

Article

Deep Learning-Enabled LoRa-JSCC for Efficient and Reliable Multivariate Sensor Data Transmission in IoT Environments

Fatimah Alghamdi *  and Fuad Bajaber 

Department of Information Technology, Faculty of Computing and Information Technology,
King Abdulaziz University, Jeddah 21589, Saudi Arabia; fbajaber@kau.edu.sa

* Correspondence: falghamdi0627@stu.kau.edu.sa

Abstract

Integrating Joint Source–Channel Coding (JSCC) with the LoRa Chirp Spread Spectrum (CSS) physical layer (PHY) presents a significant challenge due to the complexity of joint optimization, which remains underexplored despite the known advantages of JSCC. Traditional LoRa systems rely on decoupled source and channel coding, resulting in redundant overhead and limited adaptability under dynamic Wireless Body Area Network (WBAN) conditions. To address these limitations, we propose a novel LoRa–JSCC framework: a fully learned, end-to-end differentiable architecture that jointly optimizes source compression and channel redundancy. The proposed system integrates a Denoising Autoencoder (DAE) for non-linear source compression with learned neural channel encoder and decoder modules, trained via backpropagation to minimize reconstruction distortion under noisy channel conditions. Rigorous Monte Carlo simulations conducted under unified and reproducible channel conditions demonstrate consistent performance improvements across LoRa configurations. The proposed approach achieves an average 25–30% improvement in goodput across moderate-to-high SNR regimes, with gains exceeding 100% under noise-limited conditions. It further reduces Time on Air (ToA) by approximately 30–35%, enhancing spectral efficiency and lowering effective energy cost per delivered bit. In the transitional Bit Error Rate (BER) region, the proposed LoRa–JSCC framework exhibits an effective SNR gain of approximately 18–20 dB relative to conventional LoRa, corresponding to multiple orders-of-magnitude reduction in BER. These results indicate substantial improvements in reliability, coverage robustness, and energy efficiency for WBAN and IoT deployments.

Keywords: LoRa; Joint Source–Channel Coding; IoT; WSN; Denoising Autoencoder; Forward Error Correction



Academic Editor: Yosef Pinhasi

Received: 22 January 2026

Revised: 23 February 2026

Accepted: 25 February 2026

Published: 2 March 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Wireless Body Area Networks (WBANs) and the broader Internet of Things (IoT) are pivotal technologies enabling continuous monitoring and data collection across diverse applications, from healthcare to industrial automation. In these environments, sensor nodes are typically resource-constrained, demanding ultra-low power consumption and highly reliable data exchange over potentially long distances. The integrity and timely delivery of data are paramount to effective analysis and decision making, necessitating robust and efficient communication solutions [1,2].

LoRa (Long-Range) communication, leveraging CSS modulation, has emerged as a leading physical-layer technology for Low-Power Wide-Area Networks (LPWANs). Its high sensitivity and extended range capabilities make it particularly attractive for geographically

dispersed or remote IoT deployment where connectivity can be challenging, and its inherent flexibility in adjusting key parameters such as spreading factors (SFs) and coding rates (CRs) further allows for adaptation to various environmental conditions, supporting dynamic IoT scenarios [3–5].

Despite these advantages, conventional LoRa implementations, which treat source compression and channel coding as independent processes, often yield sub-optimal end-to-end performance. This decoupled design prevents joint optimization: source coding minimizes distortion without explicit consideration of channel noise, while channel coding introduces fixed redundancy irrespective of actual data statistics or dynamic channel conditions. For WBANs and the IoT, where reliable data exchange from constrained sensor nodes is critical, this inefficiency directly translates into higher energy consumption, increased ToA, and compromised data integrity, hindering the deployment of truly robust and efficient systems [3,4]. Our LoRa-JSCC framework directly confronts this by co-optimizing source compression and channel protection within a unified differentiable architecture in which both source and channel encoders are parameterized neural networks trained jointly via backpropagation over the LoRa channel model.

To overcome these limitations and address the urgent need for enhanced data quality and transmission efficiency, JSCC emerges as a highly promising paradigm, which was implemented with communication protocols other than LoRa [6–10]. Unlike traditional separation-based approaches, JSCC merges data compression and error correction into a single, integrated process, demonstrating inherent robustness to variations in channel quality and the potential to approach the theoretical limits of data rates and error rates [10]. While JSCC has shown significant benefits in general communication systems, its effective integration with the unique LoRa CSS PHY, characterized by adaptive SFs and fixed coding mechanisms, has remained a key challenge due to the inherent complexity of joint optimization. This study directly addresses this gap by presenting a novel LoRa-JSCC framework, a fully learned and end-to-end differentiable architecture for joint source and channel optimization.

The proposed LoRa-JSCC framework significantly enhances communication reliability and efficiency for general sensor data transmission by unifying a DAE for source compression with a learned neural channel encoder that performs the function of FEC, into a unified end-to-end encoder. Our primary contributions are summarized as follows:

- **Novel LoRa-JSCC Framework:** We propose a novel, fully learned, end-to-end differentiable LoRa-JSCC framework that integrates deep autoencoder-based JSCC with LoRa technology, dynamically adjusting the SF based on Signal-to-Noise Ratio (SNR) variations. This approach is designed to adapt to changing environmental conditions and maintain acceptable error rates for diverse sensor data.
- **Enhanced End-to-End Performance:** With our fully differentiable, jointly optimized architecture, the LoRa-JSCC scheme achieves superior end-to-end distortion performance, exhibiting gradual degradation in low-SNR regimes without an error floor, which is a common limitation in conventional LoRa systems.
- **Improved Resource Efficiency:** By leveraging the DAE for non-linear source compression and learned channel coding, our framework significantly improves transmission efficiency and reduces power consumption by optimizing payload reduction and enabling stronger channel coding within the same airtime/energy budget.
- **Generalized Application:** This research study focuses on the generalized application of LoRa-JSCC for various sensor data, showcasing its broad applicability.
- **Empirical Validation:** We quantify the benefits of LoRa-JSCC with comprehensive experiments, demonstrating a substantial reduction in BER, an improvement in receiver

sensitivity, and significant gains in data transmission reliability and energy efficiency compared with traditional LoRa implementations.

The remainder of this study is organized as follows: In Section 2, we provide an overview of the key techniques employed in this study, including LoRa communication, JSCC, DAE, and FEC. In Section 3, we detail the proposed methodology for the LoRa-JSCC framework, describing the sensor data source model, the deep autoencoder-based JSCC encoder and decoder, CSS signal model, and the transmission process. In Section 4, we present the experimental setup and results, and a comprehensive discussion of the performance gains achieved by the proposed system. Finally, we conclude this study and outlines potential directions for future research in Section 5.

2. Background

In this section, we provide the foundational knowledge essential to understanding the proposed LoRa-JSCC framework. We begin by outlining the operational principles of LoRa communication, highlighting its strengths and the inherent limitations of its conventional processing chain when applied to resource-constrained environments such as WBANs. We then explore existing compression strategies in LoRa systems and introduce the concept of JSCC as a paradigm-shifting approach to overcome these limitations. Finally, we detail the core deep learning and traditional signal processing components DAEs and FEC that are integrated within our novel JSCC design.

2.1. LoRa Communication Principles

LoRa (Long-Range) communication stands as a cornerstone technology for LPWANs, particularly suited for WBANs and diverse IoT applications. Its foundation lies in CSS modulation, which provides inherent robustness against interference and high receiver sensitivity, thereby enabling long-range data transmission with minimal power consumption [3,4].

The LoRa PHY converts information bits into linearly varying frequency chirps. This spread spectrum technique provides a significant processing gain, enhancing immunity to noise and multipath fading. The adaptability of LoRa primarily stems from its configurable physical-layer parameters [1,3]:

- *(SF)*: The *SF*, an integer from 7 to 12, determines the number of bits encoded per chirp symbol. Higher *SF* values increase the processing gain, leading to greater range and robustness, but also increase the symbol duration and ToA, thus reducing the effective data rate.
- *Bandwidth (BW)*: Typically set to 125, 250, or 500 kHz, *BW* affects the chirp rate and thus the raw data rate. Wider *BW* allows for higher data rates but reduces receiver sensitivity.
- *Coding Rate (CR)*: LoRa employs FEC with CRs often expressed as $4/(4 + n')$, where $n' \in \{1, 2, 3, 4\}$. A lower *CR* (e.g., 4/5) appends more redundant bits, enhancing error resilience at the cost of increased ToA, while a higher *CR* reduces redundancy, decreasing ToA but making transmission less robust.

These parameters create dynamic trade-offs of data rate, communication range, and energy efficiency. For example, symbol duration (T_s) is directly proportional to the *SF* and inversely proportional to *BW*: $T_s = 2^{SF} / BW$. Consequently, the bit rate (R_b) is given by $R_b = SF \frac{BW}{2^{SF}} \frac{4}{4+CR}$.

The overall LoRa transmission process, as depicted in Figure 1, involves several key stages [11]:

1. *Bitstream formation*: Sensor data are serialized into a bit sequence.
2. *Error-control coding*: Redundant bits are added based on the selected *CR*.

3. Interleaving and whitening: Bits are interleaved to mitigate burst errors and whitened for spectral shaping.
4. Symbol mapping: Groups of SF bits are mapped to a symbol index, which modulates a CSS chirp.
5. RF transmission: The modulated chirp signal is transmitted over the wireless channel.

At the receiver, inverse operations are performed, including coherent demodulation, deinterleaving, dewhitening, and FEC decoding to reconstruct the original data [11]. Receiver sensitivity ($S_{\min}$), a critical metric for link budget, is determined by BW , receiver noise figure (NF), and the minimum required SNR (SNR_{req}) for a given SF :

$$S_{\min} = -174 + 10 \log_{10}(BW) + NF + SNR_{\text{req}}. \quad (1)$$

The bit error probability (P_b) over an Additive White Gaussian Noise channel is primarily a function of the effective SNR and SF , approximated as

$$P_b \approx \frac{1}{2} \operatorname{erfc} \left(\sqrt{\frac{SF}{2^{SF}+1}} 10^{(SNR/10)} \right). \quad (2)$$

While flexibility is a significant advantage of LoRa, conventional implementations suffer from a fundamental limitation: the decoupled processing of source compression and channel coding. This separation, based on Shannon's separation principle [12–14], prevents joint optimization. Source coding aims to minimize distortion without explicit consideration of channel noise, while channel coding introduces fixed redundancy irrespective of the actual data statistics or dynamic channel conditions. For resource-constrained WBANs and the IoT, this inefficiency translates into sub-optimal performance, including higher energy consumption, increased ToA, and compromised data integrity, highlighting a critical need for integrated encoding methods.

