Optimizing Energy Efficiency and Data Quality in WSNs: A Distributed Approach

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***Abstract*—The integration of Social Internet of Things (SIoT) paradigms with Wireless Sensor Networks (WSNs) offers significant improvements in the efficiency, scalability, and intelligence of distributed sensing systems. However, these networks are often subject to severe resource constraints, particularly at the edge, where sensor nodes are typically battery-powered and limited in computational power, memory, and communication bandwidth. Consequently, the introduction of control and management traffic must be carefully limited to avoid compromising network performance. In this work, we tackle the problem of multi-objective optimization in resource-constrained SIoT environments. Specifically, we aim to reduce the energy consumption of edge sensor nodes while improving the quality of the received data, taking into account the underlying channel conditions. To this end, we propose a distributed optimization strategy that minimizes energy consumption and maximizes data quality, while implicitly reducing the overhead associated with signaling and control messages. This framework explores the trade-offs between energy efficiency and data reconstruction accuracy, leveraging both Compressive Sensing (CS) to effectively reduce the transmission burden, and channel coding techniques to enhance data protection in LoRa-based WSNs.**

***Index Terms*—Multi-objective optimization, Social IoT, Edge computing, Wireless Sensor Networks, Compressive Sensing, LoRa, Energy efficiency, Data quality, Pareto optimization**

I. Introduction

The Social Internet of Things (SIoT) enhances traditional IoT systems by integrating social networking principles, allowing smart objects to autonomously form relationships based on interactions, ownership, and functionality, fostering cooperation, trust management, and resource sharing, benefiting applications like smart cities, intelligent transport, and healthcare [1]. Traditional Wireless Sensor Networks (WSNs) rely on predefined routing protocols but struggle with energy constraints and adaptability. Integrating SIoT with WSNs improves efficiency and scalability by introducing a social layer, enabling nodes to establish relationships based on functions, past interactions, and trust [2]. In spite of this improvements, battery life, memory, and bandwidth still linger as challenges in implementing SIoT mechanisms due to added signaling and processing overhead. Social behaviors in humans and animals can follow centralized or distributed coordination strategies [3]. Centralized models, seen in military operations and orchestras, require continuous communication with a master entity. In contrast, distributed strategies, as seen in rescue teams, jazz bands, and bird flocks, rely on local interactions and predefined rules for efficiency. For example, bees follow centralized pheromone-based signaling [4], while migrating butterflies and sardines operate independently, optimizing survival through local adaptation. Effective distributed systems work toward a shared objective function without explicit communication. Applying this to SIoT in resource-constrained WSNs, decentralized decision-making can reduce inter-node traffic while maintaining social relationships efficiently [5].

This work proposes a distributed optimization approach that jointly minimizes energy consumption and maximizes data reconstruction quality in WSNs. While high-speed technologies, such as 5G, enable massive data transfer, low-power alternatives such as LoRa are more suitable for IoT applications, supporting long-range communication with minimal energy consumption. To enhance transmission efficiency, Compressive Sensing (CS) is employed to reduce data volume while preserving signal integrity. However, excessive compression can degrade signal reconstruction, especially in noisy environments. LoRa's forward error correction (FEC) mitigates such degradation but increases transmission overhead, creating a trade-off between energy efficiency and reliability. To address this challenge, we propose an optimization framework that balances these conflicting objectives. By leveraging Pareto Optimization, we identify optimal trade-offs rather than a single solution, allowing flexible adaptation to application requirements. The novelty of this work lies in applying Pareto Optimization to jointly optimize CS compression and LoRa coding rates.

The key contributions are:

- formulation of a Pareto Optimization framework for joint optimization of compression factor and coding rate in LoRa networks;
- exploration of the trade-offs between energy consumption and data reconstruction quality;
- use of compressive sensing to reduce transmission energy consumption;
- proposal of a distributed optimization method to enhance efficiency and reliability.

This work contributes to more sustainable and scalable SIoT systems by optimizing energy-efficient data transmission. The paper is structured as follows: Section II reviews relevant literature, Section III defines the problem and presents the framework, Section IV discusses experimental results, and the final section concludes with future research directions.

