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Optimized Resource Orchestration for CS-enabled SHM in LoRa Networks

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***Abstract*—The growing demand for sustainable monitoring solutions has positioned Wireless Sensor Networks (WSNs) and Low-Power Wide Area Networks (LPWANs) as critical enablers for Structural Health Monitoring (SHM). In this work, we propose a centralized optimization framework for LoRa-based IoT networks that jointly tunes the spreading factor, coding rate, and compression factor to balance energy efficiency and data reconstruction quality. A centralized controller dynamically adjusts communication parameters based on environmental conditions and application constraints. We evaluate system performance through extensive simulations under noisy channels. Results demonstrate the effectiveness of centralized orchestration in adapting to channel variability while minimizing the computational burden.**

***Index Terms*—Orchestration, IoT, WSN, LoRa, Compressive Sensing, SHM, Optimization**

I. Introduction

In the evolving landscape of AI-enabled applications, Structural Health Monitoring (SHM) refers to the continuous or periodic monitoring of civil infrastructures (*e.g.,* bridges, buildings, and industrial structures) through distributed sensing systems aimed at detecting anomalies, degradation, or structural damage. As infrastructures grow more complex, scalable and energy-efficient sensing frameworks become essential. The rise of the Internet of Things (IoT) has enabled large scale monitoring through Wireless Sensor Networks (WSNs), where distributed nodes autonomously gather and transmit data. Yet these networks face inherent limits in energy, bandwidth, and computation, with data transmission being especially costly, an issue for remote or battery powered deployments demanding long term sustainability. LoRa technology, central to many LPWAN solutions, provides long range, low power communication but requires careful tuning of parameters such as spreading factor and coding rate. Optimizing these settings is challenging due to varying environmental conditions and application specific fidelity needs. Within this context, we consider a conceptual centralized framework that jointly optimizes compression and channel coding parameters for LoRa-based WSNs. A gateway or fog controller dynamically adjusts communication settings according to channel conditions and application needs, reducing edge node burden while ensuring high quality data reconstruction. The motivation for a centralized optimization strategy in infrastructure monitoring lies in the topological and operational asymmetry of SHM deployments. Edge sensor nodes, often battery-powered and constrained in computational resources, are poorly suited to perform complex optimization tasks. In contrast, centralized nodes possess significantly higher computational capabilities and broader network visibility. Through a logically centralized control plane, aligned with Software-Defined Networking (SDN) principles, the orchestrator can collect global network insights, assess environmental dynamics, and compute optimal communication and compression parameters. These parameters are then disseminated to edge nodes, minimizing their computational burden and ensuring consistent, network-wide operation. Such orchestration fosters intelligent resource management and adaptability, essential for long-term sustainability and reliability in real-world SHM scenarios.

In this study, we model spreading factor, compression factor, and coding rate as decision variables. Using a MATLAB-based LoRa simulator, we evaluate how AWGN, Rayleigh, and Rician noise conditions affect energy consumption and reconstruction accuracy. Instead of fully simulating the optimization model, we adopt a hybrid approach in which the theoretical framework defines objectives and constraints, while simulation experiments provide practical insights into system behavior across different scenarios. This method allows us to investigate how physical-layer variations impact application-layer performance and to assess the feasibility of centralized parameter tuning in LoRa-based IoT systems.

The contributions of this work are summarized as follows:

- we propose a conceptual orchestration framework that leverages SDN principles to coordinate compression and coding strategies in IoT-enabled WSNs, enabling adaptive, energy efficient communication tailored to global network conditions and application requirements.
- we introduce a centralized multi objective optimization model that includes spreading factor, coding rate, and compression factor as joint decision variables.
- we present a comprehensive simulation framework for evaluating data quality and energy consumption across different LoRa configurations and noise models.

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- we provide an empirical evaluation of system behavior, highlighting the trade offs between energy and quality under various environmental conditions.

This work lays the foundation for intelligent, context aware transmission strategies in smart IoT networks, offering insights into how centralized decision making can enhance network efficiency and sustainability.

The remainder of this paper is organized as follows: Section II provides an overview of the related literature. Section III introduces the workflow followed for this paper. Section IV presents some performance results from the experimental tests. Finally, the last section concludes the paper and suggests directions for future research.

