ENHANCING WATER UTILITY BULK METER READING THROUGH IoT RETROFIT: A RELIABLE AND ENERGY EFFICIENT WIRELESS SOLUTION: THE RAND WATER CASE STUDY IN SOUTH AFRICA

By

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ABSTRACT

Water is a scarce resource and appropriate smart bulk water metering and leakage detection are crucial. Current smart bulk water metering methods at Rand Water in South Africa are moving from being essentially manual to being automated. However, the currently used methods remain operationally costly, energy inefficient and not so reliable in terms of their employed communication approaches. This often leads to suboptimal resource allocation. Additionally, most of these bulk water meters are enclosed within concrete chambers and are at mostly at low elevation or even underground.

This poses a problem in terms of identifying an efficient wireless solution for remote reading and site security. This study investigates and evaluates the performance of an appropriate Internet of Things (IoT) solution capable of reliably and in an energy efficient manner sending bulk water meter readings to a remote server for processing. The proposed solution can overcome the identified low elevation and penetration issues. It also detects possible water leakages, water chamber overflow, burst detection and any kind of site tampering in the form of alarms to ensure timely response and reduced operational cost. This study employs a simulation-based methodology using MATLAB to develop and evaluate deployment-aware models for both LoRaWAN and NB-IoT protocols, specifically incorporating the effects of reinforced concrete attenuation, low antenna elevation, and join/rejoin dynamics. This approach consists of a wireless communication feasibility study of the existing water utility infrastructure, followed by the implementation of identified low-power wide area network (LPWAN) IoT protocols suited for the application and the performance evaluation and comparison of the identified LPWAN IoT technologies in terms of energy efficiency and communication reliability. The results obtained from the proposed approach demonstrate that NB-IoT achieves superior reliability, maintaining packet delivery ratios above 0.96 even under severe concrete penetration losses up to 30 dB, while LoRaWAN exhibits a sharp degradation in reliability below 0.85 beyond 20 dB attenuation. Conversely, LoRaWAN offers better energy efficiency and extended battery lifetime under moderate conditions, whereas NB-IoT trades higher energy consumption for predictable and robust packet delivery. These findings support a deployment-aware, hybrid technology selection strategy for large-scale underground bulk water metering applications.

Keywords: Bulk water meter reading, Low Power Wide Area Networks (LPWANs), Internet of Things (IoT), Low elevation, Penetration, Reliability, Energy efficiency, Leakage detection, Water overflow, Burst-detection, Tampering.

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ACRONYMS

ACRONYMS	MEANINGS
2G	: Second Generation Cellular Network
3G	: Third Generation Cellular Network
3GPP	: 3rd Generation Partnership Project
4G	: Fourth Generation Cellular Network
5G	: Fifth Generation Cellular Network
AFA	: Adaptive Frequency Agility
AI	: Artificial Intelligence
ACK	: Acknowledgment
ADR	: Adaptive Data Rate
AMR	: Automated Meter Reading
AN	: Application Note (e.g., Semtech AN1200.13)
AP	: Access Point
ATC	: Advanced Technologies for Communications (conference)
BW	: Bandwidth
C-IDLE	: Connected Idle (state)
CE	: Coverage Enhancement
CSS	: Chirp Spread Spectrum
dB	: Decibel
dBi	: Decibel Isotropic
dBm	: Decibel Milliwatt
DoS	: Denial-of-Service
eDRX	: Extended Discontinuous Reception
eNB	: evolved Node B (LTE base station)
EU868	: European Union 868 MHz (frequency band)
gNB	: gNode B (5G NR base station)
ISM	: Industrial, Scientific, and Medical (frequency bands)
IoT	: Internet of Things
k-NN	: k-Nearest Neighbors
$Li\text{-}SOCl_2$	: Lithium Thionyl Chloride (battery chemistry)
LoRa	: Long Range
LoRaWAN	: Long Range Wide Area Network
LPWAN	: Low Power Wide Area Network

LTE	: Long Term Evolution
LTE-M	: Long Term Evolution for Machines
MAC	: Medium Access Control
ML	: Machine Learning
MNO	: Mobile Network Operator
NB-IoT	: Narrowband Internet of Things
NF	: Noise Figure
NR	: New Radio (5G)
ODeL	: Open Distance e-Learning
OTAA	: Over-The-Air Activation
PDP	: Packet Delivery Probability
PDR	: Packet Delivery Ratio
PHY	: Physical Layer
PL	: Path Loss
PRR	: Packet Reception Rate
PSM	: Power Saving Mode
QoS	: Quality of Service
RRC	: Radio Resource Control
RX	: Receive
SF	: Spreading Factor
SNR	: Signal-to-Noise Ratio
SVM	: Support Vector Machine
TX	: Transmit
UNISA	: University of South Africa
WSN	: Wireless Sensor Network

CHAPTER 1: INTRODUCTION

1.1 Background

The demand for efficient water management solutions has grown as utilities face increased pressure to minimize water losses, ensure accurate billing, and support sustainable resource usage [1], [2]. Traditional bulk water meter reading methods, often manual and time-consuming, lack the precision and immediacy needed for proactive water management. These methods can lead to delays, misallocated resources, and high operational costs, especially in extensive networks managed by large utilities.

In recent years, digital solutions have been introduced to automate and enhance water metering, such as the integration of cellular-based communication systems. However, these approaches often fall short in terms of energy efficiency and operational resilience. They are especially ill-suited to challenging environments, like the low-elevation concrete chambers that house many bulk water meters for Rand Water in South Africa. The physical barriers presented by these concrete enclosures obstruct wireless signals, complicate data transmission, and increase the risk of signal loss or interference [8]. Moreover, these chambers are prone to water ingress, tampering, and environmental degradation, further compromising the reliability and longevity of traditional solutions.

The advent of IoT-based communication networks, particularly Low Power Wide Area Networks (LPWAN), offers promising avenues to address these issues [3], [6]. IoT-based solutions provide enhanced flexibility, with options for low power consumption, extended transmission ranges, and better adaptability to a range of environmental conditions. This research focuses on evaluating IoT-based LPWAN solutions tailored to the specific requirements of Rand Water’s infrastructure, aiming to increase operational efficiency, reduce energy consumption, and strengthen infrastructure security while ensuring continuous and reliable data transmission.

Cost is a critical factor in the decision-making process for water utilities, especially in a developing country like South Africa [11]. Without clear evidence that IoT retrofits are economically viable on a large scale, utilities may hesitate to adopt such solutions. Researching the cost-effectiveness, including initial investment, operational savings, and long-term financial sustainability, is essential to guide policy makers and utility managers in their investment decisions.

Wireless communication is a cornerstone of IoT systems, and energy efficiency is crucial for long-term operations, especially in remote areas [7]. Different technologies, such as LoRaWAN and NB-IoT, offer trade-offs between range, bandwidth, and energy consumption [3], [9]. NB-IoT is standardised by the 3rd Generation Partnership Project (3GPP) to support massive machine-type communications (mMTC) within LTE evolution [5]. Understanding which of these technologies and their intricate characteristics is optimal for water utilities. Low elevation can significantly impact the effectiveness and operational costs of the retrofit system in that generally low elevated areas normally suffer from poor signal coverage which proportionally affect the power consumption of a device coming to transmission. This gap is particularly important for ensuring that these solutions remain reliable and cost-efficient in the long term.

Water utilities can greatly benefit from real-time data analysis, as it enables them to make informed decisions quickly, detect inefficiencies, and predict future demands. By developing decision support systems that integrate real-time data, utilities can reduce wastage, optimize resource allocation, and improve customer service. This research gap is vital for improving the operational efficiency of water systems and achieving sustainability goals.

The integration of IoT-based meters with legacy infrastructure is a significant challenge, especially when considering the complexity and scale of South Africa's water systems [12]. Without a reliable framework for this integration, IoT retrofits could be ineffective or lead to operational inefficiencies. Researching how to bridge this gap will help ensure that IoT systems can be easily incorporated into existing infrastructure, leading to smoother adoption and maximizing the value of previous investments.

IoT devices need to withstand the tough environments typical of water infrastructure installations [13]. Understanding their maintenance requirements, failure rates, and the expected lifespan of devices will help ensure that utilities can plan for replacement or upgrades and minimize system downtime. This research will ensure that IoT solutions remain viable and sustainable in the long term, reducing the frequency and cost of maintenance.

For IoT retrofits to be sustainable, they must not only reduce energy consumption but also operate effectively without frequent battery replacements or high energy usage. Energy efficiency is especially important for wireless sensors that need to work in remote locations. Researching power consumption and the viability of energy harvesting like solar and kinetic energy will enable the development of IoT systems that minimize operational costs and environmental impact [14].

1.2 Problem Statement

Rand Water's reliance on cellular-based bulk water meter reading methods has led to a range of operational inefficiencies and technical challenges. These challenges include the demand for significant energy resources; lack of reliability needed for meters embedded in low-elevation concrete chambers and deployed in remote locations. These challenges result in frequent transmission failures, high operational costs, and compromised data accuracy. This research seeks to address this gap by proposing an IoT-based system that leverages optimised and adaptive algorithms to enhance the LPWAN protocols specifically for such challenging environments, providing a reliable and energy-efficient solution. Through this approach, this study aims at establishing and evaluating a scalable model for improving the efficiency of bulk water meter reading in complex infrastructures.

Beyond general signal attenuation, two specific propagation phenomena degrade cellular performance in these installations. First, multipath fading arises as signals reflect off concrete chamber walls, water surfaces, and metallic pipework, causing constructive or destructive interference that creates unpredictable signal nulls at the receiver. Second, antenna detuning occurs because the proximity of steel reinforcement bars (rebar) and the grounded metering enclosure alters the antenna's impedance, reducing radiation efficiency and effective gain. These effects, which are often overlooked in standard link budget calculations, compound the penetration loss and make reliable communication significantly harder to achieve than simple distance-based models would predict.

1.3. Subproblems

1.3.1. Low Elevation Challenges: The current bulk water meters are using a 3G cellular communication approach. This approach exhibits high energy consumption and packet loss in low-elevation areas due higher transmission power requirement and low SNR. The SNR is reduced, affecting the overall data quality and throughput.

1.3.2. Concrete Chambers: The bulk water meters are not just installed in low elevation; they are also installed under a concrete chamber to mitigate theft and vandalism. The currently used cellular communication approach also struggles significantly with signal penetration in these concrete chambers, especially at higher frequencies (like 5G). This significantly affects the communication reliability and requires significant financial investments in terms of additional small cellular network cells.

1.3.3. Communication Protocols: Cellular network technologies are primarily not designed for low power communication and not for any kind of battery-powered IoT devices [6], [9]. Typically, a single 3G transmission can draw up to 2A and a battery-powered bulk water meter would not last with such high current draws. Cellular Networks support high data rates and wide coverage, but transition between generations (e.g., 4G to 5G) introduces challenges such as infrastructure costs, backward compatibility, and high-frequency signal limitations. such as infrastructure costs, backward compatibility, and high-frequency signal limitations.

1.4. Research Objectives

The objectives of this research are to investigate the use of Low Power Wide Area Network (LPWAN) technologies to address the three identified research subproblems. The study therefore models the identified challenges, assesses the performance of selected LPWAN approaches in terms of energy efficiency and network reliability, and proposes optimization strategies to enhance performance in underground reinforced concrete deployments. The specific research objectives include:

a. Model and evaluate the energy efficiency, network reliability, and scalability performance of existing cellular-based and LPWAN methods used for bulk meter reading considering low elevation challenges [15] and propose a join-aware optimization strategy that minimizes unnecessary re-joins and adaptive data rate (ADR) misconfiguration to mitigate the impact of low elevation on communication reliability and energy consumption.

b. Model and evaluate the energy efficiency, network reliability, and scalability performance of existing cellular-based and LPWAN methods used for bulk meter reading considering concrete chamber deployments and develop a coverage enhancement modelling framework that explicitly accounts for reinforced concrete attenuation, enabling quantitative assessment of penetration loss mitigation through protocol configuration and repetition mechanisms.

c. Model and evaluate the performance of existing cellular-based and LPWAN methods used for bulk meter reading considering PHY and MAC layer protocol designs in terms of energy efficiency, network reliability, and scalability, and establish a deployment-aware comparative framework that synthesizes the energy–reliability trade-offs between LoRaWAN and NB-IoT, providing evidence-based technology selection guidance for large-scale underground bulk water metering applications.

1.5. Hypotheses

1.5.1. Low elevation: By replacing 3G cellular modems with LoRaWAN endpoints transmitting at 14 dBm, the average current consumption per reporting cycle will be reduced by at least 80%, while maintaining a packet delivery ratio (PDR) above 0.90 at distances up to 2 km from the gateway.

1.5.2. Concrete Chambers: A LoRaWAN configuration using a fixed spreading factor of 12 (SF12) will achieve a PDR above 0.85 under 25 dB concrete penetration loss, whereas a cellular modem operating at the same site will exhibit a PDR below 0.60 under identical conditions.

1.5.3. Communication Protocols: An optimised LoRaWAN join policy that limits rejoin attempts to one per hour and disables ADR in high-attenuation scenarios will extend the estimated battery lifetime by at least 40% compared to the default LoRaWAN MAC specification when deployed in a concrete chamber with 20 dB additional path loss.

1.6 Research Questions

The following research questions have been formulated to guide the investigation and provide a framework for assessing the effectiveness of the proposed IoT solution. These questions are directly aligned with the research subproblems identified in Section 1.3 and the objectives stated in Section 1.4.

Subproblem 1: Low Elevation Challenges

- **RQ1:** How does the current cellular-based approach to bulk water metering impact energy efficiency and data reliability (signal-to-noise ratio and packet drop rate) in the context of low-elevation sensor deployments?
- **RQ2:** How do LPWAN technologies (LoRaWAN and NB-IoT) compare in terms of energy efficiency and data reliability when deployed in low-elevation underground environments, and what optimization strategies can mitigate the identified performance degradation?

Subproblem 2: Concrete Chamber Challenges

- **RQ3:** What is the impact of reinforced concrete chamber attenuation on signal propagation, packet delivery ratio, and energy consumption for both LoRaWAN and NB-IoT-based bulk water metering systems?
- **RQ4:** How do coverage enhancement mechanisms, specifically LoRaWAN spreading factor adaptation and NB-IoT uplink repetitions compensate for concrete penetration loss, and what are the associated energy-reliability trade-offs?

Subproblem 3: Communication Protocol Limitations

- **RQ5:** How do the fundamental PHY and MAC layer design differences between LoRaWAN (ALOHA-based, unlicensed spectrum) and NB-IoT (scheduled access, licensed spectrum) influence their respective energy efficiency, network reliability, and scalability in underground bulk water metering applications?
- **RQ6:** What are the optimal transmission parameters and protocol configurations (e.g., spreading factor selection, join/rejoin behaviour, power saving modes) for maximizing

battery lifetime while maintaining acceptable reliability in long-term underground deployments?

- **RQ7:** Based on the comparative performance analysis, what deployment-aware technology selection framework can guide water utilities in choosing between LoRaWAN and NB-IoT for large-scale underground bulk metering infrastructure?

1.7 Research Methodology

This research employs a quantitative, simulation-based methodology to evaluate the performance of LPWAN-based IoT protocols within Rand Water's infrastructure. The methodology is designed to assess key performance metrics such as energy efficiency, packet drop, signal-to-noise ratio (SNR), and latency. These metrics are crucial for understanding how well LPWAN technologies (such as LoRaWAN and NB-IoT) perform in real-world conditions where environmental factors (e.g., low elevation, concrete chambers) can impact the effectiveness of communication. The outcome of this research is to help determine the optimal communication protocol for Rand Water's IoT-based metering systems, considering both technical feasibility and cost-effectiveness in the context of their specific infrastructure.

