient LoRa Backscatter	**EG:** 0.3mW; **TP:** 10.4∼ 52.4× (39∼199.4 kbps)	Track the amplitude and phase for back-scatter signal overlaid on carrier signals
LoRaBack-scatter[109]	**App-2:** CSS coding backscatter	**RA:** 2.8 km for ES-tag distance; **EG:** 9.25μW	CSS backscatter to synthesize continuous freq modulated chirps
PLoRa [88]	**App-2:** Ambient LoRa backscatter	**RA:** GWs from 1.1 km; **EG:** 220 μW power	Ambient excitation signal, light-weight chirp modulation, low-power circuit
P^{2}LoRa [60]	**App-2:** Ambient LoRa backscatter	**RA:** GWs from 2.2 km; **TP:** 16.3× gain over PLoRa [88]	Ambient excitation signal, in-band parallel backscatter
Polar Scatter [108]	**App-2:** Ambient LoRa backscatter	**RA:** 1.8× **TP:** 10× gain over PLoRa [88]	Sozu polar codes to exploit link capacity, adjust bit rate for channel quality
BLE2LoRa [68]	**App-3:** CTC from BLE chips to LoRa	**RA:** 20× (600 m) over BLE; **TP:** 4.06 bps	a BLE device constructs chirp signals with ladder-shaped frequencies
Symphony [67]	**App-3:** CTC (BLE/ ZigBee-LoRa)	**RA:** 16× extension over BLE/ZigBee.	Narrow-band comm. by payload manipulation and parallel decoding
XFi [75]	**App-3:** CTC (ZigBee/LoRa to WiFi)	**TP:** 1.8 Mbps via 8 streams of LoRa	Low-speed IoT data hitchhikes on the high-speed WiFi packet
LoRaBee [105]	**App-3:** CTC from LoRa to ZigBee	**TP:** 281.61 bps by payload encoding	ZigBee recognizes payload chirps of LoRa by sampling the received RSS

well-known fingerprinting-based localization on LoRa signals and achieves a wide-range localization over a 227,500 m^2 area, with a median localization error of 47.1 m. By incorporating the land-cover type in satellite images across multiple gateways, SateLoc adaptively gets an accurate path loss of an arbitrary LoRa link and generates a virtual fingerprinting map to associate the physical locations with the distributed link estimations. QuAiL [34] renders a real-time heatmap of sensed data by exploiting the coherent construction of concurrent transmissions across sensor nodes at the base station to enable a larger sensing area. And a wide-area deployment at the campus of CMU demonstrates the feasibility of the quick spatial sensor heatmap generation over 3 km^2.

—**SE:** The LoRa communication of LoRa also poses security threats for wireless sensing on information disclosure. For example, EMLoRa [103] launches the LoRa EM convert channel attack via LoRa signals. Its transmitter is a user-space malware that can encode sensitive data of the infiltrated system by shaping memory **Electromagnetic Radiation** (**EMR**) into LoRa-like chirps. On the receiver side, a low-cost, portable software radio can decode EM chirps to exfiltrate sensitive data from a long distance or behind an aggressive shield. In comparison with prior EM covert channels, EMLoRa boosts communication range by 20× and improves attenuation resilience by up to 53 dB due to the interference-resilient CSS mechanism of LoRa, making existing defenses ineffective (e.g., range limitation, shielding). To secure its communication via LoRa, QuAiL [34] establishes a secure transmission for real-time sensing heatmap to specific attacks (e.g., passive eavesdrop, side-channel information disclosure) by randomizing the weights of individual sensors in signal processing.

We further discuss some studies on applying blockchain techniques on low-power IoT scenarios for security issues [25, 54, 70, 98]. To resolve trust issues between application customers and network operations, Lin et al. [70] build a trusted, decentralized LoRaWAN server architecture to verify that the data of a transaction have existed at a specific time in the network. In addition, it enables large-scale deployments of LoRa in the wild, such as animal tracking, fleet tracking, asset tracking, and smart parking. Dorri et al. [25] further propose a blockchain-based smart home framework by thoroughly analyzing its security on fundamental security goals of confidentiality, integrity, and availability.