II. Related Works

LoRa technology, operating within the LPWAN paradigm, is a key enabler for long range, low power IoT applications such as smart cities, industry, and environmental monitoring. Its Chirp Spread Spectrum (CSS) modulation provides robust communication under interference. Energy consumption in LoRa nodes is strongly influenced by parameters such as spreading factor, bandwidth, coding rate, and transmission power, with data volume playing a central role, making compression strategies particularly relevant. Prior studies have explored energy efficient LoRa configurations [1], dynamic parameter adjustment to improve communication quality [2], and optimization frameworks involving power allocation and spreading factor assignment [3]. Additional works examine frame size effects [4] and RSSI-based adaptive strategies [5]. Data compression reduces transmitted data volume and thus energy usage, though high compression levels may degrade reconstruction quality. Compressive Sensing (CS) [6], [7] offers an effective compromise by enabling signal recovery from sparse samples. Its applications span wireless data loss recovery [8] and adaptive sampling in sensor networks [9]. The authors' previous work has validated CS in real world infrastructural monitoring, focusing on implementation aspects [10] and modal analysis [11]. Within LoRa contexts, CS has been applied to analyze energy implications of temporal compression [12] and to enhance resilience in low rate communication [13]. However, the joint optimization of compression, coding rate, and spreading factor remains largely unexplored. Multi objective optimization provides a natural framework for trade offs, relying on Pareto optimality [14]. Pareto-based strategies have been used to jointly optimize energy efficiency and delivery ratio [15] or latency and energy [16], as well as adaptive SF allocation [17]. Yet, Pareto driven joint optimization of LoRa physical layer parameters and compression is still unexplored in the literature, to the best of the authors' knowledge. Orchestration plays a crucial role in distributed IoT and edge systems, enabling adaptive resource management under dynamic conditions. Recent works propose real time service orchestration across cloud/edge IoT for latency and energy aware workflows [18], while hybrid models like DO-CR combine distributed decisions with centralized refinement [19]. Broader orchestration frameworks highlight the importance of coordinating heterogeneous computing and networking resources at the edge [20]. Building on these insights, our work incorporates centralized optimization within a WSN architecture, treating LoRa transmission parameters and compression factors as dynamic control variables. This orchestration layer harmonizes edge constraints with global performance goals, enabling adaptive and energy efficient IoT monitoring.

III. Methodology

In this section, we formalize the orchestration framework under investigation, including the communication stack, the system model, and the optimization variables, as well as the MATLAB-based simulation framework that emulates the end to end process of signal acquisition, compression, LoRa transmission, and signal reconstruction. The system is composed of a set of resource constrained IoT nodes deployed within a LoRa-based WSN architecture. These nodes collect sensory data and transmit compressed information toward a central gateway, which is assumed to have sufficient computational capabilities to act as a central orchestrator for the network. The proposed architecture is illustrated in Fig.1. It is an SDN-inspired architecture where a logically centralized orchestrator acts as the control plane, collecting network and channel state information from distributed edge sensing nodes. Based on this global view, the controller computes resource allocation and physical-layer configuration policies (*e.g.,* compression factor, coding rate, and spreading factor), which are disseminated to the nodes through a lightweight control channel. The edge nodes operate as data-plane entities, performing sensing and data transmission according to the received configurations. The architecture is intended as a conceptual abstraction to enable joint optimization across layers rather than a fully specified protocol stack.

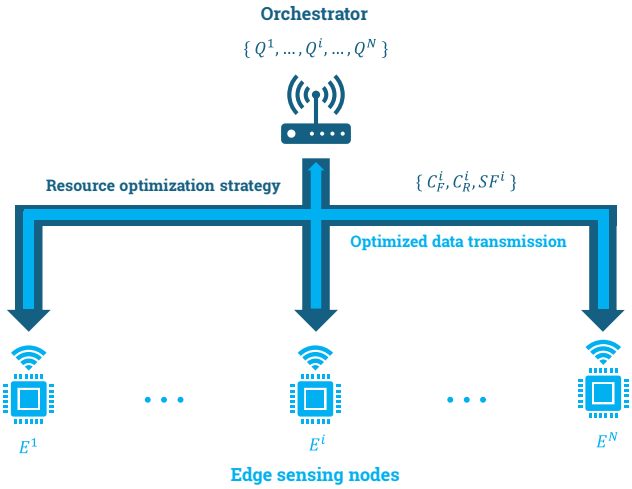

Fig. 1: The proposed centralized orchestration framework.

