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Research paper

Analysis of service oriented network slicing at infrastructure layer in LoRa for IoT applications

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ABSTRACT

The Internet of Things (IoT) comprises of innumerable heterogeneous devices. Due to spike in IoT applications, there is a need to enhance flexibility and resource utilization in the network architecture. The modified architecture should acclimate to varying energy limitations, data loads, and power needs. To meet the specific needs of various IoT applications, **network slicing** has emerged as a solution candidate. This allows the partition of network, fostering the resource optimization, reliability, and flexibility. **Long Range (LoRa)**, one of the **Low-Power Wide Area Network (LPWAN)** technologies have emerged as reliable solution by providing long-range communication among massive number of connected devices. This paper introduces the concept of strategic service-oriented network slicing framework in the proposed LoRaWAN model, based on communication parameters such as **Received Signal Strength Indicator (RSSI), Quality-of-Service (QoS) and Signal-to-Noise Ratio (SNR)**. Performance evaluation of the proposed LoRa network model highlights the impact of constrained parameter, spreading factor (SF) of LoRa, on different communication parameters. Depending on the changing needs of diverse IoT applications, the derived results from LoRa model have been utilized as the basis for dynamic resource allocation through service-oriented network slicing. Additionally, different machine learning models have been employed to evaluate the effectiveness of the proposed slice classification strategy, confirming the reliability of communication-parameter-based slice allocation.

1. Introduction

In the era of IoT, the plethora of connected devices has rendered the demand for network flexibility [1]. To provide flexibility and reliability, two of the most eminent technologies that are recognized as core elements for future networks are Network Virtualization (NV) and Software Defined Network (SDN). NV is associated with another crucial methodology know as 'Network slicing.' The primary goal of network slicing is to isolate multiple virtual networks. The isolation creates an opportunity for vital communications to be served on the basis of priority, efficiency and reliability [2]. Moreover, in IoT dense deployment, a limited number of channels are available at the gateway (GW), and thus each slice suffers performance degradation. Thus, to deal with the substantial increase in number of IoT devices, network needs to improve the quality-of-service (QoS) and data consumption. Network slicing facilitates the creation of virtualized networks optimized for specific application needs, operating on shared physical infrastructure [3]. These slices cater to diverse services and devices, necessitating methods to gather and analyze spatiotemporal data on user behavior. By utilizing machine learning, patterns and insights can be extracted, ensuring more efficient service delivery and resource management across varied network slices. The physical network is divided into separate slices of logical networks. Configuration of each slice offers specific network characteristics and network capabilities. Network slicing improves the scalability, QoS, energy efficiency, resource utilization and dynamic allocation of network resources among the slices [4]. Also, there is a huge demand of intelligent communication and data processing through smart, flexible, and low-power networks. This has increased the need for low data rates, long-range coverage, cost-effective and energy-efficient devices. These requirements need to be fulfilled by some Low-Power Wide Area Network (LPWAN) technologies. Due to the fact that SigFox is a proprietary technology, Long Range (LoRa) has been chosen as an upcoming wireless technology [5]. LoRa is particularly advantageous in indoor environments, where its long-range capabilities and strong signal penetration enable reliable communication through walls and other physical barriers. According to recent studies, LoRa performs well

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even in environments with significant signal attenuation, making it suitable for applications such as indoor asset tracking, smart home systems, and industrial IoT networks. For indoor environments, the categorization of different IoT applications is based on their communication parameters performance. These considered parameters include Received Signal Strength Indicator (RSSI), Signal-to-Noise ratio (SNR), and QoS. Applications that require high reliability includes healthcare applications and security systems. Such applications need to have high RSSI, SNR, and QoS, to account low latency and consistent performance. On the other hand, applications that operates on moderate levels of these parameters comprises of smart home automation systems. Lastly, devices which utilizes low power consumption encompasses temperature or humidity sensors. It can function efficiently with lower RSSI, SNR, and QoS, prioritizing battery longevity.

LoRa is based on the chirp spread spectrum (CSS) modulation technique, that thrives on multipath propagation, interference, and Doppler Effect [6]. As compared to traditional network technologies, this modulation technique enables low power, low cost, low receiver sensitivity, low data rates transmission and high SNR for longer ranges. Spreading factor (SF) is one of the crucial LoRa parameter that provides low data rates along with flexibility, reliability, and scalability for long-range transmission [7]. It is essential to categorize network slices based on communication parameters like QoS, RSSI, and SNR in a LoRaWAN architecture to support virtual networks. Later, this categorization conforms the optimization of different IoT applications to the appropriate network slices. This approach enhances the performance of the IoT network by improving both the efficiency and resource optimization.

The performance evaluation has been realized by deploying the LoRa network system model in a real-time environment. The system model comprises of Arduino Uno, LoRa SX1278 module, temperature and humidity sensor (DHT11), AcSIP S78S System integrated LoRa GW, ESP32 microcontroller, and other integrated hardware. While this experimental setup has been previously configured and tested by the authors, the current paper presents a completely distinct investigation, focusing on the application of service-oriented network slicing at the infrastructure layer of LoRa for IoT applications. The methodological framework, slicing strategy, analytical modeling, and machine learning-based optimization introduced in this study are original contributions developed specifically for this research. The sensed data has been transmitted from the transmitter to GW in the form of packets. The network performance has been analyzed in both Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) scenario. Later, based on recorded data, the concept of network slicing has been utilized. The slices are categorized based on high, average, and low values of QoS, RSSI, and SNR.

In this context, a dataset collected from the deployed setup has been utilized, containing QoS, RSSI, and SNR values under both LoS and NLoS conditions. Machine learning based classification is employed to predict and categorize network slices based on these parameters, achieving high accuracy. This intelligent slicing approach enables dynamic resource allocation, significantly enhancing LoRaWAN performance in indoor environments in terms of communication reliability and energy efficiency.

The major contributions of this paper are-

- Implemented the concept of network slicing in service-oriented LoRaWAN architecture to satisfy the dynamic need of effective communication parameters such as QoS, RSSI, SNR, and energy efficiency. The values of the above-defined parameters are recorded by deploying a LoRa network system model in the real-time scenario comprising of LoRa AcSIP S78S System in Package (SIP) module as GW, ESP32 microcontroller board, LoRa SX1278 transceiver module, and DHT11 sensor.
- Performed mathematical modeling to analyze the dependence of diverse parameters of LoRa over the network slices associated with the gateway.
- Analyzed the performance evaluation of LoRa's non-constrained parameters for heterogeneous deployment in the real-time scenario and hence proposed a slice categorization strategy to allocate the most effective slice based on the high, average, or low value of QoS, RSSI, and SNR.
- Utilized machine learning based classification models to predict and classify network slices based on key communication parameters such as QoS, RSSI, and SNR, enhancing the network's ability to dynamically allocate resources for efficient communication in indoor environments.

The rest of the paper is organized in the following sections - Section II discusses the related work performed in this field along with the main contributions of this paper. Later section III describes the importance of service-oriented network slicing in LoRa for indoor environment. In Section IV, the detailed experimental model and system model has been described. Section V discusses the implementation of ML-based models and the outcomes of the paper, followed by the conclusion.