Remark and Limitations. LoRa technologies featuring long-range communication capability and low power consumption enables the LoRa sensing applications for IoT consisting of many geographically distributed objects. A variety of studies mainly focuses on algorithm design and signal processing to enlarge the sensing range and optimize the performance securely. However, they underperform due to the current commodity LoRa hardware (e.g., low-resolution internal time counter) [41], which can be a promising direction for the research progress. For example, TinySDR [47] designs the hardware and protocol of a newly low-power **Software Defined Radio** (**SDR**), rendering a fully programmable testbed for large-scale deployment. It gives access to I/Q signals and, therefore, phases across the 2.4 GHz and 900 MHz bands, forming the basis for many localization algorithms [84]. Note that the newly power-constrained IoT endpoint consumes as little as 30 μW of power in sleep mode, which is 10,000× lower than existing SDR platforms.

6.2 Low-power Backscatter Radios Enabled by LoRa Techniques

Problem Statement. Driven by the vision of embedding connectivity into billions of everyday objects [53], backscatter communication holds potential for ubiquitous and low-cost connectivity among low-power IoT applications. However, they operate at a concise range or experience extremely low throughput [109], making them underperform in real-deployment. As such, recent years have seen significant innovations in designing LoRa-enabled backscatter radios to integrate the low-power backscatter with the long-range LoRa techniques [43, 46, 53, 60, 88, 108, 109]. Illustrated in Table 6, on the one hand, the backscatter communication integrates the CSS-based coding mechanism for weak signal decoding [46, 109, 115, 115]. On the other hand, the ambient LoRa transmissions can be utilized as the excitation signals, achieving a battery-free LoRa communication via backscatter [43, 53, 60, 84, 88, 108].

Current Approaches.—**RA:** For LoRa and low-cost communication, LoRaBackscatter [109] delivers the first wide-area backscatter communication system for weak backscatter signal decoding. To fully exploit the high sensitivity of the CSS mechanism, each LoRa backscatter tag in LoRaBackscatter backscatters the single tone transmitted by the **Excitation Source** (**ES**) while encoding bits into different cyclic shifts in synthesizing chirp signals. Thus, the noise-resilient CSS mechanism for backscatter modulation enables a communication range up to 2.8 km with the co-located excitation source and backscatter tags at a distance of 5 m.

—**EG:** By relying on the single tone as excitation signals for backscatter, LoRaBackscatter [109] only consumes 9.25 μW of power at the rate of 37.5 kbps. Besides, backscatter tags can also harvest energy from ambient LoRa transmissions. Therefore, they can then transmit the collected data (e.g., machine status) back to the gateway hundreds of meters away. For example, PLoRa [88] implements an ambient backscatter radio to take ambient LoRa transmissions as the excitation signals, which can be modulated into a new standard LoRa "chirp" signal to convey data. A low-power circuit is further designed for packet detection and energy management, delivering a holistic RF front-end hardware and software design, with the power cost of 220 μW. Similarly, The low-power end nodes in μLocate [84] use a micro-controller to shift signals by 1~2 MHz and backscatter it back to the gateways, delivering an energy-efficient CSS backscatter system for LoRa-based localization.

—**TP:** Analogous to LoRaBackscatter [109], NetScatter [46] also adopts the single tone as excitation signals. However, it also designs a distributed CSS coding mechanism to enable the concurrent LoRa transmissions by assigning a different cyclic shift of the chirp to each concurrent device. Thus, each device uses ON–OFF keying over these cyclically shifted chirps to convey bits, achieving a 14~62× throughput improvement against LoRaBackscatter [109]. Observing the trade-off between the data rate and the ES-tag distance, COOK [53] integrates the link estimation and bitrate adaptation to balance the communication range and rate. It thus expands the ES-tag distance up to 27 m while supporting a bitrate adaptation range of 0.33 kbps~1.2 Mbps.