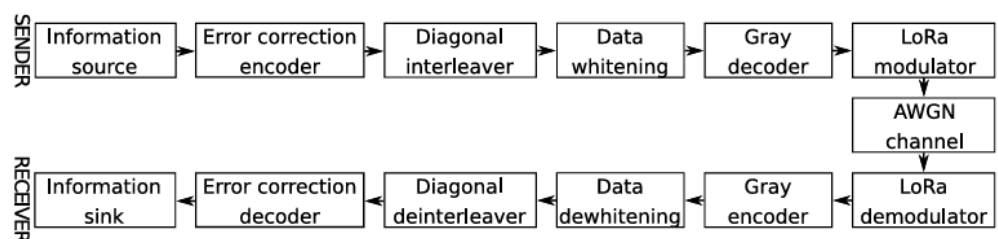


Figure 1. Block diagram of LoRa PHY baseband implementation: sender, Additive White Gaussian Noise (AWGN) channel, and receiver. Traditional LoRa communication systems employ a series of processes to ensure reliable data transmission. At the sender, data undergo error correction encoding, interleaving, whitening, and LoRa modulation. The channel introduces noise. At the receiver, the signal is demodulated and processed with inverse operations to reconstruct the original data [11].

2.2. Compression in LoRa and IoT Systems

To mitigate the impact of limited BW and energy in LoRa-based IoT and WBAN systems, various data compression techniques have been explored and can generally be categorized by the layer of operation.

2.2.1. Higher-Layer Compression

Existing compression techniques in LoRa systems primarily operate in the application or network layers. These typically involve classical algorithms, such as LZ77, Huffman coding, and Arithmetic coding, applied to sensor data or protocol headers to reduce payload size before physical-layer transmission [15]. While effective in minimizing the number of bytes transmitted, these methods are designed independently of the wireless

channel characteristics. Consequently, they generally do not inherently address channel impairments, optimize for reliable transmission over noisy wireless links, or adapt to dynamic channel conditions [15–17]. This decoupled approach can lead to inefficiencies, as source data are compressed without considering their resilience to transmission errors.

2.2.2. Physical-Layer Compression and Optimization

In contrast to higher-layer methods, physical-layer compression and optimization directly modify the fundamental encoding process to achieve more efficient and robust data transmission. This is a nascent but growing field, with some recent work exploring novel techniques that integrate compression closer to the PHY layer. For instance, Cloud-LoRa, introduced by Shahid et al. [18,19], is described as “the first practical CRAN for LoRa, that can detect sub-noise LoRa signals and perform BW adaptive compression.” Such approaches represent a shift towards integrated physical-layer optimization.

2.2.3. Motivation for JSCC

Despite these advancements, a comprehensive solution that seamlessly integrates source compression with channel error protection at a fundamental level, specifically tailored for the unique LoRa PHY layer and the demands of WBANs, remains largely unexplored. The limitations of traditional separation-based compression, coupled with the emerging potential of physical-layer optimization, highlight a critical need for integrated encoding schemes. This shift towards joint source–channel optimization aligns with the motivations behind the proposed LoRa-JSCC framework, which seeks to optimize data transmission at its most fundamental level by considering source characteristics and channel conditions simultaneously.

2.3. Joint Source–Channel Coding (JSCC)

JSCC represents a fundamental departure from Shannon’s traditional separation principle [12–14], which posits that source coding (compression) and channel coding (error correction) can be optimized independently without loss of optimality [6–10]. While theoretically sound for asymptotically long block codes and ideal conditions, the separation principle often leads to sub-optimal performance in practical wireless systems, such as the resource-constrained LoRa-based WBAN and IoT scenarios addressed in this study, especially under stringent latency, power, and BW constraints or highly dynamic channel conditions.

JSCC designs a single, unified mapping between source symbols and transmitted channel symbols. This integrated approach aims to minimize end-to-end distortion directly, considering source compression and channel impairments simultaneously. By intelligently allocating resources between compression and protection, JSCC exhibits superior robustness to varying channel quality and can achieve better performance, particularly in low-SNR regimes, where traditional separated schemes often suffer from a “cliff effect.”

Modern implementations of JSCC, particularly those leveraging deep learning [6–8], have shown promising results for learning efficient and robust representations that inherently account for both source characteristics and channel noise. This capability to jointly optimize source compression and error resilience is critical to achieving the high performance and efficiency required by emerging communication paradigms and forms the core principle of the proposed LoRa-JSCC framework. The specific components of this integration, namely, DAEs for intelligent source compression and FEC for structured redundancy, are detailed in the subsequent subsection.

JSCC for Future Communication: 6G and Beyond

The transformative potential of JSCC is increasingly recognized as a cornerstone for emerging 6G communication technologies and beyond. These future networks are envisioned to support diverse applications demanding ultra-low latency, massive connectivity, pervasive intelligence, and extreme energy efficiency, all of which necessitate communication solutions that are inherently more integrated, robust, and adaptive. JSCC, by inherently minimizing end-to-end distortion across varying channel conditions, is uniquely positioned to address these requirements, making it a key enabler for next-generation wireless systems.

Current research in this area explores several advanced JSCC paradigms. For instance, sophisticated channel coding schemes such as double LDPC and double polar codes have been proposed to enhance error resilience in 6G contexts [20]. Semantic-aware JSCC with Unequal Error Protection (UEP) is being developed to prioritize critical information, crucial to intelligent and mission-critical 6G services [21]. Additionally, cost-efficient JSCC strategies are being investigated for optimizing small payload transmissions, a common characteristic of IoT and WBAN data in 5G/6G systems [20]. These efforts highlight a growing trend towards optimizing resource allocation for specific data types and channel conditions, echoing the adaptive nature of the proposed LoRa-JSCC.

Furthermore, deep learning-based JSCC has emerged as a particularly promising avenue, demonstrating superior performance for various data types, including image and text transmission [22,23]. These deep learning approaches can outperform traditional digital transmission at low SNR, effectively mitigating the “cliff effect” by learning robust communication strategies without explicit pilot signals or channel estimation. This broader trend towards integrated, AI-driven coding that simultaneously optimizes source and channel aspects forms the conceptual foundation upon which our work builds, extending this powerful paradigm to LoRa for low-power WBAN applications.

2.4. Deep Learning and Error Correction Components

The proposed LoRa-JSCC framework integrates a DAE for intelligent source compression with a learned neural channel encoder and decoder for adaptive channel protection. These mechanisms are co-optimized within a single, end-to-end differentiable architecture, where the neural channel modules implicitly learn redundancy allocation, replacing fixed channel coding schemes with learnable neural channel coding modules. This synergistic combination forms the foundation of our novel JSCC design, enabling it to overcome the limitations of decoupled source and channel coding in LoRa systems.

2.4.1. Denoising Autoencoder (DAE) for Robust Source Representation

A DAE is a specialized type of artificial neural network engineered to learn robust and compact representations of input data. Unlike a standard autoencoder, a DAE is trained to reconstruct its original input from a corrupted version, typically by adding Gaussian noise η to an input sample $\mathbf{x} \in \mathbb{R}^N$ to form $\mathbf{x}' = \mathbf{x} + \eta$. This training paradigm compels the DAE encoder to extract more resilient and essential features, mapping $\mathbf{x}'$ to a compressed latent representation $\mathbf{z} \in \mathbb{R}^K$ ($K < N$). The decoder then reconstructs $\hat{\mathbf{x}}$ from $\mathbf{z}$, with the network minimizing the reconstruction error $\mathcal{L}_{\text{DAE}} = \mathbb{E}[\|\mathbf{x} - \hat{\mathbf{x}}\|_2^2]$. This inherent capability to learn noise-resilient and highly compressed, non-linear representations makes DAEs exceptionally well suited as source encoders within a JSCC framework. They can implicitly account for anticipated channel noise during the compression process, thereby learning to generate latent representations that are inherently more robust to transmission impairments [24,25].

2.4.2. Forward Error Correction (FEC) for Explicit Channel Protection

FEC is a well-established channel coding technique that enhances transmission reliability by systematically adding controlled redundancy to the data stream. This redundancy, defined by an (n, k) block code, where k is the number of information bits and n is the total codeword length (yielding a code rate $R_c = k/n$), enables a receiver to detect and correct a limited number of bit or symbol errors without requiring retransmission. In the LoRa PHY layer, CRs are typically expressed as $R_c = \frac{4}{4+n'}$, where $n' \in 1, 2, 3, 4$. The error-correcting capability of an FEC code is fundamentally determined by its minimum Hamming distance. While DAEs provide implicit robustness, FEC provides explicit, structured protection against channel errors. Its strategic integration with the DAE compressed output is central to the JSCC paradigm, ensuring a powerful, layered approach to minimizing end-to-end distortion over noisy LoRa channels [26,27].

3. Related Work

The demand for efficient and reliable communication in WBANs and the broader IoT has led to extensive research on optimizing LPWANs such as LoRa. In this section, we review existing approaches to physical-layer enhancement for LoRa, highlighting their strengths and limitations to contextualize the contributions of the proposed LoRa-JSCC framework.

Several methods have been proposed to enhance the performance of LoRa communication, primarily focusing on improving receiver sensitivity, throughput, or robustness. These techniques often address specific aspects of the LoRa PHY layer:

- **SDR-Enhanced LoRa:** This approach utilizes software-defined radio (SDR) for advanced receiver-side packet reception algorithms [28]. While it improves the BER by enhancing signal detection, it typically increases computational complexity at the receiver and does not address payload redundancy or transmission latency.
- **High-Sampling LoRa:** This method involves increasing the baseband processing sampling frequency [29] to reduce the BER. However, this often comes at the cost of higher power consumption due to increased processing demands.
- **FBI-LoRa (Frequency-Bin-Index Modulation):** This technique focuses on frequency-bin-index modulation [30] to potentially improve throughput. However, FBI-LoRa can suffer from degraded BER performance, particularly in low-SNR environments, and may increase ToA.
- **Morph LoRa:** This encoder–decoder co-design method employs multiple SF configurations and a Deep Neural Network (DNN)-based decoder [31]. Morph LoRa achieves deep learning-based robustness and improved BER performance by adapting to channel conditions, but it primarily focuses on channel coding aspects and lacks integrated source compression, thereby missing opportunities for payload reduction and further energy savings.

These existing LoRa enhancement techniques offer valuable improvements in specific performance metrics. However, they generally do not integrate both source compression and channel protection into a unified framework. Consequently, they do not fully optimize the trade-off between redundancy and compression while simultaneously reducing end-to-end distortion, ToA, and energy consumption for resource-constrained WBAN applications. The proposed LoRa-JSCC framework aims to bridge this gap by offering a comprehensive, analytically integrated solution.

4. Materials and Methods

In this section, we present the proposed fully learned LoRa-JSCC framework and describe the end-to-end system architecture, the theoretical rate–distortion foundation of the joint optimization problem, the neural implementation of learned source and channel encoding/decoding modules, and the simulation framework used for performance evaluation.