2. Related work

Although IoT has a broad scope in the upcoming generation, there are several challenges associated with it. The major challenges are scalability, reliability, QoS, and energy consumption. To cope with these standard problems, many recent research works have been developed which discusses the network slicing in different IoT architectures. Network slicing divides a network into distinct logical segments, each tailored to fulfill the specific needs of various applications. This approach ensures isolated resources and guarantees service quality across the different slices where separate services are deployed [8]. Table 1 summarizes some of the recent work based on the challenges and requirements of the standard IoT architecture.

Despite growing interest in network slicing for IoT and LoRaWAN environments, current research reveals several critical gaps. While numerous studies have explored resource scheduling, QoS-aware clustering, and architectural frameworks, many of these approaches rely solely on simulation environments without real-world deployment or validation. Techniques like federated reinforcement learning and multi-agent scheduling often are complex with limited interpretability. This makes practical implementation in constrained IoT environments challenging. Moreover, existing work tends to focus narrowly on optimizing throughput, delay, or energy efficiency, often overlooking service-oriented differentiation and the dynamic nature of QoS demands. Notably, few literatures have addressed slice categorization using physical-layer communication parameters such as RSSI, SNR, and real-time service behavior.

Motivated by these gaps, the present work introduces a practical and scalable solution that integrates real-time service-oriented slicing into a LoRaWAN-based IoT infrastructure. Unlike prior studies, this approach incorporates a measurable link between slice classification and physical communication metrics, enabling adaptive resource allocation that aligns with actual service needs. Different ML-based classification models is employed to map communication parameters (RSSI, SNR, QoS) to service categories, thereby facilitating efficient, interpretable, and data-driven slice prediction. The experimental deployment of this framework validates its real-world applicability and demonstrates its potential to improve network resource utilization and QoS delivery in diverse indoor IoT environments. This contribution addresses a key shortcoming in the literature by offering both a deployable architecture and an interpretable machine learning strategy tailored for practical slicing in LoRa networks. The next section outlines about the implementation of network slicing in LoRaWAN for indoor environment and its applications.

Table 1
Comparison of recent work based on network slicing in IoT architecture and communication technology.

Refs.	Approach	Key Outcomes	Limitations
[9]	Evaluated basic LoRa 2.4 GHz performance in indoor environments, focusing on RSSI and SNR readings across various physical locations.	RSSI and SNR thresholds were recorded; basic link-level performance was measured.	No slicing, no ML model, and lacks service-oriented framework or QoS-based adaptation.
[10]	Used Random Forest to classify RSSI/SNR values from various floor levels in a multistorey LoRa network for environment inference.	RF accuracy: 87.95 % for spatial environment classification.	Focuses on data classification, not resource allocation or service-aware slicing.
[11]	Implemented supervised ML to monitor LoRa-based patient data transmission, with high accuracy focused on healthcare use cases.	RF achieved 96 % accuracy for healthcare-specific IoT scenarios.	Application-specific and lacks any network slicing or communication-parameter-based resource management.
[12]	Proposed a two-tier DFQL (Deep Federated Q-Learning) model for device- and network-level resource optimization. Designed a five-slice model for throughput, delay, and energy-based allocation.	Achieved simulation-based improvement in throughput, delay, and energy across slices; introduced SF adaptation and slice migration logic.	Complex federated RL not interpretable; no real-time deployment; limited to simulation without physical-layer parameter integration (e.g., RSSI/SNR).
[13]	Developed a multi-agent framework for slot-based scheduling in multi-SF LoRaWAN. Validated guard time and slot length strategies in ChirpStack emulator.	Improved network capacity via optimized scheduling for different deployment types (urban/rural).	Focuses on MAC-level scheduling, not slicing. No ML, no service mapping, no physical layer parameter-based classification.
[14]	Introduced MixRA-H and MixRA-Opt algorithms combining radio and frequency allocation to meet heterogeneous QoS requirements. Entirely simulation-based.	Improved throughput and differentiated PDR under cluster-based QoS scenarios.	QoS Simulation-only; no real-world testing, and no ML-driven service classification or slicing strategy.
[15]	Applied three MAB-based algorithms (UCB, Q-UCB, ARIMA-UCB) for dynamic slice resource allocation based on service weights.	All solutions met SLA targets; ARIMA-UCB performed best with time-series predictions.	No deployment; service classification is weight-driven, not based on real-time QoS metrics or physical communication parameters.
[16]	Updated LoRaWAN reference architecture with vLNS schemes and air-interface QoS differentiation modules; focused on virtualization and orchestrator separation.	Provided a modular slicing blueprint for LoRaWAN; suggested business-driven architectural decoupling.	Architecture-only; no algorithmic slicing method, classification model, or real-time evaluation with measured parameters.
Proposed Work	**Implements real-time service-oriented slicing in LoRaWAN using a deployed setup. Applies machine learning classifiers to classify and allocate slices based on live QoS, RSSI, and SNR values.**	**Achieved 98.55 % classification accuracy; effective slice prediction and dynamic allocation; improved reliability and energy efficiency in real deployment.**	**This research fills existing gaps with real-time slicing, interpretable ML, and physical parameter-based service classification.**

3. Service oriented network slicing in lorawan for indoor environment

The advancement of IoT devices necessitates innovative solutions to address the diverse and stringent requirements of various applications. To meet the service-based demands of different IoT applications, service-oriented network slicing in LoRaWAN, offers a promising approach to efficiently optimize network resources. Traditional network slicing models depend extensively on SDN. Whereas, the proposed service-oriented network slicing enhances performance and reliability for indoor environments by emphasizing on resource allocation optimization based on application needs [17].

The characteristics of the physical space in indoor conditions—such as walls, floors, doors, furniture, and human presence—drastically impact signal quality and overall network performance [18]. These obstacles lead to increased signal attenuation, multipath propagation, and variability in RSSI and SNR values. For instance, dense concrete walls can cause significant path loss, while metallic surfaces often introduce signal reflections that degrade the effective signal-to-noise ratio. Heating, Ventilation, and Air Conditioning (HVAC) ducts and electrical wiring can create interference zones that introduce fluctuations in data transmission quality. These environment-induced impairments make static network configurations inefficient for meeting diverse QoS requirements.

Service-oriented slicing enables the network to align its configuration with varying application demands by referencing real-time communication parameters such as RSSI and SNR. Unlike traditional SDN-based slicing approaches, which primarily manage traffic flows at the control layer, the proposed framework emphasizes performance awareness at the physical and MAC layers. In this study, slice categories were defined through empirical thresholding, where RSSI, SNR, and QoS values from the collected dataset were analyzed to assign each data instance to one of three performance tiers: high, medium, or low. This heuristic labeling strategy, informed by domain-relevant benchmarks and statistical distributions, served as the basis for simulating adaptive slice behavior. Although the system does not incorporate automated online adaptation techniques such as reinforcement learning, the use of pre-annotated slice classes enables it to reflect dynamic performance differentiation in a controlled and interpretable manner.

LoRaWAN is well-suited for indoor applications due to its long-range transmission capabilities and low power consumption. Operating in unlicensed frequency bands, LoRa enables extensive coverage while supporting a massive number of connected devices. It has been observed that service-oriented slicing significantly improves QoS by categorizing network load according to the requirements of applications. These applications include smart home systems, industrial monitoring, and healthcare devices. To ensure that critical applications receive the required resources, each slice needs to be configured such that it prioritizes key performance indicators like RSSI, SNR. Fig. 1 illustrates a service-oriented network slicing approach in a LoRa network for an indoor environment.