To improve the network throughput in LoRa backscatter systems, PolarScatter [108] adopts the channel polarization in LoRa backscatter links by designing *Sozu polar codes* to exploit the link capacity and automatically adjust to an effective bit rate for different channel quality. Furthermore, a low-cost encoder is proposed to accommodate polar codes on resource-constrained tags, achieving up to 10× throughput gain against PLoRa [88]. Building on the LoRa battery-free LoRa backscatter [88], Aloba [43] provides flexible data rate and transmission range using ON–OFF Keying for different IoT applications and deployments. The backscatter radio reflects the signal when transmitting a bit one and absorbs the signal when transmitting a bit zero. Methodologies on phase alignment and signal reconstruction are further designed for backscatter signal demodulation overlaid on the carrier LoRa signals. Circuit implementation shows Aloba [43] can detect the ambient LoRa signal as low as −60 dBm with 0.3 mW power consumption, achieving 39.5~199.4 kbps data rate at various distances, 10.4~52.4× higher than PLoRa [88]. P^2LoRa [60] uses multiple tags to shift the frequency of ambient LoRa signal to achieve parallel backscatter. The excitation signal and multi-channel backscatter signal in P^2LoRa share the frequency band, which enables a small spectrum consumption. The decoded data of the excitation signal is used to eliminate the interference, which extents the communication range of the backscatter signal. P^2LoRa achieves 16.3× higher throughput compared with PLoRa [88] with 1.67× communication range extension.

Remark and Limitations. LoRa backscatter enabled applications generally demand moderate-throughput (i.e., tens of Kbps) communication links for sensing data forwarding in a low-power and LoRa manner. And the effective communication range and energy efficiency are still two key performance metrics in the research field. On the one hand, the backscatter range scales with the strength of backscatter signals, which is orders of magnitude weaker than the carrier signal. Hence, how to further increase the backscatter range remains open with several promising solutions. For example, leveraging beamforming techniques or negative impedance components like tunnel diode [43]. On the other hand, most existing ambient LoRa backscatter systems [88] adopt a palm-size solar panel to harvest energy. To further reduce the power consumption on packet detection, one possible solution could be implementing the packet detection module on **Application-specific integrated circuit** (**ASIC**) [43].

6.3 Cross-technique Communication by Integrating LoRa Sensors

Problem Statement. Wireless Personal Area Network technologies (e.g., Bluetooth, ZigBee, and WiFi) have been widely used in our daily life. However, their short transmission distances and high power consumption hinder further connectivity into billions of everyday objects. Thus, recent **Cross-Technology Communication** (**CTC**) advancements have built direct communications across heterogeneous technologies with LPWANs.

Current Approaches.—**RA:** Observing that the heterogeneous communication in CTC inevitably incurs extra hardware cost, deployment inconvenience, and traffic overhead from gateways, BLE2LoRa [68] proposes the BLE-to-LoRaWAN CTC to utilize the frequency shifting ability of the BLE device to emulate LoRa's chirp signal. On the one hand, a LoRa device can demodulate BLE frames without any hardware modification at the transceiver side. On the other hand, a long distant CTC can be achieved based on the high sensitivity of the LoRa base station, leading to over 600 m communication distance, which is over 20× range extension over native Bluetooth. Symphony [67] further connects Bluetooth and ZigBee into LPWANs through payload manipulation. Besides, it enables concurrent transmissions from heterogeneous radios (e.g., BLE, ZigBee, and LoRa) at a LoRaWAN base station by cross-technology parallel decoding, achieving a concurrent wireless communication from BLE, ZigBee, and LoRa commercial chips to a LoRaWAN base station over 500 m, 16× range extension over native BLE/ZigBee.