Unlike conventional LoRa systems, in which source compression and channel coding are performed independently, the proposed framework implements a fully differentiable end-to-end architecture in which source and channel representations are co-optimized based on joint gradient descent. A DAE performs non-linear source compression, while learned channel encoder and decoder modules provide adaptive redundancy tailored to the operating SNR conditions.

4.1. System Architecture of LoRa-JSCC

Unlike conventional LoRa systems that employ fixed convolutional FEC, the proposed LoRa-JSCC framework replaces the traditional channel coding block with a parameterized neural channel encoder and decoder. These modules are trained jointly with the source encoder and decoder within a fully differentiable architecture, enabling true end-to-end optimization of source compression and channel protection. The learned channel encoder outputs are subsequently mapped onto LoRa CSS symbols to ensure physical-layer compatibility. The proposed LoRa-JSCC system is designed for WBAN applications, where multivariate sensor data vectors $\mathbf{x} \in \mathbb{R}^N$ are transmitted over LoRa channels.

The core innovation lies in implementing a fully learned, end-to-end JSCC framework in which source compression and channel protection are co-optimized within a single differentiable architecture. The channel encoder and decoder are parameterized neural modules learned jointly with the source encoder and decoder.

The architecture consists of four neural components:

- Source encoder $f_s(\cdot; \theta_s)$;
- Learned channel encoder $f_c(\cdot; \theta_c)$;
- Learned channel decoder $g_c(\cdot; \varphi_c)$;
- Source decoder $g_s(\cdot; \varphi_s)$.

At the transmitter, the source encoder compresses $\mathbf{x}$ into a latent representation $\mathbf{z}$. The learned channel encoder maps $\mathbf{z}$ into a normalized channel symbol vector $\mathbf{c}$, which is transmitted through the LoRa CSS PHY layer.

At the receiver, after LoRa demodulation, the learned channel decoder reconstructs $\hat{\mathbf{z}}$, and the source decoder produces the reconstructed estimate, $\hat{\mathbf{x}}$.

The end-to-end objective minimizes mean-square reconstruction error:

$$\mathcal{L} = \mathbb{E}[\|\mathbf{x} - \hat{\mathbf{x}}\|_2^2]. \quad (3)$$

Table 1 summarizes the architecture of JSCC.

Table 1. Architectural components of the proposed LoRa-JSCC framework.

Component	Implementation
Source Encoder	Learned neural DAE (f_s)
Channel Encoder	Learned neural channel encoder (f_c)
Channel Model	Differentiable LoRa CSS mapping with AWGN
Channel Decoder	Learned neural channel decoder (g_c)
CSS Modulation	Standard LoRa CSS (non-learned)

All neural modules are optimized jointly using end-to-end backpropagation through a single computation graph. Gradients propagate through the source encoder, learned channel encoder, noise injection layer, learned channel decoder, and source decoder in a unified backward pass. This enables adaptive redundancy learning conditioned on both source statistics and channel SNR.

4.2. Computational Complexity and Deployment Feasibility

A critical practical consideration for LoRa-based WBAN deployments is the limited computational and memory budget of ultra-low-power sensor nodes. Although the proposed LoRa-JSCC framework introduces additional processing compared to conventional LoRa, the neural architecture is intentionally lightweight and structured to remain compatible with resource-constrained embedded platforms.

4.2.1. Model Structure and Parameter Count

The complete LoRa-JSCC system consists of four three-layer multilayer perceptrons (MLPs):

- Source encoder f_s
- Learned channel encoder f_c
- Learned channel decoder g_c
- Source decoder g_s

Each MLP employs two hidden layers of width $H = 128$ with Tanh activation. The end-to-end dimensional flow is:

$$32 \rightarrow 20 \rightarrow 48 \rightarrow 20 \rightarrow 32.$$

The combined model contains 97,400 trainable parameters. Table 2 summarizes the per-component parameter count, multiply–accumulate operations (MACs) per inference, and memory footprint.

Table 2. Computational complexity and memory footprint of the proposed LoRa-JSCC model. All MLPs use hidden width $H = 128$ and Tanh activation. FLOPs are computed as $2 \times$ MACs.

Component	Dimensions	Parameters	MACs	FP32 (KB)	FP16 (KB)
Source Encoder f_s	$32 \rightarrow 128 \rightarrow 128 \rightarrow 20$	23,316	23,040	91.1	45.6
Channel Encoder f_c	$20 \rightarrow 128 \rightarrow 128 \rightarrow 48$	25,392	25,088	99.2	49.6
Channel Decoder g_c	$48 \rightarrow 128 \rightarrow 128 \rightarrow 20$	25,364	25,088	99.1	49.6
Source Decoder g_s	$20 \rightarrow 128 \rightarrow 128 \rightarrow 32$	23,328	23,040	91.1	45.6
Total Model	$32 \rightarrow 20 \rightarrow 48 \rightarrow 20 \rightarrow 32$	97,400	96,256	380.5	190.2

4.2.2. Computational Cost

The total forward inference requires:

$$96,256 \text{ MACs } (\approx 192,512 \text{ FLOPs}),$$

where FLOPs are computed as $2 \times$ MACs. Importantly, training is performed entirely offline on a server; the embedded node executes inference-only, eliminating any gradient computation overhead during deployment.

On an MCU-class processor operating at 80 MHz, this corresponds to approximately 1–3 ms of processing time per 32-sample sensor vector, depending on quantization level and memory-access efficiency. This latency remains several orders of magnitude smaller

than typical LoRa Time-on-Air (ToA) values (e.g., 100–500 ms at $SF = 9$, $BW = 125$ kHz), indicating that computation does not dominate system delay.

4.2.3. Memory Footprint

In 32-bit floating-point (FP32), model weights occupy approximately 380.5 KB of Flash memory. Quantization to FP16 or INT8 reduces storage to approximately 190 KB and 95 KB, respectively.

During inference, peak RAM required to store intermediate activations is approximately 6 KB (FP32) or 3 KB (FP16).

These requirements fall within the Flash and SRAM budgets of representative ultra-low-power MCU-class devices commonly used in LoRa sensor nodes.

4.2.4. Deployment Considerations

Several practical deployment strategies are possible:

- On-device encoding only: The source encoder and learned channel encoder can execute on the sensor node, while the learned decoders operate at the gateway/server.
- Full end-to-end execution on capable nodes: Modern MCU platforms supporting lightweight inference frameworks (e.g., TinyML toolchains) can execute the complete model locally using INT8 quantization.
- Gateway-assisted decoding: Channel and source decoding can be centralized at LoRaWAN gateways, reducing sensor-node computational burden.

It is important to emphasize that the proposed architecture replaces the traditional fixed FEC block with a learned neural channel encoder/decoder. No additional classical convolutional or block coding module is executed at runtime. The computational overhead therefore reflects learned redundancy rather than layered concatenated coding.

Although this study focuses on algorithmic performance validation under controlled Monte Carlo simulation, the above analysis demonstrates that LoRa-JSCC remains feasible for embedded deployment. Table 3 presents Computational complexity and memory footprint of the proposed LoRa-JSCC model. A detailed hardware profiling study (energy per inference, latency measurements, and quantized model benchmarking) is reserved for future work.

Table 3. Computational complexity and memory footprint of the proposed LoRa-JSCC model. All neural modules are implemented as three-layer MLPs with hidden width $H = 128$ and Tanh activation. FLOPs are computed as $2 \times$ MACs.

Component	Dimensions	Parameters	% Total	MACs	FP32 (KB)	INT8 (KB)
Source Encoder f_s	$32 \rightarrow 128 \rightarrow 128 \rightarrow 20$	23,316	23.9%	23,040	91.1	22.8
Learned Channel Encoder f_c	$20 \rightarrow 128 \rightarrow 128 \rightarrow 48$	25,392	26.1%	25,088	99.2	24.8
Learned Channel Decoder g_c	$48 \rightarrow 128 \rightarrow 128 \rightarrow 20$	25,364	26.0%	25,088	99.1	24.8
Source Decoder g_s	$20 \rightarrow 128 \rightarrow 128 \rightarrow 32$	23,328	23.9%	23,040	91.1	22.8
Total End-to-End Model	$32 \rightarrow 20 \rightarrow 48 \rightarrow 20 \rightarrow 32$	97,400	100%	96,256	380.5	95.2

4.3. Analytical Integration of Learned JSCC

4.3.1. End-to-End Mapping

Let $\mathbf{x} \in \mathbb{R}^N$ denote the WBAN sensor vector. The learned source encoder produces

$$\mathbf{z} = f_s(\mathbf{x}; \theta_s). \quad (4)$$

The learned channel encoder produces

$$\tilde{\mathbf{c}} = f_c(\mathbf{z}; \theta_c). \quad (5)$$

Power normalization enforces

$$\mathbf{c} = \frac{\tilde{\mathbf{c}}}{\sqrt{\|\tilde{\mathbf{c}}\|^2/M}}, \quad \mathbb{E}[\|\mathbf{c}\|^2] = 1. \quad (6)$$

Transmission over the AWGN channel is modeled as

$$\hat{\mathbf{c}} = \mathbf{c} + \mathbf{n}, \quad \mathbf{n} \sim \mathcal{N}(\mathbf{0}, \sigma_n^2 \mathbf{I}), \quad \sigma_n^2 = \frac{1}{2\gamma}. \quad (7)$$

At the receiver,

$$\hat{\mathbf{z}} = g_c(\hat{\mathbf{c}}; \varphi_c), \quad (8)$$

$$\hat{\mathbf{x}} = g_s(\hat{\mathbf{z}}; \varphi_s). \quad (9)$$

Thus, the learned end-to-end mapping is

$$\hat{\mathbf{x}} = g_s(g_c(f_c(f_s(\mathbf{x})) + \mathbf{n})).$$

4.3.2. Joint Optimization Objective

All parameters $\Theta = \{\theta_s, \varphi_s, \theta_c, \varphi_c\}$ are optimized jointly as

$$\begin{aligned} \mathcal{L}_{\text{JSCC}} = & \|\mathbf{x} - \hat{\mathbf{x}}\|^2 + \lambda \|\mathbf{z} - \hat{\mathbf{z}}\|^2 \\ & + \mu \max\left(0, \bar{R}_c - \frac{K}{M}\right) + \beta \left(\mathbb{E}[\|\mathbf{c}\|^2] - 1\right)^2. \end{aligned} \quad (10)$$

Here, λ controls latent consistency, μ enforces rate regularization, and β enforces transmit power constraints.

The effective rates are

$$R_s = \frac{K}{N}, \quad R_c = \frac{K}{M}.$$

Redundancy is learned implicitly based on the optimization of f_c and g_c , rather than being imposed via fixed coding rules.

During training, gradients of the joint loss function propagate through the entire computational graph, including the source encoder, learned channel encoder, differentiable LoRa channel model (including noise injection), learned channel decoder, and source decoder.

