



Evaluating Performance Parameters of Long-Range IoT Communication Protocols

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Abstract: *The rapid proliferation of IoT devices has introduced significant challenges in optimizing power consumption and communication efficiency, particularly in energy-constrained environments. LoRa, a widely used Low Power Wide Area Network (LPWAN) technology, offers long-range communication with minimal energy usage. However, static configurations often result in suboptimal performance under dynamic network conditions. This paper focuses on analyzing and optimizing the LoRa wireless protocol to enhance energy efficiency without compromising network reliability. Key performance metrics such as latency, packet error rate (PER), scalability, and energy consumption are evaluated. By implementing Adaptive Data Rate (ADR) mechanisms and optimizing protocol parameters, this research aims to extend battery life while maintaining seamless connectivity. The findings contribute to the development of sustainable IoT networks, with applications in smart cities, industrial automation, and environmental monitoring. The proposed optimizations enable intelligent, energy-aware communication strategies, ensuring efficient and scalable IoT deployments.*

Keywords: IoT, Energy Efficiency, LoRa, Adaptive Data Rate, Scalability, Latency, Network Optimization.

I. INTRODUCTION

The Internet of Things (IoT) has transformed industries by enabling seamless device-to-device communication, enhancing automation, monitoring, and control across diverse applications, from smart homes to large-scale industrial systems. This interconnected network relies heavily on efficient communication protocols, particularly in power-constrained environments where devices operate on limited battery resources. Low Power Wide Area Network (LPWAN) technologies such as LoRa (Long Range) have gained prominence due to their ability to support long-range communication with minimal energy consumption.

Existing research has extensively analyzed LoRa's performance in terms of latency, energy consumption, and bandwidth utilization. However, most implementations operate on static configurations, leading to suboptimal performance in varying environmental conditions and network loads. A key challenge remains in dynamically adapting LoRa parameters such as spreading factor, transmission power, and data rate to optimize energy efficiency while maintaining reliable communication. This paper addresses these challenges by implementing adaptive algorithms that adjust LoRa configurations based on real-time environmental factors and network demands. By leveraging intelligent optimization techniques, the proposed approach aims to enhance the energy efficiency of IoT deployments, extending device lifespan and improving overall network performance.



Parameter	LoRaWAN	Sigfox	NB-IoT	LTE-M	Zigbee (802.15.4)	Wi-Fi
Throughput	10 kbps - 50 kbps	Up to 100 kbps	Up to 200 kbps	Up to 1 Mbps	20 kbps - 250 kbps	54 Mbps - 1.3 Gbps
Packet Error Rate (PER)	Low at low data rates, increases with distance	Low	Medium	Medium	High in dense networks	High in congested areas
Bit Error Rate (BER)	Low for SF12, higher for SF7	High due to ultra-narrowband	Medium	Medium	High	Low
Latency	High (~1-10 sec, depends on SF and payload size)	Very high (~10 sec)	Medium (~1 sec)	Low (~50 ms)	Low (~10-50 ms)	Very low (~1-10 ms)
Efficiency	High for low-power applications	Low due to message size limitations	Medium	Medium	Low	Low
Coverage	2 km – 20 km	3 km – 50	1 km – 10 km	1 km-10 km	30m – 100m	15 m – 100 m
Battery Life	10+ years	10+ years	~5 years	~3-5 years	1-2 years	<1 year

Table 1: Comparison of Various LPWAN Technologies [14]

LoRa is a better option for low-power wide-area IoT devices because it has long range, low power requirements, and is economical. It provides wide coverage and is best suited for smart agriculture, industrial automation, and smart cities. LoRa operates in unlicensed spectrum, thus keeping costs lower than that of NB-IoT and LTE-M. Its adaptive data rate and spreading factors provide power efficiency optimization, enabling 10-year battery life.

II. LITERATURE REVIEW

The increasing adoption of the Internet of Things (IoT) has led to the exploration of various communication protocols, with Low Power Wide Area Networks (LPWANs) emerging as a prominent solution for long-range, low-power connectivity. Among LPWANs, LoRa and LoRaWAN have gained significant attention due to their suitability for smart cities and industrial applications [1].

Centenaro et al. [1] discussed the role of LoRaWAN in unlicensed frequency bands, emphasizing its potential in large-scale IoT deployments. Their study highlighted the advantages of LoRaWAN in terms





of cost-efficiency and coverage. Augustin et al. [2] conducted a detailed analysis of LoRa technology, discussing its modulation scheme, energy efficiency, and applicability in various IoT use cases.