A. Signal Acquisition and Compression

Each sensor node collects a raw signal $\boldsymbol{x} \in \mathbb{R}^N$, representing environmental or contextual data. To reduce the volume of data transmitted over the constrained LoRa link, the node

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applies Compressive Sensing (CS), generating a compressed measurement vector $\boldsymbol{y} = \Phi \boldsymbol{x} \in \mathbb{R}^M$, with $M < N$ where N is the number of original entries and M is the size of the compressed vector, and $\Phi \in \mathbb{R}^{M \times N}$ is a sensing matrix. The compression factor C_F is defined as the ratio $C_F = M/N$, and is treated as a tunable parameter in the system.

B. Communication Model

The compressed vector $\boldsymbol{y}$ is transmitted over a LoRa physical channel. The transmission is characterized by three configurable parameters:

- **Coding Rate C_R:** determines the level of Forward Error Correction (FEC). It is selected from a finite set, as per LoRa specification:

$$C_R \in \left\{ \frac{4}{5}, \frac{4}{6}, \frac{4}{7}, \frac{4}{8} \right\} \tag{1}$$

- **Spreading Factor SF:** affects the data rate and sensitivity of the LoRa signal. The SF is chosen, again as specified in technical documentation, from:

$$SF \in \{7, 8, 9, 10, 11, 12\} \tag{2}$$

- **Channel noise model:** we consider Additive White Gaussian Noise (AWGN), Rayleigh fading, and Rician fading to simulate different environmental and propagation conditions. The SNR level, ξ, varies within a predefined range (*e.g.,* from –20 dB to +20 dB), which is the one supported by the LoRaPHY tool [21].

The transmission time T_{pkt}, and consequently the energy consumed by the node, depends on the SF, C_R, and message size B (which is a function of the compression factor C_F). A simplified energy model is:

$$E(C_F, C_R, SF) = k_P T_{pkt}(B(C_F), C_R, SF) \tag{3}$$

where k_P is the transmission power and T_{pkt} is derived from the LoRa specification. The time on air (ToA) for a LoRa transmission can be computed as [22]:

$$T_{pkt} = T_{preamble} + T_{payload} \tag{4}$$

where

$$T_{preamble} = (N_{preamble} + 4.25) \times T_s \tag{5}$$

and

$$T_{payload} = \Big(8 + \max\Big(N_{sym} \cdot (C_R + 4), 0\Big)\Big) \cdot T_s \tag{6}$$

with

$$T_s = \frac{2^{\mathrm{SF}}}{\mathrm{BW}} \tag{7}$$

and

$$N_{sym} = \left\lceil \frac{8 \cdot PL - 4 \cdot SF + 28 + 16 \cdot CRC - 20 \cdot H}{4 \cdot (SF - 2 \cdot DE)} \right\rceil \tag{8}$$

where:

- N_{preamble}: number of preamble symbols,
- PL: payload length in bytes,
- SF: spreading factor,
- C_R: coding rate,
- CRC: 1 if CRC enabled, 0 otherwise,
- H: 0 for explicit header mode, 1 for implicit,
- DE: low data rate optimization flag (1 if enabled),
- BW: bandwidth.

C. Reconstruction Quality

The compressed signal received at the gateway is affected by channel noise and decoding errors. The quality of the reconstructed signal $\hat{x}$ is evaluated using a function:

$$Q(C_F, C_R, SF) = g(C_F) + \eta(C_R, SF) \tag{9}$$

where $g(C_F)$ reflects the loss induced by the compression ratio, and η models the error introduced by the channel.

To assess the effectiveness of the proposed approach, Compressive Sensing was applied to the considered signals, and its reconstruction performance was compared when applying different spreading factors under the same compression ratio. The overall quality is evaluated using Normalized Mean Squared Error (nRMSE) between $\boldsymbol{x}$ and $\hat{\boldsymbol{x}}$ as well as their cosine similarity.

The nRMSE quantifies the relative point by point discrepancy between the original and reconstructed signals by rescaling the root mean square error with respect to the maximum absolute value of the original signal. It is computed as:

$$nRMSE = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x_i})^2}{N}} * \frac{1}{\max |\boldsymbol{x}|}, \tag{10}$$

Cosine similarity was used to complement this metric by evaluating the structural similarity between the original and reconstructed signals, regardless of amplitude differences. It is defined as:

$$sim(\boldsymbol{x}, \hat{\boldsymbol{x}}) = \frac{\boldsymbol{x} \cdot \hat{\boldsymbol{x}}}{||\boldsymbol{x}|| \cdot ||\hat{\boldsymbol{x}}||}, \tag{11}$$

where values close to $+1$ indicate high similarity in the overall shape of the signals.