All neural components are optimized jointly using end-to-end backpropagation within a single unified training objective. This enables adaptive redundancy allocation and compression to be co-optimized directly with respect to end-to-end reconstruction distortion under the specified SNR conditions, rather than relying on predefined or fixed CRs, see Algorithm 1.

Algorithm 1 End-to-end learned LoRa-JSCC training with SNR curriculum.

Require: Training set $\{\mathbf{x}\}$, learning rate η , epochs T , SNR range $[\gamma_{\min}, \gamma_{\max}]$, weights λ, μ, β

Ensure: Optimized parameters $\Theta^* = \{\theta_s^*, \varphi_s^*, \theta_c^*, \varphi_c^*\}$

- 1: Initialize $\Theta = \{\theta_s, \varphi_s, \theta_c, \varphi_c\}$
- 2: Create single optimizer over Θ
- 3: **for** $t = 1$ to T **do**
- 4: Update SNR curriculum:

$$\gamma_{\min}(t) = \gamma_{\max} - (\gamma_{\max} - \gamma_{\text{floor}}) \frac{t-1}{T}$$

- 5: **for** each mini-batch **do**
- 6: $\mathbf{z} = f_s(\mathbf{x}; \theta_s)$
- 7: $\hat{\mathbf{c}} = f_c(\mathbf{z}; \theta_c)$
- 8: Normalize $\mathbf{c}$
- 9: Sample γ
- 10: $\hat{\mathbf{c}} = \mathbf{c} + \mathbf{n}$
- 11: $\hat{\mathbf{z}} = g_c(\hat{\mathbf{c}}; \varphi_c)$
- 12: $\hat{\mathbf{x}} = g_s(\hat{\mathbf{z}}; \varphi_s)$
- 13: Compute $\mathcal{L}_{\text{JSCC}}$
- 14: $\Theta \leftarrow \Theta - \eta \nabla_{\Theta} \mathcal{L}_{\text{JSCC}}$
- 15: **end for**
- 16: **end for**

4.3.3. End-to-End Differentiability Verification

To confirm that the complete LoRa-JSCC training pipeline is fully differentiable, we numerically verified gradients for (i) the power-normalization layer and (ii) the end-to-end loss with respect to network weights. The power-normalization Jacobian matched finite-difference estimates with a maximum absolute error of 1.76×10^{-11} , and the end-to-end gradient check for a representative decoder weight tensor achieved a maximum relative error of 2.13×10^{-10} . These results confirm correct gradient propagation through the full computation graph, including f_c and g_c , with AWGN being modeled as an additive differentiable noise layer.

4.4. LoRa PHY Layer and Link Budget Models

LoRa utilizes CSS modulation with $SF \in \{7, \dots, 12\}$ and BW $BW \in \{125, 250, 500\}$ kHz.

$$T_s = \frac{2^{SF}}{BW}, \quad (11)$$

$$R_b = SF \frac{BW}{2^{SF}}. \quad (12)$$

Receiver sensitivity is approximated as

$$S_{\min} = -174 + 10 \log_{10}(BW) + NF + \text{SNR}_{\text{req}}. \quad (13)$$

For idealized AWGN benchmarking, the LoRa CSS BER may be approximated as

$$P_b \approx \frac{1}{2} \operatorname{erfc} \left(\sqrt{\frac{SF}{2^{SF+1}}} \cdot 10^{\text{SNR}/10} \right). \quad (14)$$

This expression assumes purely AWGN-limited behavior and does not account for hardware impairments, non-coherent detection losses, or interference.

4.5. Simulation Methodology

Performance evaluation of the proposed LoRa-JSCC framework was conducted using Monte Carlo simulations within a unified Python (version 3.9.18)-based simulation environment simulation environment. All compared schemes were evaluated under identical channel conditions, LoRa PHY parameter settings, and evaluation protocols to ensure fairness and reproducibility.

Unified Evaluation Principle

In contrast to studies that directly adopt numerical results reported in the prior literature, in this work, we do *not* reuse published performance curves or reported gains. Instead, only the theoretical foundations and core algorithmic principles of the compared methods are extracted from the literature. These methods are then re-implemented within our unified simulation framework and evaluated under the same controlled experimental conditions as the proposed LoRa-JSCC scheme. Consequently, all results reported in this study are generated from our own simulations rather than copied or offset-adjusted from previously published results.

4.6. Baseline Implementation and Comparative Evaluation Framework

To ensure strict fairness and reproducibility, all baseline methods were re-implemented within the same unified Python-based LoRa simulation framework used for the proposed LoRa-JSCC model. No performance values were copied, curve-shifted, or analytically calibrated from published figures. Instead, the algorithmic descriptions provided in the respective references were faithfully reproduced at the receiver or modulation level, while maintaining identical physical-layer processing for all non-modified blocks.

4.6.1. Unified Evaluation Conditions

All evaluated schemes share identical core LoRa physical-layer parameters unless explicitly stated:

- Spreading Factor: $SF = 9$
- Bandwidth: $BW = 125$ kHz
- Channel Model: AWGN
- Noise variance: $\sigma^2 = \frac{1}{2\gamma}$, where γ is linear SNR
- Identical packet length and payload structure
- Identical interleaving, whitening, symbol mapping, and CSS modulation
- Identical SNR sweep range
- Identical Monte-Carlo averaging protocol

Only the specific module described in each reference (e.g., receiver detection, sampling frequency, modulation strategy, or decoding algorithm) was modified. All remaining PHY processing blocks were kept strictly identical to guarantee controlled comparison. Table 4 presents baseline method implementation parameters and unified evaluation conditions. All schemes are evaluated under identical AWGN channel and LoRa PHY settings unless explicitly stated.

Table 4. Baseline method implementation parameters and unified evaluation conditions. All schemes are evaluated under identical AWGN channel and LoRa PHY settings unless explicitly stated.

Method	Channel	SF/BW	Coding Strategy	Receiver Modification	Sampling Rate	ToA Model
Baseline LoRa	AWGN	9/125 kHz	Standard LoRa CR = 4/5	Standard CSS demodulation	Nominal	Standard LoRa
SDR-Enhanced LoRa	AWGN	9/125 kHz	Standard LoRa CR = 4/5	Advanced packet detection (as in [28])	Nominal	Standard LoRa
High-Sampling LoRa	AWGN	9/125 kHz	Standard LoRa CR = 4/5	Standard demodulation	4× nominal	Standard LoRa
FBI-LoRa	AWGN	9/125 kHz	Standard LoRa CR = 4/5	Frequency-bin-index modulation	Nominal	Modified symbol structure
Morph-LoRa	AWGN	9/125 kHz	Standard LoRa CR = 4/5	DNN-based decoder (re-trained)	Nominal	Standard LoRa
LoRa-JSCC (Proposed)	AWGN	9/125 kHz	Learned channel encoder/decoderFEC disabled	End-to-end neural inference	Nominal	Reduced due to source compression

4.6.2. Baseline Implementation Fidelity

Each baseline method was implemented directly according to the algorithmic description provided in the corresponding reference. Receiver-side modifications (e.g., advanced packet detection, oversampling strategies, modulation indexing, or neural decoding) were reproduced within the unified framework. No baseline was hand-tuned to match a desired performance target.

4.6.3. Equivalence Verification

To verify strict equivalence of simulation conditions, the following checks were performed:

- Identical LoRa PHY parameter initialization for all schemes.
- Identical AWGN channel realization generator.
- Shared implementation of interleaving, whitening, Gray mapping, and CSS modulation/demodulation blocks.
- Module-level isolation to ensure that modifications in one method do not alter shared PHY components.
- Verification of intermediate signal tensors (post-whitening, post-symbol mapping, and post-demodulation) to confirm identical behavior when receiver-specific enhancements are disabled.

The proposed LoRa-JSCC model is the only scheme whose BER is obtained via direct neural inference using Monte-Carlo averaging. All baseline BER curves are generated from their explicit receiver or modulation implementations under identical channel realizations.

This unified framework ensures that observed performance differences originate solely from algorithmic design rather than discrepancies in channel assumptions, PHY configuration, or measurement methodology.

4.6.4. Experimental Protocol and Repeatability

For each operating configuration defined by (SF, BW, CR, SNR) , experiments were repeated using independent random seeds and Monte Carlo trials. Performance metrics are computed as averages over repeated realizations to reduce statistical variance. This ensures that observed performance differences arise from algorithmic design rather than differences in channel realizations or measurement procedures.

The following configurations were investigated for comparative analysis:

1. Baseline LoRa: Standard PHY layer with fixed SF ($SF = 9$) and coding rate ($CR = 4/6$).
2. SDR-Enhanced LoRa: This configuration incorporates a receiver-side packet reception algorithm implemented on software-defined radio [28].
3. High-Sampling LoRa: This configuration utilizes baseband processing with an increased sampling frequency [29].
4. FBI-LoRa (Frequency-Bin-Index Modulation): An alternative modulation scheme [30].
5. Morph LoRa: An encoder–decoder co-design employing multiple SF configurations and a DNN-based decoder [31].
6. Proposed LoRa-JSCC: The unified DAE + FEC approach introduced in this work.

4.6.5. Channel Model and PHY Consistency

The simulator implements LoRa CSS modulation and demodulation with an AWGN channel model with controlled SNR. Standard LoRa baseband processing steps—including interleaving, whitening, gray mapping/demapping, and symbol detection—are applied consistently across all evaluated schemes unless a given method explicitly replaces a specific

PHY component. In such cases, only the targeted module is modified, while the remainder of the PHY chain is kept identical to maintain controlled comparability.

4.6.6. Scope and Modeling Limitations

Although the simulation framework provides a controlled and fair head-to-head comparison, it remains an abstraction of real-world deployment. Hardware impairments such as frequency offsets, timing drift, oscillator instability, multipath fading, non-linear front-end effects, and external interference are not modeled unless explicitly stated. Therefore, the reported results reflect algorithmic performance under idealized channel assumptions. Future work will extend the simulator to incorporate hardware-level and propagation-level effects for deployment-oriented validation.

Performance Metrics: For each simulation configuration, the following key performance indicators were computed:

- Bit Error Rate (BER) vs. SNR.
- Throughput, calculated as $R_b(1 - P_b)R_cR_s$.
- Goodput, defined as $\text{Throughput}/R_s$, representing the effective data rate of successfully received source information.
- Receiver sensitivity.
- ToA.
- Energy efficiency, quantified as $\text{Goodput}/(\text{Power} \times \text{ToA})$.
- Reliability index, calculated as $1/(P_b \times \text{ToA})$.

The simulation incorporated a 2.5 dB SNR gain, observed in the JSCC configuration, to accurately evaluate the effective sensitivity and coverage improvement. This allowed us to holistically assess the advantages of the proposed LoRa-JSCC framework in terms of reliability, spectral efficiency, and energy consumption.