The empirical categorization of slices in this study establishes a practical framework for aligning application requirements with network performance levels. Slice assignments were derived from threshold values observed in RSSI, SNR, and QoS distributions, allowing applications to be mapped according to their latency sensitivity, data criticality, and tolerance to signal variation. For example, real-time alert systems like fire alarms and health monitors, which require high reliability and minimal delay, were associated with high-priority slices. In contrast, applications such as environmental or occupancy sensors, which can tolerate occasional data loss or delay, were assigned to lower-priority slices. This heuristic mapping strategy supports service-aware resource planning and reflects common practices in performance-driven IoT network design. As shown in Fig. 1, a LoRa Gateway in the center is responsible for connecting and managing three distinct network slices. The connectivity between each application and its respective slice, shows how LoRa technology enables efficient resource allocation and optimizes the network to ensure high-quality performance for various IoT applications in the building.

The infrastructure layer consists of GWs linked in a star of stars network topology. The centralized controller controls the assignment of slicing configuration through switches and retains the channels for every slice accordingly. Three slices at infrastructure layer have been considered, and all the slices have been differently categorized inside the network, and each slice highlights the importance of QoS, RSSI, and SNR, respectively. The slicing priority is the requisite for reliability and QoS [19]. Secondly, the orchestration of the centralized unit in the control plane is managed by various switches of LoRaWAN gateways in the control layer. The features of the data plane provide flexibility to achieve perfect network slicing implementation. Each IoT node is assigned a virtual slice to fulfill the QoS requirements and allows resource utilization.

Fig. 2 shows the network slicing that has been done by keeping the important communication parameters as the base parameters. A particular slice gets allocated different IoT indoor applications depending on the effective values of defined parameters. To optimize network configuration, the major aspects to be considered are QoS, RSSI, SNR, and energy consumption.

The categorization of slices based on the applications are stated below-

Gateway Receiver Bandwidth: 250kHz	**SLICE 1** Higher QoS (>70%), Higher SNR (> 7dB) and Higher RSSI (> -70 dBm)
	SLICE 2 Average QoS (>22%), Average SNR (5 dB to 7dB) and Average RSSI (-70 dBm to -90 dBm)
	SLICE 3 (Low QoS (7%), Low SNR (< 5dB) and Low RSSI (<-90 dBm)

Fig. 2. Network slicing over LoRa GW.

- Slice 1 (High QoS, SNR, RSSI): Critical applications that requires low latency and high reliability, such as healthcare monitoring devices, video surveillance, and fire security systems are served by this slice.
- Slice 2 (Average QoS, SNR, RSSI): It caters to moderate-priority applications such as smart lighting, HVAC control, and smart meters that can bare occasional signal loss or slight delays.
- Slice 3 (Low QoS, SNR, RSSI): This slice handles low-priority applications where data transmission can be less frequent, such as temperature sensors, occupancy sensors, and water leak detectors

Unlike conventional slicing models that depend on pre-defined network topologies or static rule-based segmentation, the proposed approach emphasizes adaptability, simplicity, and physical-layer awareness. Traditional SDN-driven slicing requires significant control overhead and relies heavily on centralized reconfiguration logic. In contrast, service-oriented slicing in LoRaWAN enables lightweight, application-centric segmentation without excessive infrastructure dependencies—making it better suited for low-power, large-scale IoT environments with heterogeneous service profiles.

While the proposed model offers a scalable and flexible framework, it also faces practical challenges. Variability in indoor signal propagation may cause temporary misclassification of devices if thresholds are not carefully tuned. The absence of automated adaptation mechanisms

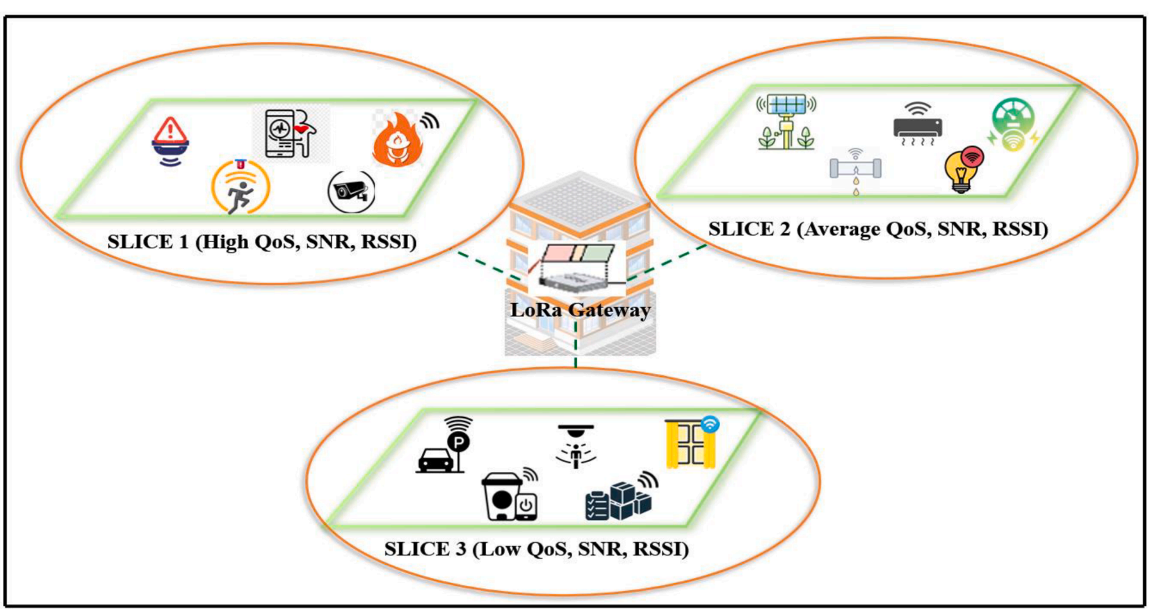


Fig. 1. Illustration of LoRa service oriented network slicing in an indoor environment.

limits responsiveness to highly dynamic environments. Future improvements could include integrating lightweight reinforcement learning techniques for real-time slice reassignment and developing hybrid models that combine heuristic thresholds with predictive analytics.

Service-oriented network slicing in LoRaWAN for indoor environments enhances resource utilization and application performance by tailoring slices to meet specific service requirements. By leveraging real-time data analytics and intelligent resource management, this approach not only improves QoS but also ensures that the growing demands of diverse IoT applications are met efficiently. The following section explains the experimental setup and system model which has been deployed in the real-time scenario.

4. Experimental setup and system model

The experimental setup of the LoRa network system model has been deployed in a building located in Delhi, India and has been depicted in Fig. 3. The building includes ground floor and first floor having thick concrete walls, doors, and furniture, which collectively introduce signal attenuation, multipath effects, and potential interference. These conditions simulate a realistic indoor IoT environment. The implemented system model network has been diverted into two sections- Sensing and Transceiver section and Gateway section. The sensing and transceiver section consists of the following components- LoRa SX1278 module, DHT11 sensor, and Arduino Uno. DHT11 sensor is used to detect humidity temperature and humidity. DHT11 sensor sends the detected atmospheric humidity and temperature values from Arduino Uno to the LoRa SX1278 module.

