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Predictive Battery Life Modeling for LoRaWAN Sensors Using Real-World Deployment Data

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Abstract

This study presents a comprehensive analysis of LoRaWAN-based IoT communication in an agricultural monitoring context. The research is grounded in long-term experimental data collected from four environmental sensors deployed in the Czech Republic, focusing on temperature and humidity measurements. Beyond the environmental data, the study emphasizes the technical performance of the deployed devices, particularly in terms of signal quality and energy efficiency.

We analyzed 14 key transmission parameters, including RSSI, SNR, Time on Air, and gateway reception metrics, to evaluate the communication reliability and network coverage.

A significant contribution of this work is the development of a data-driven model for estimating battery life based on real-world usage patterns and spreading factor distributions. This model enables predictive maintenance planning and supports energy-efficient network design. The study builds on previous research and contributes to the growing body of literature on holistic performance evaluation in IoT systems.

Keywords

LoRaWAN, RSSI, SNR, spreading factor, battery life, energy consumption, adaptive data rate, IoT, wireless communication, agricultural monitoring.

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Introduction

Importance of connectivity in IoT systems

In IoT systems, ***connectivity is a fundamental component*** that enables communication between end devices and central servers. For optimal use of wireless communication, it is essential to determine the ***radio characteristics of the network*** and key parameters such as signal strength, signal-to-noise ratio, and transmission frequency. These parameters are critical for evaluating the performance of wireless transmission .(Lin and Chang, 2023; Lynn et al., 2020)

During the deployment or analysis of an operational IoT system, ***measured signal parameters serve as key indicators*** of system performance. If these parameters reveal alarming or critical values, they can be used to ***optimize connectivity*** and prevent potential system failures that may lead to financial losses (Lynn et al., 2020). Without proper signal analysis, wireless network optimization may become unnecessarily costly and inefficient (Choudhary, 2024).

Research motivation and context

This study involves experimental measurements of temperature and humidity for projects where sensor data is crucial. However, the technical solution is also important, so we focused on analyzing the technical performance of our devices, both in terms of signal quality and battery life. These aspects are interconnected. The result is that through a thorough analysis of real data over a long period, we have developed a reliable model for estimating the battery life of devices, allowing us to predict when the battery will need to be replaced.

The main data sources for agricultural enterprises are the farm itself, suppliers, government, market, and research. The use of smart solutions, artificial intelligence, and other innovative practices in agriculture is discussed at many conferences, in various journals, strategies and project plans. Data is the essential raw material for all these solutions.(Jarolímek et al., 2024)

Materials and methods

Device specifications and energy model

According to the manufacturer, the Milesight EM300-TH is a compact LoRaWAN-based sensor designed for temperature and humidity monitoring in remote or agricultural environments. It is powered by a 4000 mAh ER18505 Li-$SOCl_2$ battery, with a claimed operational life of up to 5 years under standard conditions (Milesight, 2025). The device transmits data via LoRaWAN and supports various spreading factors (SF7–SF12), which significantly influence both signal range and energy consumption.

The actual power consumption of the device depends on several factors:

- Measurement and transmission frequency
- Spreading factor (SF) used
- Environmental conditions (e.g., temperature)
- Enabled features such as retransmission or local data storage

Higher spreading factors (e.g., SF12) result in longer Time on Air (ToA) and thus higher energy usage per transmission. For instance, a single transmission at SF12 can consume up to 30 times more energy than one at SF7 (Muthanna et al., 2019). This trade-off between range and energy efficiency is a key consideration in LoRaWAN network design. (Khan et al., 2022)

To evaluate the real-world performance, we analyzed long-term data from deployed sensors and developed a battery life estimation model. This model accounts for the actual distribution of spreading factors and transmission intervals, allowing us to predict battery replacement cycles with high accuracy. Such predictive maintenance is essential for large-scale IoT deployments, where manual battery checks are impractical.

Description of the sensor deployment and data collection

The dataset used in this study was collected from four agricultural monitoring sensors deployed in the village of Kozinec (Prague-West district) between March 31, 2024, and November 19, 2024, resulting in a total of 154 MB of data. These sensors continuously measured temperature and humidity in an open-field environment, providing a rich dataset for both environmental and technical analysis.