1.7.1 Simulation Setup

- Infrastructure Modelling: The first step involves creating a simulation model of Rand Water's infrastructure, which includes the locations of bulk meters, base stations, network nodes, and communication paths (e.g., in low-elevation environments and concrete chambers). This model will simulate the environmental conditions where the LPWAN-based IoT protocols will operate.
- Selection of LPWAN Protocols: Based on the infrastructure requirements, LPWAN protocols (e.g., LoRaWAN and NB-IoT) will be selected for simulation. The model will focus on the communication characteristics of LPWAN, particularly in terms of range, signal attenuation, and interference typical of Rand Water's environment.

  Simulation Tool: MATLAB will be used to model the communication network. MATLAB provides a platform for simulating wireless network performance, including the key metrics of interest.

1.7.2 Energy Efficiency Evaluation

- Energy Consumption Models: The simulation will include energy consumption models for both IoT devices (sensors or meters) and network infrastructure (base stations, gateways). These models will simulate the energy usage of the devices under various conditions, including:
    - Data transmission frequency.
    - Transmission power needed to overcome signal attenuation.
    - Duty cycle and sleep modes to minimize power consumption.
- Energy Efficiency Metrics: The primary metric for energy efficiency will be the average energy consumption per device per data transmission cycle. This will allow for a comparison of how well LPWAN protocols (e.g., LoRaWAN and NB-IoT) perform in low-elevation and concrete chamber environments compared to other technologies like cellular networks.

1.7.3 Packet Drop Evaluation

- Packet Loss Modelling: The simulation will calculate the packet drop rate, which is the percentage of data packets that fail to reach their destination due to various factors such as:
    - Signal attenuation in low-elevation and concrete chamber environments.
    - Interference caused by physical obstacles or other environmental conditions.
- Factors Affecting Packet Loss:
    - Signal strength and SNR at different distances from the base station.
    - Multipath interference in low elevation environments.
    - Re-transmission mechanisms in LPWAN protocols, like LoRaWAN's use of acknowledgments and retries.
- Packet Loss Metrics: The simulation will produce metrics such as:
    - Average packet drop rate for devices operating in different environments (low elevation vs concrete chambers).
    - Impact of re-transmission schemes on reducing packet loss.

1.7.4 Signal-to-Noise Ratio (SNR) Evaluation

- SNR Modelling: The simulation will calculate the SNR at various points within Rand Water's infrastructure, considering factors such as:

  - Propagation models that account for signal degradation due to environmental factors like concrete and metal pipes.
  - Interference from external sources, such as other wireless networks or equipment.
- SNR Metrics: Key metrics related to SNR will include:
  - Average SNR at various points in the network, especially at locations that simulate low-elevation or concrete chamber environments.
  - Correlation between SNR and packet delivery success, as higher SNR typically leads to better communication reliability.
- Environmental Impact: The simulation will show how different environmental factors affect SNR for LPWAN protocols, and how cellular networks might compare in these environments.

1.7.5 Latency Evaluation

- Latency Modelling: The simulation will assess the latency of data transmission, which includes:
  - Transmission delays, which are the time it takes to send data from the device to the base station.
  - Processing delays, which are introduced at both the device and network levels.
  - Retransmission delays, which occur when packets are lost and need to be retransmitted.
- Factors Affecting Latency:
  - Distance between devices and base stations (which will be influenced by low-elevation or concrete chamber placement).
  - Channel access mechanisms, including the time it takes to transmit data over shared channels in LPWAN systems.
  - Network congestion and the need for backoff or retransmission in case of collisions.
- Latency Metrics: Key latency metrics will include:
  - Average round-trip time for data packets.
  - Maximum latency due to retransmissions and signal degradation in low-SNR environments.
  - Latency variation (jitter) due to interference or network congestion.

1.7.6 Justification for Simulation-Based Approach

A purely simulation-based methodology was adopted for three primary reasons. First, Rand Water's operational bulk metering infrastructure cannot be interrupted for experimental reconfiguration, making controlled field trials infeasible. Second, simulation enables systematic isolation of individual variables (e.g., concrete penetration loss, distance, spreading factor) that would be impossible to control independently in a live underground environment. Third, the Monte Carlo approach used here allows statistical characterisation of performance over thousands of reporting cycles, providing confidence intervals that a limited-duration field trial could not achieve. Future work should complement these simulations with targeted field measurements at representative sites.

1.8 Comparison of LPWAN and Cellular Networks (NB-IoT, LTE-M)

The simulation will also include a comparison between LPWAN protocols (like LoRaWAN and NB-IoT) and cellular networks (like 3G) based on the metrics of energy efficiency, packet loss, SNR, and latency.

- Analysis Criteria: The comparison will focus on:
  - Energy efficiency: Which protocol provides better battery life for IoT devices in the given environmental conditions?
  - Packet loss: How well do each of the protocols perform in terms of data reliability?
  - SNR: Which protocol maintains a higher SNR and can better cope with obstacles like concrete or underground conditions?
  - Latency: Which protocol provides faster data transmission with lower delay?

Table 1.1: Summary of Key Stages

Stage	**Description**
Simulation Setup	Model Rand Water’s infrastructure, select IoT protocols, and set up simulations.
Energy Efficiency Evaluation	Assess the power consumption of IoT devices and network infrastructure.
Packet Drop Evaluation	Evaluate packet loss under different environmental conditions.
SNR Evaluation	Model the impact of environmental factors on the signal-to-noise ratio.
Latency Evaluation	Measure data transmission delays, including retransmissions and processing times.
Comparison of Protocols	Compare LPWAN vs Cellular networks based on energy, packet loss, SNR, and latency.
Conclusion	Analyse simulation results and recommend the optimal communication protocol.

This methodology will allow for a comprehensive evaluation of LPWAN-based IoT protocols under Rand Water's operational conditions, providing valuable insights for optimizing their bulk metering infrastructure.

1.9 Research Benefits

This study aims to produce practical insights that can support the water utility industry’s shift toward IoT-based infrastructure management. Key benefits include:

- Operational Efficiency: The IoT solution will enable automated, continuous monitoring, improving efficiency by reducing the need for manual interventions and routine maintenance checks.
- Enhanced Data Accuracy: By automating meter readings and providing real-time data, the solution will reduce human error and ensure a higher degree of accuracy in water usage reporting and billing.
- Conceptualisation of an ML-Based Anomaly Detection Framework: This study proposes a conceptual framework for applying machine learning techniques (e.g., threshold-based and simple pattern recognition) to detect anomalies such as leaks and tampering in underground metering applications. The framework, implemented within the simulation environment, serves as a proof-of-concept for future field implementations.
- Improved Infrastructure Security: Tampering and overflow alerts will enable rapid response to potential security issues, safeguarding metering equipment and maintaining data integrity.
- Simulation of an Optimized LPWAN Communication Model Tailored for Underground Bulk Water Metering: This contribution involves designing a communication model based on Low Power Wide Area Network (LPWAN) technologies specifically optimized for the unique challenges of underground bulk water metering [4], [8]. This model addresses issues such as signal attenuation, power consumption, and data transmission reliability, particularly in environments with limited connectivity such as underground water chambers [16], [17]. By customizing the LPWAN protocol (LoRaWAN or NB-IoT), this solution ensures efficient and reliable communication for large-scale water metering applications [16].
- First Comparative Analysis of LPWAN (LoRaWAN/NB-IoT) for Signal Reliability in Concrete-Embedded Water Chambers: This contribution presents the first comprehensive comparative study evaluating the performance of different LPWAN technologies (LoRaWAN and NB-IoT) in terms of their ability to maintain reliable signal transmission in challenging environments, such as concrete-embedded underground

water chambers. The analysis includes factors like range, signal degradation due to environmental interference, and data packet loss, providing critical insights into the best-fit technology for long-term, dependable water metering systems [16]–[18].

- Implementation of ML-Based Anomaly Detection for Leak and Tamper Detection in Underground Metering Applications on simulation: This novel contribution introduces the application of machine learning (ML) techniques to detect anomalies in water metering data, specifically for identifying leaks and tampering in underground installations. By leveraging algorithms trained on historical data, the system can identify patterns that deviate from normal behaviour, enabling real-time detection of issues like water leaks or unauthorized tampering. This proactive approach enhances the accuracy, security, and efficiency of water management systems, significantly reducing water waste and operational costs [19].
- Publication in High-Impact IoT or Smart Grid Journals: Publishing the research findings in high-impact journals that focus on IoT, smart grids, or related fields will ensure that the novel contributions reach a broader academic and professional audience. These journals typically have a rigorous peer-review process, ensuring the quality, relevance, and innovation of the research. Moreover, such publications offer visibility and credibility, potentially influencing future research, standardization efforts, and adoption of the proposed communication model, anomaly detection techniques, and IoT-based water metering solutions.
- Publishing in high-impact journals can also lead to citations, further validating the research in the scientific community. This dissemination can catalyse further advancements in the integration of IoT and LPWAN technologies in water management and smart grid systems, accelerating the development of smart cities and sustainable infrastructure.
- Development of an Open-Source Simulation Model for IoT-Based Water Metering: The development of an open-source simulation model would provide the academic, industrial, and research communities with a powerful tool to experiment, test, and improve IoT-based water metering systems. Given that water metering often involves complex, dynamic environments (e.g., underground chambers, varying levels of water consumption, diverse topographies), having a simulation model can help stakeholders better understand system behaviours, optimize configurations, and plan for real-world

implementations [20]. The open-source nature of this model would promote collaboration, encouraging others to contribute to its development, improving its accuracy and scalability.

- This model can serve as a foundation for both researchers and practitioners to evaluate the performance of LPWAN technologies (LoRaWAN, NB-IoT) in diverse conditions, simulate various water consumption scenarios, and develop and test new algorithms for leak detection, tamper detection, and energy optimization. It can also be integrated with machine learning models for advanced predictive analytics. As an open-source tool, it democratizes access to these capabilities, fostering innovation in IoT-based water metering across different industries and regions, potentially leading to widespread adoption of sustainable water management practices [20].

1.10 Delimitations of the Study

This research is specifically focused on simulating retrofitting IoT solutions for bulk water meters located in low-elevation, concrete-embedded chambers managed by Rand Water. The scope does not extend to other water utility meters, regions, or alternative infrastructure environments. Additionally, the study focuses primarily on LPWAN technologies and does not include cellular or short-range communication technologies beyond comparative analysis. The study primarily evaluates LPWAN protocols and does not consider other IoT communication technologies like Wi-Fi, Zigbee, or Bluetooth. The comparison is limited to LPWAN and cellular networks (e.g 3G), as these are the most relevant for bulk metering applications. The research is limited to low-elevation and concrete chamber environments. It does not evaluate other environmental factors like extreme weather conditions or urban/rural settings. The focus is on the conditions Rand Water operates in, but it doesn't extend to all possible geographical scenarios. The study uses simulation tools to model performance, which means the results are based on idealized assumptions of network behaviour. Real-world results may vary depending on un-modelled factors, such as network congestion, interference from external sources, and device hardware constraints. The research is specifically concerned with bulk metering applications within Rand Water’s infrastructure. It does not consider other types of IoT applications (e.g., smart city or agricultural use cases) or the full range of IoT-based water management systems.

1.11 Key Evaluation Metrics

To assess the performance of the proposed simulation for an IoT-based retrofit solution, several key metrics are defined:

Energy Efficiency: Evaluating the overall power consumption and battery longevity for each tested protocol [16], [17].

Network Reliability: Measuring the consistency, accuracy, and robustness of data transmission under the specific environmental constraints posed by low-elevation concrete chambers [16], [18].

Data Security: simulating and testing security measures to protect data from unauthorized access or tampering and ensuring data accuracy [19].

Cost-Effectiveness: Analysing the potential cost savings and economic benefits of the IoT solution relative to current methods [18], [20].

1.12 Outline of the Dissertation

The dissertation is organized as follows:

Chapter 1: Introduction

This chapter introduces the research problem of energy efficiency and network reliability in underground bulk water metering deployments. It defines the research objectives, hypotheses, research questions, and methodological approach adopted to evaluate LoRaWAN and NB-IoT under reinforced concrete attenuation conditions. The chapter further outlines the contribution of the study and establishes the evaluation metrics that guide the modelling and simulation framework.

Chapter 2: Literature Review

This chapter presents a systematic review of recent research on LPWAN technologies, underground wireless propagation, and IoT-based bulk water metering systems. It critically analyses LoRaWAN and NB-IoT architectures, energy models, reliability mechanisms, and deployment limitations in deep-indoor and underground environments. The chapter concludes by identifying research gaps, particularly the lack of harmonised deployment-aware comparative modelling frameworks.

Chapter 3: Modelling Energy Efficiency of LoRa and LoRaWAN Sensor Nodes in Bulk Metering Applications

This chapter develops a deployment-aware analytical model for LoRaWAN sensor nodes operating in underground reinforced concrete chambers. It formulates state-based energy consumption equations, join/rejoin dynamics, retransmission behaviour, and SNR-dependent reliability degradation. MATLAB-based simulations are then used to quantify energy consumption, packet delivery performance, and battery lifetime under varying attenuation conditions.

Chapter 4: Modelling Energy Efficiency and Network Reliability of NB-IoT Sensor Nodes in Bulk Metering Applications

This chapter presents a harmonised modelling framework for NB-IoT under identical underground deployment assumptions used for LoRaWAN. It derives energy consumption models incorporating attachment procedures, control signalling, coverage enhancement repetitions, and power saving mechanisms. Reliability, latency, and battery lifetime are evaluated using SNR-based success modelling and deterministic scheduling characteristics of cellular IoT networks.

Chapter 5: Simulation Results and Comparative Performance Analysis

This chapter presents the simulation results and provides a side-by-side comparative evaluation of LoRaWAN and NB-IoT. Key metrics analysed include packet delivery ratio, energy per reporting cycle, energy per successful packet, battery lifetime, and latency under varying underground attenuation levels. The chapter synthesises the trade-offs and develops a deployment-aware technology selection framework for bulk water utilities.

Chapter 6: Conclusions and Recommendations

This chapter summarises the principal findings of the dissertation relative to the research questions and highlights the major technical contributions of the work. It discusses practical deployment implications for underground bulk water metering and identifies limitations of the modelling approach. Finally, it provides recommendations for future research, including field validation, hybrid LPWAN architectures, and extended multi-technology IoT integration for smart water networks.

1.13 Research Contribution and Outputs

This research contributes to the field of water utility management by proposing an innovative IoT-based retrofit solution for bulk water meters, specifically designed for challenging environments such as low-elevation concrete chambers. By addressing critical issues such as energy efficiency, network reliability, data accuracy, and infrastructure security, the study offers a comprehensive framework for modernizing water utility infrastructure in a sustainable and cost-effective manner. The findings of this research are expected to benefit Rand Water utility by providing practical insights into the deployment and management of IoT-enabled systems for efficient and reliable metering operations.

1.13.1 Research Outputs

Table 1.2 shows two peer-reviewed conference publications that are a product of this study. The first, presented at the 2024 International Multi-Disciplinary Information Technology and Engineering Conference (IMITEC) in Vanderbijlpark, South Africa, reports preliminary findings on the efficacy of LPWAN IoT protocols in mitigating data transmission challenges inherent to concrete-encased bulk water meters [Dlamini, Migabo, & Sumbwanyambe]. The second, delivered at the Southern Africa Telecommunication Networks and Applications Conference (SATNAC) 2025, proposes a join-aware optimisation framework for LoRaWAN nodes deployed in underground concrete chambers. The framework explicitly models OTAA (re)join procedures, receive windows, and adaptive data rate (ADR) behaviour; simulation results demonstrate improved energy efficiency, reduced unnecessary rejoins, and extended battery lifetime relative to conventional strategies [Dlamini, Migabo, Sotenga, & Sumbwanyambe].