LoRa GW and ESP32 microcontroller reside in the gateway section. AcSIP S78S System in Package (SIP) module has been included in the LoRa GW. It contains a Semtech SX1278 radio module operating in the ISM band and a 32-bit ARM-based Cortex microcontroller. SIP module is capable of two-way communication and interfaces multiple ports (I2C/SPI/UART/GPIO). The signal characterization has been achieved through the interdependence of RSSI and SNR on the obstacle and distance covered. To compute RSSI and SNR, two ideal situations of wave propagation are considered-LoS and NLoS. During deployment, maintaining consistent signal quality was a challenge due to the dynamic indoor environment. Interference from existing Wi-Fi signals, human movement, and multipath fading caused fluctuations in RSSI and SNR measurements. Additionally, empirical thresholding for slice categorization required careful tuning to avoid overlaps. The methodological workflow illustrated in Fig. 4 outlines the complete process followed in this study, beginning with the deployment of the LoRa-based system model.

Fig. 4 details the dual environmental conditions (LoS and NLoS)

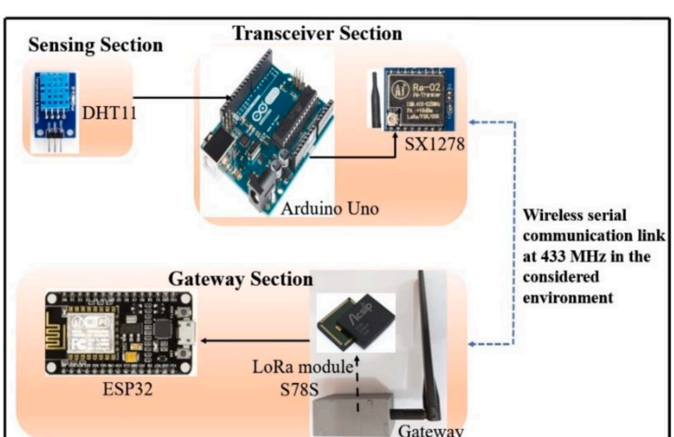


Fig. 3. Block diagram of implemented LoRa network system model.

considered for data collection, the empirical slice categorization based on observed RSSI, SNR, and QoS parameters, and the application of different ML classifiers for validating slice prediction. This flowchart also highlights the final stage of performance evaluation, demonstrating a complete pipeline from real-time experimentation to machine learning-based analysis. To complement this visual summary, the following algorithm outlines the step-by-step execution of the proposed methodology. It captures the operational logic behind data collection, slice classification, and ML-based validation, offering a structured representation of how the slicing model was implemented in practice. Algorithm 1 shows the working of the proposed system model for strategically categorizing the network slices based on the recorded communication parameters from the dataset. The recorded dataset contains 1200 elements of data comprising of 100 data packets for different values of SF and considered surrounding environment.

The proposed slicing algorithm and its implementation over the LoRa module demand high reliability and low latency to ensure accurate classification and optimal resource allocation. To evaluate the effectiveness of virtual slice assignment, performance was analyzed under different SF configurations, identifying the most suitable slice allocation for various LoRa devices. However, achieving optimal resource utilization remains challenging due to the inherent complexity and heterogeneity of LoRa parameters such as SF, bandwidth (BW), and coding rate (CR). These parameters significantly influence key performance metrics like delay and throughput, which are critical for QoS in IoT networks. The throughput R_b and delay (d) in LoRa can be mathematically expressed as [20]:

$$\text{Throughput } (R_b) = SF * \frac{BW}{2^{SF}} * \frac{4}{4+CR} \tag{1}$$

$$\text{Delay}(d) = \frac{L}{R_b} \tag{2}$$

In (2), L represents the total length of bits uploaded for transmission. The ToA defines the amount of time each device is transmitting. ToA is entirely dependent on the configuration parameters like SF, CR, throughput, and BW [21].

$$ToA = (N_{payload} + n_{preamble} + 4.25)\frac{SF * CR}{R_b} \tag{3}$$

Eq. (3) plays a critical role in quantifying transmission time and helps analyze the cascading effect of ToA, SF, and CR on network delay. The delay, in turn, can be estimated using the below formula:

$$\text{Delay} = \frac{L * ToA * 2^{SF}}{(N_{payload} + n_{preamble} + 4.25)SF * CR} \tag{4}$$

The QoS metric for each virtual slice in the LoRa gateway is influenced by these transmission parameters and can be expressed as a function of throughput R_b and delay d [22] and is given in (5) as –

$$QoS_{max} = \sum \alpha(R_b + (1-d)) \tag{5}$$

The key features of QoS requirements for wireless IoT end devices are energy utilization and reliability of end nodes. On the receiver side (Rx), the RSSI denotes the minimum signal power required to decode the received signal strength. It is beneficial in determining whether the received signal strength is enough to initiate an excellent wireless connection [23]. SNR measures the receiver sensitivity. The higher the SNR, the better will be the receiver performance. With the help of noise figure (NF), transmitted power ($P_{Tx)}$, and RSSI value, the SNR can be easily calculated as [24]-

$$SNR = RSSI - P_{tx} + 174 - 10\log_{10}(BW) - NF \tag{6}$$

To calculate the total energy consumption in LoRa devices, the energy consumption is divided into sleep state and active state. LoRa promises that the long life of a node is possible by a careful selection of

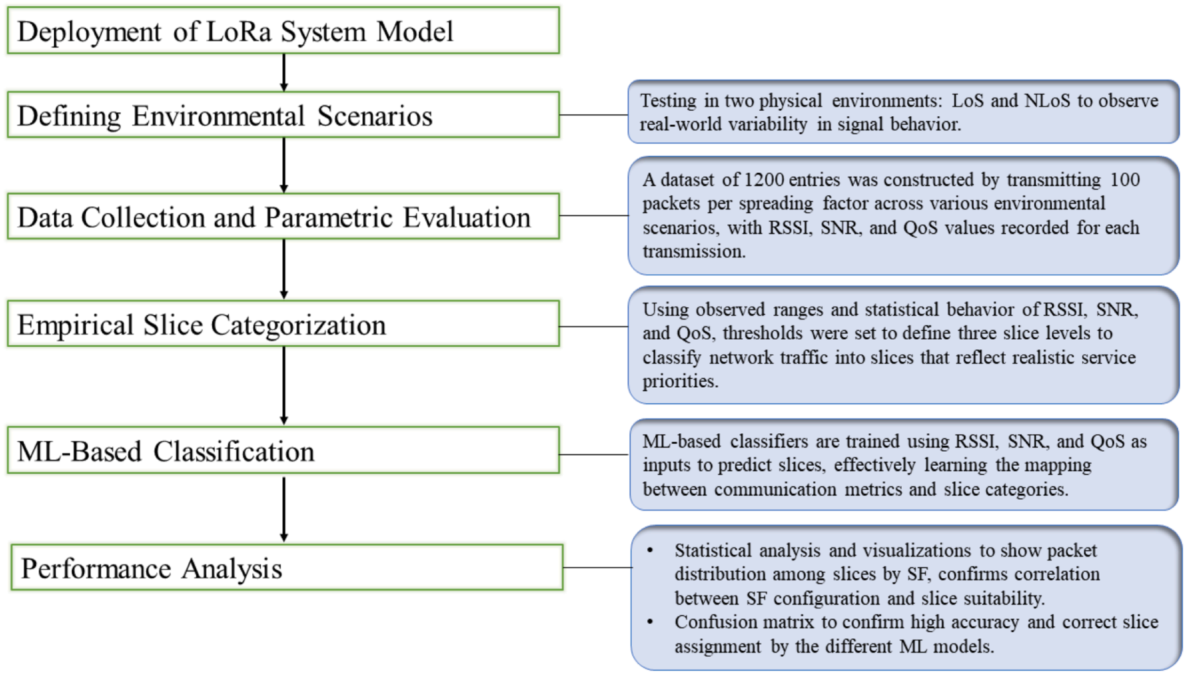


Fig. 4. Methodological workflow.