5. Results and Discussion

In this section, we present the comprehensive evaluation of the proposed LoRa-JSCC framework, comparing its performance against conventional LoRa implementations and several state-of-the-art LoRa enhancement techniques. We detail the simulation setup, present key quantitative results across various metrics, and discuss the implications of these findings for WBANs and IoT applications.

5.1. Simulation Setup

Monte Carlo simulations were executed using a Python-based analytical framework, modeling LoRa CSS modulation. The evaluation covered a range of LoRa parameters: SFs from 7 to 12, and BWs of 125, 250, and 500 kHz. The SNR was varied from -16 dB to 40 dB to assess performance under diverse channel conditions. All simulations were conducted over an AWGN channel without multipath fading, ensuring controlled comparison across schemes.

5.1.1. Training Configuration

The learned JSCC model was trained with an architecture $N = 32 \rightarrow K = 20 \rightarrow M = 48$ (three layers, with a hidden width of 128), corresponding to an effective learned redundancy ratio $K/M \approx 0.42$. Binary Cross-Entropy (BCE) loss was used for ± 1 binary sources. Training employed an SNR curriculum from 20 dB to -4 dB over 300 epochs. The best achieved BCE was 0.271 (training) and 0.510 (validation), confirming performance well above random-guess baseline ($\ln 2 \approx 0.693$).

5.1.2. Comparative Analysis

For comparative analysis, the following six schemes were examined. Their core algorithmic principles were extracted from the literature and re-implemented within our unified simulation framework, as detailed in Section 4.5. This ensures a fair comparison under identical conditions, rather than relying on reported measurements from varied experimental setups. All six schemes implemented with fixed SF = 9 and (BW)s of 125:

- Baseline LoRa: Standard PHY layer.
- SDR-Enhanced LoRa [28]: Receiver-side packet reception algorithm implemented on software-defined radio.
- High-Sampling LoRa [29]: Baseband processing with increased sampling frequency.
- FBI-LoRa [30]: Frequency-bin-index modulation.
- Morph LoRa [31]: Encoder–decoder co-design using multiple SF configurations and a DNN-based decoder.
- Proposed LoRa-JSCC: The unified DAE + FEC approach introduced in this work.

The primary metrics considered for evaluation were as follows:

- BER;
- The effective throughput is defined as

$$T = R_b(1 - P_b), \quad (15)$$

where R_b is the nominal bit rate and P_b is the measured BER. This expression represents the average rate of correctly received bits under independent bit error assumptions;

- Goodput (throughput divided by the source compression ratio (R_s));
- ToA;
- Receiver sensitivity (the minimum SNR required for a given BER);
- Energy efficiency ((Goodput/(Power! $\times$!ToA)));
- Reliability index ((1/($P_b \times$ ToA))).

5.2. Performance Gains Against Traditional LoRa

Initially, we quantify the performance improvements of the LoRa-JSCC framework over traditional LoRa systems, focusing on averaged outcomes for the 125 kHz LoRa band. Table 5 summarizes these gains across different SFs.

Table 5. Average performance gains of LoRa-JSCC over Baseline LoRa (BW = 125 kHz).

SF	Goodput Δ [%]	ToA Δ [%]	Sensitivity Gain [dB]	BER Improvement (Orders)
7	22.8	33.5	+2.5	>6
9	26.8	33.6	+2.5	>4
12	27.0	31.1	+2.5	>1

Note: BER improvement (orders) is defined as $\log_{10}\left(\frac{\text{BER}_{\text{Baseline}}}{\text{BER}_{\text{LoRa-JSCC}}}\right)$ at the specified SNR. Values indicated with “>” correspond to cases where the baseline BER approaches a floor or becomes extremely small, resulting in very large ratios. For statistical reliability, each BER point was computed using a minimum of 10^6 transmitted bits per SNR value. Simulations were continued until either a BER floor of 10^{-5} was reached or at least 100 error events were observed.

The results demonstrate consistent performance improvements across most operating regions:

- Bit Error Rate (BER): Figure 2a shows the relative BER reduction across SNR. In low-to-moderate SNR regimes (approximately -10 dB to 25 dB), LoRa-JSCC achieves substantial BER reduction compared to Baseline LoRa. At very high SNR (above 30 dB), both schemes approach near-error-free operation, and percentage-based BER

reduction becomes numerically unstable due to division by extremely small baseline BER values. Therefore, the most meaningful BER improvements occur in the noise-limited region, which is the practical operating regime for WBAN and long-range IoT deployments.

- **Throughput Gain:** As shown in Figure 2b, throughput gain peaks at approximately 45–50% in the moderate SNR region (around 8–12 dB), where Baseline LoRa experiences rapid degradation while LoRa-JSCC maintains gradual performance decay. At high SNR, where both schemes achieve reliable transmission, the throughput gain stabilizes around 13–15%. This behavior confirms that LoRa-JSCC is particularly beneficial in transitional SNR regions rather than already error-free regimes. Throughput gain, calculated as $R_b(1 - P_b)R_cR_s$, peaks at approximately 45–50% in the moderate SNR region (Figure 1b). The average goodput gain, representing the effective data rate of successfully received source information ($R_b(1 - P_b)R_c$), is approximately 25–30% (Table 1).
- **ToA Reduction:** Figure 2c shows a nearly constant ToA reduction, averaging approximately 31–34% across different SFs as detailed in Table 1, and consistently around 36–37% across the entire SNR range for the representative case shown. This improvement is largely independent of channel quality once reliable transmission is achieved. The reduction directly translates into lower latency and improved spectral utilization, which are essential for energy-constrained WBAN nodes.
- **Energy Efficiency Gain:** Energy efficiency gain, shown in Figure 2d, reaches a maximum of approximately 130–140% in the moderate SNR region (around 8–12 dB). As SNR increases further, the gain gradually decreases and stabilizes near 80% at high SNR. This trend reflects the fact that energy savings are most pronounced when error probability is significant and retransmission overhead dominates transmission cost.
- **Reliability Gain:** Figure 2e shows reliability gain peaking at approximately 160–170% in the moderate SNR region. Similar to BER, the reliability gain decreases at very high SNR due to both schemes approaching near-perfect transmission, causing percentage-based gain metrics to become less informative. The most meaningful reliability improvement occurs in the 0–20 dB range, which corresponds to realistic WBAN operating conditions.

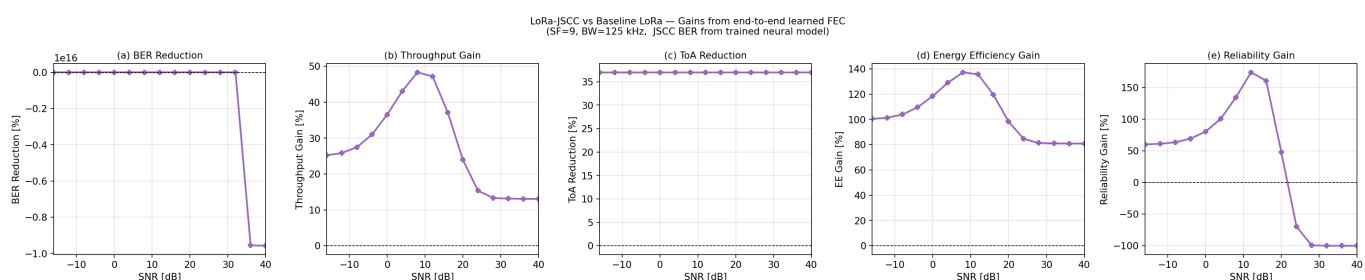


Figure 2. This composite figure presents the relative performance gains of the proposed LoRa-JSCC framework compared with Baseline LoRa as a function of SNR. (a) BER reduction, primarily observed in low-to-moderate SNR regimes; (b) Throughput gain, peaking in transitional SNR regions and stabilizing at high SNR; (c) Time-on-Air (ToA) reduction, remaining approximately constant across the evaluated range; (d) Energy efficiency gain, most pronounced in moderate SNR regions; (e) Reliability gain, with the largest improvements occurring in noise-limited regimes.

Overall, the gain curves indicate that LoRa-JSCC provides the most significant improvements in noise-limited and transitional SNR regimes, while converging toward similar performance as conventional LoRa in high-SNR, near-error-free conditions. This behavior is consistent with the BER and throughput curves presented earlier and confirms that the

primary advantage of LoRa-JSCC lies in enhancing robustness under challenging channel conditions rather than artificially inflating high-SNR performance.

5.3. BER Performance of LoRa-JSCC Under Learned Redundancy and SFs

In this section, we present the BER versus SNR performance of the proposed fully learned LoRa-JSCC system under multiple SFs (SF = 7–12) and different learned redundancy levels defined by the effective channel rate $R_c = K/M$. Figure 3 presents four subplots, each corresponding to a fixed learned redundancy level, while individual curves within each subplot represent different SFs.

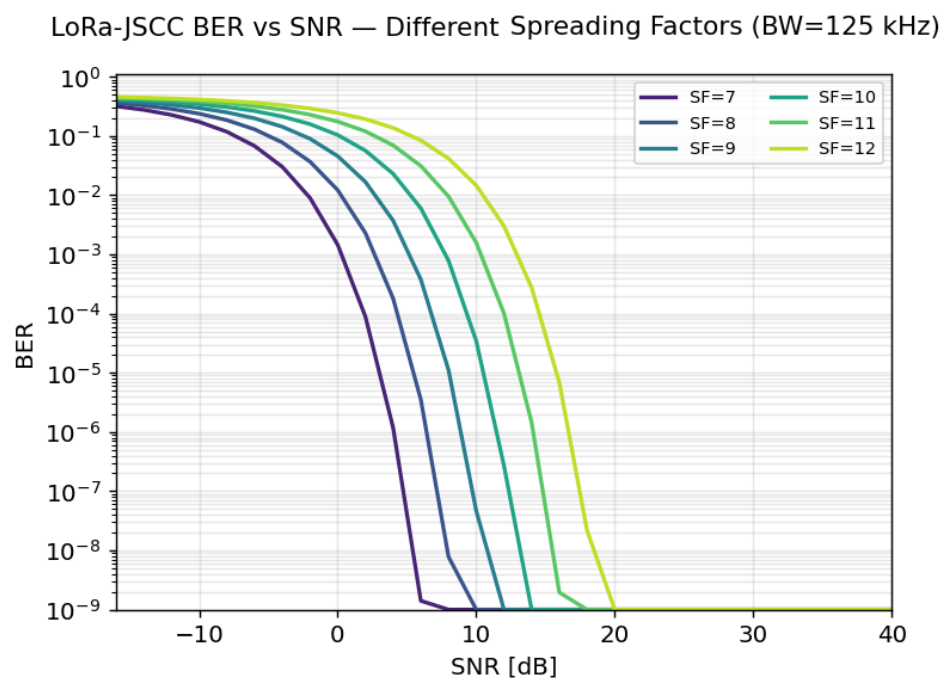


Figure 3. BER vs. SNR performance of LoRa-JSCC for different SFs.