II. Related Works

Data compression reduces transmission volume, conserving energy but often degrading signal quality. Compressive Sensing (CS) offers a promising solution, enabling signal recovery from limited data samples [6]. It has been widely applied in IoT, including wireless sensor network data recovery [7], health monitoring [8] and adaptive sampling [9]. Additionally, [10] integrates CS into an energy-efficient scheduling method while [11] applies it to secure key delivery in LoRa networks. Previous works by the authors explored CS for infrastructural monitoring, examining its effectiveness in real-world applications [12], [13].

LoRa, a key Low Power Wide Area Network (LPWAN) technology, is widely used in IoT applications like environmental monitoring and smart cities due to its long-range communication and low power needs. It employs Chirp Spread Spectrum (CSS) for robust transmission with parameters such as spreading factor, bandwidth, and coding rate influencing its functioning. Since data volume directly impacts energy consumption, efficient compression is essential. Various studies have explored energy-efficient LoRa communication: [14], [15] propose dynamic adaptation strategies based on transmission conditions, while [16] analyzes the effect of frame size on energy consumption. Other works, such as [17], optimize signal parameters for better coverage and resource efficiency and lastly [18], [19], address energy efficiency in uplink LoRa through nonconvex optimization.

Multi-objective optimization balances conflicting goals, with Pareto optimality providing solutions where improving one metric degrades another [20]. Pareto methods have been applied in IoT, such as adaptive LoRa network tuning [21], optimizing power allocation for packet delivery [22], and minimizing energy and latency [23]. Despite extensive research, the joint optimization of compression and coding rate in LoRa remains an open problem, which this paper aims to address.

III. Methodology

LoRa is a low-power, long-range communication technology based on Chirp Spread Spectrum (CSS), operating in sub-GHz ISM bands (e.g., 868 MHz in Europe, 915 MHz in North America). It offers robust connectivity over kilometers while resisting interference and Doppler effects, making it ideal for IoT applications like smart metering and industrial automation. Key transmission parameters include the Spreading Factor (SF), which balances range and data rate (higher SF means longer range but lower throughput), and the Coding Rate (CR), which improves error correction but increases airtime. Optimizing these parameters is crucial for energy-efficient and reliable communication.

CS is a signal processing technique that reconstructs sparse signals using fewer measurements than required by Nyquist sampling. It exploits signal sparsity in domains like wavelets or Fourier transforms, enabling efficient data acquisition and transmission. CS uses a sensing matrix to project signals into a lower-dimensional space, with common recovery methods including Basis Pursuit (BP) and Orthogonal Matching Pursuit (OMP). In IoT applications, CS reduces data transmission needs, conserving energy while maintaining signal integrity, making it valuable for resource-constrained networks like LoRa. However, designing efficient sensing matrices and ensuring robust reconstruction remain key challenges.

A. System Model and Problem Formulation

Energy consumption in a LoRa node mainly depends on transmission related parameters, such as amount of transmitted data, transmission power, spreading factor. Compressing the amount of data to be sent allows for energy saving, while introducing a potentially degraded reconstruction quality at the receiver. On the contrary, lower compression allows for increased quality at the cost of energy consumption.

The two opposing objectives are then:

- **Minimization of energy consumption**: by maximizing compression and reducing redundancy.
- **Maximization of reconstruction quality**: by preserving data and using higher error correction.

Balancing these requires a multi-objective optimization approach rather than a single-focus optimization.

When optimizing for both energy consumption and data quality, key factors influencing performance include:

- **Compression Factor ($\mathbf{C_F}$)**: controls data reduction before transmission. Higher compression saves energy but may degrade data quality.
- **Coding Rate ($\mathbf{C_R}$)**: adds redundancy to sent data for improved noise resilience. A higher coding rate leads to increased energy consumption but improves received signal quality.

A Pareto Optimization framework is used to balance energy efficiency and data quality. The Pareto front identifies optimal trade-offs where improving one factor worsens the other.