—**TP:** LoRaBee [105] first connects LoRa and ZigBee via payload encoding in the Sub-GHz bands, in which ZigBee can recognize data encoded in LoRa payloads through sampling the Received Signal Strength. By elaborately tuning the LoRa's central carrier frequency and packet chirps, LoRaBee achieves a throughput of up to 281.61 bps. By integrating WiFi and IoT devices (e.g., LoRa, ZigBee), XFi [75] achieves the wide-area data collection with a throughput of 1.8 Mbps via concurrently two streams of ZigBee or eight streams of LoRa. The critical point is the intentional collisions induced by the hitchhiking IoT data over WiFi payloads, which can be reconstructed and decoded at the WiFi side, even after WiFi demodulation.

7 ISSUE AND CHALLENGE

While recent advancements of LoRa techniques demonstrate the promising ubiquitous IoT connection, several open issues and challenges remain to be addressed. By exploring our down-to-top architecture of LoRa networking, we present the issues and challenges as follows.

7.1 Network Scalability

Low-cost deployment is necessary to initialize IoT systems in the wild. Although the COTS Semtech LoRa radio [101] is cheap, the communication range also determines the deployment cost as the system scales up. And LoRa nodes can be scaled readily at a low cost if transceivers can reliably cover a large area. However, existing range-expansion approaches from different network layers inevitably increase human-labored site surveys' computation and energy consumption.

In the PHY layer, the basic idea to increase LoRa nodes' communication range is to capture extra SNR gain at gateways for weak signal decoding. For example, Charm [24] achieves 1–3 dB SNR gains with 2–8 gateways by coherent combining decoding. Choir [26] further coordinates 30 co-located end nodes for the exact data packet decoding, achieving a 2.65× longer communication distance than using the single LoRa node. Although the communication range is enlarged, the deployment cost is sacrificed [26]. Meanwhile, the decoding process must be offloaded to the cloud incurring extra computation costs if signals are collected from multiple gateways [24].

In the Link layer, link estimation is helpful to understand communication scalability. Correspondingly, we can determine the optimal gateway deployment for an optimal communication range and reliability as the network scales up. Taking the land cover and distance as inputs, DeepLoRa [74] proposes a DNN approach to estimate the link path loss, with the error of less than 4 dB. Flauzaci et al. [31] enable two-hop relay to increase the communication range and reliability of isolated LoRa nodes. However, to achieve accurate link estimation, DeepLoRa needs to collect training data with the extra site survey cost, and the online link estimation consumes extra energy for link-state maintenance. For low duty-cycle and energy-constrained LoRa nodes, the energy cost cannot be neglected.

Overall, how to enhance network scalability is still an open issue. The challenge lies in reducing the extra negative cost, including deployment, computation, energy, and site survey.

7.2 Network Capacity

Network capacity is essential in a large-scale IoT deployment to tolerate the potential inter-network inference among massive LoRa nodes. B. Ghena et al. [39] raise the capacity issue if directly adopting default LoRaWAN techniques. Recent LoRa techniques have been proposed to improve the network throughput in different layers. However, existing solutions suffer from the gap between the inherent constraints in theory and the complex network environment in practice for LoRa Networking.

In the PHY layer, the time-domain and hardware features [26, 52, 117, 121] are extracted to resolve collisions for potential network throughput gains, respectively. However, all require a large SNR (i.e., 0 dB), which is inevitably prohibited in real-life deployment. As such, CoLoRa [112] and NScale [111] achieve the low-SNR collision resolving from concurrent transmissions of LoRa nodes, but still introduce 1.7 dB SNR loss over the SNR bound of a LoRa link.

In the Link layer, several methods [33, 76, 82] guarantee the packet delivery reliability in a dense deployment by adjusting the link configurations (e.g., frequency, SF). However, the performance highly depends on the accuracy of link state estimation, and will be degraded if the link states change quickly in dynamic networking environments.