Table 1.2: Conference publications

[1] A. Dlamini, E. Migabo, and S. Mbuyu, "Low Power Wide Area Networks (LPWAN) Technologies for Bulk IoT: A Critical Review of Reliability and Energy Efficiency," in *2024 4th International Multidisciplinary Information Technology and Engineering Conference (IMITEC)*, Vanderbijlpark, South Africa, 2024, pp. 351–360, doi: 10.1109/IMITEC60221.2024.10851092.

[2] A. M. Dlamini, E. M. Migabo, P. Z. Sotenga, and M. M. Sumbwanyambe, "Join-aware energy modelling and optimisation of LoRaWAN nodes for underground bulk water metering," in *Proceedings of the Southern Africa Telecommunication Networks and Applications Conference (SATNAC)*, Western Cape, South Africa, Sep. 2025, p. 404. ISBN: 978-1-0492-3850-0.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter delves into the current state of the art in IoT retrofit approaches for enhancing bulk water metering infrastructure smart monitoring and management. It critically examines existing technologies, detailing their benefits and drawbacks to identify existing gaps in reliability and energy efficiency. By evaluating these approaches, this review aims to lay the groundwork for proposing a more robust and efficient wireless solution for water utility bulk meter reading.

2.2 Systematic Review Methodology (PRISMA)

The systematic review process for this study employs the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, which is widely regarded for its structured and transparent approach to literature selection. PRISMA's four-stage approach—Identification, Screening, Eligibility, and Inclusion—ensures that only the most relevant and high-quality studies are reviewed, allowing a focused investigation into the specific challenges and advancements associated with IoT-enabled bulk meter reading in water utilities. Each phase of PRISMA is detailed below to provide a comprehensive understanding of how studies were selected, filtered, and analysed.

2.2.1 Identification

The identification phase serves as the foundation of the systematic review process, designed to capture an exhaustive list of potentially relevant studies on IoT applications in water utility metering, with a specific focus on wireless communication protocols, energy efficiency, and sensor-based data collection methods. The databases selected for this search were IEEE Xplore, ScienceDirect, and Google Scholar, each offering extensive collections of academic and technical literature across the domains of IoT, wireless communication, and smart utility management.

To maximize the relevance of results, a combination of Boolean operators and specific keywords was employed. Keywords such as “IoT for bulk meter reading,” “wireless water metering,” “energy-efficient water utility,” and “LoRaWAN for utilities” were used. For example, a query like “(IoT AND bulk meter reading) OR (wireless water metering AND energy efficiency)” was instrumental in refining search outcomes to studies closely aligned with this study’s objectives.

The initial search returned approximately 2,500 articles across all databases. These results were exported to reference management software, enabling streamlined tracking of sources, the removal of duplicates, and categorization for further analysis.

Table 2.1 provides an overview of the inclusion and exclusion criteria that were later applied, setting boundaries on the types of studies considered relevant for the review.

Table 2.1: Inclusion and Exclusion Criteria for Literature Review

Table 2.1: Inclusion and Exclusion Criteria for Literature Review
Inclusion Criteria
• Studies on IoT applications for water utility metering
• Wireless communication protocols (e.g., LoRaWAN, NB-IoT)
• Relevant to energy efficiency and network reliability
• Contains quantitative performance metrics (e.g., energy consumption)

2.2.2 Screening

Following identification, the screening phase sought to refine the initial set of articles by eliminating duplicates and studies outside the scope of IoT-enabled water utility metering. Approximately 700 duplicate entries were removed, reducing the dataset to 1,800 unique records. Next, a preliminary review of titles and abstracts was conducted to assess relevance based on defined criteria, emphasizing IoT applications in utility settings, wireless communications, and energy management in urban or semi-urban contexts.

Articles that focused on unrelated IoT applications (e.g., IoT in agriculture, healthcare monitoring) or general studies on wireless communication protocols without specific applications to water utilities were excluded during this phase. After this initial filtering, 500 studies were retained for the eligibility phase.

Figure 2.1 presents a **PRISMA Flow Diagram** summarizing the progression of articles through each phase, from identification to inclusion, providing a clear overview of the narrowing process.

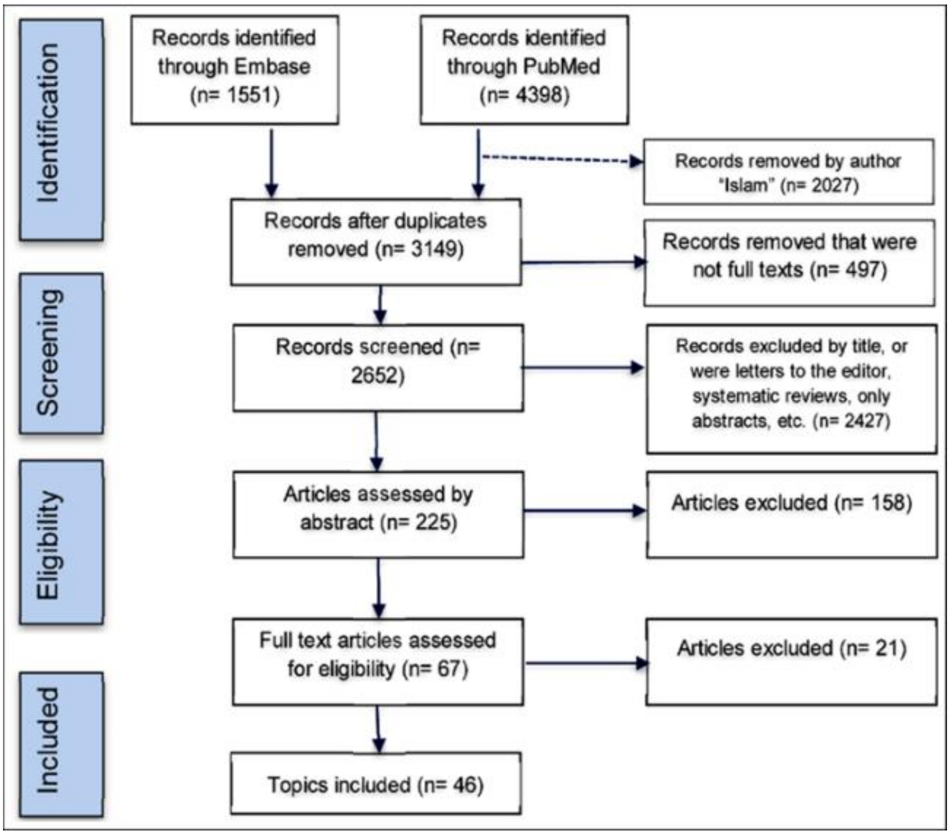

Figure 2.1: Prisma Flow Diagram of The Literature Selection Process

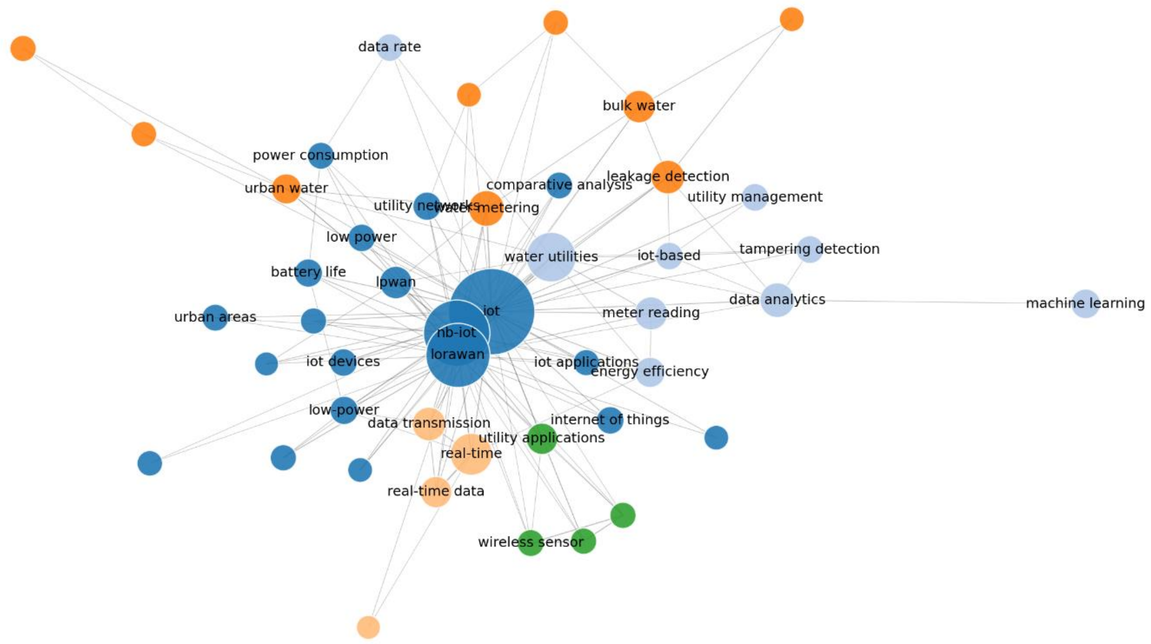

Figure2.2: Bibliography-based keyword co-occurrence map highlighting IoT retrofit, bulk water meter management, wireless reliability, and energy efficiency themes.

2.2.3 Eligibility

The eligibility phase entailed a full-text review of each of the 500 remaining studies, applying stricter criteria to ensure relevance and quality. The objective was to identify studies that not only discussed IoT solutions for water utility metering but also provided insights into quantitative performance metrics related to energy consumption, communication range, data reliability, and sensor network scalability.

The criteria for eligibility were as follows:

- **Inclusion of Wireless Protocols in Utility Applications**: Only studies exploring LPWAN technologies (e.g., LoRaWAN, NB-IoT) or Wireless Sensor Networks (WSNs) tailored for utility environments were selected. Studies focusing on specific protocols without a utility context were excluded.

- **Energy Efficiency**: Studies had to include discussion or experimentation on power consumption, sensor battery life, or energy-saving mechanisms in IoT networks for bulk meter reading.

- **Communication Reliability in Challenging Environments**: Given the Rand Water context, priority was given to studies exploring solutions for environments with limited line-of-sight, interference from urban infrastructure, or other obstacles impacting wireless communication.

During this phase, studies lacking quantitative data or experimental validation of IoT protocols in water metering contexts were excluded. This rigorous filtering reduced the pool to 100 articles that offered in-depth technical evaluations relevant to water utility IoT applications.

Figure 2.3 illustrates the **Distribution of Studies by Database Source**, with IEEE Xplore contributing the majority, followed by ScienceDirect and Google Scholar.

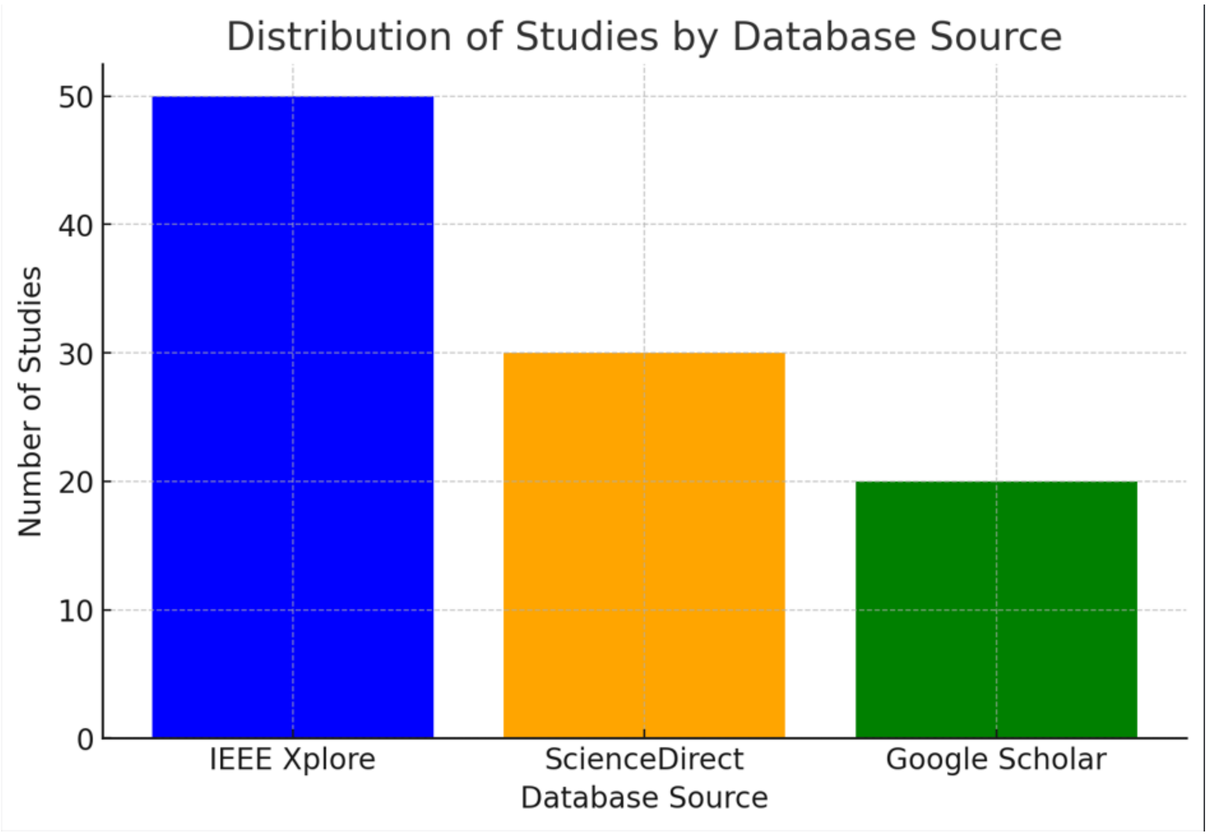

Figure 2.3: Distribution of Studies by Database Source

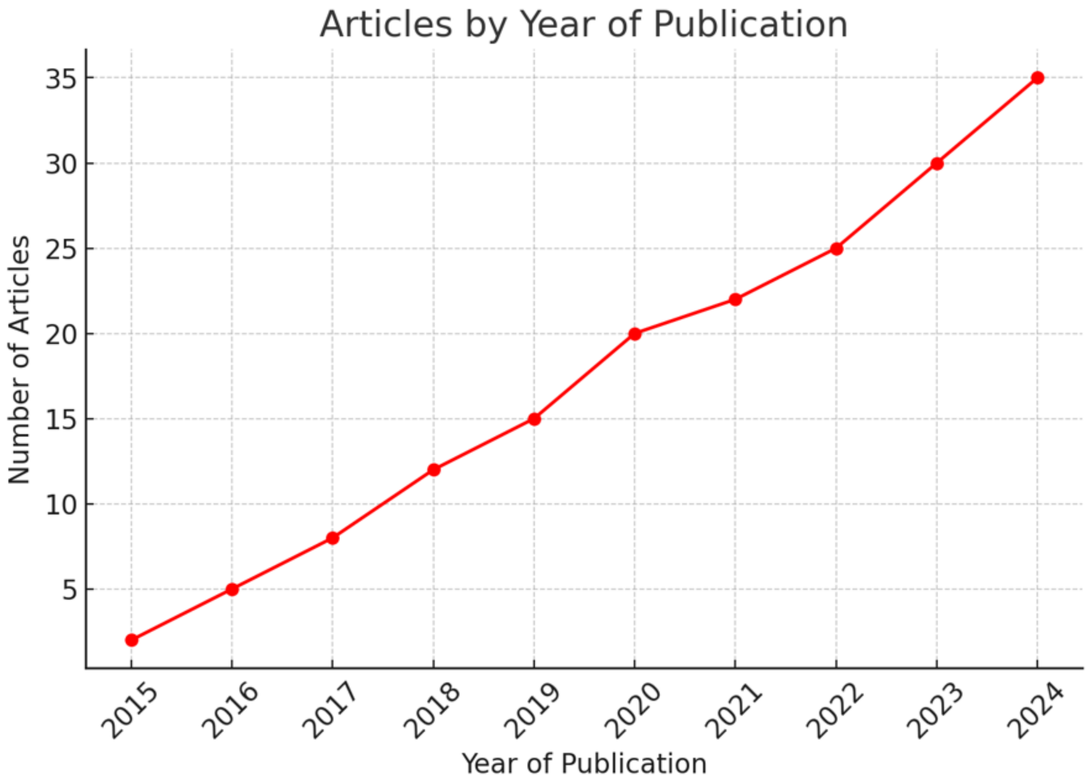

Figure 2.4: Articles by Year of Publication

Figure 2.4 shows the number of articles vs articles by year of publication. The inclusion process facilitated a highly focused review, ensuring that the final selection of articles addressed the technological, operational, and environmental aspects relevant to the implementation of IoT-enabled bulk water metering solutions for Rand Water.