Similarly, Raza et al. [3] provided an overview of LPWAN technologies, comparing LoRaWAN with other alternatives such as Sigfox and NB-IoT. The limitations of LoRaWAN, particularly in dense network environments, have been explored by multiple researchers. Adelantado et al. [4] analyzed the scalability challenges of LoRaWAN and proposed solutions to mitigate network congestion. Bor et al. [5] examined the potential of LoRa for IoT applications, identifying interference and data rate limitations as key issues.

Further, researchers have evaluated the performance of LoRaWAN under different environmental conditions. Rademacher et al. [6] conducted large-scale measurements to study path loss in urban LoRa networks, demonstrating variations in signal propagation due to building density and interference. Jones and Hasan [7] explored time-synchronization techniques in LoRaWAN to enhance network reliability. Additionally, Hou et al. [8] proposed a blockchain-enabled LoRa system with edge computing, aiming to enhance data security and processing efficiency. Recent studies have focused on optimizing LoRaWAN deployments for IoT applications.

Thyagarajan et al. [9] provided a comprehensive analysis of network planning strategies, considering factors such as gateway placement and transmission power adjustments. Sanchez-Iborra et al. [12] evaluated the impact of environmental conditions on LoRaWAN performance, finding that interference and humidity levels significantly affect data transmission. Campos et al. [13] utilized NS-3 simulations to model LoRa network behavior under different configurations.

Moreover, advancements in adaptive communication techniques have been explored. Mathews et al. [15] investigated packet error rates in LoRa networks with increasing node density, suggesting adaptive spreading factor selection as a potential solution. Bankov et al. [18] developed a mathematical model to estimate packet collision probability and optimize transmission power in LoRaWAN networks. In addition, studies have examined the application of machine learning and artificial intelligence in LoRa optimization. The LoRA+ framework, proposed in 2023, introduced an efficient low-rank adaptation technique for large models, which could be extended to LoRa-based systems [10]. Similarly, the LoRA-GA model applied gradient approximation to optimize LoRaWAN deployments [11].

Overall, the literature suggests that while LoRaWAN offers significant advantages in IoT communication, challenges related to scalability, interference, and performance optimization must be addressed for widespread adoption. Future research should focus on hybrid network models, integrating LoRaWAN with AI-driven techniques for enhanced efficiency and reliability.

IV. METHODOLOGY

The methodology adopted for this research work focuses on optimizing LoRa parameters to achieve energy-efficient communication while maintaining reliable network performance. The study involves hardware implementation, simulation, and mathematical analysis related to the given parameters.

Key Methods and Functionalities:



1. Hardware Implementation:

The experimental setup for evaluating LoRa performance involves various hardware components, including LoRa transceivers, microcontrollers, gateways, and sensors. These components are configured to simulate real-world IoT deployment scenarios in both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) environments.

- LoRa 3 Modules (SX1276/SX1278-based)
- STM32 Microcontroller
- Sensors (Temperature, Humidity, etc.)
- Gateway (LoRaWAN-enabled)
- Power Supply Unit (Battery or DC source)

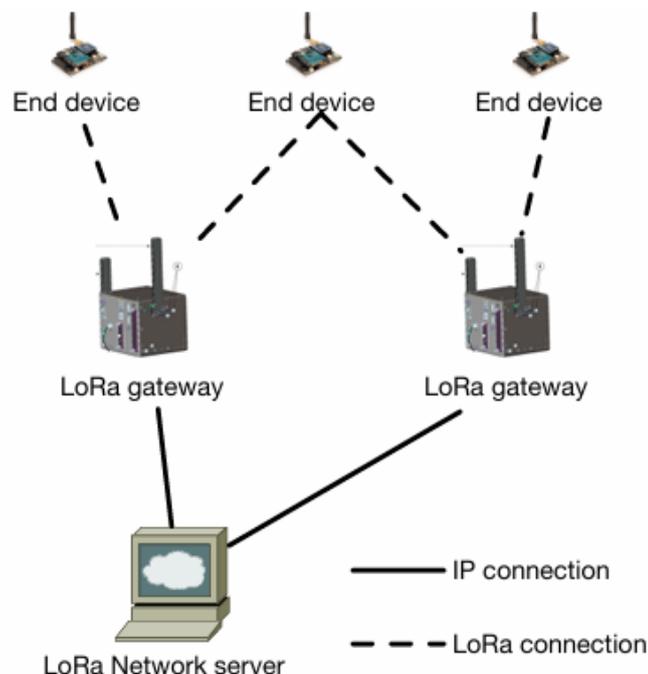


Figure 1: LoRa network Architecture [2]

The basic architecture of a LoRaWAN network is as follows: end-devices communicate with gateways using LoRa with LoRaWAN. Gateways forward raw LoRaWAN frames from devices to a network server over a backhaul interface with a higher throughput, typically Ethernet or 3G. Consequently, gateways are only bidirectional relays, or protocol converters, with the network server being responsible for decoding the packets sent by the devices and generating the packets that should be sent back to the devices. There are three classes of LoRa end-devices, which differ only with regards to the downlink scheduling [2].