Due to the volume and fragmentation of the data across multiple files, it was necessary to consolidate and process the dataset using custom Python scripts. Python was chosen for its flexibility and efficiency in handling large-scale data processing, which is essential for extracting meaningful insights from IoT sensor networks (Zhang et al., 2022).

Key parameters in LoRaWAN message structure

Our dataset includes approximately 14 key parameters that characterize the signal transmission and reception process. These parameters are essential for evaluating the technical performance of the IoT network:

Transmission characteristics:

- ***EUI*****:** A unique identifier of the device, used to distinguish which device sent the message.
- ***Frequency:*** The transmission frequency (e.g., 868.1 MHz), which also determines the frequency channel used.
- ***Data Rate:*** Includes the Spreading Factor (SF) and bandwidth, defining the speed and robustness of the transmission.
- ***Time On Air (ToA):*** The duration of the message transmission, directly affecting energy consumption.
- ***Frame Counter:*** A sequential counter of transmitted messages. It is crucial for detecting message loss, as missing values in the sequence indicate dropped packets.

Gateway reception parameters:

- ***RSSI:*** Received Signal Strength Indicator – measures the power level of the received signal.
- ***SNR:*** Signal-to-Noise Ratio – indicates the quality of the received signal relative to background noise.
- ***Timestamp (ts):*** The exact time the message was received by each gateway.
- ***Gateway EUI (gweui):*** A unique identifier of the receiving gateway.

Recent studies have emphasized the importance of understanding how signal transmission parameters—such as RSSI, SNR, and Time on Air—affect the battery life of sensor nodes. (Ghaderi and Amiri, 2024) developed a comprehensive energy model for LoRaWAN sensor nodes, demonstrating that spreading factor selection and transmission frequency significantly influence energy efficiency and device longevity (Ghaderi and Amiri, 2024) Our work confirms these findings and further contributes by applying this analysis to real-world, long-term datasets collected from agricultural deployments.

Moreover, our approach aligns with the broader trend in IoT research that seeks to integrate signal diagnostics with predictive maintenance strategies. By correlating transmission parameters with battery consumption, we were able to construct a data-driven model for estimating device lifetime, which is essential for planning maintenance in large-scale sensor networks.

Unlike many simulation-based studies, our analysis is grounded in empirical data collected over several months from a real deployment. This allows us to validate theoretical models and provide practical insights into the operational behavior of LoRaWAN devices under varying environmental and network conditions (IEEE, 2021).

In summary, our work contributes to the growing body of literature that emphasizes the need for holistic performance evaluation in IoT systems—combining signal quality, energy modeling, and spatial analysis to support more efficient and sustainable deployments.

This work builds on the author's previous publication ***Experimental Evaluation of the Availability of LoRaWAN Frequency Channels in the Czech Republic*** (Novák et al., 2021)

The following Table 1 illustrates the context and structure of the collected data, both from the perspective of the sensor device and the LoRaWAN gateways that received the transmitted messages. It provides an overview of the number of gateways that successfully received each message, offering insight into network coverage and redundancy.

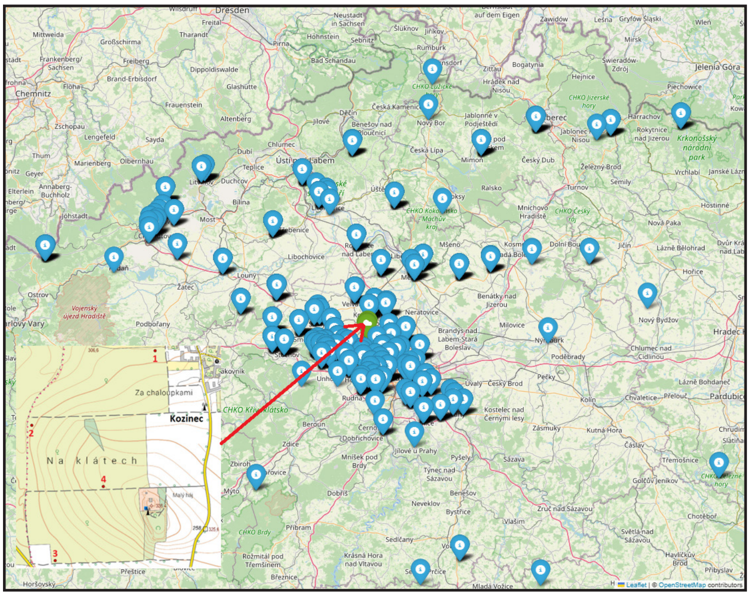
Map index	Sensor DevEUI:	Number of gates
1	24E124136C374657	80
2	24E124136C404199	65
4	24E124136C404741	108
3	24E124136C404764	81