2.3 Wireless Sensor Networks for Meter Reading

Wireless Sensor Networks (WSNs) are increasingly pivotal in the automation of meter reading systems within water utilities. As a distributed collection of sensor nodes, WSNs facilitate real-time data acquisition, transmission, and processing, allowing for automated and remote water meter readings that minimize the need for labour-intensive, manual measurements. The architecture of WSNs, their integration into water utilities, and their adaptation to address challenges such as energy consumption, signal interference, and harsh environmental conditions make them a foundational technology in modern IoT-enabled utility management. This section provides an in-depth exploration of WSNs' operational principles, network design considerations, and energy efficiency techniques, with a specific focus on their application in bulk water meter reading for utility providers.

2.3.1 Architecture and Components of WSNs

The architecture of a Wireless Sensor Network typically consists of multiple spatially distributed sensor nodes that communicate wirelessly to a central gateway or base station. In water utility applications, sensor nodes are deployed at various points of interest, such as bulk water meters, pipelines, and distribution points, where they monitor and transmit data on water flow, usage, pressure, and other parameters. Each node is composed of four main components: a sensing unit, a processing unit, a communication unit, and a power supply.

1. **Sensing Unit**: In water meter reading applications, the sensing unit captures data relevant to water flow and volume measurements. Common sensors include ultrasonic flow meters, which measure water velocity through the Doppler effect, and electromagnetic flow sensors, which monitor water movement based on Faraday's Law of electromagnetic induction [21].

2. **Processing Unit**: This unit processes raw data from the sensing unit before transmission, often employing data aggregation and compression algorithms to reduce data load and conserve bandwidth [22].

3. **Communication Unit**: Responsible for data transmission, the communication unit uses wireless protocols such as Zigbee, LoRa, or Wi-Fi. Protocol selection depends on factors such as distance, data rate, and power requirements. Zigbee, for example, is suitable for short-range applications, whereas LoRa provides extended range and low-power operation, making it ideal for water utilities with dispersed infrastructure [23].

4. **Power Supply**: Typically powered by batteries or energy-harvesting technologies, the power supply is a critical component, particularly for remote or underground installations where regular maintenance is challenging. Techniques such as duty cycling, which alternates between active and sleep modes, help extend battery life [24].

In a typical WSN configuration, nodes operate in a multi-hop relay manner to transmit data to the central gateway, where further analysis and data storage occur. This configuration enables WSNs to cover extensive areas, making them suitable for large water distribution networks.

2.3.2 Data Collection and Transmission

Data collection in WSNs for meter reading applications must be both frequent and reliable, ensuring timely updates without significant packet loss. In water utilities, data collected by WSNs includes metrics such as flow rate, pressure, temperature, and sometimes chemical properties of the water, depending on the specific monitoring requirements. Collected data is often used for billing purposes, operational monitoring, and proactive maintenance.

Multi-hop Transmission: WSNs utilize a multi-hop transmission model, where data is relayed from node to node until it reaches the gateway. This setup conserves power by reducing the transmission distance for each node and mitigates signal attenuation, particularly in environments with physical obstacles like underground chambers and concrete walls [25].

Data Aggregation Techniques: To minimize network traffic, data aggregation methods are implemented at the node level. By combining readings from multiple sensors into a single packet or performing local averaging, WSNs can reduce the frequency of data transmission, saving energy and bandwidth [26]. Studies have shown that aggregation techniques can reduce data volume by up to 50% in water utilities, significantly improving energy efficiency [27]

2.3.3 Energy Efficiency Strategies

Energy consumption remains a primary concern in WSNs, particularly in utility applications where sensor nodes are deployed in hard-to-access locations, making battery replacement difficult. Several strategies are employed to optimize energy usage and extend the operational life of each node, ensuring the network remains functional for extended periods without requiring frequent maintenance.

1. **Duty Cycling**: By alternating between active and sleep states, nodes can significantly conserve energy. In low-activity periods, such as nighttime when water usage decreases, nodes enter a low-power sleep mode, waking only periodically to transmit essential updates [28].

2. **Data Reduction Techniques**: Data reduction techniques like adaptive sampling adjust the frequency of data collection based on usage patterns, reducing unnecessary transmissions. For instance, in periods of low water consumption, the network can decrease sampling frequency without compromising data quality [29].

3. **Energy Harvesting**: Recent advancements in energy harvesting technologies have introduced the potential to use solar or vibrational energy sources to recharge sensor batteries. In certain water utility applications, energy-harvesting methods have demonstrated the ability to extend battery life by up to three times, significantly reducing the operational cost and environmental impact of WSN deployments [30].

2.3.4 Network Topologies for Water Metering

Selecting an appropriate network topology is essential to optimize coverage, connectivity, and resilience in WSNs for water meter reading. Common topologies used in these networks include star, tree, and mesh configurations, each offering distinct advantages for water utility applications.

- **Star Topology**: In star networks, each sensor node communicates directly with a central hub. This topology simplifies network management and is energy-efficient due to reduced routing complexity. However, it lacks redundancy, making it vulnerable if the central hub fails [31].

- **Tree Topology**: Tree networks, also known as hierarchical topologies, offer improved scalability by structuring nodes in layers. Data is passed up through the network hierarchy, reducing the load on any single node and distributing energy consumption more evenly across the network [32].

- **Mesh Topology**: Mesh networks provide the highest level of redundancy, as data can take multiple paths to the central hub. This redundancy enhances network reliability, particularly in environments with physical obstructions, making it an ideal choice for large water distribution systems. Mesh topologies, however, are more energy-intensive due to the complexity of routing algorithms and frequent communication between nodes [33].

2.3.5 Applications in Water Utilities

The adoption of WSNs in water utilities has led to numerous applications beyond simple meter reading, offering utilities the ability to monitor infrastructure conditions in real time, detect leaks or tampering, and optimize resource allocation.

- **Real-Time Monitoring and Billing**: WSNs facilitate continuous monitoring of water consumption, enabling utilities to provide real-time billing services. This system allows users to access accurate billing information and adjust their usage habits based on real-time feedback [34].

- **Leakage and Tampering Detection**: By monitoring flow rates and pressure fluctuations, WSNs can identify leaks or tampering incidents in near real time. These capabilities are crucial for preventing water loss and maintaining the integrity of the water distribution system. Studies have shown that early leak detection via WSNs can reduce water losses by up to 20% [35].

- **Predictive Maintenance**: Advanced WSN implementations incorporate predictive maintenance algorithms that analyse sensor data trends to forecast equipment failure. This proactive approach allows utilities to schedule maintenance before issues escalate, minimizing operational disruptions and extending the lifespan of critical infrastructure [38].

2.3.6 Limitations and Future Directions

While WSNs offer significant advantages in terms of flexibility and functionality for water meter reading, they are not without limitations. Challenges such as limited bandwidth, signal attenuation, and energy constraints can hinder WSN performance. Future research is focusing on integrating WSNs with other communication technologies, such as Low Power Wide Area Networks (LPWANs), to overcome these limitations. Hybrid WSN-LPWAN systems could enhance range, data rate, and reliability, making them more suited for large-scale deployments in urban water utilities [36],[37].

2.4 LoRaWAN-Based Solutions

LoRaWAN (Long Range Wide Area Network) has emerged as a prominent communication protocol within the Internet of Things (IoT) ecosystem, particularly suited for applications requiring long-range, low-power data transmission. Designed to support massive IoT deployments, LoRaWAN provides a scalable and cost-effective solution for water utilities that need reliable, remote, and energy-efficient meter reading capabilities. In the context of utility services, LoRaWAN's unique characteristics—such as extensive range, low power consumption, and efficient data transmission—address many challenges associated with conventional metering systems, particularly those that involve geographically dispersed or hard-to-access infrastructure. This section delves into the architecture, operational principles, advantages, limitations, and specific applications of LoRaWAN in water utilities, with a focus on its suitability for bulk water meter reading.

2.4.1 LoRaWAN Architecture and Protocol Design

LoRaWAN operates on a star-of-stars topology, where multiple end devices communicate with central gateways, which in turn connect to a network server. The protocol relies on LoRa (Long Range) modulation, a type of chirp spread spectrum (CSS) modulation, enabling long-distance communication over unlicensed sub-gigahertz frequency bands (e.g., 868 MHz in Europe, 915 MHz in North America). The LoRaWAN architecture consists of three main layers: end devices (e.g., sensors), gateways, and network/application servers [39].

1. **End Devices**: In a LoRaWAN-enabled water utility network, end devices are the smart meters or sensors installed at various points of the distribution system, including bulk water meters, pipelines, and storage tanks. These devices collect real-time data on parameters such as flow rate, volume, and pressure, which are essential for accurate metering and operational monitoring. The low-power nature of LoRa technology allows these devices to function for extended periods on battery power, reducing maintenance frequency and costs [40].

2. **Gateways**: Gateways are responsible for receiving data from multiple end devices and forwarding it to the network server. In the context of water utilities, gateways are typically strategically positioned to maximize coverage over wide geographic areas, making LoRaWAN an ideal solution for utilities that span rural and urban regions [41].

3. **Network/Application Servers**: The network server manages data routing, security, and device authentication, while the application server processes the data for actionable insights. This architecture provides a highly flexible and secure environment, with end-to-end encryption protecting data integrity and privacy. Network redundancy through multiple gateways can enhance reliability, especially in challenging environments where signal obstruction may occur.

2.4.2 Advantages of LoRaWAN in Water Metering

LoRaWAN offers several advantages that make it well-suited for water utility applications, especially in environments requiring low power, long-range communication, and minimal infrastructure investment.

- **Extended Range**: LoRaWAN can achieve communication ranges of up to 15 km in rural areas and up to 5 km in urban areas, making it highly suitable for geographically dispersed water utilities. Studies have demonstrated that LoRaWAN's range significantly exceeds that of conventional wireless solutions, allowing water utilities to connect devices located in remote or difficult-to-reach areas [42].

- **Low Power Consumption**: A critical feature of LoRaWAN is its low power requirement, which enables battery-operated devices to function for years without replacement. This characteristic is especially beneficial for water utilities where devices are often installed underground or in areas where frequent maintenance is impractical [43].

- **Scalability**: LoRaWAN networks can support thousands of end devices, making the technology highly scalable. This scalability is essential for water utilities that manage extensive infrastructure and need to deploy large numbers of sensors across the distribution network. LoRaWAN's architecture allows seamless addition of new devices without significantly impacting network performance [44].

- **Cost Efficiency**: LoRaWAN operates in unlicensed ISM (Industrial, Scientific, and Medical) bands, reducing operating costs associated with licensed spectrum use. This cost efficiency makes LoRaWAN a compelling choice for utility providers seeking to implement IoT solutions on a large scale without incurring prohibitive costs [45].

2.4.3 Limitations of LoRaWAN

While LoRaWAN offers several benefits, certain limitations must be addressed to optimize its use in water metering applications. Key limitations include data rate constraints, limited support for high-frequency data transmission, and vulnerability to interference.

- **Data Rate Constraints**: LoRaWAN's data rates, which range between 0.3 kbps to 50 kbps, are significantly lower than those of other communication protocols like NB-IoT. This limitation restricts the protocol to low-bandwidth applications, such as periodic data updates rather than continuous streaming, which may be insufficient for applications requiring real-time high-resolution data [46].

- **Duty Cycle Restrictions**: LoRaWAN operates under duty cycle regulations, which limit the amount of time a device can occupy the channel. For example, in the European 868 MHz ISM band, the duty cycle is typically 1%, meaning devices can only transmit data for 1% of each hour. This limitation impacts the protocol's suitability for applications that require frequent updates, such as real-time leakage detection [47].

- **Interference and Urban Obstacles**: In dense urban environments, LoRaWAN signals can experience interference and attenuation from physical obstacles, such as buildings and underground chambers. This limitation is especially relevant for water utilities operating in densely populated areas, where signal reliability may be compromised. Strategies such as deploying additional gateways or optimizing gateway placement can mitigate some of these issues [48].

2.4.3.1 Empirical Validation in Underground and Indoor Environments

While simulation studies dominate LPWAN literature, recent empirical measurements have provided critical validation of LoRaWAN performance in constrained spaces. Theissen et al. [163] conducted propagation measurements in underground potash salt mines, observing that tunnel geometry can create waveguide-like effects that extend range beyond free-space predictions, but only when the antenna is correctly polarised relative to the tunnel axis. Conversely, Lorincz et al. [164] performed controlled indoor experiments showing that each additional concrete wall (150 mm thickness) introduces between 4 dB and 7 dB of additional loss, and that signal variability increases with the number of obstructions due to multipath. Pagano et al. [165] further demonstrated that in mixed indoor-underground deployments, the dominant failure mode is not distance, but the number of reinforced concrete boundaries traversed. These empirical findings directly support the deployment-aware modelling approach taken in this thesis, particularly the use of concrete penetration loss (*L_concrete*) as a key simulation variable.

Complementing these field studies, Rahman et al. [161] proposed the MAME (Material Aware Measurement Enhanced) model, which integrates physics-based propagation equations with empirical data from small-scale testbeds to predict wireless packet delivery from underground sensor nodes; their model, validated for LoRaWAN networks across varying soil moisture levels, was subsequently integrated into the NS3 simulator, directly validating the simulation-based methodology adopted in this thesis.

2.4.4 Applications of LoRaWAN in Water Utilities

LoRaWAN has proven effective in various water utility applications, particularly in enabling automated meter reading, remote monitoring, and operational efficiency improvements.

1. **Automated Meter Reading**: LoRaWAN enables the deployment of automated meter reading (AMR) systems, which provide utilities with accurate, real-time data on water consumption. This system eliminates the need for manual readings, reducing labour costs and minimizing human error. Studies have shown that AMR systems can improve billing accuracy and enhance customer satisfaction by providing detailed consumption insights [49].

2. **Leakage and Tampering Detection**: LoRaWAN's ability to support remote monitoring allows utilities to detect leaks or tampering incidents more effectively. Sensor nodes placed along the distribution network can monitor pressure changes, which indicate potential leaks, while tampering detection sensors can alert operators to unauthorized access. These capabilities are crucial for ensuring infrastructure integrity and reducing water loss [50].

3. **Predictive Maintenance**: By collecting historical data on flow rates and pressure, LoRaWAN networks enable predictive maintenance strategies. These strategies leverage data analytics to forecast equipment failure or pipeline wear, allowing utilities to conduct maintenance proactively. Such an approach not only reduces unplanned downtime but also extends the lifespan of critical assets [51]..

2.4.5 Comparative Analysis of LoRaWAN and Other LPWAN Technologies

When considering LPWAN technologies for water utilities, LoRaWAN is often compared to alternatives such as NB-IoT, Sigfox, and Weightless. Each of these technologies offers distinct advantages and trade-offs, depending on application requirements.