In MAC Layer, we can adopt several efficient channel utilization approaches [15, 34, 36, 46, 100, 134] for channel contention/collision avoidance. For example, DeepSense [15] and LMAC [36] develop efficient carrier sense techniques. And Wichronos [100] increases the efficiency of ALOHA by changing the coding strategy, while NetScatter [46] increases the number of orthogonal logical channels with a specially designed coding mechanism. QuAiL [33] and Zorbas et al. [134] further explore the time synchronization information to coordinate the channel access. Although these methods work well for dense LoRa networks, the coordination cost degrades the energy efficiency in sparse ones.

Overall, to achieve a high network capacity in practice, we need further bridge the gap between the applicable assumptions and the real environments to achieve a general model in practice.

7.3 Network Lifetime

Besides network scalability and capacity, long network lifetime is another essential feature in LoRa networking, enabling multiple long-term IoT applications. And most LoRa techniques aim at optimizing the energy consumption of LoRa nodes from the Link layer [33, 66, 107] and MAC layer [6, 36, 100, 127].

In the PHY layer, Charm [24] and LiteNap [122] separately use spatial and temporal features of LoRa signals to save energy. The former relies on multiple gateways to tolerate the low SNR communication for energy efficiency at low-SFs. At the same time, the latter reduces the energy consumption on packet reception by using down-sampling techniques.

In the Link layer, adapting the parameter settings (e.g., SFs and frequency) of LoRa nodes can trade-off its energy consumption with the communication data rate and distance. Given the known link-state, we can adaptively select the transmission parameters to guarantee a reliable data delivery and keep the energy consumption as low as possible. For example, DyLoRa [66] establishes an efficient energy model to associate the link properties (i.e., PDR, SNR, and SFs) with transmission parameters (SF, power). And AdapLoRa [38] uses a linear regression process to estimate the network lifetime periodically for optimal parameter settings.

In the MAC layer, the carrier sense techniques [36] avoid the extra energy consumption on packet re-transmission. Besides, OPR [6] utilizes multiple gateways to correct the corrupted packet and saves the energy of re-transmission. Moreover, Joltik [127] uses the universal sketching to enable a LoRa node to report information summaries instead of energy-exhausted packet transmission.

Overall, although we can save energy by enhancing physical SNR tolerance, it is still challenging in practice to improve the model generality and reduce the extra energy consumption by adapting the link-state, avoiding re-transmission, and exploring information compression.

7.4 Network Security

Network security in IoT has become a more critical research issue as we have experienced several attacks through the vast amount of IoT devices in the real world.

In LoRa networking, Sundaram et al. [102] demonstrate that the security of LoRa spans over a range of attacks, covering jamming attacks, replay attacks, beacon synchronization attacks, traffic analyses, and man-in-the-middle attacks. Even though recent advancements enhance the security of the existing LoRa standards, an end-to-end security framework has not been discussed from the down-to-top architecture of LoRa networking. On the one hand, a variety of possible security threats are still undisclosed in large-scale deployments. For example, as LoRa networks are widely deployed for various IoT applications, Fahmida et al. [28] propose that peer-to-peer communication can be adopted for packet offloading across LoRa nodes to prolong the lifetime. On the other hand, however, it exposes issues on the privacy preservation of packets while offloading. On the other hand, security issues emerge with more advanced techniques in LoRa networking, such as side-channel information disclosure [51, 103] and deep learning attacks [15, 34, 104]. For example, QuAiL [34] points out the necessity of securing private data for inference using neural networks and shows how to ensure anonymization and privacy of client's data.

Overall, the existing LoRa networking stack mainly focuses on improving the performance rather than keeping the networks secure. The newly designed networking stack may expose new ways to compromise the whole network. Moreover, the low-cost LoRa nodes and large-scale deployment increase the difficulty of designing and implement complex security mechanisms for preventing all kinds of potential attacks from down-to-top layers.