Source: Authors

Table 1: Maximum number of gateways that have received messages from the sensor.

Additionally, a map of sensor locations (Figure 1) is included to show the spatial distribution of the deployed devices. This is followed by a map of all gateways that received the messages, which helps visualize the geographical reach and signal propagation within the LoRaWAN network.

These visualizations are essential for understanding the spatial dynamics of communication, identifying potential coverage gaps, and evaluating the performance of the network infrastructure.



Source: Authors

Figure 1: The positions of each gateway that received the message.

Methodology for calculating energy per transmission

To quantify the energy consumption of a single LoRaWAN transmission, we used a standardized calculation based on the device's electrical characteristics and the Time-on-Air (TOA) for each Spreading Factor (SF). The following steps outline the conversion from TOA to energy in micro-watt-hours (µWh):

Conver TOA form milliseconds to seconds:

$$t = \frac{TOAms}{1000} \tag{1}$$

Calculate energy in joules:

$$E_j = I \times V \times t \tag{2}$$

Convert joules to watt-hours:

$$E_{Wh} = \frac{EJ}{3600} \tag{3}$$

Convert watt-hours to micro-watt-hours:

$$E\mu Wh = EWh \times 10^6 \tag{4}$$

Final combined formula:

$$E\mu Wh = \frac{I \times V \times TOAms}{3600 \cdot 1000} \times 10^6 \tag{5}$$

This formula was used to compute the energy cost per transmission for each SF, assuming a peak transmission current of 40 mA and a supply voltage of 3.3 V.

Results and discussion

The practical part of this study focuses on evaluating the energy efficiency of LoRaWAN communication based on the use of different Spreading Factors (SF). The goal is to understand how the choice and distribution of SFs in a real-world network affect the battery life of end devices and to identify opportunities for optimization.

To achieve this, we followed a structured analytical workflow, illustrated in Figure 2. The process begins with the measurement of energy consumption for individual SFs, followed by the collection of real-world transmission data from a deployed LoRaWAN network. These two datasets are then combined to calculate the weighted average battery life of a typical device. Finally, the results are interpreted to provide practical recommendations for improving energy efficiency through network design and adaptive data rate (ADR) strategies.

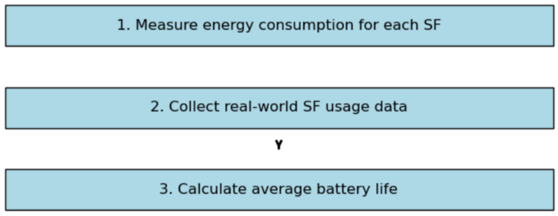


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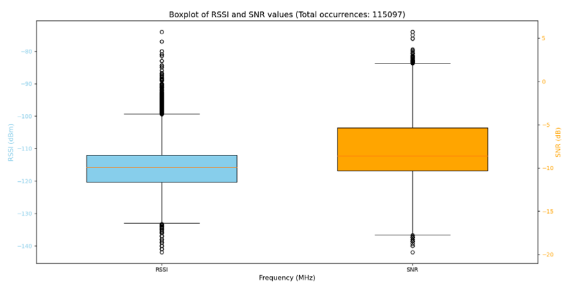
Figure 2: A structured analytical workflow.

RSSI and SNR across frequencies

We analyzed the average values of RSSI (Received Signal Strength Indicator) and SNR (Signal-to-Noise Ratio), see Figure 3, for various frequencies in LoRaWAN technology. The data was obtained from measurements conducted at frequencies ranging from 867.1 MHz to 868.5 MHz.