- **LoRaWAN vs. NB-IoT**: While LoRaWAN operates on unlicensed spectrum, NB-IoT uses licensed bands, providing greater protection against interference. However, LoRaWAN's unlicensed operation makes it more cost-effective for large-scale deployment. NB-IoT supports higher data rates and reliability, but LoRaWAN's longer battery life is advantageous for remote, low-power applications [52].

- **LoRaWAN vs. Sigfox**: Both LoRaWAN and Sigfox are suited for low-power, long-range communication. However, Sigfox operates with a lower data payload limit, making it suitable for infrequent, small data transmissions. LoRaWAN offers greater flexibility in data rate and payload capacity, making it a more versatile choice for water utilities requiring more frequent updates [53].

- **LoRaWAN vs. Weightless**: Weightless offers higher data rates compared to LoRaWAN but at the cost of shorter range and higher power consumption. Weightless networks are often less scalable than LoRaWAN, limiting their applicability in widespread utility networks [54].

Table 2.2 presents a summary comparison of key LPWAN technologies, highlighting the trade-offs between range, data rate, power consumption, and scalability.

Table 2.2: Comparison of LPWAN Technologies for Water Utilities

Technology	**Spectrum**	**Range (Urban)**	**Data Rate**	**Battery Life**	**Scalability**
LoRaWAN	Unlicensed	Up to 5 km	0.3 - 50 kbps	Long	High
NB-IoT	Licensed	Up to 10 km	Up to 200 kbps	Moderate	High
Sigfox	Unlicensed	Up to 10 km	100 bps	Long	Limited
Weightless	Licensed/Unlicensed	Up to 2 km	Up to 10 Mbps	Short	Moderate

2.4.6 Future Directions for LoRaWAN in Water Metering

While LoRaWAN has demonstrated significant potential in utility applications, ongoing research focuses on addressing its limitations and enhancing its capabilities. Some key areas of development include:

1. **Multi-Gateway Architectures**: The use of multiple gateways in LoRaWAN networks can improve data reliability and mitigate interference issues in urban settings. By strategically positioning gateways to cover overlapping areas, utilities can reduce packet loss and ensure consistent data transmission, even in challenging environments [55].

2. **Hybrid Network Solutions**: Integrating LoRaWAN with other LPWAN technologies, such as NB-IoT, is another emerging approach. Hybrid solutions can offer the best of both technologies, combining LoRaWAN's low power and cost-efficiency with NB-IoT's reliability in licensed bands. Such integration could enable water utilities to scale their networks while ensuring data quality and connectivity across diverse geographical areas [56].

3. **Advanced Data Analytics and Machine Learning**: By incorporating advanced data analytics and machine learning techniques, LoRaWAN-enabled water utilities can extract more value from collected data. Predictive analytics can optimize meter reading schedules, enhance leakage detection, and improve infrastructure maintenance planning. These techniques transform data into actionable insights, allowing utilities to operate more efficiently and sustainably [57].

LoRaWAN's low-power, long-range capabilities, coupled with its scalability, make it a valuable solution for water utilities seeking to modernize their infrastructure through IoT-enabled bulk meter reading. Despite some limitations, continuous advancements in network design, data analytics, and hybrid architectures promise to address these challenges, paving the way for LoRaWAN's broader adoption in the utility sector.

2.5 NB-IoT for Urban Metering

Narrowband IoT (NB-IoT) is a Low Power Wide Area Network (LPWAN) technology designed to support large-scale IoT deployments, particularly in urban environments where challenges such as signal interference, building penetration, and dense infrastructure are prevalent. As a cellular-based technology standardized by the 3rd Generation Partnership Project (3GPP), NB-IoT operates on licensed spectrum bands, providing advantages in terms of data security, reliability, and coverage. These characteristics make NB-IoT an attractive option for water utilities seeking to implement IoT-based urban metering solutions that require consistent, real-time data transmission in densely populated areas. This section provides an in-depth analysis of the architecture, operational advantages, limitations, and specific applications of NB-IoT in water utility metering.

2.5.1 NB-IoT Architecture and Protocol Design

NB-IoT builds on the existing cellular infrastructure, allowing it to benefit from extensive global networks already deployed by mobile network operators (MNOs). Unlike other LPWAN technologies such as LoRaWAN or Sigfox, which rely on unlicensed spectrum, NB-IoT operates in licensed bands, typically around 800 MHz, 900 MHz, or 1800 MHz. This provides higher levels of interference protection, reliability, and controlled quality of service (QoS), which are critical in urban settings.

The NB-IoT architecture is designed to facilitate three main communication modes:

1. **Stand-Alone Mode**: NB-IoT can operate independently within its own spectrum band. This mode is ideal for areas where NB-IoT deployments are dense and require dedicated resources to maintain network stability [58].

2. **In-Band Mode**: In this configuration, NB-IoT shares spectrum resources with an existing Long-Term Evolution (LTE) network, allowing it to co-exist with LTE traffic. This mode is particularly beneficial in densely populated urban environments, as it utilizes existing LTE infrastructure without the need for additional spectrum allocation [59].

3. **Guard-Band Mode**: NB-IoT can be deployed in the guard bands of an LTE carrier, which are typically unused spectral resources located between LTE bands. This mode optimizes spectral efficiency and minimizes network deployment costs for MNOs [60].

Each of these modes supports coverage and deployment flexibility, enabling NB-IoT to adapt to various urban metering requirements. The protocol utilizes narrowband transmissions (180 kHz per channel) and is highly energy-efficient, making it suitable for battery-powered sensors in remote or hard-to-access urban areas.

2.5.2 Advantages of NB-IoT in Urban Metering

NB-IoT offers several advantages for urban water metering applications, including superior building penetration, low power consumption, and high device density support. These features align well with the needs of urban water utilities that require reliable, long-term metering solutions.

- **Enhanced Building Penetration**: NB-IoT's low-frequency bands improve signal penetration, allowing it to reach sensors located underground, in basements, or behind dense infrastructure. This capability is crucial for water utilities, as meters are often situated in locations where signal propagation is otherwise limited [61].

- **Long Battery Life**: NB-IoT is designed for low power consumption, with devices typically operating for 10 to 15 years on a single battery. This characteristic reduces maintenance costs and is advantageous for utilities deploying many meters, as it minimizes the need for frequent battery replacement [62].

- **High Device Density**: NB-IoT can support up to 100,000 devices per cell, making it highly scalable for urban environments where large numbers of sensors and meters are concentrated within a single area. This scalability ensures that NB-IoT networks can accommodate expanding utility infrastructures as cities grow [63].

- **Reliability and QoS**: Operating in licensed spectrum, NB-IoT provides consistent quality of service, which is particularly important in urban areas where network congestion and interference from other wireless technologies are common. NB-IoT's guaranteed QoS makes it well-suited for applications that require real-time data transmission [64].

2.5.3 Limitations of NB-IoT for Urban Metering

Despite its advantages, NB-IoT also has certain limitations that water utilities must consider when deploying urban metering solutions. Key limitations include data rate constraints, dependency on cellular infrastructure, and deployment costs associated with licensed spectrum.

- **Lower Data Rates Compared to LTE**: While NB-IoT supports reliable connectivity, its data rates (typically up to 250 kbps) are lower than those provided by LTE. This limitation restricts NB-IoT to applications that do not require high data throughput, making it less suitable for applications involving continuous or high-resolution data streaming [65].

- **Dependency on Cellular Infrastructure**: NB-IoT relies on cellular infrastructure, which means that network availability and coverage depend on MNOs. In areas where cellular infrastructure is underdeveloped or lacks redundancy, NB-IoT connectivity may be inconsistent, impacting metering reliability [66].

- **Higher Deployment Costs**: NB-IoT requires licensed spectrum, which can increase operating costs compared to unlicensed LPWAN options such as LoRaWAN. This cost factor can be a barrier for utilities with limited budgets, especially in regions where spectrum fees are high [67].

2.5.4 Applications of NB-IoT in Water Utilities

NB-IoT is widely used in various water utility applications, particularly in urban areas where meter density and infrastructure complexity require robust connectivity solutions. These applications include automated meter reading, leakage detection, and infrastructure monitoring.

1. **Automated Meter Reading (AMR)**: NB-IoT enables remote, real-time meter reading, which allows utilities to collect accurate usage data without manual intervention. This system improves billing accuracy and helps utilities monitor consumption patterns more effectively. In urban environments, where thousands of meters may be located within a compact area, NB-IoT's scalability ensures that all meters can transmit data simultaneously without network congestion [68].

2. **Leakage Detection**: By enabling continuous monitoring of flow rate and pressure, NB-IoT-based sensors help utilities detect leaks promptly. Leak detection is particularly important in urban settings where undetected leaks can lead to significant water loss and structural damage. Studies have shown that NB-IoT-enabled leak detection systems can reduce water loss by up to 20% in urban distribution networks [69].

3. **Infrastructure Monitoring**: NB-IoT supports remote monitoring of key infrastructure components, such as pipelines, valves, and storage tanks. By monitoring pressure and other parameters, NB-IoT devices can identify early signs of wear or failure, enabling proactive maintenance. This capability is essential for urban utilities, where infrastructure access can be limited and repair costs are high [70].

2.5.5 Comparative Analysis of NB-IoT and Other LPWAN Technologies

When selecting LPWAN technologies for urban water metering, utilities often compare NB-IoT with other options, including LoRaWAN and Sigfox. Each technology offers distinct advantages and trade-offs in terms of range, data rate, power consumption, and cost.

- **NB-IoT vs. LoRaWAN**: While both NB-IoT and LoRaWAN offer low-power, long-range connectivity, NB-IoT's licensed spectrum provides better interference protection, making it more suitable for dense urban areas. LoRaWAN, on the other hand, is more cost-effective and supports a wider range of deployment environments, though its unlicensed spectrum may face interference challenges [71].

- **NB-IoT vs. Sigfox**: Sigfox operates at a lower data rate and is generally limited to infrequent data transmissions, making it suitable for basic metering applications. NB-IoT, with higher data rates and licensed spectrum, offers more reliable service in congested urban settings, where data reliability is crucial for utility operation [72].

Table 2.3 presents a summary comparison of key LPWAN technologies, illustrating how NB-IoT compares with LoRaWAN and Sigfox across metrics relevant to urban water metering.

Table 2.3: Comparison of LPWAN Technologies for Urban Water Metering

Technology	**Spectrum**	**Range (Urban)**	**Data Rate**	**Battery Life**	**Scalability**
NB-IoT	Licensed	Up to 10 km	Up to 250 kbps	Moderate	High
LoRaWAN	Unlicensed	Up to 5 km	0.3 - 50 kbps	Long	High
Sigfox	Unlicensed	Up to 10 km	100 bps	Long	Limited

2.5.6 Future Directions for NB-IoT in Water Metering

Ongoing advancements in NB-IoT technology are focused on improving its efficiency, adaptability, and integration with other IoT systems, particularly for complex urban metering environments. Key areas of research include:

- **Advanced Power-Saving Mechanisms**: Enhancements in power-saving modes, such as Extended Discontinuous Reception (eDRX) and Power Saving Mode (PSM), are expected to further extend battery life for NB-IoT devices, reducing operational costs for utilities [73].

- **Integration with 5G Networks:** As cellular networks transition to 5G, NB-IoT is expected to be an integral part of 5G’s massive IoT ecosystem. 5G will provide enhanced connectivity, higher device density, and improved data handling, making it a viable option for utilities that require large-scale, high-density deployments. NB-IoT's integration with 5G will enhance its potential in urban metering, enabling more efficient data aggregation and transmission [74].

- **Enhanced Security Protocols:** Given the sensitivity of utility data, security is a growing area of focus in NB-IoT development. Future NB-IoT systems are expected to incorporate advanced security protocols, such as stronger encryption algorithms and multi-factor authentication, to protect data integrity and privacy in utility networks [75].

The NB-IoT’s strengths in coverage, battery life, and scalability make it a promising solution for urban water metering applications. Its ongoing development, particularly in power management, 5G integration, and security enhancements, will further solidify its role in supporting water utilities’ IoT strategies in densely populated areas.

2.6 Bulk Water Leakage Detection

Bulk water leakage is a significant challenge for water utilities, as undetected leaks can lead to substantial water losses, infrastructure damage, and increased operational costs. With urban water demand rising and aging infrastructure under strain, effective bulk water leakage detection has become a priority for utilities worldwide. The integration of IoT-based sensors, advanced data analytics, and wireless communication networks, such as LoRaWAN and NB-IoT, enables utilities to detect leaks in real time, facilitating rapid response and minimizing water loss. This section explores various methodologies for bulk water leakage detection, including sensor-based techniques, data analytics, and communication protocols, as well as the challenges and limitations of these methods.

2.6.1 Importance of Bulk Water Leakage Detection

Water leakage contributes significantly to the non-revenue water (NRW) of utilities, representing water that is lost before it reaches the end consumer. Estimates suggest that global NRW rates range between 20% to 30% of total water production, with leakages accounting for a major portion of this loss [76]. Beyond financial implications, undetected leaks can lead to structural damage in the distribution network, undermine water quality, and deplete local water resources. Effective leakage detection is therefore essential for water utilities to reduce operational costs, conserve resources, and enhance service reliability.

2.6.2 Sensor-Based Leakage Detection Techniques

One of the most effective approaches for detecting leaks in bulk water systems is the deployment of sensor-based technologies that monitor critical parameters, such as pressure, flow rate, and acoustic signals. Commonly used sensor types include pressure sensors, acoustic sensors, and flow meters, each of which provides unique insights into potential leakage points within the network.

- **Pressure Sensors**: Pressure sensors are often placed along distribution pipelines to monitor pressure fluctuations. A sudden drop in pressure, when not associated with routine demand variations, can indicate a leak. Advanced pressure sensors are capable of transmitting real-time data to central monitoring systems, allowing for early detection and prompt response to pressure anomalies [77].

- **Acoustic Sensors**: Acoustic sensors detect leaks by capturing sound waves generated by water escaping through a crack or fissure in the pipeline. This technology, often referred to as "leak noise correlation," is particularly effective in pressurized systems where leaks produce detectable noise levels. Studies have shown that acoustic leak detection can identify leaks with high accuracy, especially when combined with machine learning algorithms to distinguish leak noise from background noise [78].

- **Flow Meters**: Flow meters are used to monitor water flow rates at various points in the distribution network. A discrepancy between the measured flow at different points, which cannot be explained by known usage patterns, may suggest a leak. Flow meters are often installed at key junctions or segments within the network to track water flow dynamics and detect abnormal flow behaviour [79].

These sensor-based approaches are frequently combined to enhance the accuracy and reliability of leak detection, providing a multi-faceted view of network conditions. By deploying sensors in a strategic manner across the distribution network, utilities can establish a comprehensive monitoring system capable of identifying leaks before they escalate.

2.6.3 Wireless Communication Integration for Real-Time Detection

To ensure real-time data transmission from sensor nodes to central monitoring systems, wireless communication technologies are essential. Among the most widely used protocols in leakage detection are LoRaWAN, NB-IoT, and Zigbee, each offering specific advantages for different water utility environments.

- **LoRaWAN**: LoRaWAN's long-range capability makes it particularly suitable for monitoring bulk water systems that span large geographical areas. LoRaWAN supports low power consumption and extended transmission ranges, allowing leakage data to be transmitted from remote areas to a central server without frequent battery replacement. This feature is especially beneficial for underground or rural pipelines that require extensive monitoring [80].

- **NB-IoT**: NB-IoT provides reliable, high-penetration coverage, enabling data transmission in dense urban settings and hard-to-reach locations. NB-IoT’s licensed spectrum minimizes interference, ensuring that leakage alerts reach operators with minimal delay. Given its low power requirements, NB-IoT devices can operate for years, making them ideal for utility networks with limited access to power sources [81].