2. Simulation:



Simulation is an important aspect of this research since it enables us to simulate how the LoRa network performs under various conditions without the need to create physical prototypes for each case. Although there are numerous tools for simulation, we used Python since it is flexible, simple to use, and has a vast number of libraries that make it ideal for data analysis, visualization, and modeling. There are several tools for simulating IoT networks, such as NS-3, OMNeT++, MATLAB, and LoRaSim. However, for this study, we use Python because of its powerful libraries for data analysis, visualization, and numerical computing.

Need for Selecting Python as a Simulation Tool:

- **Ease of Use:** Python is easy to use and has a clean syntax, which makes it easier to use even for programming students who are beginners.
- **Powerful Libraries:** Python provides us with powerful libraries such as NumPy, Matplotlib, SciPy, and Pandas that assist us in processing data, doing complex computations, and visualizing things.
- **Flexibility:** Python enables us to model various network conditions, including different numbers of devices, environmental barriers, and signal interference.

Tools and Techniques:

- **NumPy:** Utilized for numerical computation, e.g., signal strength analysis and packet transmission rates.
- **Matplotlib:** Utilized to plot graphs and visualizations, e.g., plotting packet error rate vs. distance.
- **SciPy:** Utilized for high-level mathematical functions, e.g., network parameter optimization.
- **Pandas:** Utilized to structure and analyze large data sets, e.g., sensor data gathered from the network.
- **I-CUBE-LRWAN:** A software package that emulates the LoRaWAN protocol, which allows us to see how data is received and sent in an actual LoRa network.

Implementation in Simulation:

- **Network Modeling:** We simulated a virtual LoRa network with several devices transmitting data to a central gateway. This allowed us to see how the network behaves when lots of devices are transmitting at the same time.
- **Environmental Conditions:** We modeled various environments, e.g., cities with high-rise buildings (which may interfere with signals) and open countryside (where signals can propagate further).
- **Parameter Optimization:** We experimented with various LoRa parameters, e.g., Spreading Factor (SF), Bandwidth (BW), and Coding Rate (CR), to observe their impact on performance. For instance, we varied the Spreading Factor to observe its effect on battery life and signal range.

3. Mathematical Analysis:



- **Packet Error Rate (PER) vs. Number of Nodes:**

Definition: PER represents the probability that a transmitted packet is received with errors. It increases as the number of nodes in a LoRa network increases due to collisions and interference.

Mathematical Model:

$$PER = 1 - (1 - P_c)^N$$

Where:

P_c = Collision probability for a single node

N = Total number of nodes in the network

Analysis:

- As NNN increases, PERPERPER increases due to more overlapping transmissions.
- To mitigate this, techniques like Adaptive Data Rate (ADR) and optimized channel allocation can be employed [2].
- This theoretical graph serves as a reference for our ongoing research, where we have modified certain parameters to improve network performance.