By jointly employing these two metrics, it is possible to obtain a comprehensive assessment of the quality of the reconstructed signals and, consequently, a reliable measure of the effectiveness of the employed compression and decompression strategies.

D. Optimization Objective

The central goal is to find a configuration (C_F, C_R, SF, ξ) that minimizes energy consumption while ensuring a desired minimum level of reconstruction quality Q_{min}. This leads to a constrained multi objective optimization problem:

$$\begin{cases} \min_{C_F, C_R, SF} \; E(C_F, C_R, SF, \xi) \\ \max_{C_F, C_R, SF} \; Q(C_F, C_R, SF, \xi) \\ Q(C_F, C_R, SF, \xi) \geq Q_{\min} \\ \text{s.t. } C_F \in [0, 1], \; C_R \in [\frac{4}{5}, \frac{4}{6}, \frac{4}{7}, \frac{4}{8}], \; SF \in [7, ..., 12] \end{cases} \tag{12}$$

This model is not directly solved in simulation, but rather guides the selection of parameters to explore via empirical evaluation.

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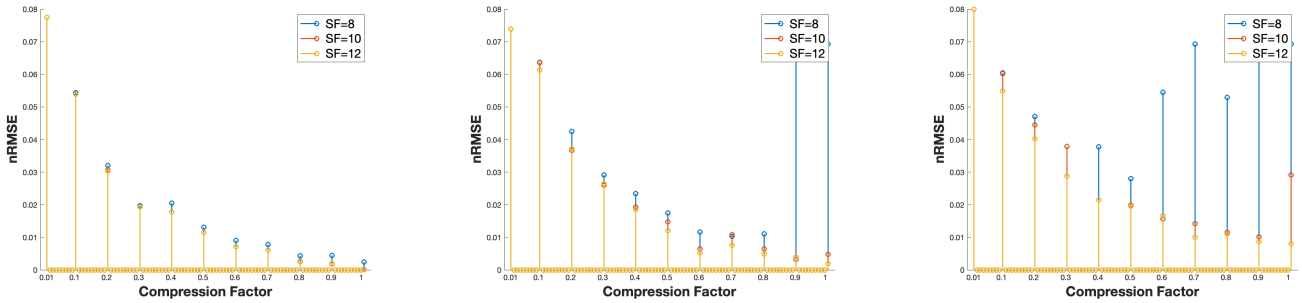

(a) AWGN - Railway Bridge [23], [24] (b) Rician Fading + AWGN - Railway Bridge (c) Rayleigh Fading + AWGN - Railway Bridge

Fig. 2: nRMSE values for the railway bridge cases (frequency domain, ξ = -18dB)

IV. Results

This section presents the results of the MATLAB-based simulations designed to analyze how spreading factor (SF), coding rate (C_R), compression factor (C_F), and channel conditions affect both node energy consumption and reconstruction quality at the gateway. The aim is to characterize the trade-offs between energy consumption, reconstruction quality, and channel conditions under centralized parameter tuning.

A. Simulation Pipeline

Each simulation trial consists of the following steps

- **Signal acquisition:** various signals have been acquired from real world structures and used for this simulation; publicly available data, such as that from a dataset [23], [24] capturing train induced vibrations on a railroad bridge, was also used.
- **Compression via CS:** the signal is compressed by pseudosampling it, leading to a target $C_F = M/N$;
- **LoRa transmission modeling:** the compressed signal is encoded using the selected Coding Rate and Spreading Factor, then the encoded signal is passed through a simulated channel model, where AWGN, Rayleigh, or Rician noise is added, with ξ varying from –20 dB to +20 dB. Finally, the received signal is demodulated and decoded.
- **Signal reconstruction:** the received and possibly corrupted compressed signal is reconstructed using Basis Pursuit CS recovery.
- **Metric computation:** after reconstruction, signal quality is evaluated using the normalized Root Mean Square Error (nRMSE) and cosine similarity, capturing both amplitude accuracy and shape preservation. Additionally, Time on Air (ToA) is computed to assess transmission latency, providing a clear view of the trade offs between quality, energy, and communication time.