The highest average RSSI value was recorded at the frequency of 868.1 MHz with a value of -113.3 dBm. This frequency exhibits the best signal quality, which may be due to lower interference levels or better signal propagation conditions. Conversely, the lowest average RSSI value was recorded at the frequency of 867.9 MHz with a value of -118.548818 dBm, indicating a weaker signal at this frequency.

Regarding SNR, the highest average SNR value was recorded at the frequency of 867.3 MHz with a value of -7.1 dB. A higher SNR value indicates a lower noise level, which is positive for communication quality. On the other hand, the lowest average SNR value was recorded at the frequency of 867.5 MHz (red bar on Figure 4) with a value of -9.9 dB, indicating a higher noise level and potential issues with signal quality.



Source: Authors

Figure 3: Boxplot of RSSI and SNR values.

The frequency of 867.9 MHz was measured most frequently, which may indicate its significance in the network or higher usage in practical applications. Conversely, the frequency of 868.1 MHz was measured least frequently, which may indicate its lower usage.

A crucial element (that is currently missing) is a graph illustrating the number of received messages per specific frequency. Such a graph would provide valuable insight, as it would demonstrate that certain frequencies are subject to higher noise levels across most gateways. Consequently, signal reception on these frequencies is reduced, thereby limiting the effective range of the gateway on those specific channels.

This phenomenon is also reflected in the observed data, where the highest number of received messages occurred at 867.9 MHz, whereas the lowest number was recorded at 868.1 MHz. This discrepancy is not coincidental. End devices are designed to randomly alternate among the available frequencies. Therefore, with a sufficiently large dataset, one would expect the number of received messages to be evenly distributed across all eight operational frequencies. However, this is not the case in practice due to the heavy utilization of the 868 MHz band by other systems within the Czech Republic.

The presence of such external transmissions, or more precisely their associated energy in the radio spectrum, increases the noise floor during LoRaWAN signal reception - particularly on the side of LoRaWAN gateways, which are typically installed outdoors at elevated locations such as rooftops or telecommunications towers. The gateways' extended range comes at the cost of an elevated noise floor on certain frequencies. This is further evidenced by instances where a low signal-to-noise ratio (e.g., -15 dB) is accompanied by a relatively strong received signal strength indicator (e.g., -96 dBm).

Based on practical experience and long-term measurements, we have identified the following frequencies as particularly problematic in most locations:

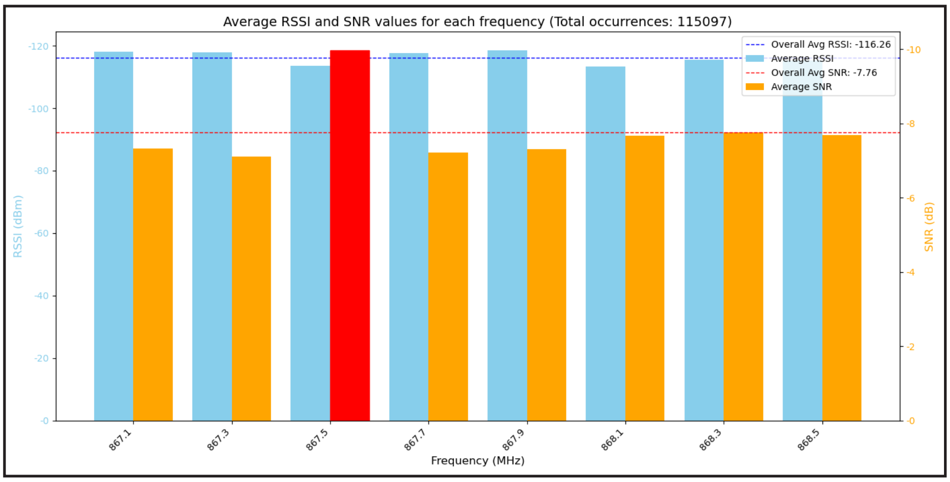
- 867.5 MHz: interference from UHF RFID systems
- 868.1, 868.3, and 868.5 MHz: interference from security systems and remote metering technologies operating on other wireless protocols

Conversely, the frequencies 867.1, 867.3, 867.7, and 867.9 MHz tend to be less affected by such interference. This correlates with a consistently higher number of successfully received messages by LoRaWAN gateways on these channels.