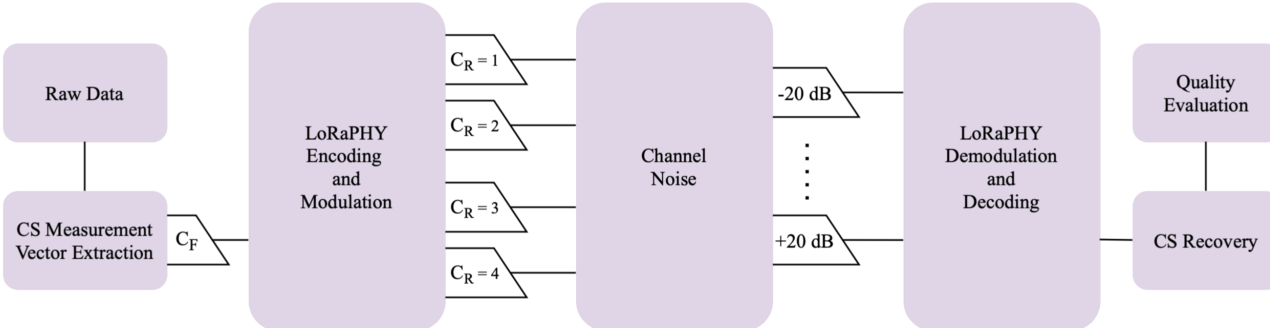

Fig. 1. A diagram summarizing the workflow and methodology employed in the experimental tests.

B. Proposed Distributed Multi-Objective Optimization

The Pareto optimization problem is formulated as:

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

The challenge lies in balancing two opposing goals: reducing energy consumption, $E(C_F, C_R)$, while simultaneously enhancing data reconstruction quality, $Q(C_F, C_R)$. This optimization must adhere to predefined constraints on C_F and C_R and guarantee that the reconstruction quality does not fall below Q_{min}, ensuring satisfactory data fidelity at the receiver.

The weighted sum function:

$$J(C_F, C_R) = \alpha E(C_F, C_R) - \beta Q(C_F, C_R) \tag{2}$$

where γ and δ adjust the trade-off between consumed energy $E(C_F, C_R)$ and reconstruction quality $Q(C_F, C_R)$. This method efficiently explores different Pareto-optimal solutions based on system constraints and channel conditions, ensuring energy-aware and quality-preserving transmissions.

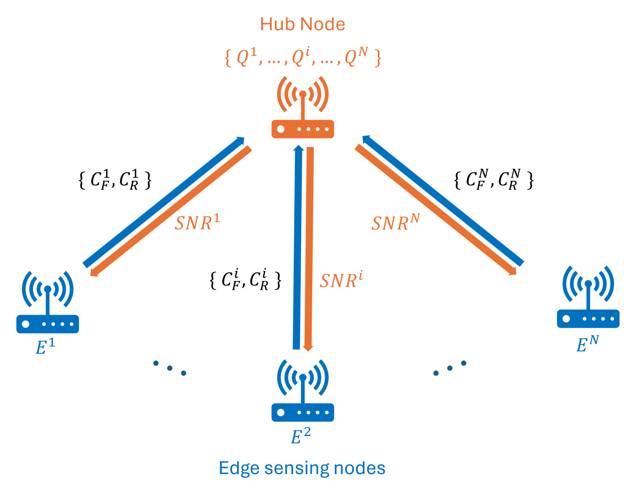

Fig. 2. A scheme illustrating the reference scenario and the parameters used in the experimental analysis.

IV. Results

The experimental setup involves deploying N sensing nodes to monitor signals, where each node transmits data to a central hub. Fig.2 illustrates the reference scenario and the parameters used in the experimental analysis. Energy consumption E^i and reconstruction quality Q^i are the key metrics, influenced by the communication parameters C_F^i and C_R^i as well as the channel state, summarized by the signal-to-noise ratio SNR^i, as shown in Figure 1. Using LoRaPHY in Matlab [24], [25], the study simulates LoRa communications under Additive White Gaussian Noise (AWGN) with SNR^i ranging from -20 to $+20$ dB. This setup enables analysis of how compression factor, coding rate, and noise levels affect data transmission and recovery. Real-life signals from an experimental structure and a road bridge were compressed at various rates, transmitted, and reconstructed using compressive sensing (CS). The study assesses the impact of these parameters on reconstruction accuracy through regression analysis, predicting $Q(C_F, C_R)$ based on channel state while keeping the spreading factor constant. Figure 3 shows an example of computed regression curves for nRMSE values at varying C_F and C_R values.