Algorithm 1
Working of system model and slice categorization strategy.

Step1: Developed and deployed the LoRa network system model.
Step2: Considered two environment conditions- LoS and NLoS.
{
The transceiver and GW in the IoT model were placed in LoS (no obstruction)
{
Sent 100 packets of data for each SF.
Recorded the RSSI, SNR and QoS values on serial monitor of Arduino Software.
}
The transceiver and GW in the IoT model were placed in NLoS (range of 20 m).
{
Sent 100 packets of data for each SF.
Recorded the RSSI, SNR and QoS values on serial monitor of Arduino Software.
}
}
Step3: The values of parameters are recorded, and dataset is created.
Step4: Proposed three divisions of slice categorization strategy.
{
The most effective parametric combination- **First Slice.**
Effective parametric combination- **Second Slice**
Less effective parametric combination- **Third Slice**
}
Step5: The slices have been designated to different packets of the recorded dataset according to effective parametric combination.
{
First Slice: Packets having signals with higher RSSI, SNR and QoS.
Second Slice: Packets having signals with high RSSI, SNR and QoS.
Third Slice: Packets having signals with low RSSI, SNR and QoS.
}
Step6: ML-based classification models have been applied to the dataset to categorize packets into their respective slices based on the recorded RSSI, SNR, and QoS parameters.
Step7: The classification accuracy of the preferred model is evaluated and analyzed to assess the effectiveness of the slicing strategy

duty cycle and parametric configuration. The ratio of the time during which the device is in an active state to the total time (i.e., active state and sleep state) is known as the duty cycle and is mathematically defined [25] as –

$$\text{Duty Cycle} = \frac{\text{Active Time}}{\text{Sleep Time} + \text{Active Time}} \tag{7}$$

The sleep state is scheduled cyclically. When the node does not receive an activation command, it goes into the sleep state to save the energy and utilize it in the next transmission cycle. The total energy consumption is given by equation below [25] –

$$E_{total} = E_{sleep} + E_{active} \tag{8}$$

These mathematical models provide a deeper understanding of how LoRa's constrained parameters influence system performance, delay, energy usage, and ultimately, the slicing strategy. In the next section, the values of the constrained and non-constrained parameters of LoRa are considered, and their effects have been analyzed with the help of MATLAB software along with the slicing strategy.

5. Dataset analysis and performance evaluation

In the current work, the proposed setup is analyzed in the realistic LoRa scenario where packets are transmitted and received by LoRa GW. The dataset consists of 1200 labeled entries, with each entry representing a single transmitted packet. For every packet, the following communication parameters were recorded: RSSI, SNR, delay, throughput, SF, and QoS. Data has been collected over a span of five consecutive days during varied time intervals to account for environmental and interference variability. Each SF has been used to transmit 100 packets under both LoS and NLoS scenarios. Packet interval was fixed at 20 s. Slice labels (Slice 1, 2, or 3) were assigned based on empirically derived thresholds for RSSI, SNR, and QoS, simulating service-aware traffic classification. The different considered constrained, and non-constrained parameters of Lora have been listed in Table 2.

The goal of our objective is to analyze the effect of variables in the considered scenario. In the proposed IoT system model, realization is done by analyzing the effect and QoS, RSSI, Delay, SNR, and total energy consumption. To evaluate the performance of the proposed LoRa-based slicing model, a comprehensive analysis has been carried out focusing on key communication parameters in the next sub-section.

5.1. Exploratory data analysis of lora parameters in the system model

This section presents both the behavior of signal-related metrics across different spreading factor configurations and their implications for reliable transmission. The insights gained here serve as the foundation for defining and validating the slice categorization strategy discussed in the following sub-sections. QoS defines the performance of high-priority applications and traffic-control mechanisms under limited network capacity. The basic measurement parameters of QoS are throughput and delay. The impact of different SFs on QoS, throughput, and latency has been analyzed in Fig. 4 in terms of reliability. Fig. 5(a) concludes that for maximum QoS, the delay should be minimum, and throughput should be higher.

The delay is directly proportional to the SF and total length of bits uploaded. Therefore, as the spreading factor increases, the QoS decreases. This increases packet loss, and hence the QoS of the network decreases. Secondly, the total network capacity relies on payload size and preamble size. LoRaWAN enables device-to-device communications through the GW and monitors energy because better energy management goes hand in hand from one IoT application to another. Transmission of packets starts from one end-device to the GW or vice-versa. This leads to a hike in energy consumption. In Fig. 5(b), as the SF increases, the total energy consumption (in mJ) also increases due to a surge in redundant bits. As higher SF affects the energy consumption, it also makes the communication range longer.

The proposed system model considers two environment ranges- LoS and NLoS. The LoRa end device has been moved from one place to another, whereas the GW had a fixed position. A higher positive SNR indicates better reception of the signal. RSSI ranging from −60 dBm to −20 dBm is considered good in LoRa. The impact of different SFs on RSSI and SNR for considered environment ranges has been shown in Fig. 5. The RSSI and SNR of the transmitted packet have been measured at the gateway.

Table 2
Simulation parameters.

Parameters	Value
Carrier Frequency	433 MHz
Bandwidth (BW)	250 kHz
Transmission Power	13 dBm
Coding Rate (CR)	4/5
Payload Length	25 bytes
Spreading Factor (SF)	7 to 12

Fig. 6 reveals the evolution of RSSI and SNR as the function of the distance between the transceiver and GW for different SFs. It has also been observed that different SF configurations have a significant impact on both RSSI and SNR. Long-range coverage requires a higher value of SF, but this also leads to an increase in ToA. Henceforth, ToA also decreases the packet delivery ratio. The RSSI decreases logarithmically with the distance and obstructions from the GW but prevails the effective values within LoS. Similarly, the SNR also insights a rapid decrease in value due to an increase in distance. The lower value of SNR indicates higher noise interference, and hence increase in SF decreases the SNR. Sensitivity and coverage also increase with the simultaneous increase in SNR.

The reliability of the communication network is impaired by the link between the sensor node and GW. Due to consequent packet loss, the LoRaWAN supports the retransmission of unconfirmed messages. This retransmission consumes additional energy, which simultaneously impacts the battery life. Thus, it becomes compulsory to keep an eye on the set of LoRa configurations and link quality factors that affect the total energy consumption by the end node.