- **Zigbee**: Zigbee is often deployed in mesh configurations, where data can be relayed between multiple nodes before reaching the central server. This topology enhances network resilience by providing alternative transmission paths, which is useful in urban areas where signal interference may obstruct direct communication. Although Zigbee is more commonly used for short-range applications, it can complement LoRaWAN and NB-IoT in multi-tiered monitoring systems [82].

The integration of wireless communication technologies in leakage detection systems enables continuous data flow, allowing utilities to respond to leaks as soon as they are detected. This capability is crucial for urban water utilities, where even minor leaks can result in significant water losses and infrastructure damage if left undetected.

2.6.4 Data Analytics and Machine Learning in Leakage Detection

Advancements in data analytics and machine learning have significantly improved the accuracy and efficiency of leakage detection systems. By analysing patterns in sensor data, these technologies can identify subtle signs of leaks that might be missed by traditional methods.

- **Anomaly Detection Algorithms**: Machine learning algorithms, such as support vector machines (SVM) and neural networks, can be trained to recognize normal operational patterns in water distribution systems. Any deviation from these patterns, such as unusual pressure drops or abnormal flow rates, can trigger a leak alert. Anomaly detection algorithms are particularly effective in large, complex networks where manual monitoring is impractical [83].

- **Correlation Analysis**: By correlating data from multiple sensors, such as pressure and flow meters, utilities can localize leaks with greater precision. For example, if a pressure drop is detected by one sensor corresponds with a flow anomaly detected downstream, the likelihood of a leak in that segment increases. Correlation analysis thus reduces the risk of false positives and improves the efficiency of the response process [84].

- **Predictive Maintenance Models**: Predictive models, often built using historical data, can forecast areas of the network at higher risk of leaks based on factors like pipeline age, material, and historical performance. These models allow utilities to prioritize maintenance activities in areas most susceptible to leaks, reducing overall maintenance costs and enhancing network reliability [85].

The combination of real-time sensor data with predictive analytics enables a proactive approach to leakage management, allowing utilities to anticipate and address issues before they result in significant water loss.

2.6.5 Limitations and Challenges in Bulk Water Leakage Detection

Despite advancements in sensor technology and data analytics, several challenges persist in bulk water leakage detection. Key limitations include sensor accuracy, environmental interference, and data transmission constraints.

- **Sensor Accuracy and Calibration**: The accuracy of pressure and flow sensors can degrade over time due to environmental factors or sensor drift, leading to false positives or missed leaks. Regular calibration and maintenance are essential to ensure that sensors continue to provide reliable data, although these tasks can be labour-intensive and costly [86].

- **Environmental Interference**: Acoustic sensors are susceptible to interference from background noise in urban areas, such as traffic vibrations or construction activity. This interference can hinder the accuracy of acoustic leak detection, making it difficult to distinguish leak noise from ambient sounds [87].

- **Data Transmission Constraints**: For utilities operating in remote or rural areas, transmitting sensor data to central monitoring systems can be challenging due to limited network coverage. While LPWAN technologies like LoRaWAN and NB-IoT offer extended range, transmission reliability can still be compromised in areas with challenging topography or dense infrastructure [88].

Efforts to address these challenges are ongoing, with researchers exploring alternative sensor designs, advanced signal processing techniques, and hybrid communication networks to enhance the robustness and reliability of leakage detection systems.

2.7 Burst Pipe Detection

Burst pipes in water distribution networks are a critical issue for utilities, leading to substantial water loss, infrastructure damage, and potential service disruptions. The detection of burst pipes is complex due to varying water pressure, flow dynamics, and network layout. However, advancements in IoT, sensor technology, and data analytics have introduced more effective methods for detecting burst events early, minimizing water loss and enabling rapid response.

This section explores the methodologies for burst pipe detection, including pressure monitoring, acoustic detection, and machine learning algorithms for real-time data analysis.

2.7.1 Pressure-Based Burst Detection

Pressure monitoring is one of the most widely used methods for detecting burst pipes in water networks. Sudden drops in pressure often signal the occurrence of a burst, especially when these fluctuations cannot be attributed to normal usage patterns.

- **Pressure Transient Analysis**: Pressure transients, or sudden changes in water pressure, can indicate the presence of a burst. By placing pressure sensors strategically across the network, utilities can monitor real-time pressure data to identify abnormal patterns associated with burst events. Studies have shown that pressure transients are highly correlated with burst pipe events, particularly in older infrastructure where pipes are more susceptible to sudden failures [89].

- **Distributed Pressure Monitoring**: Distributed pressure sensors across the network allow for a comprehensive view of pressure dynamics in various segments. When sensors detect a significant drop in pressure at multiple points within a short timeframe, the probability of a burst is high. Such systems enable quick isolation of the affected segment, minimizing water loss and infrastructure damage [90].

2.7.2 Acoustic-Based Burst Detection

Acoustic sensors have proven effective for burst detection by capturing sound waves generated by the sudden release of water through a burst point. These sensors detect and analyse the frequency and intensity of sound waves, which differ from those produced during normal water flow.

- **Leak Noise Correlation**: Acoustic leak detection employs correlation techniques to pinpoint the location of a burst. When water escapes under high pressure, it generates specific noise frequencies that can be captured by acoustic sensors. By correlating noise data from sensors placed along the pipeline, the exact location of the burst can be estimated. This approach is highly accurate, particularly when used in conjunction with pressure monitoring [91].

- **Advanced Signal Processing**: Advanced signal processing algorithms, including Fourier Transform and wavelet analysis, are used to distinguish burst noise from background noise. These algorithms enhance the accuracy of acoustic sensors, even in noisy urban environments where external factors like traffic or construction can interfere with detection [92].

2.7.3 Machine Learning and Data Analytics in Burst Detection

Machine learning and data analytics have introduced more sophisticated approaches to burst detection, enabling utilities to identify bursts based on complex patterns and trends in sensor data.

- **Anomaly Detection Models**: Anomaly detection algorithms, such as Support Vector Machines (SVM) and k-nearest neighbours (k-NN), can be trained to recognize typical water flow patterns in a distribution network. When a burst occurs, the sudden change in flow dynamics is flagged as an anomaly. These models have been shown to reduce false positives in burst detection by accounting for seasonal or demand-based fluctuations in water use [93].

- **Predictive Modelling for High-Risk Areas**: Predictive models use historical data to identify sections of the network most susceptible to bursts. Factors such as pipe material, age, historical maintenance records, and pressure conditions are incorporated into these models, allowing utilities to proactively monitor high-risk areas. Predictive modelling enables a targeted approach, reducing the likelihood of burst events and allowing for preventive maintenance before failures occur [94].

2.8 Water Overflow Detection Methods

Water overflow events, such as those occurring in tanks, reservoirs, or stormwater systems, present significant challenges for utilities due to the potential for water waste, environmental impact, and damage to infrastructure. Detecting overflow early is essential for effective water management, especially in urban areas where runoff can exacerbate flooding. Various sensor-based methods, including ultrasonic, capacitive, and radar-based detection, are employed to monitor water levels and identify overflow risks.

2.8.1 Ultrasonic Sensors for Overflow Detection

Ultrasonic sensors are commonly used for monitoring water levels and detecting overflow conditions in storage tanks and reservoirs. These sensors emit high-frequency sound waves, which reflect off the water surface, allowing the sensor to measure the distance to the water surface based on the time it takes for the sound wave to return.

- **High-Resolution Level Monitoring**: Ultrasonic sensors offer high-resolution measurements of water levels, enabling utilities to monitor slight changes in water height. This precision is critical for early overflow detection, as even small variations in water level can indicate the onset of overflow conditions [95].

- **Non-Contact Measurement**: Since ultrasonic sensors operate without physical contact with the water, they are ideal for environments where contamination or fouling may impact sensor performance. Their non-invasive nature makes them suitable for monitoring tanks or reservoirs where hygiene and maintenance considerations are essential [96].

2.8.2 Capacitive Sensors for Overflow Detection

Capacitive sensors detect water levels based on changes in capacitance, which vary with the proximity of water to the sensor’s electrodes. These sensors are sensitive to the presence of liquid and can be calibrated to trigger alerts when water reaches a specified threshold, such as near the tank’s overflow point.

- **Continuous Level Monitoring**: Capacitive sensors provide continuous monitoring, making them suitable for applications requiring frequent updates on water levels. This characteristic is beneficial for utilities that need real-time alerts on overflow conditions to activate control measures, such as closing valves or diverting water [97].

- **Resilience in Harsh Conditions**: Capacitive sensors are highly resilient to environmental factors, including temperature and pressure changes, which can affect other sensor types. They are particularly effective in detecting overflow in stormwater systems where sudden influxes of water during heavy rain events require immediate attention [98].

2.8.3 Radar Sensors for Overflow Detection

Radar sensors are increasingly used in water overflow detection due to their high accuracy and robustness in diverse environmental conditions. Radar sensors emit electromagnetic waves that reflect off the water surface, and the distance to the surface is calculated based on the time taken for the wave to return. Unlike ultrasonic or capacitive sensors, radar sensors are less affected by environmental variables, making them suitable for applications requiring high reliability.

- **High Precision and Reliability**: Radar sensors provide high-precision measurements of water levels, with accuracy unaffected by factors like temperature, humidity, or pressure. This reliability makes radar sensors ideal for overflow detection in reservoirs and large storage tanks, where maintaining accurate water level readings is critical [99].

- **Application in Open-Channel Systems**: Radar sensors are also effective in open-channel water monitoring, such as in stormwater and wastewater management. Their ability to monitor water flow and level continuously allows utilities to detect overflow risks in real time, activating preventive measures to mitigate flooding and protect infrastructure [100].

2.8.4 Integration of IoT and Data Analytics for Overflow Detection

IoT-enabled sensors, combined with data analytics, have significantly advanced water overflow detection capabilities, enabling utilities to predict and prevent overflow events. By continuously monitoring water levels and flow rates, these systems provide real-time data that can be analysed to identify patterns indicative of impending overflow.

- **Threshold-Based Alerts and Alarms**: IoT platforms enable utilities to set thresholds for water levels, activating alerts when levels approach the overflow point. This approach allows operators to take preventive action, such as diverting water flow, adjusting valve positions, or activating pumps to reduce water volume before overflow occurs [101].

- **Predictive Overflow Modelling**: Using machine learning algorithms, predictive models can forecast overflow conditions based on historical data and real-time inputs, such as rainfall patterns, tank inflow rates, and previous overflow incidents. These models allow utilities to anticipate overflow risks under specific conditions, enabling proactive management of water resources [102].

2.9 Site and Bulk Water Metering Infrastructure Tampering Detection

Water utilities increasingly face the challenge of tampering with metering infrastructure, which can result in inaccurate readings, revenue loss, and compromised data integrity. Tampering involves deliberate attempts to manipulate metering devices or associated infrastructure, often to avoid accurate billing. With advancements in IoT and smart metering technology, water utilities can leverage new tampering detection techniques to enhance security and safeguard metering accuracy. This section examines various approaches to tampering detection in water utilities, including physical sensors, data analytics, and the integration of IoT-based monitoring.

2.9.1 Physical Tamper Detection Sensors

Physical sensors can detect unauthorized access or manipulation of metering devices. These sensors are directly attached to the metering infrastructure to monitor physical conditions and respond to tampering attempts.

- **Tilt and Vibration Sensors**: Tilt sensors are commonly used to detect any changes in the position of a water meter, which might indicate tampering. When a meter is tilted or moved, the sensor detects this change and sends an alert to the utility’s monitoring centre. Vibration sensors are similarly used to monitor sudden shocks or vibrations that might occur during unauthorized attempts to access or damage the meter [103].

- **Seal Integrity Sensors**: Some tampering detection systems include seals that incorporate electronic components to verify their integrity. Any attempt to break or remove the seal triggers an alert. These sensors are especially useful for bulk water metering infrastructure, which may be more vulnerable to tampering due to their higher value and volume. Electronic seals can provide utilities with real-time notifications if tampering is detected at critical points in the network [104].

2.9.2 Data Analytics for Tampering Detection

Data analytics plays a significant role in detecting tampering through the analysis of usage patterns, data inconsistencies, and anomalies. By analysing historical and real-time data, utilities can identify deviations indicative of tampering.

- **Consumption Pattern Analysis**: Utilities can use data analytics to analyse consumption patterns and detect anomalies that may indicate tampering. For example, a sudden drop in consumption that does not align with historical usage trends may suggest tampering. Machine learning algorithms, such as anomaly detection models, can be trained on normal usage patterns and then detect deviations that signal potential tampering [105].

- **Comparative Analysis of Site Data**: By comparing data from multiple sites or meters within a geographical area, utilities can identify inconsistencies that may suggest tampering. For instance, if one meter shows significantly lower consumption than nearby meters under similar conditions, it may indicate unauthorized interference. Comparative analysis methods are especially useful for bulk water meters, where tampering can have significant financial implications [106].

2.9.3 IoT-Based Tampering Detection

IoT-based tampering detection leverages connectivity and remote monitoring to identify tampering attempts in real time. IoT-enabled meters can transmit tampering alerts directly to utility operators, who can then investigate the issue promptly.

- **Edge Computing and Localized Monitoring**: Edge computing allows for localized tamper detection by enabling meters to process data independently and trigger alerts without requiring continuous connectivity to a central server. This approach is beneficial in remote or low-connectivity areas where real-time communication may be challenging. Edge-enabled meters can detect and report tampering attempts even if they are temporarily offline, ensuring continuous security [107].

- **Cloud-Based Tamper Detection and Analytics**: Cloud-based platforms offer advanced analytics and data storage capabilities, allowing utilities to monitor tampering across a large network of devices. Through cloud computing, data from multiple meters can be analysed collectively to detect widespread tampering patterns, identify high-risk areas, and enhance security across the entire metering infrastructure [108].

These tampering detection strategies collectively enhance the ability of water utilities to maintain accurate billing, protect infrastructure, and deter unauthorized interference. By combining physical sensors, data analytics, and IoT-based monitoring, utilities can create a comprehensive tampering detection framework that addresses both physical and digital security concerns.

2.10 Challenges of Existing Solutions

While various technologies and methodologies have advanced the capabilities of water utilities in areas such as metering, leakage detection, and tampering prevention, several challenges continue to hinder the effectiveness and scalability of these solutions. Understanding these challenges is essential for developing future innovations that can better address the needs of urban and rural water networks.

2.10.1 High Deployment and Maintenance Costs

Implementing smart water metering systems, advanced sensors, and IoT connectivity can be costly, especially for large-scale deployments. The expense associated with purchasing, installing, and maintaining these devices can be prohibitive for many utilities, particularly those operating in resource-constrained regions. Maintenance costs are also significant, as devices may need regular calibration, firmware updates, and repairs to maintain performance. Additionally, replacing batteries in remote or hard-to-access locations further increases operational costs [109].

2.10.2 Energy Limitations and Power Management

Many IoT devices in water utilities rely on battery power due to their remote or underground placements, where access to traditional power sources is limited. Although low-power technologies, such as LoRaWAN and NB-IoT, offer extended battery life, these devices still face limitations in terms of energy efficiency, especially in applications that require continuous monitoring or real-time data transmission. Power management remains a key challenge, with researchers exploring solutions such as energy harvesting and improved battery technology to extend device lifespans [110].

2.10.3 Data Reliability and Connectivity Issues

Data reliability is crucial for effective water utility management, yet connectivity challenges persist, particularly in urban areas with dense infrastructure or rural regions with limited network coverage. LPWAN technologies like LoRaWAN and NB-IoT offer long-range capabilities, but signal attenuation and interference from buildings, underground chambers, and natural obstructions can affect data accuracy and reliability. Connectivity issues may result in delayed data transmission or data loss, undermining the effectiveness of real-time monitoring and early detection efforts [111].