B. Numerical Outcomes

We first assessed the relationship between SF, signal to noise ratio (ξ), and Compressive Sensing reconstruction under an AWGN channel. The results highlight the trade off: low SF values (e.g., 7–8) reduce time on air and energy consumption but suffer in low SNR regimes, while high SF values (11–12) improve robustness and reconstruction quality at the cost of higher energy usage. Figures 2a and 3a confirm that this sensitivity is most pronounced at very low SNR, whereas at higher SNR LoRa mitigates noise regardless of SF and C_R.

To capture more realistic propagation conditions, we also evaluated Rayleigh and Rician fading models. Rayleigh produced the strongest degradation, with large RMSE fluctuations, particularly at low C_R where error correction is limited. Rician performance lays between AWGN and Rayleigh. These results emphasize that relying solely on AWGN leads to optimistic performance estimates, underscoring the need for realistic channel modeling.

The interplay between SF and C_R also directly affects time on air (ToA), and thus energy consumption and system scalability. Low SF and low C_R configurations minimize ToA and energy cost, making them suitable when energy efficiency and network capacity are primary goals. Higher SF and C_R significantly increase ToA but improve resilience to channel impairments, offering higher reconstruction reliability, beneficial in harsh or noisy environments.

These findings highlight the advantages of centralized control for parameter selection in constrained IoT systems. Although a direct comparison with distributed adaptation is left for future work, the results indicate that centralized orchestration allows more coherent adjustment of parameters across heterogeneous nodes, balancing energy usage and fidelity while reducing unnecessary retransmissions. It also enables enforcement of application level requirements, such as minimum reconstruction quality or prioritization of critical data streams.

Overall, the simulations confirm that careful centralized tuning of compression, coding, and transmission parameters enables LoRa-based IoT systems to achieve a balanced compromise between energy savings and reconstruction performance, supporting scalable and sustainable monitoring deployments.

V. Conclusion and Future Developments

In this work, we examined a centralized optimization framework for LoRa-based IoT networks operating under strict energy, bandwidth, and computational constraints, and subject to realistic AWGN, Rayleigh, and Rician fading. By varying

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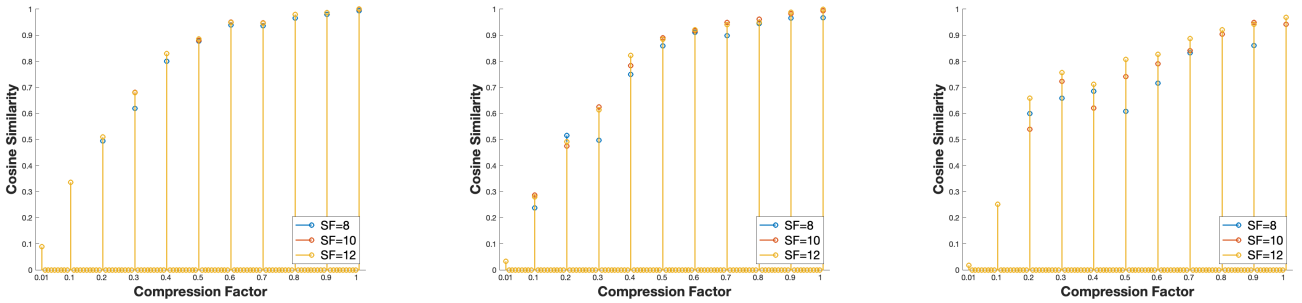

(a) AWGN - Road Bridge (b) Rician Fading + AWGN - Road Bridge (c) Rayleigh Fading + AWGN - Road Bridge

Fig. 3: Cosine similarity values for the road bridge cases (frequency domain, ξ = -18dB)

spreading factor, coding rate, and compression factor, we evaluated how these parameters jointly affect the trade off between energy consumption and Compressive Sensing reconstruction quality. The simulations reveal clear trade offs that centralized control can exploit to balance efficiency and fidelity. Higher spreading factors and coding rates improve robustness in low ξ and fading conditions, whereas compression reduces bandwidth usage but must be tuned to avoid excessive quality loss. Overall, centralized orchestration effectively adapts parameters to channel variations and application requirements, supporting scalable and energy efficient operation in constrained environments. Future work includes developing lightweight predictive models for real time parameter selection, integrating centralized scheduling based on data priority and battery status, extending the framework to account for mobility induced Doppler and cross network interference, validating the approach on physical LoRa testbeds, and exploring more advanced coding strategies to enhance resilience while reducing energy cost. These efforts will further advance intelligent, sustainable IoT systems capable of delivering reliable, high quality data in distributed sensing applications.

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