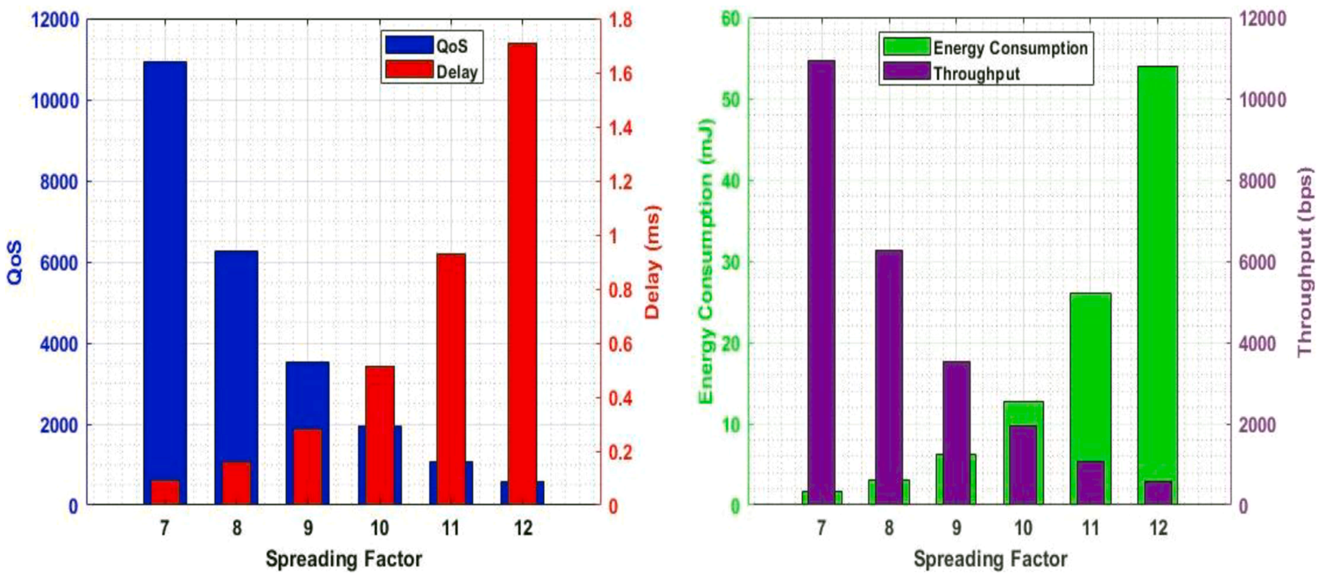
In Fig. 7 it has been discovered that with the minimum SF, the total energy consumption by the node decreases. An increase in SF shoots up TOA, and this leads to more processing time. Thus, the energy consumption also doubles up. Also, as the distance between the end node and GW, the RSSI and energy consumption increases rapidly due to frequent packet loss and retransmissions.

These findings establish the foundational behavior of key LoRa parameters under varying SF configurations and environmental conditions, providing critical insights for designing an effective slice categorization strategy. The next sub-section builds on this analysis to formulate and apply the slicing logic using empirically defined thresholds.

5.2. Slicing strategy based on empirical thresholds

There always exists a trade-off between the above-analysed parameters of LoRa to improve the reliability in LoRa-based IoT applications. So, it is necessary to propose a slicing protocol in the control plane for automated slice resource allocation. The network slicing has been done based on effective link quality parameters, and the specific slice is allocated accordingly. The concept of network slicing was being applied to the created dataset containing 1200 data packet entries with their link parameters. The packets which characterize the improved QoS and the most effective values of communication parameters are allocated to Slice1, followed by Slice2 and Slice3 having effective and less effective values.

Fig. 8. denotes the total number of packets allocated to the respective slices. It is visible that due to the proposed slicing categorization, >70 % of data packets will be assigned the effective slices, and hence it will help to improve the reliability. It also increases the signal quality and resource utilization capability in the network. The parameters of signal quality highly depend on the different SFs configurations because minimum SF has less TOA, and this reduces the interference and packet loss ratio, thereby increasing the values of link quality parameters. Although the EDA in Fig. 4 through Fig. 6 included all spreading factors, only SF7, SF10, and SF12 were selected for slice classification analysis shown in Figs. 7 and 8. This decision was made to reduce redundancy and highlight performance at low (SF7), medium (SF10), and high (SF12) ends of the SF spectrum. SF7 offers low ToA and high data rate suitable for short-range communication, SF10 balances coverage and reliability, and SF12 supports long-range, low-rate transmissions with high ToA. Including these three SFs ensures that slicing evaluation captures performance extremes and trade-offs while avoiding redundancy from intermediate SFs with overlapping behavior. The intermediate SFs (SF8, SF9, SF11) showed performance trends similar to their adjacent values and did not significantly impact slice boundaries, thus were omitted for



(a) (b)

Fig. 5. Effect of different SFs on (a) QoS and delay (b) Total energy consumption and throughput.

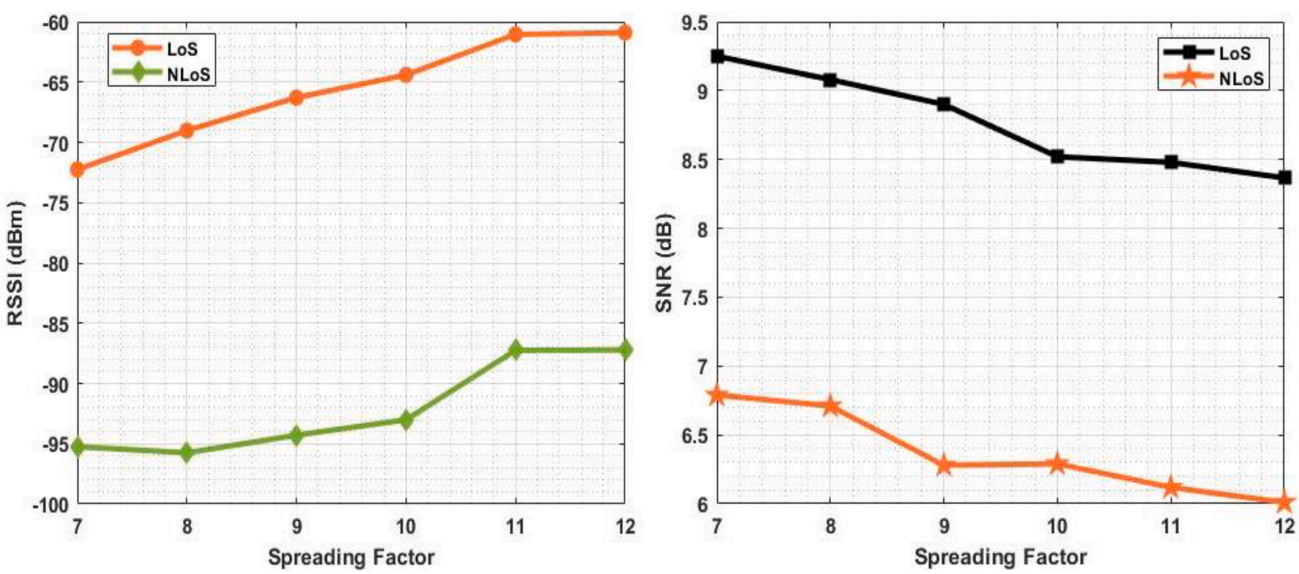


Fig. 6. Effect of different SFs on RSSI and SNR in LoS and NLoS scenario.

visual and analytical clarity.Fig. 9 shows the SF categorization in terms of the percentage of packets allocated to all three slices.