8 FUTURE TREND

Issues and challenges provide promising research directions toward pervasive IoT connections. And we present several future trends to bootstrap the widespread of LoRa across **Deep Learning** (**DL**), data processing approach, and communication protocol with COTS LoRa devices, respectively.

8.1 Deep AI Augmentation

Most existing approaches rely on physical model analysis and demonstrate promising potentials for performance improvement as the data-driven **Deep Neural Networks** (**DNN**) and AI techniques have been used in other wireless systems [64]. The AI-enabled approaches can benefit from the massive wireless training data to guarantee high performance for various practical IoT applications due to its robust feature learning ability. For example, a review of nearly 65 papers [91] presents several machine-learning algorithms adaptable for lung cancer detection linked in medical IoT. In LoRa networks, DeepLoRa [74] uses the Bi-LSTM model to estimate the signal path loss in a complicated environment. Evaluation results show high accuracy and low retraining cost while transferring a model from one gateway to another. Meanwhile, DeepSense [15] achieves a DNN-based carrier sense mechanism, enabling high network capacity and scalability. NELoRa [65] incorporates ML techniques into signal demodulation to improve the packet reception rate and extend the battery life for sensor nodes at the campus scale. Moreover, the FPGA on TinySDR [47] can potentially support deep AI algorithms on-board, which boosts the research on AI-augmented LoRa networks. And we believe the deep AI augmentation techniques can bring a new direction to the design of communication stack and sensing applications for LoRa networking.

8.2 In-network Processing

Given the dense LoRa deployment, how to improve LoRa communication and sensing efficiency by exploiting the spatial and temporal diversity should not be neglected. For example, we can use in-network processing to compress the total data instead of returning all sensing data. Thus, it can extend the network lifetime and avoid contention/collision for efficiency. Specifically, QuAiL [34] exploits the concurrent transmissions to enable faster information retrieval represented by the accumulated TP. Joltik [127] proposes a compression framework to reduce the energy consumption among multiple LoRa transceivers exceptionally. To further enhance the efficiency of the LoRa networking stack, the in-network processing provides a new angle to save energy consumption and onboard computation resources.

8.3 Cross-layer Design

Recent advancements in LoRa networking mainly optimize network performance in separate layers. And we point out that it is possible to optimize the network performance and control the extra cost thoroughly if we break the boundary of the layers and allow layers to share information. For example, Fahmida et al. [28] and Flauzaci et al. [31] explore the multi-hop relay to improve energy efficiency and communication range for those isolated LoRa nodes. By combining the information from the link layer and MAC layer, an efficient multi-hop relay can be modeled and established. Besides, Cross-layer network stack design also enables a new paradigm to optimize the network performance and save the total cost of LoRa network maintenance.

8.4 Stateless Network Design

The estimation and maintenance of network state on LoRa nodes/gateways require extra deployment cost. Furthermore, Manfredi et al. [77] show that the benefits of link-state estimation would be compromised if network states change frequently. In LoRa, Choir [26] explores the beamforming to increase the link SNR, which can combat the unpredictable path loss. Meanwhile, Glossy [30] and LWB [29] are the successful stateless network design for wireless sensor networks by exploring constructive interference. The stateless network design is an alternative network stack to reduce the deployment cost by avoiding unnecessary maintenance on the network state.

9 CONCLUSIONS

In this survey, we review recent research advancements on LoRa networking. We propose a 2D taxonomy to categorize and compare the cutting-edge LoRa networking techniques to explore open issues and future trends. On the one hand, from down to the top, current solutions can be divided into PHY, link, MAC, and app layers in the LoRa networking stack, each of which contains sub-branches on respective research subjects. On the other hand, research efforts from the down-to-top architecture have been undertaken to compare and improve various performance metrics (i.e., range, throughput, energy, and security). Our literature taxonomy provides an overview of the open issues and challenges, followed by our observed future trends for the LoRa community. This survey aims at inspiring more research systems and advancements on LoRa networking, leading to a brand-new step toward the pervasive IoT at LoRa and low cost.

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