Overall, it can be said that the frequency of 868.1 MHz exhibits the best average RSSI value, indicating a stronger signal, while the frequency of 867.3 MHz exhibits the best average SNR value, indicating a lower noise level. These results can be useful for optimizing frequency planning in LoRaWAN technology and improving communication quality.

Distribution of transmission parameters across frequencies and data rates

Figure 5 presents a detailed breakdown of the number of transmissions observed across various frequency channels and data rate (DR) configurations in a deployed LoRaWAN network. Each DR corresponds to a specific Spreading Factor (SF) and bandwidth (BW), which directly influence the time-on-air (TOA) and energy consumption of each transmission.



Source: Authors

Figure 4: Average RSSI and SNR values for each frequency.

Figure 5 description:

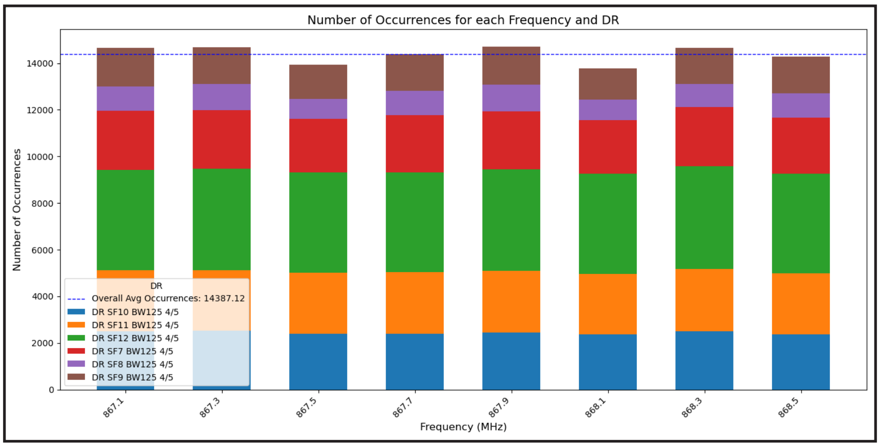
- The x-axis represents frequency channels in the 867.1–868.5 MHz range.
- Each bar is segmented by DR, with colors indicating different SFs (SF7 to SF12, all with BW125 and coding rate 4/5).
- A dashed blue line marks the average number of transmissions across all frequencies: 14,387.

This visualization reveals a non-uniform distribution of transmission activity. Higher SFs such as SF11 and SF12 dominate the traffic, particularly on certain frequencies. This suggests that many end devices operate at the edge of network coverage, where higher SFs are required to maintain connectivity. While this ensures reliable communication, it comes at the cost of significantly increased energy consumption and reduced battery life.

Energy consumption measurements: SF7 vs. SF12

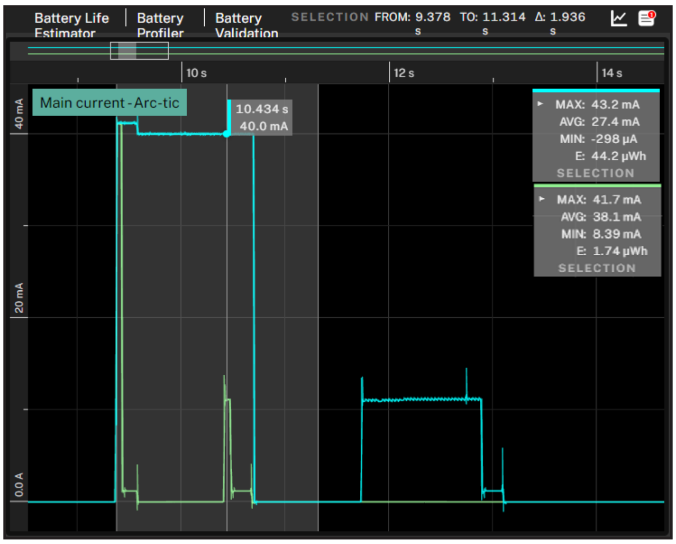
To further investigate the energy implications of different SFs, we conducted practical measurements of energy consumption for SF7 and SF12 transmissions. These measurements Figure 6 were obtained from an open-source dataset available on GitHub and are consistent with theoretical models.