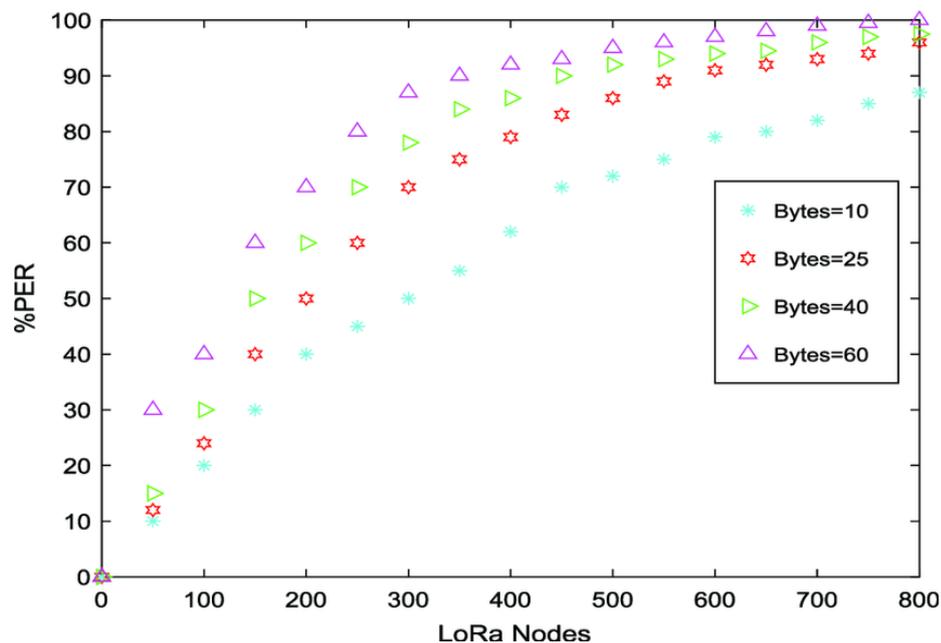


Figure 2: Packet Error Rate (PER) vs. Number of LoRa Nodes [15]

- **Time-on-Air Analysis with Payload for Different Coding Rates:**

Definition: Time-on-Air (ToA) is the duration a LoRa packet occupies the channel. It depends on spreading factor (SF), payload size, bandwidth, and coding rate (CR).

Mathematical Model:



$$ToA = (PreambleTime + PayloadTime)$$

where:

$$PayloadTime = \frac{8 + \max\left(\frac{(8 \times PL - 4 \times SF + 28 + 16 - 20 \times H)}{4 \times (SF - 2DE)}, 0\right) \times (CR + 4)}{BW}$$

PL = Payload size (bytes)

SF = Spreading Factor

CR = Coding Rate

BW = Bandwidth

H = Header mode (0 for explicit, 1 for implicit)

DE = Low Data Rate Optimization

Analysis:

- A higher SF increases ToA, reducing network capacity.
- Optimizing coding rate and payload size can reduce ToA while maintaining reliable communication [9].
- This theoretical graph serves as a reference for our ongoing research, where we have modified certain parameters to improve network performance.

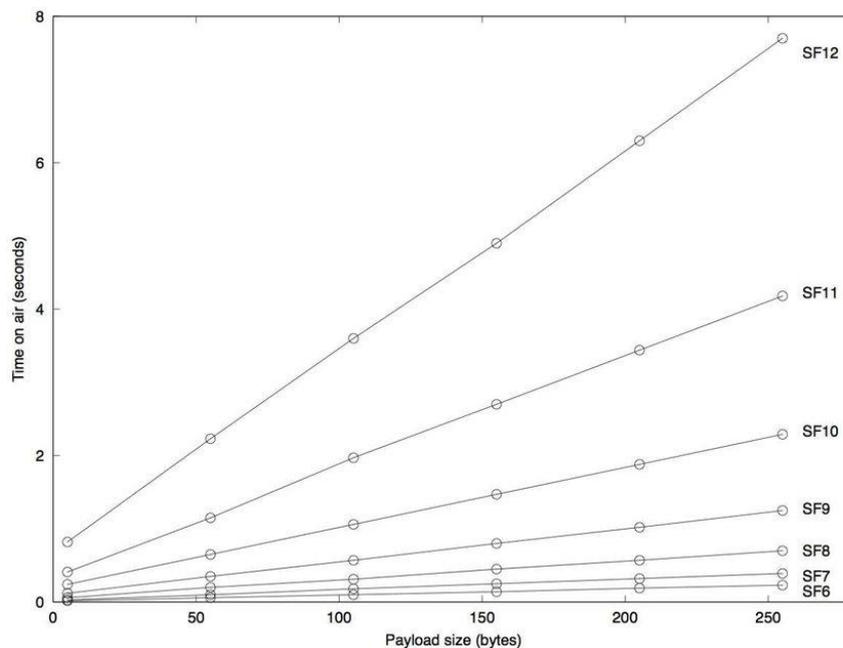


Figure 3: Time on Air vs. Payload Size for different Spreading Factors in LoRa networks [16]

• **Throughput & Data Rate Analysis:**

Definition: Throughput is the effective data transmission rate in the network. It depends on the data rate, time-on-air, and network congestion.