For the proposed system model working on constant bandwidth (250 kHz), the SF determines the data rate. To control the data rate, the diversity of choosing SF increases the coexistence of LoRa devices. It leads to a significant increase in multiple access efficiency of LoRa, and hence the concept of network slicing comes into existence. The performance of LoRa slices with different SF configurations for 1200 data packets has been evaluated in Fig. 8. In Slice 1, SF10 (44.2 %) and SF12 (35 %) packets dominate, indicating a mix of medium-to-long range communication needs. Slice 2 has a substantial allocation of packets with SF12 (48.1 %), followed by SF10 (35.2 %), making it ideal for applications requiring longer-range communication due to SF12′s low data rate and high Time on Air (ToA). Slice 3 contains a balanced distribution of SF7 (24.8 %), SF10 (41 %), and SF12 (34.2 %), offering a trade-off between data rate and communication range. Overall, packets with SF7 and SF10, due to their lower ToA and link budget requirements, are ideal for close-range communication, optimizing the efficiency of Slice 1 and Slice 2. Slice 2 shows higher values in communication parameters, indicating its suitability for long-range, high-quality communication. Typically, LoRa SNR values lie between −20 dB to 10 dB. In the recorded dataset, the value of SNR is greater than 0 dB, denoting the optimal value for LoRa communication. Hence, the packets in slice3 will also show good signal quality and improved QoS.

Compared to traditional LoRa systems that operate without network slicing, where all devices share the same communication configuration irrespective of application priority or link quality, the proposed slicing model introduces substantial performance benefits. Without slicing, high-priority traffic may suffer from congestion, inefficient allocation, or high delay. The proposed slice-based approach ensures that devices are grouped by signal conditions and QoS needs, resulting in more efficient packet delivery, reduced energy consumption, and higher service differentiation. This layered allocation strategy improves both scalability and reliability for dense IoT deployments.

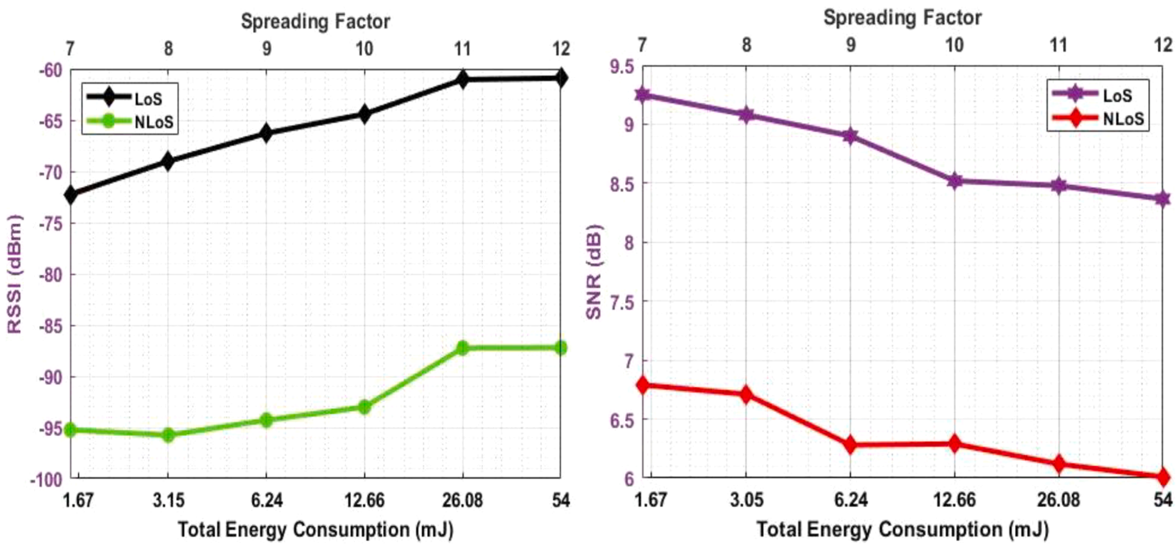


Fig. 7. Performance evaluation of SFs and total energy consumption on RSSI and SNR in LoS and NLoS scenario.

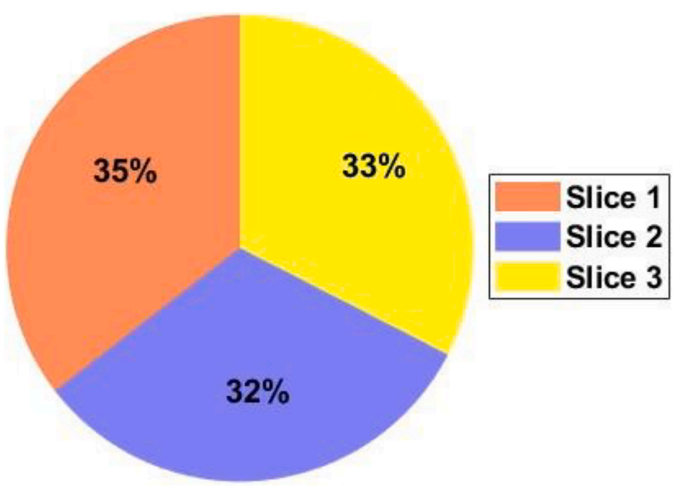


Fig. 8. Percentage of data packets allocation to different slices.

The empirical slicing framework, based on categorized link quality, enables more targeted and adaptive resource allocation. To validate this approach, the following section applies a machine learning model to assess the accuracy and reliability of the proposed slice classification.

5.3. Implementation of machine learning-based slice classification

Machine learning algorithms makes it possible to categorize network loads dynamically and adapt optimal slicing strategies that meet the varying communication requirements of diverse IoT applications in real-time scenarios [26]. The data-driven insights collected from the proposed network model improves overall service delivery in LoRaWAN environments. In the proposed work, machine learning classifiers were employed to predict network slice assignments based on observed communication parameters — RSSI, SNR, and QoS. The input dataset consisted of 350 samples extracted from the full annotated dataset of 1200 entries. This helps in class balancing and reducing computational complexity, hereby maintaining representative distribution for effective model training. Each record included three features — RSSI, SNR, and QoS — and a corresponding slice category as the label. An 80:20 train-test split was applied. Accuracy has been computed and a confusion matrix, as shown in Fig. 10, is visualized via a seaborn heatmap for classification validation. Among the evaluated models, KNN achieved the highest performance, with a classification accuracy of **98.55 %**, slightly outperforming Random Forest (RF) and Linear Discriminant Analysis (LDA). The model accuracy comparison is represented in Table 3. The KNN model has been implemented using the scikit-learn library with default settings (n_neighbors=5 and Euclidean distance).

KNN is selected as the preferred model due to its simplicity, low training overhead, and strong classification performance, particularly in structured datasets where class boundaries are well defined. Its non-parametric nature and ease of implementation make it suitable for real-time IoT environments with constrained computational resources. RF is included in the comparison due to its robustness, ensemble-based design, and ability to handle both continuous and categorical features [27]. LDA, a commonly used linear classifier, is evaluated to compare against simpler statistical models. Although its accuracy was slightly lower, it still validated the reliability of communication parameters in predicting slice assignments. The consistently high accuracy across all three models confirms the strong correlation between communication metrics and slice categories. However, KNN stands out for its simplicity, minimal parameter tuning, and computational efficiency, making it ideal for real-time, resource-constrained IoT environments such as indoor LoRaWAN deployments. It optimizes network slicing strategies by efficiently assigning devices with varying performance needs to appropriate slices. The application KNN to LoRaWAN slicing provides a reliable method for classifying communication scenarios based on real-time metrics such as RSSI, SNR, and QoS. IoT-based systems like LoRa benefit from KNN's simplicity and high accuracy, making it ideal for indoor scenarios such as smart buildings, industrial monitoring, and healthcare environments. Given that continuous manual monitoring is impractical, KNN facilitates intelligent, instance-based decisions about device classification and slice allocation. This leads to more responsive and adaptive resource management within the network, improving both system reliability and service quality.