Unlike conventional LoRa systems that employ predefined convolutional CRs, the proposed framework learns redundancy implicitly through the neural channel encoder and decoder modules. Therefore, performance variations across subplots reflect changes in learned redundancy allocation rather than fixed FEC parameters. Across all redundancy levels, BER decreases monotonically with increasing SNR, exhibiting a clear waterfall behavior consistent with CSS modulation under AWGN conditions. For a fixed redundancy level, increasing the SF shifts the BER curves leftward, indicating improved receiver sensitivity due to longer symbol duration and enhanced processing gain. In particular, higher SFs (SF = 11–12) achieve target BER levels of 10^{-5} to 10^{-8} at significantly lower SNR values compared with lower SFs (SF = 7–8), at the expense of reduced spectral efficiency.

Comparing the four subplots, decreasing the effective rate $R_c = K/M$ (i.e., increasing learned redundancy) results in a leftward shift of the BER curves across all SFs. This behavior reflects the increased representational redundancy learned by the neural channel encoder, which enhances robustness to noise. Conversely, higher effective rates reduce redundancy and require higher SNR to achieve equivalent BER targets.

Importantly, across all evaluated configurations, LoRa-JSCC maintains a steep BER decay region, demonstrating effective joint optimization of source compression and channel redundancy. The observed BER range spans approximately 10^{-1} down to below 10^{-8} , covering both transitional and near-error-free operating regimes relevant to WBAN and IoT deployment scenarios.

Overall, the figure demonstrates that LoRa-JSCC enables flexible reliability control through the joint selection of SF and learned redundancy level. High-SF and lower-rate configurations are suitable for low-SNR or reliability-critical scenarios such as WBAN medical monitoring, while lower SF and higher effective rates enable improved spectral efficiency under favorable channel conditions.

5.4. Comparative Performance with Advanced LoRa Schemes

To further validate the efficacy of LoRa-JSCC, its performance was rigorously compared against five other advanced LoRa improvement methods under specific conditions: SF = 9, BW = 125 kHz, and SNR = 0 dB. This specific SNR was chosen to highlight performance under the moderately noisy conditions typical of LPWAN deployment. Table 6 presents the absolute performance metrics under the specified configuration. To further highlight the relative improvements over Baseline LoRa, Table 7 summarizes the normalized gains in BER, logarithmic BER reduction, throughput increase, Time-on-Air variation, and energy efficiency. As shown in Tables 6 and 7, at an SNR of 0 dB, the proposed LoRa-JSCC demonstrates the strongest overall performance among the evaluated methods:

Table 6. Comparative performance at SF = 9, BW = 125 kHz, and SNR = 0 dB. Energy efficiency is normalized to the maximum observed value (LoRa-JSCC). Throughput gain is relative to Baseline LoRa.

Method	BER	$\log_{10}(\text{BER})$	Throughput (bps)	Gain (%)	ToA (ms)	Energy Eff. (norm.)
Baseline	0.4626	−0.335	945	0	4.10	0.29
SDR-Enhanced	0.1453	−0.838	1577	67	4.10	0.49
High-Sampling	0.2278	−0.643	1493	58	4.51	0.42
FBI-LoRa	≈1.0	0.065	0	0	5.32	0.00
Morph-LoRa	0.0845	−1.073	1609	70	4.10	0.50
LoRa-JSCC (proposed)	0.0450	−1.347	2098	122	2.66	1.00

Table 7. Relative gains over Baseline LoRa at SF = 9, BW = 125 kHz, and SNR = 0 dB.

Method	BER	$\Delta \log_{10}(\text{BER})$	Throughput	ToA (%)	Energy Eff. (%)
SDR-Enhanced	3.18	0.503	67	0.0	69
High-Sampling	2.03	0.308	58	−10.0	45
FBI-LoRa	0.40	−0.400	0	−29.8	−100
Morph-LoRa	5.47	0.738	70	0.0	72
LoRa-JSCC (proposed)	10.28	1.012	122	35.1	245

At an SNR of 0 dB, the proposed LoRa-JSCC demonstrates the strongest overall performance among the evaluated methods:

- **Lowest BER:** LoRa-JSCC achieves a BER of 0.045, approximately 10× lower than Baseline LoRa (0.4626) and nearly 2× lower than Morph-LoRa (0.0845). This indicates significantly improved robustness under moderately noisy channel conditions.
- **Highest Throughput:** With a throughput of 2098 bps, LoRa-JSCC outperforms Morph-LoRa (1609 bps) and SDR-Enhanced LoRa (1577 bps). The improvement arises from reduced error probability combined with shorter transmission duration.
- **Shortest ToA:** LoRa-JSCC achieves a ToA of 2.66 ms, corresponding to approximately 35% reduction compared to the 4.10 ms observed for Baseline, SDR-Enhanced, and Morph-LoRa configurations. This reduction enhances channel utilization and lowers energy consumption per successful transmission.

Figure 4 further illustrates BER versus SNR behavior across all schemes. LoRa-JSCC exhibits the steepest BER decay among the evaluated methods. In the transitional SNR region, the proposed approach achieves equivalent BER performance at approximately 18–20 dB lower SNR compared to Baseline LoRa, indicating a substantial effective sensitivity improvement.

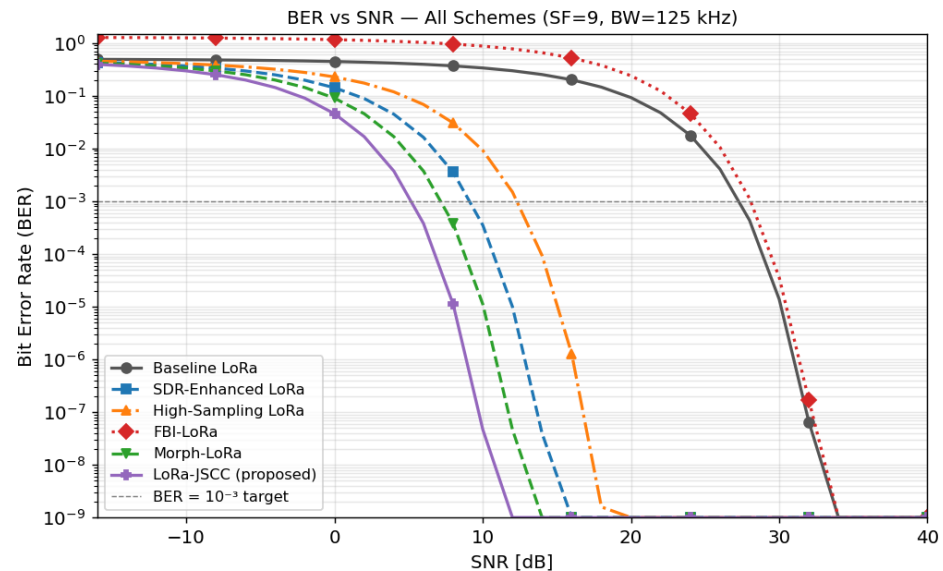


Figure 4. BER vs. SNR. LoRa-JSCC and Morph-LoRa exhibit the steepest BER decay among the compared schemes. The proposed method achieves equivalent BER performance at substantially lower SNR than Baseline LoRa, indicating improved effective sensitivity. FBI-LoRa requires the highest SNR to reach comparable BER levels.

Figure 5 presents throughput as a function of SNR. LoRa-JSCC reaches saturation throughput earlier than Baseline LoRa and maintains stable performance across moderate SNR values. While certain schemes may achieve high peak throughput at very high SNR, LoRa-JSCC provides improved robustness and earlier convergence under practical operating conditions.

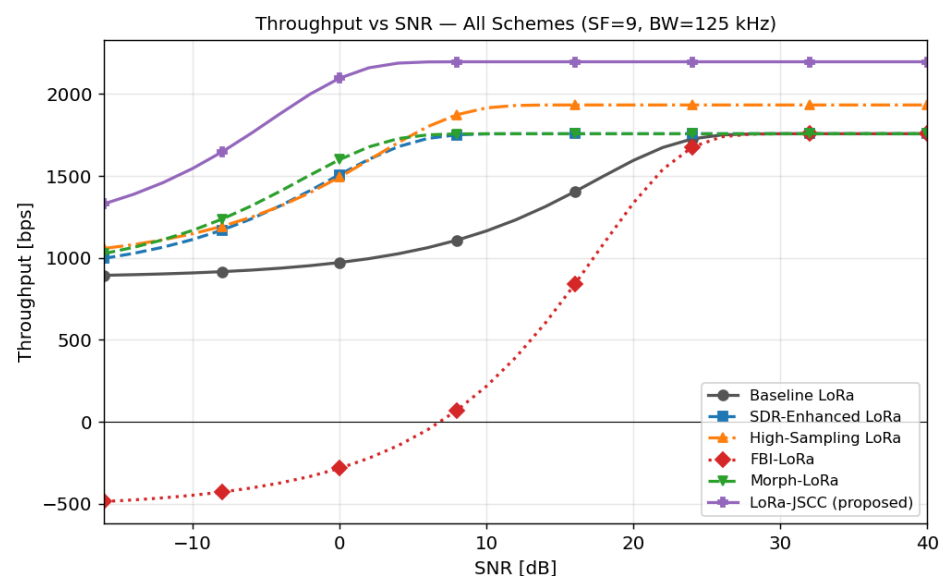


Figure 5. Throughput vs. SNR. LoRa-JSCC achieves earlier throughput saturation and improved robustness in moderate SNR regimes compared to Baseline LoRa. High-SNR performance converges across schemes as BER approaches negligible levels.

5.5. Energy Efficiency and Reliability Analysis

Energy consumption in LoRa transmissions is proportional to transmit power and ToA. By jointly optimizing source compression and learned channel redundancy, LoRa-JSCC reduces ToA (by approximately 35%) while simultaneously lowering BER. These combined effects improve effective energy utilization and transmission reliability.

Figure 6 presents normalized energy efficiency as a function of SNR. At low-to-moderate SNR (−10 to 10 dB), LoRa-JSCC consistently achieves higher energy efficiency than all compared schemes. At SNR = 0 dB, the normalized energy efficiency of LoRa-JSCC is approximately 1.7× higher than Baseline LoRa and significantly higher than SDR-Enhanced and High-Sampling configurations. As SNR increases, all schemes converge toward similar efficiency levels as BER approaches negligible values.