The results confirm that SF12 transmissions are over 25 times more energy-intensive than SF7. This is primarily due to the exponential increase in TOA with higher SFs. In energy-constrained IoT applications, such as battery-powered sensors, this difference has a profound impact on device longevity.



Source: Authors

Figure 5: Number of ocurrences for each frequency and DR.



Source: Authors

Figure 6: Measurements of energy consumption for SF7 and SF12 transmissions.

Battery life estimation based on sf usage

To quantify the impact of SF selection on battery life, we modeled the expected battery life of a typical LoRaWAN device (e.g., Milesight EM300-TH) under standardized conditions:

- Battery capacity: 4000 mAh (Li-SOCl$_2$)
- Peak transmission current: 40 mA
- Sleep current: 10 µA
- Transmission frequency: 144 messages/day (every 10 minutes)

Spreading Factor	Battery Life (days)	Battery Life (years)
SF7 BW125	3 997	10.95
SF8 BW125	3 236	8.87
SF9 BW125	2 415	6.62
SF10 BW125	1 542	4.22
SF11 BW125	894	2.45
SF12 BW125	511	1.40

Source: Authors

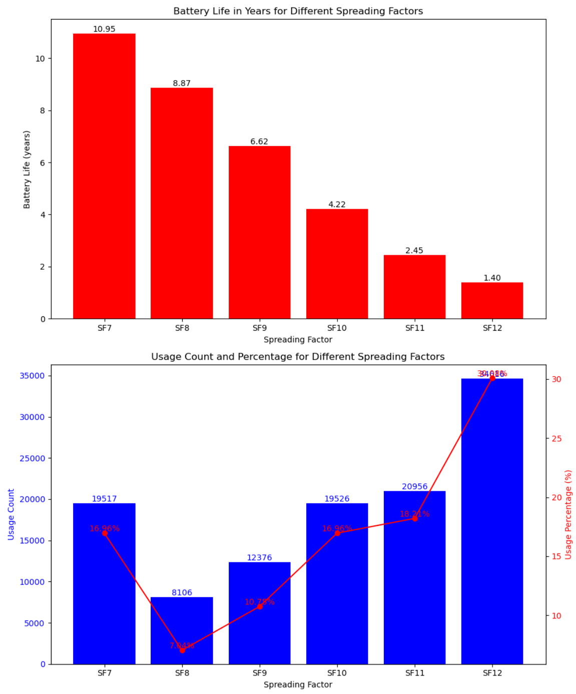
Table 2: Battery life estimation base on spreding factor.

These values clearly demonstrate on Figure 8 the steep decline in battery life with increasing SF. While SF7 enables nearly 11 years of operation, SF12 reduces this to just over one year.

Figure 7 depicts the ***battery life and usage distribution*** across spreading factors in bar charts.

The ***top chart*** shows the estimated ***battery life (in years)*** for a LoRaWAN device using a single spreading factor (SF7 to SF12) under standardized conditions. Battery life decreases significantly with increasing SF, ranging from ***10.95 years (SF7) to 1.40 years (SF12).***

The ***bottom chart*** displays ***the real-world usage distribution*** of spreading factors in a deployed network, both in ***absolute counts and percentage share.*** The most frequently used SF is ***SF12 (30.06%),*** followed by ***SF11 (18.21%)*** and ***SF10 (16.96%).*** Lower SFs, despite offering better energy efficiency, are used less frequently.



Source: Authors

Figure 7: Battery life and usage distribution across spreading factors.

Weighted average battery life based on real-world sf distribution

To assess the real-world impact of SF usage, we analyzed the distribution of transmissions across SFs in the deployed network:

Spreading Factor	Usage Share (%)
SF7	5.00
SF8	10.00
SF9	15.00
SF10	20.00
SF11	25.00
SF12	30.00

Source: Authors

Table 3: The distribution of transmissions across SFs in the deployed network.