6. Conclusion

The proposed work in this paper highlights the impact of network slicing in a LoRa network system model deployed in a real-time indoor environment. It strengthens the performance metrics such as resource optimization, reliability, network traffic management, and energy efficiency. Computational intelligence has been integrated into the LoRa gateway using the proposed slicing framework to achieve the improvised operation of system model. The slicing methodology for each LoRa slice has been defined through a structured strategy and it has been

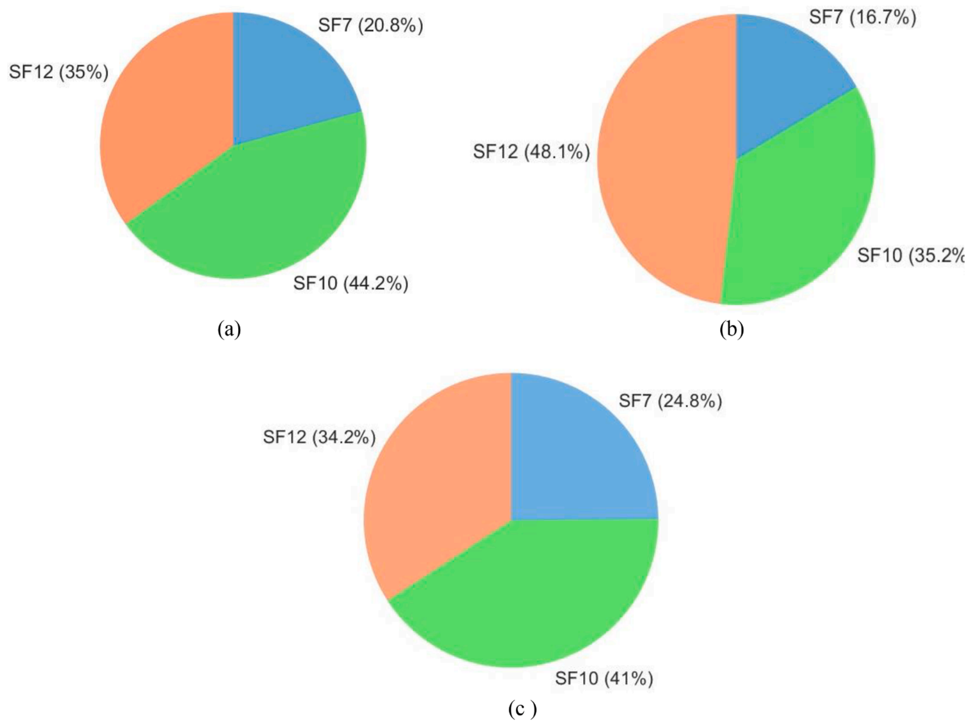


Fig. 9. Spreading factor categorization analysis in (a) Slice1 (b) Slice2 (c) Slice3.

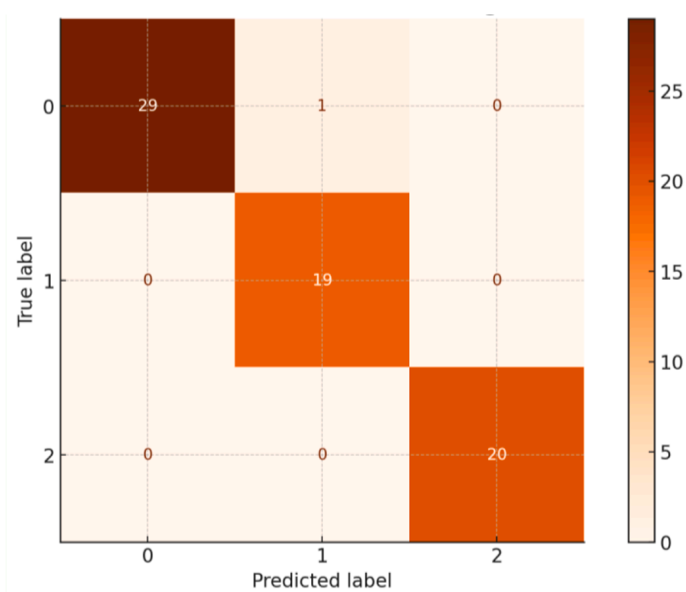


Fig. 10. KNN confusion matrix.

Table 3
Model accuracy comparison table.

Classifier	Accuracy (%)
K-Nearest Neighbors (KNN)	98.55
Random Forest (RF)	98.52
Linear Discriminant Analysis (LDA)	97.10

designed to maximize signal strength, quality and QoS across diverse communication scenarios.

The proposed slice categorization strategy ensures efficient distribution of resources by giving precedence to communication parameters like RSSI, SNR, and QoS. The evaluated results indicate that in the congested environment, the network slicing approach has proven to be beneficial by dynamically adjusting the changing QoS requirements of connected devices. It also improves resource utilization and QoS over the data packets. Most of the data packets having SF7 and SF10 are assigned to Slice 1 and Slice 2, reflecting good signal quality. Slice 2 caters to applications like smart home automation systems which require moderate latency and signal strength. On the other hand, Slice 3, meets the need of simpler applications like temperature sensors, parking management, and wearables with lower signal strength and reduced QoS. Additionally, the integration of ML-based classification demonstrates impressive accuracy of 98.52 %. This integration contributes to the precision of slice allocation, maximizing resource utilization and overall optimization of the LoRa model network's performance.

In comparison, the authors of related work [9], conducted static performance evaluation of LoRa in indoor scenarios without applying any slicing or classification model. Their analysis showed a predictable decline in SNR and RSSI with increased distance and obstructions, but no adaptation or optimization to improve resource distribution. Similarly, [10] explored RSSI and SNR-based positioning and achieved a maximum of 88.57 % accuracy using a modified KNN model. However, their work did not implement slicing or adaptive QoS-based classification. By contrast, our approach leverages empirical slicing and supervised learning to dynamically map devices to virtual slices, improving QoS in environments where signal variability is common.

While this study was conducted in a multi-floor academic building, the slicing strategy and classification model are applicable to other indoor environments such as hospitals, smart offices, or industrial IoT deployments. However, environmental factors like wall density, interference sources, and node placement may influence signal propagation and should be considered when generalizing this approach. Future work can evaluate this framework in more complex indoor conditions or multi-gateway deployments. Furthermore, combining SDN with machine learning could enable multiple virtualized network functions within each slice, by predicting and optimizing resource utilization thereby enhancing QoS for diverse IoT applications. This integration would also support scalability, robustness, interoperability and efficiency for large-scale IoT deployments.

CRediT authorship contribution statement

Shilpi Verma: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sindhu Hak Gupta:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vipin Balyan:** Writing – review & editing, Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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