Numerical results indicate that polynomial regression effectively models $Q(C_F, C_R)$ across different coding rates and noise levels. Representative cases for SNR = $\{-18, -15, -12\}$ dB illustrate system behavior under varying noise conditions. They are shown in Tables I, II, III, IV, V and VI. Highly sparse vibrational signals from the experimental structure achieve low normalized RMSE (nRMSE), confirming CS's efficiency. The study establishes an empirical threshold of 0.03 for well-recovered signals and shows that higher C_R values enhance CS recovery by improving noise resilience. Even under the effect of noise, CS reconstructs signals effectively by mitigating distortions at the byte level.

Setting the coding rate to $C_R = 4/8$ generally results in higher amount of transmitted packets, influencing energy efficiency. A benchmark comparison with an ideal noise-free CS scenario provides insight into performance limitations. To make a fair comparison related to the effect of varying C_R on data reconstruction, all tests performed at the same C_F start from the same CS measurement vector, thus removing

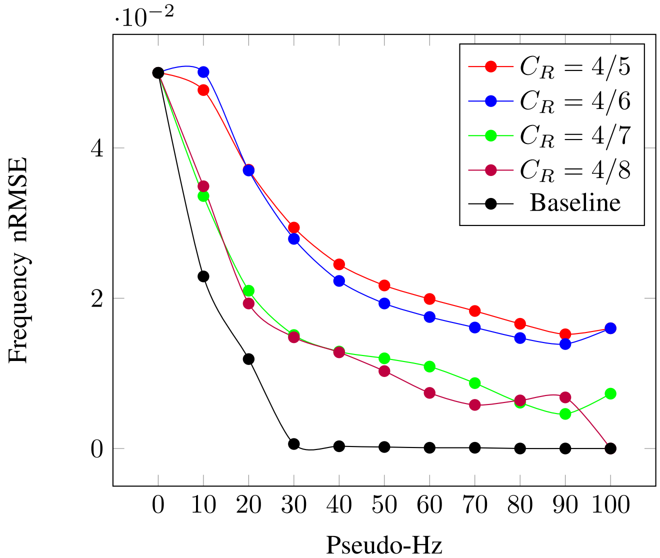

Fig. 3. Comparison of nRMSE values obtained while varying C_F (Pseudo-Hz) and C_R values.

TABLE I
SHAKER NRMSE (FREQUENCY DOMAIN), -18DB

PsHz \ CR	4/5	4/6	4/7	4/8	No Noise
10	0.0477	0.0501	0.0336	0.0349	0.0230
20	0.0371	0.0370	0.0210	0.0193	0.0119
30	0.0294	0.0279	0.0151	0.0148	0.0067
40	0.0245	0.0223	0.0129	0.0128	0.0038
50	0.0217	0.0193	0.0120	0.0103	0.0023
60	0.0199	0.0175	0.0109	0.0074	0.0017
70	0.0183	0.0161	0.0087	0.0058	0.0012
80	0.0166	0.0147	0.0061	0.0064	0.0007
90	0.0152	0.0139	0.0046	0.0068	0.0004
100	0.0160	0.0160	0.0073	0.0000	0.0000

the dependency of the result on the compressive sensing recovery algorithm. Signals from the bridge, being less sparse, experience slightly higher nRMSE values, though they follow similar trends. At reduced noise levels (LoRaPHY shows that noise impact becomes negligible above -10 dB), regression curves for different C_R values converge, aligning closely with theoretical best-case performance.

V. Conclusion

In this work, we tackled the challenge of multi-objective optimization in resource-constrained SIoT environments, focusing on minimizing the energy consumption of edge WSN nodes while optimizing the quality of received data based on channel conditions. In particular, we propose a distributed optimization strategy that simultaneously minimizes energy consumption and maximizes data quality, while implicitly reducing the overhead from signaling and control messages. To this end, we formulate a Pareto optimization framework that