2.10.4 Scalability Constraints

The scalability of smart water metering and monitoring systems remains a significant challenge for water utilities. As cities grow and water infrastructure expands, utilities must ensure that their metering and monitoring systems can accommodate the increased number of connected devices. Current IoT solutions may struggle to handle the high device density required for large urban networks. Additionally, integrating new devices into existing infrastructure can create compatibility issues, requiring careful planning and system upgrades to maintain network performance [112].

2.10.5 Data Security and Privacy Concerns

As water utilities adopt IoT-enabled metering and monitoring solutions, concerns around data security and privacy have intensified. Unauthorized access to metering infrastructure can compromise data integrity, leading to inaccurate billing or even sabotage of the water supply. IoT devices are often vulnerable to cyber-attacks, such as denial-of-service (DoS) attacks or unauthorized data access, which can disrupt operations. Protecting sensitive consumer data, such as consumption patterns, from unauthorized access is essential to maintain consumer trust and comply with regulatory standards [113].

2.10.6 Environmental and Operational Challenges

Environmental factors such as temperature extremes, humidity, and corrosion can adversely affect the performance of sensors and meters. In outdoor or underground installations, exposure to water, dirt, and varying temperatures can degrade device accuracy and longevity. Operational challenges also arise in managing the vast amounts of data generated by IoT devices. Ensuring that data is processed, stored, and analysed effectively requires significant computing resources and infrastructure, which may be beyond the capacity of smaller or under-resourced utilities [114].

Addressing these challenges requires continued research and innovation in the fields of sensor technology, IoT connectivity, data analytics, and cybersecurity. By developing cost-effective, energy-efficient, and resilient solutions, the water utility sector can overcome these limitations, enhancing operational efficiency and service reliability.

Here is an academically rigorous and detailed write-up for Section 2.11: Comparative Analysis of Existing Solutions and Section 2.12: Summary and Research Gaps, with references starting from [115].

2.11 Comparative Analysis of Existing Solutions

The implementation of IoT-based solutions in water utilities has introduced diverse approaches to address challenges in metering, leakage detection, tamper prevention, and system monitoring. Each of the primary technologies discussed—LoRaWAN, NB-IoT, Wireless Sensor Networks (WSNs), and various sensor technologies—offers distinct advantages and limitations depending on specific application requirements. This section presents a comparative analysis of these technologies, evaluating them on parameters critical to water utility operations, such as range, data rate, power consumption, scalability, and cost-effectiveness.

2.11.1 Range and Coverage

One of the most critical factors in selecting a technology for water utility applications is the range, as utilities often operate in geographically dispersed areas that require extensive coverage.

LoRaWAN: Known for its long-range capabilities, LoRaWAN can cover distances of up to 15 km in rural settings and around 5 km in urban areas. This range makes it highly suitable for monitoring bulk water meters and pipelines spread across vast geographical areas [115].

NB-IoT: Although generally not as far-reaching as LoRaWAN, NB-IoT operates in licensed bands that provide strong penetration, particularly in dense urban environments. NB-IoT can reliably transmit data from underground locations and areas with significant physical obstructions, such as urban buildings [116].

WSNs: Traditional WSNs, while effective in short-range applications, require relay nodes to extend their range, making them less cost-effective and more complex to deploy for large-scale utility networks. However, they remain valuable in enclosed spaces or small distribution zones [117].

2.11.2 Data Rate and Transmission Frequency

Different IoT technologies vary in their data rate and transmission frequency capabilities, which directly impact their suitability for specific monitoring needs.

LoRaWAN: With data rates between 0.3 kbps to 50 kbps, LoRaWAN is ideal for periodic, low-bandwidth applications such as daily water meter readings and infrequent leakage notifications. However, it may be insufficient for applications requiring high-frequency data or real-time monitoring [118].

NB-IoT: Offering data rates up to 250 kbps, NB-IoT provides a better balance for applications requiring more frequent data transmission, such as continuous monitoring of pressure or flow. NB-IoT's ability to handle higher data rates allows it to support more complex data analytics and real-time anomaly detection [119].

WSNs: WSNs offer moderate data rates and can support applications requiring relatively frequent updates. However, their limited range and reliance on multi-hop communication can reduce data reliability, especially in large or complex water networks [120].

2.11.3 Power Consumption and Battery Life

Battery life and power consumption are significant considerations, particularly for devices located in remote or hard-to-reach locations where regular maintenance is challenging.

LoRaWAN: LoRaWAN is designed to be ultra-low power, making it suitable for devices that need to operate for extended periods (5 to 10 years) without battery replacement. This characteristic is especially beneficial for rural water utilities, where devices are widely distributed [121].

NB-IoT: NB-IoT devices consume slightly more power than LoRaWAN, particularly in applications requiring continuous or real-time data transmission. However, NB-IoT power-saving features, such as eDRX and PSM, can significantly extend battery life in less frequent monitoring scenarios [122].

WSNs: WSN nodes tend to consume more power, particularly when configured for multi-hop communication. The need for frequent battery replacements can make WSNs more suitable for accessible areas or where external power sources are available [123].

2.11.4 Scalability and Cost-Effectiveness

Scalability and cost-effectiveness are essential factors, especially for utilities with limited budgets and large networks.

LoRaWAN: LoRaWAN's unlicensed operation and minimal infrastructure requirements make it highly scalable and cost-effective for widespread deployment. Its low deployment cost allows utilities to cover extensive areas without substantial investment in infrastructure [124].

NB-IoT: While NB-IoT provides robust connectivity and quality of service due to its licensed operation, spectrum costs can increase overall deployment expenses. Nevertheless, NB-IoT’s superior penetration and reliability justify its cost for critical urban and high-density areas [125].

WSNs: WSNs are less scalable compared to LPWAN technologies due to their limited range and high dependency on relay nodes. Consequently, deployment costs can increase significantly for large-scale applications, making WSNs more suitable for localized utility management within confined areas [126].

2.11.5 Security and Data Integrity

Security and data integrity are increasingly important for IoT-enabled utility networks, as cyber threats continue to evolve.

LoRaWAN: Operating in the unlicensed spectrum, LoRaWAN can be susceptible to interference and certain cyber-attacks. However, its encryption protocols and network-layer security measures provide reasonable protection against data breaches [127].

NB-IoT: NB-IoT benefits from the inherent security of cellular networks, including advanced encryption standards and secure communication channels, making it one of the most secure options for water utilities concerned with data integrity [128].

WSNs: Security in WSNs is limited, particularly in large networks where managing encryption keys and protecting data from unauthorized access becomes challenging. As a result, WSNs may be more vulnerable to cyber-attacks if not managed properly [129].

Table 2.4: summarizes this comparative analysis across various parameters, providing a clear overview of how each solution aligns with the needs of water utilities.

Table 2.4: Comparative Analysis of IoT Solutions for Water Utilities

Parameter	LoRaWAN	NB-IoT	WSN
Range	High	Moderate to High	Low
Data Rate	Low	Moderate	Moderate
Power Consumption	Low	Moderate	Moderate to High
Scalability	High	Moderate to High	Low
Security	Moderate	High	Low to Moderate
Cost-Effectiveness	High	Moderate	Low

This comparative analysis highlights that LoRaWAN is optimal for wide-range, low-cost applications with limited data needs, whereas NB-IoT is best suited for environments requiring robust security, moderate data rates, and high device density. WSNs remain valuable for confined, accessible areas but face limitations in scalability and security.

2.12 Summary and Research Gaps

In reviewing the existing solutions for water utility management—spanning metering, leakage detection, tampering prevention, and overflow monitoring—it is evident that IoT-based technologies have significantly advanced the capabilities of water utilities. Technologies like LoRaWAN, NB-IoT, and WSNs provide unique advantages tailored to specific aspects of water management. However, these solutions are not without limitations, and there are substantial research gaps that need to be addressed to improve the efficiency, cost-effectiveness, and resilience of water utility IoT deployments.

2.12.1 Key Findings

LoRaWAN offers an economical and scalable solution for utilities with extensive networks, especially in rural or suburban areas. Its low-power, long-range capabilities are advantageous, but its data rate limitations constrain its applicability in real-time, high-frequency monitoring scenarios.

NB-IoT provides secure and reliable data transmission with excellent penetration, suitable for dense urban settings. However, its reliance on licensed spectrum increases deployment costs, which can limit scalability in resource-constrained settings.

WSNs are effective in localized monitoring but face challenges in large-scale applications due to high power requirements, limited range, and security vulnerabilities.

2.12.2 Research Gaps

Energy-Efficient Solutions for High-Density Applications: While NB-IoT and LoRaWAN provide low-power options, extending battery life remains a key challenge, especially for applications requiring frequent or real-time data transmission. Research into energy-harvesting methods, such as solar or kinetic energy, could help reduce reliance on batteries [130].

Integration of Hybrid IoT Networks: Future research should explore hybrid solutions combining multiple IoT protocols (e.g., LoRaWAN with NB-IoT) to leverage the strengths of each technology. Hybrid networks could enable seamless coverage across diverse urban and rural settings, enhancing scalability and flexibility for water utilities [131].

Enhanced Security Protocols: As IoT adoption grows, so does the need for advanced security measures. Developing lightweight, efficient encryption methods for low-power devices is essential to ensure data privacy and integrity in utility networks [132].

Improved Data Analytics and AI Applications: Advanced data analytics and AI models are needed to process large volumes of sensor data, enabling predictive maintenance, anomaly detection, and operational optimization. Continued research into machine learning algorithms for resource-constrained devices could enhance data analytics capabilities at the network edge [133].

Standardization and Interoperability: The lack of standardization across IoT platforms can limit interoperability, complicating large-scale deployments. Standardizing communication protocols and data formats could help reduce compatibility issues and streamline integration of diverse IoT devices within utility networks [134].

In conclusion, while IoT-based solutions have revolutionized water utility management, there is significant potential for further advancements. Addressing the identified research gaps, such as enhancing energy efficiency, developing hybrid networks, strengthening security, advancing data analytics, and promoting standardization, will allow water utilities to leverage IoT more effectively. Through these innovations, IoT-enabled systems can provide more accurate, reliable, and secure solutions for water monitoring, leakage detection, and metering infrastructure management, supporting sustainable water resource management and improved operational efficiency.

Despite advancements in IoT-enabled metering solutions, significant gaps persist in achieving a reliable, energy-efficient, and secure infrastructure for bulk water metering, particularly in environments such as the Rand Water utility’s low-elevation concrete chambers. These identified research gaps highlight the limitations of existing solutions and the necessity for targeted innovations to overcome these challenges effectively.

2.12.2.1 Energy Efficiency

Current bulk water metering solutions often rely on cellular-based communication (e.g., 3G/4G), which, while offering adequate data transmission capabilities, impose considerable energy demands on metering devices. This high energy consumption leads to frequent battery replacements, increased maintenance costs, and interrupted service, especially in remote or hard-to-access locations. Thus, a primary research gap is the lack of IoT communication protocols tailored to ultra-low-power applications for long-term metering operations without regular battery maintenance to address energy efficiency have led to the adoption of Low Power Wide Area Networks (LPWANs) such as LoRaWAN and NB-IoT, yet further research is needed to assess their performance and feasibility specifically in bulk metering contexts. The integration of energy-saving modes, such as sleep cycles and adaptive sampling, in tandem with power-efficient transmission protocols, remains a critical area for exploration to achieve sustainability in long-term deployment.

2.12.2.2 Reliability and Signal Penetration

The placement of water meters in low-elevation or underground concrete chambers presents substantial barriers to signal penetration, reducing network reliability. Traditional wireless communication protocols struggle in such environments due to signal attenuation caused by concrete, metallic obstructions, and underground placement. This issue is exacerbated in dense urban settings, where the interference from surrounding infrastructure further compromises data reliability.

Existing solutions using LPWANs partially address this gap by providing extended range and penetration capabilities, but their effectiveness in deeply embedded environments like underground concrete chambers has not been fully established. Research into hybrid solutions combining multiple protocols or enhancing antenna design for improved signal resilience and penetration is essential to ensure data reliability and continuity under challenging environmental conditions.

2.12.2.3 Tampering, Lever flow Detection

Infrastructure security is a growing concern for water utilities, particularly regarding unauthorized tampering, water leakage, and overflow events within metering chambers. Current metering systems often lack integrated mechanisms for detecting such events, relying primarily on manual inspections, which are time-consuming and inefficient. Tampering or damage to metering infrastructure not only results in revenue loss but also compromises data integrity and increases the risk of physical damage to the surrounding environment.

Advanced tampering detection methods, such as vibration and tilt sensors, combined with machine learning algorithms capable of identifying abnormal patterns in flow and pressure data, represent a promising area for research. Effective detection mechanisms must be developed to ensure the integrity of metering infrastructure, reduce manual oversight, and enable real-time alerts for operational anomalies such as unauthorized access or water overflow.

2.12.2.4 Real-Time Data Accessibility Efficiency

Real-time data access is essential for utilities to monitor water usage patterns, detect leaks or tampering, and respond to operational issues without delay. However, existing systems are often constrained by limitations in data transmission frequency, with many relying on daily or periodic updates rather than real-time data. The cost implications of achieving continuous, real-time monitoring are also a barrier, as more frequent data transmission requires additional power and network resources, driving up operational expenses.

While IoT solutions such as NB-IoT and edge computing have improved data accessibility and minimized transmission delays, further research is needed to create a cost-effective framework that can provide real-time insights without compromising energy efficiency. Additionally, methods for predictive analytics that can work within a cost-effective, real-time data framework are necessary to enhance decision-making and reduce the operational costs associated with water utility monitoring.

2.13 Conclusion

This literature review has provided a comprehensive examination of current IoT-enabled solutions and technologies for water utility applications, focusing on wireless sensor networks (WSNs), Low Power Wide Area Networks (LPWANs) like LoRaWAN and NB-IoT, and specific applications for water metering, leakage detection, tampering prevention, and overflow monitoring. Starting with the introduction of wireless networks and IoT systems, each section has highlighted critical advancements and limitations associated with these technologies. WSNs, while useful in localized monitoring, struggle with scalability and energy efficiency in large networks. In contrast, LPWANs, particularly LoRaWAN and NB-IoT, have shown potential for extensive and energy-efficient coverage, making them more suitable for large, distributed water utility networks.

Despite these advancements, several research gaps persist. Energy efficiency remains a primary concern, especially for devices placed in remote or hard-to-reach areas where regular maintenance is difficult. Technologies like LoRaWAN and NB-IoT offer improvements, yet there is still a need for more robust energy solutions, possibly through hybrid network approaches or energy harvesting methods. Network reliability and signal penetration, particularly in challenging environments like underground chambers or concrete-embedded meters, are also ongoing challenges. While LPWAN technologies have improved signal penetration, further research into network designs that enhance connectivity in obstructive environments is essential.

In addition, security and infrastructure integrity are paramount. The risk of tampering, leaks, and overflow incidents calls for integrated monitoring and alert systems that combine physical sensors with real-time data analytics. Data accessibility and cost efficiency are equally critical; utilities require cost-effective solutions that provide real-time or near-real-time data to improve decision-making and reduce operational delays. However, achieving this level of monitoring without compromising energy efficiency remains a challenge.

This review also identified the need for predictive analytics and machine learning models to proactively manage infrastructure. By developing systems capable of predictive maintenance, utilities can reduce operational costs, extend the life of their infrastructure, and optimize resource allocation.

In summary, while current IoT technologies provide a strong foundation, addressing the identified gaps—energy efficiency, network reliability, tampering and anomaly detection, real-time data accessibility, and predictive analytics—will be critical for advancing IoT-enabled water utility management. These areas of future research will support the development of a more resilient, efficient, and secure IoT framework for sustainable water resource management.