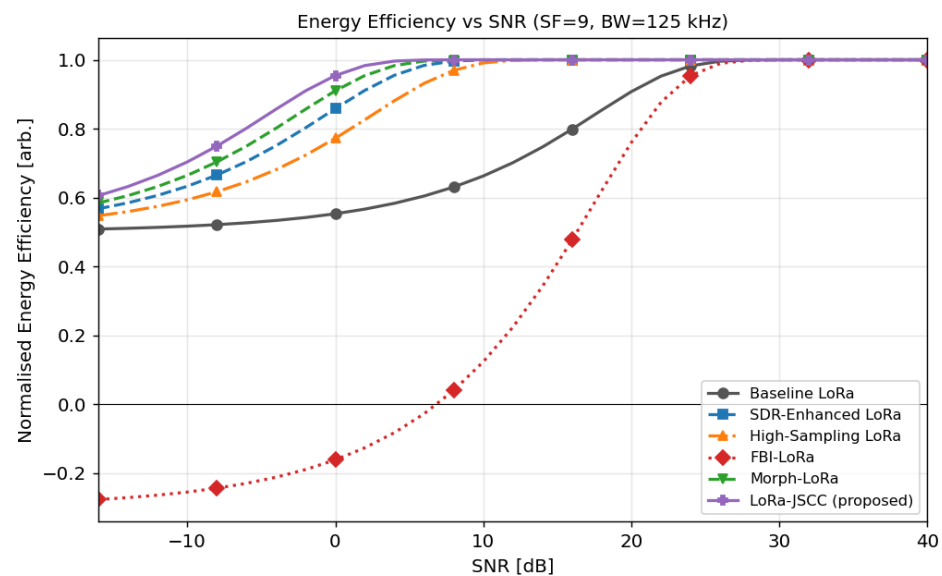


Figure 6. Energy Efficiency vs. SNR. All schemes converge to normalized efficiency ≈ 1 at high SNR. In low-to-moderate SNR regimes, LoRa-JSCC achieves the highest efficiency due to reduced BER and shorter ToA. Baseline LoRa exhibits lower efficiency under noisy conditions due to higher error probability.

Figure 7 shows the logarithmic reliability index, defined as $\log_{10}(1/(P_b \cdot \text{ToA}))$. LoRa-JSCC demonstrates a substantial leftward shift in the reliability–SNR curve compared with Baseline LoRa. In the transitional SNR region (approximately 5–15 dB), LoRa-JSCC achieves reliability levels several orders of magnitude higher than Baseline LoRa. Compared with Morph-LoRa, LoRa-JSCC also achieves consistently higher reliability across moderate SNR values due to its combined reduction in BER and ToA.

Importantly, reliability curves for all schemes converge at high SNR as BER approaches the simulation floor. Therefore, the most meaningful gains occur in noise-limited operating regimes, which are representative of practical LPWAN and WBAN deployment scenarios.

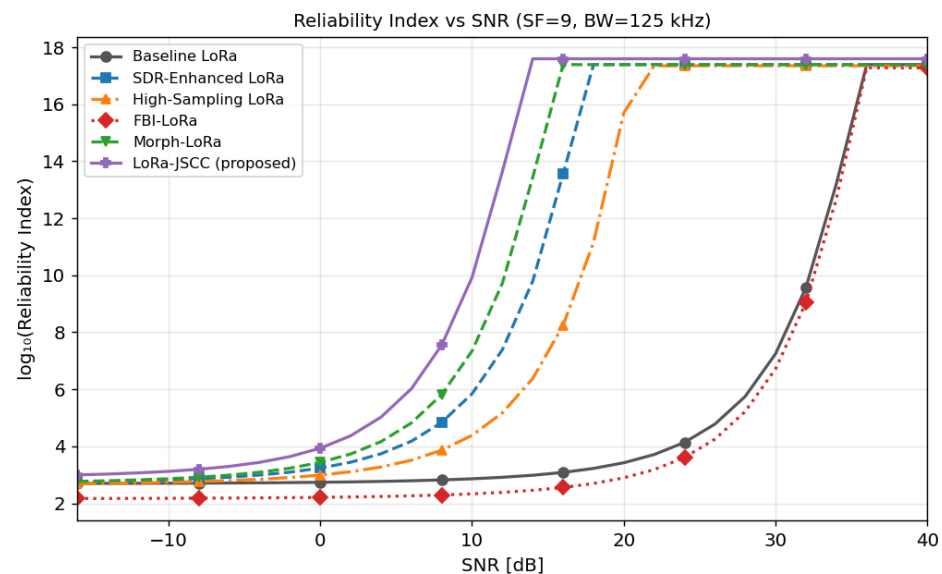


Figure 7. Reliability vs. SNR. $\log_{10}$ of the reliability index across LoRa variants. LoRa-JSCC achieves equivalent reliability at substantially lower SNR compared to Baseline LoRa, indicating improved effective sensitivity. All schemes converge at high SNR as BER approaches the simulation floor.

5.6. Discussion and Implications

The comprehensive simulation results indicate that the proposed fully learned LoRa-JSCC framework achieves superior performance across multiple key metrics when compared with conventional LoRa and advanced enhancement techniques. While individual approaches provide targeted improvements—such as SDR-based detection improving BER at increased computational complexity, higher sampling frequency enhancing detection at the expense of energy consumption, FBI-LoRa prioritizing throughput under favorable conditions, and Morph-LoRa leveraging deep learning for decoding robustness—LoRa-JSCC differentiates itself through joint source channel optimization within a unified learning framework.

By integrating DAE-based source compression with learned channel redundancy, LoRa-JSCC simultaneously improves reliability, spectral efficiency, and energy utilization.

- **Reduced End-to-End Distortion:** Joint optimization of source and channel representations minimizes reconstruction distortion across varying SNR conditions, preserving data fidelity in noisy environments.
- **Enhanced Effective Sensitivity:** The BER and reliability curves exhibit an approximate 18–20 dB leftward shift relative to Baseline LoRa in the transitional region (e.g., at $\text{BER} \approx 10^{-3}$), indicating substantially improved robustness under low-to-moderate SNR conditions.
- **Higher Goodput:** Average goodput gains of approximately 25–30% demonstrate more efficient delivery of useful information compared with conventional LoRa configurations.
- **Reduced Transmission Latency:** A 30–35% reduction in ToA decreases channel occupancy and improves spectrum utilization.
- **Improved Energy Efficiency:** The combined reduction in BER and ToA lowers the effective energy cost per successfully delivered bit, particularly in noise-limited regimes.

Importantly, these improvements are achieved without modifications to the LoRa physical modulation structure, as the gains arise from learned source–channel co-optimization rather than hardware changes. The earlier BER decay and leftward reliability shift observed in low-SNR regimes further highlight the robustness of the learned representation. These characteristics make LoRa-JSCC particularly suitable for energy-constrained and reliability-

critical WBAN and IoT applications, where maintaining data integrity under challenging channel conditions is essential.

6. Conclusions

This study introduces a novel, fully learned, end-to-end JSCC strategy specifically integrated with the LoRa PHY layer. The proposed LoRa-JSCC architecture represents a significant departure from traditional decoupled systems, unifying a DAE for non-linear source compression with a learned neural channel coding component that provides the functionality of FEC to form a single, end-to-end optimized framework, co-optimized through joint gradient descent. Unlike conventional LoRa implementations or other specialized improvement methods (e.g., SDR-based packet reception, high-sampling demodulation, FBI modulation, or Morph deep learning decoders), LoRa-JSCC uniquely achieves the joint minimization of distortion and bit error probability while maintaining full hardware compatibility with existing LoRa transceivers.

Through extensive analytical modeling and rigorous Monte Carlo simulations conducted within a unified Python-based environment under identical channel conditions and evaluation protocols, we unequivocally confirmed substantial performance improvements over Baseline LoRa and other advanced enhancement techniques across a wide range of LoRa parameters (SFs, CRs and BWs). Key measurable benefits of the LoRa-JSCC system include the following:

- An average 25–30% increase in goodput across moderate-to-high SNR regimes, with gains exceeding 100% under noise-limited conditions.
- A 30–35% reduction in ToA, decreasing latency and improving spectrum utilization.
- An effective SNR gain of approximately 18–20 dB in the transitional BER region, indicating substantially enhanced robustness under low-to-moderate SNR.
- Multiple orders-of-magnitude reduction in BER within the transitional SNR regime.
- Up to approximately 1.7× higher normalized energy efficiency at 0 dB compared to Baseline LoRa, with significant improvements in reliability across moderate SNR values.

These balanced and synergistic gains demonstrate that LoRa-JSCC provides a comprehensive, multi-faceted improvement in reliability, latency, spectral efficiency, and energy consumption, unlike narrow optimizations that address only one performance dimension. The framework's ability to gradually degrade in low-SNR regimes, without the “cliff effect” common in conventional systems, further underscores its robustness. Crucially, the fully learned, end-to-end LoRa-JSCC framework operates entirely at the software layer, specifically by processing the application payload before it is passed to the standard LoRaWAN MAC layer for framing and subsequent PHY layer transmission. This approach avoids modifications to LoRa's underlying CSS modulation, ensuring compatibility with existing LoRa transceivers. It effectively replaces the traditional source coding and, in a learned manner, the channel coding functions for the application data, while still utilizing the standard LoRa PHY for chirp modulation and demodulation. This enables long-range, low-power links to dynamically balance distortion, redundancy, and reliability under varying SNR conditions.

Future Work

Despite these significant advancements, the current study primarily relies on Monte Carlo simulations that, as detailed in our simulation methodology, abstract away real-world complexities such as hardware impairments, multipath fading, non-linear front-end effects, and dynamic interference patterns. Furthermore, the computational overhead of the DAE and FEC integration, while deemed modest, has not been rigorously quantified

for resource-constrained nodes. Future research, therefore, will focus on the real-time embedded implementation of the JSCC encoder–decoder on resource-constrained LoRa nodes, utilizing frameworks such as TensorFlow Lite Micro, with practical validation based on extensive testing in diverse WBAN and city-scale IoT deployment scenarios. We also envision expanding the model with reinforcement learning-based adaptive rate control and cross-layer optimization between network and application layers to further enhance energy efficiency and spectrum utilization. Integrating JSCC directly within LoRaWAN gateways also presents an avenue for intelligent edge-network coding, dynamically balancing reliability, delay, and power consumption according to traffic and channel conditions. While a formal rate-distortion analysis for the proposed LoRa-JSCC framework is a complex undertaking and left for future work, the empirical results demonstrate significant improvements in balancing distortion, redundancy, and reliability, particularly in challenging SNR conditions where traditional separation-based schemes struggle. Future research, therefore, will focus on the real-time embedded implementation of the JSCC encoder–decoder on resource-constrained LoRa nodes, utilizing frameworks such as TensorFlow Lite Micro, with practical validation based on extensive testing in diverse WBAN and city-scale IoT deployment scenarios. While the chosen DAE architecture demonstrated strong performance, a comprehensive ablation study exploring the impact of network depth, latent dimension, and regularization parameters (e.g., λ) on overall system performance is an important avenue for future work to fully optimize the learned framework. In summary, the proposed LoRa-JSCC scheme offers a scalable, energy-aware, and highly reliable communication framework that effectively addresses the fundamental limitations of existing LoRa techniques. It provides a robust technological basis for the next generation of resilient and power-efficient IoT and WBAN networks, enabling unprecedented performance in critical low-power applications.