TABLE II
SHAKER NRMSE (FREQUENCY DOMAIN), -15DB

PsHz \ CR	4/5	4/6	4/7	4/8	No Noise
10	0.0301	0.0340	0.0262	0.0263	0.0230
20	0.0168	0.0162	0.0107	0.0112	0.0119
30	0.0128	0.0124	0.0065	0.0068	0.0067
40	0.0114	0.0112	0.0054	0.0054	0.0038
50	0.0098	0.0087	0.0041	0.0037	0.0023
60	0.0074	0.0056	0.0021	0.0016	0.0017
70	0.0053	0.0043	0.0006	0.0004	0.0012
80	0.0045	0.0059	0.0005	0.0008	0.0007
90	0.0051	0.0076	0.0015	0.0018	0.0004
100	0.0047	0.0000	0.0000	0.0000	0.0000

TABLE III
SHAKER NRMSE (FREQUENCY DOMAIN), -12DB

PsHz \ CR	4/5	4/6	4/7	4/8	No Noise
10	0.0244	0.0245	0.0244	0.0244	0.0230
20	0.0097	0.0097	0.0097	0.0097	0.0119
30	0.0057	0.0056	0.0057	0.0057	0.0067
40	0.0047	0.0046	0.0047	0.0047	0.0038
50	0.0035	0.0035	0.0035	0.0035	0.0023
60	0.0018	0.0018	0.0018	0.0018	0.0017
70	0.0005	0.0006	0.0006	0.0006	0.0012
80	0.0006	0.0006	0.0007	0.0007	0.0007
90	0.0013	0.0013	0.0013	0.0013	0.0004
100	0.0000	0.0000	0.0000	0.0000	0.0000

jointly addresses data compression and channel coding, exploring the inherent trade-offs between energy efficiency and signal reconstruction accuracy. Our approach leverages compressive sensing to significantly reduce transmission energy requirements, and integrates channel coding techniques to enhance communication reliability. By tackling these aspects, we lay the foundation for energy-efficient communications in LoRa networks, enabling the development of sustainable and scalable IoT systems.

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TABLE IV
BRIDGE nRMSE (FREQUENCY DOMAIN), -18dB

PsHz \ CR	4/5	4/6	4/7	4/8	No Noise
10	0.0538	0.0528	0.0507	0.0515	0.0479
20	0.0375	0.0380	0.0352	0.0349	0.0360
30	0.0288	0.0307	0.0279	0.0268	0.0255
40	0.0235	0.0264	0.0231	0.0220	0.0217
50	0.0193	0.0225	0.0183	0.0179	0.0151
60	0.0154	0.0180	0.0132	0.0135	0.0107
70	0.0119	0.0133	0.0086	0.0090	0.0082
80	0.0090	0.0091	0.0055	0.0054	0.0046
90	0.0071	0.0064	0.0038	0.0035	0.0012
100	0.0053	0.0056	0.0017	0.0036	0.0000

TABLE V
BRIDGE nRMSE (FREQUENCY DOMAIN), -15dB

PsHz \ CR	4/5	4/6	4/7	4/8	No Noise
10	0.0554	0.0544	0.0543	0.0543	0.0479
20	0.0378	0.0376	0.0368	0.0366	0.0360
30	0.0278	0.0285	0.0271	0.0267	0.0255
40	0.0219	0.0227	0.0210	0.0206	0.0217
50	0.0175	0.0179	0.0162	0.0160	0.0151
60	0.0135	0.0136	0.0120	0.0120	0.0107
70	0.0099	0.0100	0.0083	0.0083	0.0082
80	0.0068	0.0072	0.0053	0.0052	0.0046
90	0.0046	0.0042	0.0030	0.0028	0.0012
100	0.0031	0.0024	0.0002	0.0006	0.0000

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TABLE VI
BRIDGE nRMSE (FREQUENCY DOMAIN), -12dB

PsHz \ CR	4/5	4/6	4/7	4/8	No Noise
10	0.0513	0.0512	0.0511	0.0508	0.0479
20	0.0359	0.0358	0.0356	0.0354	0.0360
30	0.0263	0.0265	0.0262	0.0261	0.0255
40	0.0201	0.0205	0.0202	0.0201	0.0217
50	0.0156	0.0160	0.0156	0.0156	0.0151
60	0.0119	0.0121	0.0117	0.0116	0.0107
70	0.0085	0.0084	0.0080	0.0079	0.0082
80	0.0053	0.0050	0.0045	0.0045	0.0046
90	0.0025	0.0023	0.0016	0.0016	0.0012
100	0.0006	0.0005	0.0000	0.0000	0.0000

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