Using this distribution, we computed the weighted average battery life:

Calculation results

- Weighted average daily consumption (transmissions only): 3.33 Wh = 3,325,468 µWh
- Total daily consumption (including 10 µA standby current): 4.05 Wh = 4,045,468 µWh

- Estimated battery life: 3,560 days ≈ 9.75 years
- The device, under the given SF distribution and a 10-minute transmission interval, is expected to last nearly 10 years, which aligns with the manufacturer's specification.
- SF12, with a 30% occurrence rate, contributes the most to overall energy consumption – optimizing the ADR (Adaptive Data Rate) mechanism could further extend battery life.
- The continuous standby current of 10 μA accounts for approximately 17% of the total daily energy consumption.

$$Weighted\ Battery\ Life\ =$$

$$= \frac{\sum (Battery\ Life \times Usage\ Count)}{Total\ Usage} = 4{,}78\ years$$

This result highlights a critical insight: although low-SF transmissions are significantly more energy-efficient, their limited usage in the network leads to a substantial reduction in average device longevity.

Implications and recommendations

The findings presented in this section underscore the importance of adaptive data rate (ADR) strategies and network planning in LoRaWAN deployments. Key takeaways include:

High SF usage (SF11 and SF12) dominates network traffic, drastically reducing battery life.

Energy-efficient SFs (SF7–SF9) are underutilized, despite offering significantly longer operational lifespans.

ADR mechanisms should be actively employed to dynamically assign the lowest viable SF to each device, balancing coverage and energy efficiency.

Network topology optimization, including the strategic placement of gateways, can reduce the need for high-SF transmissions.

Given the high level of utilization of the 868 MHz band by other services and technologies, it is generally recommended to reduce the radio distance between the end device and the LoRaWAN gateway. However, this should be considered only as the first step toward improved performance. The second (and equally important) step involves the installation of LoRaWAN Pico Gateways (PicoGWs) in indoor environments located close to the end devices themselves.

The deployment of PicoGWs offers several advantages: low initial costs, ease of installation, and most notably, reduced exposure to unwanted interference. This is because parasitic signals from the outdoor environment tend to penetrate indoor spaces to a significantly lesser extent, providing a natural shielding effect when the PicoGW is installed indoors.

While the effective range of a PicoGW is considerably smaller than that of a Macro Gateway (MacroGW), this limitation is more than compensated for by the improved signal reception across all eight communication channels - including the problematic frequencies previously mentioned (867.5, 868.1, 868.3, and 868.5 MHz).

By implementing these strategies, network operators can significantly extend the operational life of battery-powered devices, reduce maintenance costs, and improve the overall sustainability of IoT deployments.

Conclusion

This study provides a comprehensive analysis of the energy efficiency and usage patterns of LoRaWAN Spreading Factors (SF) in a real-world deployment. Through a combination of theoretical modeling, empirical measurements, and network data analysis, we have demonstrated the significant impact that SF selection has on device battery life and overall network energy efficiency.

Key findings include:

- ***Battery life decreases exponentially*** with increasing SF due to longer Time-on-Air and higher energy consumption per transmission.

- ***SF12 and SF11***, despite being the most energy-intensive, are the most frequently used in the observed network, accounting for nearly ***50% of all transmissions***.

- The ***weighted average battery life*** of a typical LoRaWAN device under real-world SF distribution is only ***4.78 years***, compared to over ***10 years*** when using SF7 exclusively.

- ***Energy consumption per transmission*** increases from just ***2.03 µWh*** at SF7 to over ***27 µWh*** at SF11, and potentially more than ***54 µWh*** at SF12.

These results highlight the critical importance of ***Adaptive Data Rate (ADR)*** mechanisms and ***network optimization*** strategies. By minimizing the use of high SFs where possible and improving gateway placement, network operators can significantly extend the operational lifespan of battery-powered devices, reduce maintenance costs, and enhance the sustainability of IoT deployments.

Future work may include dynamic SF allocation algorithms, real-time energy profiling, and integration of machine learning techniques to further optimize LoRaWAN performance in diverse deployment scenarios.

The results of this study demonstrate a method for predicting the battery life of devices utilizing LoRaWAN technology. This capability is crucial for predictive maintenance, as it enables efficient planning of service interventions and optimization of operational costs. Consequently, the proposed approach can have a significant economic impact, particularly in large-scale IoT deployments. Practical validation of the predicted battery lifespan in real-world conditions—due to the inherently long duration of such testing—will be time-consuming and represents an important direction for future research.

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