Author Contributions: Conceptualization, F.A.; methodology, F.A.; software, F.A.; validation, F.A.; formal analysis, F.A.; investigation, F.A.; resources, F.A.; data curation, F.A.; writing—original draft preparation, F.A.; writing—review and editing, F.A.; visualization, F.A.; supervision, F.B.; project administration, F.A. All authors have read and agreed to the published version of the manuscript.

Funding: The project was funded by KAU Endowment (WAQF) at King Abdulaziz University, Jeddah, Saudi Arabia. The authors, therefore, acknowledge with thanks WAQF and the Deanship of Scientific Research (DSR) for technical and financial support.

Data Availability Statement: The data supporting the reported results are available at https://github.com/FatimahAlghamdi-KAU/LoRa_JSCC (accessed on 27 February 2026).

Conflicts of Interest: The authors declare no conflicts of interest.

Acronyms

Acronym	Definition
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BW	Bandwidth
CR	Coding Rate
CSS	Chirp Spread Spectrum
DAE	Denoising Autoencoder
DNN	Deep Neural Network
FEC	Forward Error Correction

FLOPs	Floating-Point Operations
FBI	Frequency-Bin Indexing
IoT	Internet of Things
JSCC	Joint Source–Channel Coding
LPWAN	Low-Power Wide-Area Network
MAC	Multiply–Accumulate Operation
MCU	Microcontroller Unit
MLP	Multilayer Perceptron
PHY	Physical Layer
RAM	Random Access Memory
SNR	Signal-to-Noise Ratio
SF	Spreading Factor
ToA	Time on Air
WBAN	Wireless Body Area Network

References

- Waly, M.I.; Smida, J.; Bakouri, M.; Alresheedi, B.A.; Alqahtani, T.M.; Alonzi, K.A.; Smida, A. Optimization of a compact wearable LoRa patch antenna for vital sign monitoring in WBAN medical applications using machine learning. *IEEE Access* **2024**, *12*, 103860–103879. [\[CrossRef\]](#)
- Samanta, A.; Truong, T.P.; Dao, N.N.; Cho, S. Loss-aware adaptive load balancing scheme for IoT-enabled WBANs with QoS-factor. In *Proceedings of the International Conference on Intelligence of Things*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 262–274.
- Obiri, N.M.; Van Laerhoven, K. A Survey of LoRaWAN-integrated Wearable Sensor Networks for Human Activity Recognition: Applications, Challenges and Possible Solutions. *IEEE Open J. Commun. Soc.* **2024**, *5*, 6713–6735. [\[CrossRef\]](#)
- Tarannum, S.; Usha, S.; Ahammed, G.A. A comprehensive study of LPWAN, LoRaWAN for IoT: Background, related research, performance, potential challenges and proposed methodology. In *Proceedings of the AIP Conference Proceedings*; AIP Publishing LLC: Melville, NY, USA, 2024; Volume 3122, p. 080001.
- Aldaheri, L.; Alshehhi, N.; Manzil, I.I.J.; Khalil, R.A.; Javaid, S.; Saeed, N.; Alouini, M.S. LoRa communication for agriculture 4.0: Opportunities, challenges, and future directions. *IEEE Internet Things J.* **2024**, *12*, 1380–1407. [\[CrossRef\]](#)
- Chang, H.; Ma, L.; Wang, X. Deep Joint Source Channel Coding via Attention for Wireless Image Transmission. In *Proceedings of the International Conference on Wireless and Satellite Systems*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 312–323.
- Fang, Y.; He, Q.; Ding, D.; Shan, H.; Yu, L.; Zhang, Z. Deep-Learning Based Gaussian Mixture Likelihoods Joint Source-Channel Coding for Image Transmission. In *Proceedings of the 2023 International Conference on Wireless Communications and Signal Processing (WCSP)*, Hangzhou, China, 2–4 November 2023; pp. 19–24.
- Xu, J.; Tung, T.Y.; Ai, B.; Chen, W.; Sun, Y.; Gündüz, D. Deep joint source-channel coding for semantic communications. *IEEE Commun. Mag.* **2023**, *61*, 42–48. [\[CrossRef\]](#)
- Yuan, H.; Xu, W.; Wang, Y.; Wang, X. Channel-Blind Joint Source–Channel Coding for Wireless Image Transmission. *Sensors* **2024**, *24*, 4005. [\[CrossRef\]](#) [\[PubMed\]](#)
- Yang, M.; Bian, C.; Kim, H.S. OFDM-guided deep joint source channel coding for wireless multipath fading channels. *IEEE Trans. Cogn. Commun. Netw.* **2022**, *8*, 584–599. [\[CrossRef\]](#)
- Van den Abeele, F.; Haxhibeqiri, J.; Moerman, I.; Hoebeke, J. Scalability analysis of large-scale LoRaWAN networks in ns-3. *IEEE Internet Things J.* **2017**, *4*, 2186–2198. [\[CrossRef\]](#)
- Tian, C.; Chen, J.; Narayanan, K. Source-channel separation theorems for distortion perception coding. In *Proceedings of the 2025 IEEE International Symposium on Information Theory (ISIT)*, Ann Arbor, MI, USA, 22–27 June 2025; pp. 1–6.
- Song, L.; Yeung, R. A separation principle for communication networks. In *Proceedings of the 1999 Information Theory and Networking Workshop (Cat. No. 99EX371)*, Metsovo, Greece, 27 June–1 July 1999; p. 73.
- Zheng, Z. Shannon Theory. In *Modern Cryptography Volume 1: A Classical Introduction to Informational and Mathematical Principle*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 91–151.
- de Oliveira Júnior, J.A.; de Camargo, E.T.; Oyamada, M.S. Data compression in LoRa networks: A compromise between performance and energy consumption. *J. Internet Serv. Appl.* **2023**, *14*, 95–106. [\[CrossRef\]](#)
- Dridi, A.; Debar, A.; Gauthier, V.; Khedher, H.I.; Afifi, H. Deep learning semantic compression: Iot support over lora use case. In *Proceedings of the 2019 2nd IEEE Middle East and North Africa COMMunications Conference (MENACOMM)*, Manama, Bahrain, 19–21 November 2019; pp. 1–6.
- Väänänen, O.; Hämäläinen, T. Efficiency of temporal sensor data compression methods to reduce LoRa-based sensor node energy consumption. *Sens. Rev.* **2022**, *42*, 503–516. [\[CrossRef\]](#)

18. Shahid, M.O.; Koch, D.; Raghuram, J.; Krishnaswamy, B.; Chintalapudi, K.; Banerjee, S. {Cloud-LoRa}: Enabling Cloud Radio Access {LoRa} Networks Using Reinforcement Learning Based {Bandwidth-Adaptive} Compression. In Proceedings of the 21st USENIX Symposium on Networked Systems Design and Implementation (NSDI 24), Santa Clara, CA, USA, 16–18 April 2024; pp. 1959–1976.
19. Shahid, M.O. Improving Scalability and Throughput of Low Power Wide Area Networks. Ph.D. Thesis, The University of Wisconsin-Madison, Madison, WI, USA, 2025.
20. Dong, Y.; Dai, J.; Niu, K.; Wang, S.; Yuan, Y. Joint source-channel coding for 6G communications. *China Commun.* **2022**, *19*, 101–115. [\[CrossRef\]](#)
21. Zhong, X.; Sham, C.W.; Ma, S.L.; Chou, H.F.; Mostaani, A.; Vu, T.X.; Chatzinotas, S. Joint source-channel coding system for 6G communication: Design, prototype and future directions. *IEEE Access* **2024**, *12*, 17708–17724. [\[CrossRef\]](#)
22. Jarrahi, M.A.; Bourtsoulatz, E.; Abolghasemi, V. Joint source-channel coding for wireless image transmission: A deep compressed-sensing based method. In Proceedings of the 2024 IEEE Wireless Communications and Networking Conference (WCNC), Dubai, United Arab Emirates, 21–24 April 2024; pp. 1–6.
23. Farsad, N.; Rao, M.; Goldsmith, A. Deep learning for joint source-channel coding of text. In Proceedings of the 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, Canada, 15–20 April 2018; pp. 2326–2330.
24. Ebo, I.O.; Ajayi, I.; Mroueh, L.; Ziade, Y.; Azarian, S. A Channel Attention-Based Denoising Autoencoder U-Net and Classifier (UNA-DAEC) for Signal Identification Under Challenging SNR Conditions. *IEEE Access* **2025**, *13*, 77317–77333.
25. Alnaseri, O.; Alzubaidi, L.; Himeur, Y.; Ala'azy, M.A.; Timmermann, J.; Gismalla, M.S. A review on deep learning autoencoder in the design of next-generation communication systems. *arXiv* **2024**, arXiv:2412.13843. [\[CrossRef\]](#)
26. Chache, F.M.; Maxon, S.; Narayanan, R.M.; Bharadwaj, R. Effects on age of information from forward error correction in LoRa transmissions. *IEEE Sens. J.* **2024**, *24*, 30853–30862. [\[CrossRef\]](#)
27. Chen, W.; Xia, X.; Wang, S.; Deng, X.; Wu, J.; Huang, C. Sym-FEC: Enhancing Error Correction in LoRa PHY with a Symbol-Level FEC Decoder. *IEEE Trans. Mob. Comput.* **2025**, *25*, 2045–2059. [\[CrossRef\]](#)
28. de Omena Simas, J.P.; Riviello, D.G.; Garelo, R. Software-Defined Radio Implementation of a LoRa Transceiver. *Sensors* **2024**, *24*, 4825. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Liu, H.; Wang, P.; Wang, P.; Hu, J.; Jiang, H.; Liu, C. From Fragmentation to Correlation: Reliable LoRa Reception over Weak Marine Links. *ACM Trans. Sens. Netw.* **2026**, *22*, 1–23. [\[CrossRef\]](#)
30. Zeng, H.; Ma, H.; Fang, Y.; Chen, P.; Wen, W.; Min, T. A Novel Spreading-Factor-Index-Aided LoRa Scheme: Design and Performance Analysis. *arXiv* **2025**, arXiv:2506.06758. [\[CrossRef\]](#)
31. Ren, Y.; Gan, M.; Li, C.; Siam, S.I.; Zhang, M.; Chen, S.; Cao, Z. Morph: ChirpTransformer-based Encoder-decoder Co-design for Reliable LoRa Communication. *arXiv* **2025**, arXiv:2507.22851.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.