Mathematical Model:



$$DR = \frac{SF \times BW}{2^{SF}}$$

$$T = \frac{\sum_{i=1}^N P_i}{ToA}$$

Where:

DR= Data Rate (bps)

BW = Bandwidth (Hz)

SF = Spreading Factor

T = Throughput (bps)

Pi= Successfully transmitted packets

Analysis:

- Lower SF values yield higher data rates but reduce range.
- Optimizing SF dynamically can improve network efficiency [9].
- This theoretical graph serves as a reference for our ongoing research, where we have modified certain parameters to improve network performance.

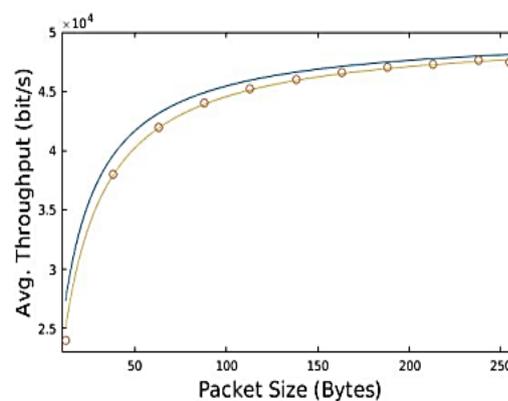
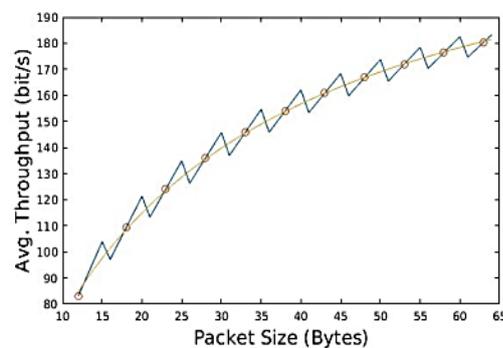


Figure 4: Throughput vs. Packet Size analysis, showing increased throughput with larger packet sizes until saturation [17].

- **Energy Efficiency Analysis with Different Spreading Factors:**

Definition: Energy efficiency measures how effectively the LoRa device transmits data while minimizing power consumption.

Mathematical Model:

$$E = \frac{D}{P_{tx} \times T_{oA} + P_{rx} \times T_{rx} + P_{idle} \times T_{idle}}$$

Where:

E= Energy efficiency (bits/Joule)

D = Data transmitted (bits)

P_{tx}, P_{rx}, P_{idle} = Power consumption in transmission, reception, and idle modes

T_{oA}, T_{rx}, T_{idle}= Time spent in respective states

Analysis:

- Higher SF increases power consumption due to longer ToA.
- Energy-efficient strategies include Adaptive SF selection and duty cycling to reduce idle power consumption [9].
- This theoretical graph serves as a reference for our ongoing research, where we have modified certain parameters to improve network performance.

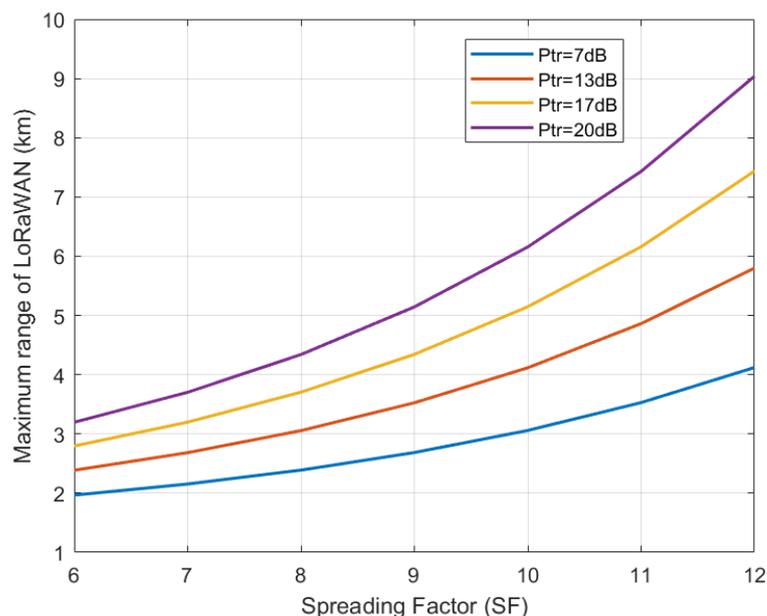


Figure 5: Maximum range of LoRaWAN as a function of spreading factor (SF) for different transmission power levels (Ptr). [18].

IV. DATA FLOW



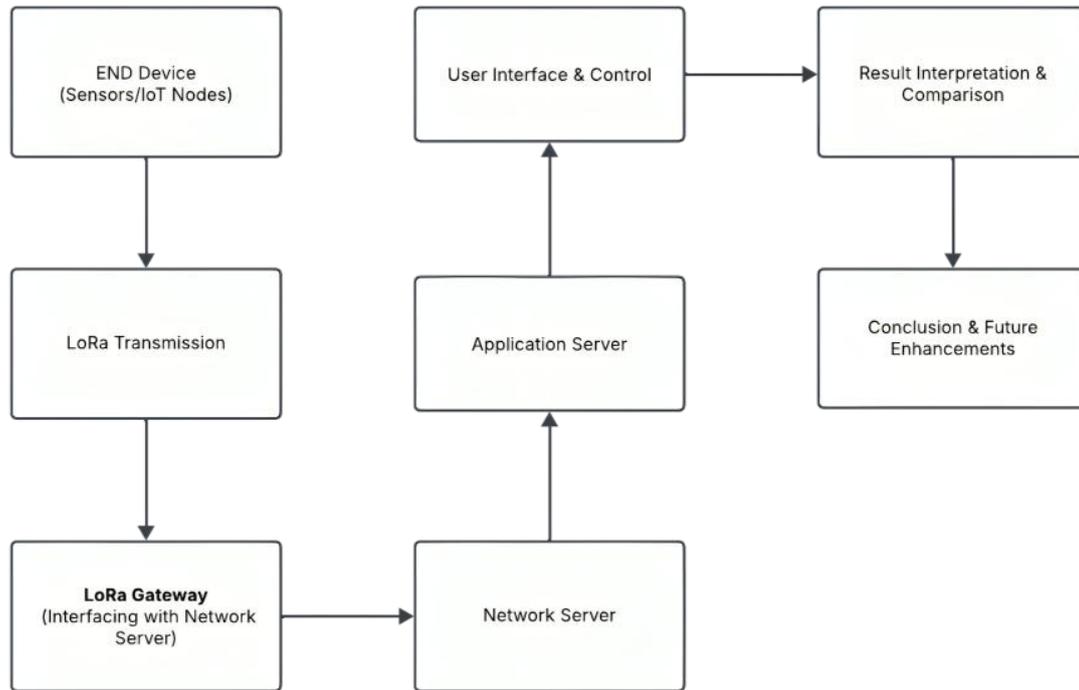


Figure 6: Overview of the Project with Detailed Data Flow

The system follows an organized data flow to ensure smooth communication and processing, from IoT end devices to result interpretation. The key stages of this flow are:

1. END Device (IoT Nodes/Sensors)

- IoT nodes equipped with sensors collect environmental or operational data.
- These devices process the raw data, making it suitable for transmission over a low-power network.

2. LoRa Transmission

- The collected data is sent using the LoRa (Long Range) communication protocol.
- LoRa is preferred for its energy efficiency and extended range, making it ideal for IoT applications.

3. LoRa Gateway (Interface to Network Server)

- The transmitted LoRa signals are received by a LoRa Gateway, which serves as a bridge between IoT devices and the core network.
- The gateway forwards the data to the network server via an internet connection.

4. Network Server



- The network server verifies and processes the received data before forwarding it to the application server.
- This step ensures secure and efficient handling of information.

5. Application Server

- The application server processes the data for visualization, analysis, and decision-making.
- AI/ML algorithms can be applied at this stage for optimization and predictive analytics.

6. User Interface & Control

- The processed data is presented to users through a web or mobile interface.
- Users can monitor real-time system parameters and modify settings as needed.

7. Result Interpretation & Comparison

- The system derives insights by comparing collected data with predefined benchmarks.
- This stage includes performance analysis, anomaly detection, and efficiency evaluation.

8. Conclusion & Future Enhancements

- The insights gained are documented, and potential improvements are proposed to optimize the system further.
- Recommendations focus on enhancing energy efficiency, transmission reliability, and system scalability.

VI. CONCLUSION

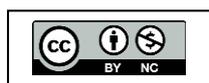
The importance of optimizing LoRa to gain improved energy efficiency and reliability in networks is stressed in this work. From this work, it is understood that IoT network sustainability can be significantly improved through adaptive rates of data transmission and protocol configurations. Future work can focus on applying optimized LoRa protocols in practice, in concert with AI-assisted network management, and strengthening security to avoid potential threats in IoT communication. All these can further solidify the viability of LoRa in extensive IoT deployments in making communication reliable and energy efficient.

VI. ACKNOWLEDGMENT

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