CHAPTER 3: MODELLING ENERGY EFFICIENCY OF LORA AND LORAWAN SENSOR NODES IN BULK METERING APPLICATIONS

3.1 Introduction

This chapter presents a comprehensive modelling framework for evaluating the energy efficiency of LoRa and LoRaWAN-based sensor nodes deployed in bulk metering applications, using the Rand Water infrastructure in South Africa as a case study. The Rand Water deployment scenario presents unique environmental and topographical challenges. These include the installation of bulk meters at low elevation, often within enclosed, thick-walled concrete chambers designed for physical protection and access control. These environmental characteristics significantly influence radio propagation, resulting in increased signal attenuation, reduced signal-to-noise ratio (SNR), and degraded packet delivery performance, as previously discussed in the context of LoRaWAN constraints and scalability limitations [123], [121], [122], especially when using low-power wide-area network (LPWAN) technologies like LoRaWAN.

In such constrained environments, energy efficiency becomes a critical design metric. Battery-operated sensor nodes must operate over long lifetimes without frequent maintenance, while ensuring reliable data delivery typically once per day to a remote network server. The LoRaWAN communication stack, particularly its Adaptive Data Rate (ADR) and Join cycle algorithms, plays a significant role in managing this trade-off between energy consumption and communication reliability, [123], [127].

The proposed model incorporates:

- **Environment-specific constraints**, including signal attenuation through concrete and low antenna height due to low elevation.
- **Communication parameters**, such as packet size (M bytes), spreading factor (SF), and acknowledgment (ACK) requirements per LoRaWAN Class A specification.
- **Energy breakdown analysis** covering the transmit, receive, idle, and sleep modes of a LoRaWAN sensor node.

- **Join and re-join mechanisms** as defined in the LoRaWAN 1.1 specification, which require a sensor node to reattempt network joining starting from SF9 up to SF12, should an ACK not be received within a predefined receive window timeout.

The modelling and simulation are implemented in MATLAB to evaluate multiple LoRaWAN configurations under the influence of:

- Varying transmission distances,
- Environmental obstructions (modelled as additional path loss),
- Spreading factors (SF7 to SF12),
- Transmission classes (Class A, B, and C where applicable),
- Re-join cycles due to failed downlink (ACK) reception.

Simulation outputs provide insights into:

- The average energy consumed per successfully delivered packet,
- The probability of re-join under realistic channel conditions,
- Optimal SF configurations for reduced energy usage under Rand Water deployment conditions.

3.1.1. Theoretical Context and Literature Alignment

Prior LPWAN studies have established that reliability and energy efficiency are co-dependent design objectives in massive/bulk IoT deployments, especially where endpoints are battery-powered and operate under harsh propagation conditions. Critical review findings show that underground or concrete-chamber deployments amplify penetration loss and shadowing, which in turn increases retransmissions, OTAA re-join frequency, and time spent in Class-A receive windows.

3.1.2. Research Gap and Chapter Contributions

However, many existing energy models assume ideal downlink availability, ignore join/re-join overhead, or treat packet success as a binary threshold without capturing the probability transition near sensitivity limits. This chapter addresses these gaps by developing a join-aware, chamber-aware modelling framework that jointly quantifies (i) coverage and packet delivery behaviour under concrete attenuation and low antenna height, and (ii) the resulting energy-per-success and lifetime impacts for bulk metering reporting profiles.

3.1.3. Technology Selection Rationale for Rand Water Bulk Metering

LoRaWAN was selected as the primary communication technology for modelling in this study due to its suitability for low-data-rate, battery-powered bulk metering applications requiring long-range coverage and minimal infrastructure cost. Unlike cellular-based LPWAN technologies such as NB-IoT, LoRaWAN supports private network deployment, enabling Rand Water to retain control over gateway placement, network configuration, and operational costs an important consideration for geographically distributed bulk metering assets. The daily transmission profile of bulk water meters, typically comprising short payloads (16–64 bytes) transmitted once per day, aligns well with LoRaWAN's low-duty-cycle, low-throughput design philosophy. Furthermore, LoRa modulation enables extended communication range at reduced transmission power through configurable spreading factors, facilitating long battery lifetimes often exceeding several years under optimal conditions. Gateway deployment flexibility also allows strategic placement on elevated structures to compensate for the low-elevation positioning of meters installed in concrete chambers.

However, LoRaWAN presents known limitations that are particularly relevant in underground or concrete-enclosed deployments. These include susceptibility to penetration losses, reduced signal-to-noise ratio (SNR) under thick concrete attenuation, downlink bottlenecks due to Class A receive window constraints, and scalability challenges arising from ALOHA-based medium access and duty-cycle restrictions in the EU868 band. In addition, confirmed uplink traffic and OTAA re-join cycles can introduce significant energy overheads when ACK reception is unreliable an issue amplified in obstructed propagation environments. Given that the author's prior peer-reviewed work specifically investigated join-aware energy modelling, reliability degradation under constrained SNR conditions, and mitigation strategies within LoRaWAN deployments, the modelling framework developed in this chapter focuses on LoRa and LoRaWAN to extend and contextualize those contributions within the specific operational environment of Rand Water's bulk metering infrastructure.

The remainder of this chapter details the modelling framework (Section 3.2), parameter assumptions (Section 3.3), the energy consumption model for LoRaWAN sensor nodes (Section 3.4), the Join/Re-join dynamics (Section 3.5), and simulation results (Section 3.6).

3.2 Modelling Framework for Energy Efficiency Evaluation

This section details the modelling framework used to evaluate the energy efficiency of LoRa and LoRaWAN sensor nodes in the Rand Water bulk metering application. The model integrates physical, environmental, and protocol-level parameters to reflect the real-world deployment conditions encountered in the Rand Water infrastructure particularly the placement of battery-powered sensor nodes inside low-elevation, thick-walled concrete chambers. These nodes transmit meter readings once daily and rely on the LoRaWAN Class A communication model Class A communication model as defined in the LoRaWAN 1.1 specification and validated in constrained deployments, which includes downlink acknowledgment (ACK) reception as per the LoRaWAN 1.1 specification [123], [127].

To capture this context, the framework is divided into five major subsystems:

- Environmental and deployment modelling
- Radio propagation and link budget estimation
- LoRa/LoRaWAN communication stack modelling
- Node energy state modelling
- Cumulative energy efficiency metrics computation

These are summarized in the logic flow shown in Figure 3.1: Block Diagram of the Energy Efficiency Modelling Framework.

These features introduce the following deployment-specific parameters: Table 3.1

Table 3.1: Deployment-specific parameter 1

Parameter	**Symbol**	**Typical Value**	**Description**
Concrete attenuation loss	$L_{concrete}$	$15 - 30\ dB$	Wall penetration loss based on chamber thickness
Antenna height (sensor node)	h_{tx}	$0.3 - 1.0\ m$	Within or just above the chamber lid
Gateway height	h_{rx}	$10 - 30\ m$	Mounted on towers or buildings
Distance to gateway	d	$0.5 - 3.0\ km$	Line-of-sight or obstructed paths
Transmission frequency	f	$868\ MHz$	LoRaWAN EU868 band
Packet size	M	$16 - 64\ bytes$	Daily payload size including timestamp, reading, and signature

3.2.1 Environmental and Deployment Modelling

To accurately model the energy consumption and communication reliability of LoRaWAN sensor nodes, it is essential first to establish the physical and operational context of the Rand Water bulk metering infrastructure. The deployment environment imposes unique constraints that fundamentally influence radio frequency (RF) propagation, link budget calculations, and ultimately the energy-reliability trade-offs analysed in this chapter. This subsection provides a detailed description of the Rand Water deployment environment, explaining the specific characteristics that distinguish it from conventional above ground or residential IoT installations.

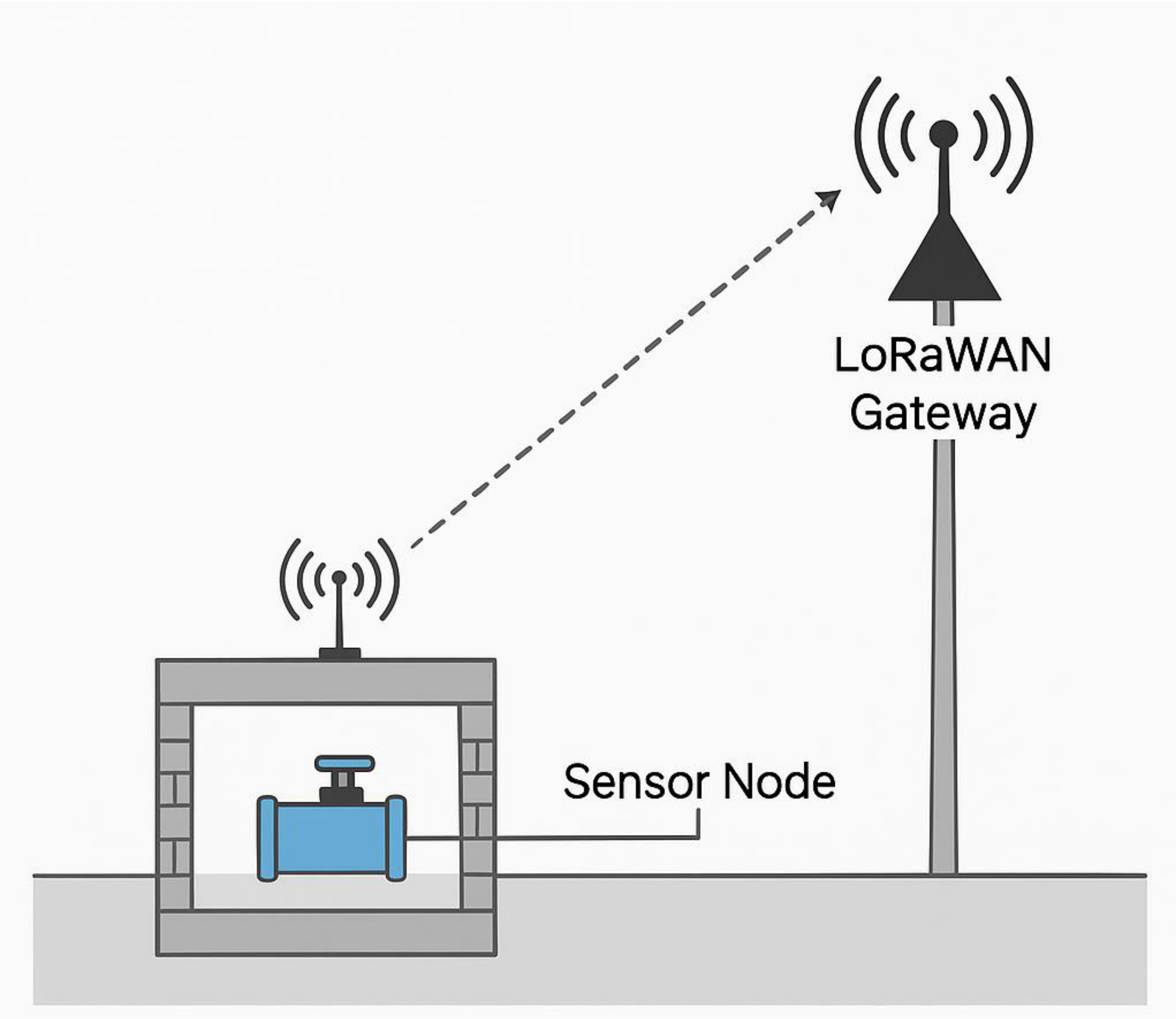

Figure 3.1: Representative Layout of Rand Water IoT Node Deployment

Low Elevation and Underground Installation

In the context of this study, "low elevation" refers specifically to the placement of bulk water meters below ground level within enclosed concrete chambers. Unlike residential water meters, which are typically installed at ground level in accessible pits or inside buildings, Rand Water's bulk meters are deliberately installed underground to protect critical infrastructure from vandalism, theft, and environmental exposure. These chambers are typically constructed of reinforced concrete and are designed to house large-diameter flow meters, valves, and associated telemetry equipment.

The simulation represents a distributed network of sensor nodes retrofitted to “Isoil magnetic flow meters” installed in submerged or low-elevation concrete chambers. Each sensor node is responsible for:

- Measuring water flow once daily.
- Transmitting a daily report of size M bytes.
- Waiting for a downlink ACK from the gateway
- Rejoining the LoRaWAN network if ACK is not received.

The sensor node antenna is therefore positioned at a height of approximately 0.3 to 1.0 metres below ground level, within the concrete structure. This is fundamentally different from a "flat terrain" deployment, where the antenna might be at ground level but still in free air. The underground placement has two significant consequences for wireless communication:

- **Signal Attenuation:** The radio signal must propagate through the concrete chamber walls and the surrounding soil before reaching open air. Reinforced concrete contains steel rebar that acts as a partial Faraday cage, particularly at higher frequencies, introducing substantial penetration loss.
- **Reduced Antenna Efficiency:** The proximity to conductive materials, including reinforcing steel within the concrete, metal pipes carrying water, and potentially standing water within the chamber detunes the antenna and reduces radiation efficiency. This further degrades the effective link budget beyond simple path loss calculations. This low-elevation, underground installation represents one of the most challenging environments for LPWAN communication and is the primary motivation for developing the deployment-aware models presented in this chapter.

Concrete Chamber Enclosure

Bulk water meters are enclosed within thick-walled reinforced concrete chambers for several critical operational reasons:

- **Physical Security:** The chambers prevent unauthorized access, tampering, and theft of expensive metering equipment. Bulk water meters represent a significant capital investment and measure high-value water flows, making them targets for interference.
- **Environmental Protection:** The enclosure shields sensitive electronic components from direct exposure to weather, flooding, temperature extremes, and accidental damage from surface activities.

• **Infrastructure Integration:** Chambers provide a controlled environment for pipe connections, isolation valves, pressure regulators, and ancillary monitoring equipment, allowing maintenance personnel to access the infrastructure safely.

However, from a radio propagation perspective, these concrete chambers act as significant barriers. The signal must penetrate the concrete walls, which introduces several complex propagation effects:

• **Reflection and Multipath:** Signals reflect off internal surfaces (concrete walls, water surface, metal pipes), creating multipath interference that can either constructively or destructively combine at the receiver. This makes the received signal strength highly sensitive to precise antenna placement within the chamber.

• **Absorption:** Concrete absorbs RF energy, converting it to heat and reducing the signal power available for transmission. The moisture content of the concrete and soil further increases absorption.

• **Diffraction:** Signals must bend around corners and through any available openings (such as access hatches or cable entries), further reducing power density and introducing additional path loss.

• **Frequency-Dependent Penetration:** Lower frequencies penetrate concrete more effectively than higher frequencies. This is one reason why sub-GHz frequencies (such as the 868 MHz band used by LoRaWAN) are preferred for such applications.

These effects are collectively modelled through the concrete penetration loss parameter introduced later in the simulation setup.

Long-Range Communication to Gateways

Rand Water's bulk metering network spans an extensive geographical area, with meter installations distributed across long-distance pipelines and regional distribution networks. Unlike a smart home or building automation system where a gateway can be placed within metres of every sensor, water utility infrastructure requires a different architectural approach.

Gateways cannot be co-located with every meter due to several constraints:

• **Cost:** Deploying a gateway at every meter location would be economically prohibitive for large-scale networks.

• **Infrastructure Access:** Many meter locations are in remote or restricted areas where installing gateway equipment with reliable power and backhaul connectivity is impractical.

• **Elevation Requirements:** Gateways achieve their long-range capability through elevated placement (on towers, buildings, or existing telecommunication structures), which is not possible at underground meter locations.

Consequently, sensor nodes must communicate over considerable distances to reach the nearest gateway. In the Rand Water context, "long-range communication" means link distances ranging from approximately 0.5 kilometres to 3.0 kilometres. This range is typical for LoRaWAN deployments in semi-urban and rural environments, but it introduces several challenges:

• **Geometric Path Loss:** Free-space path loss increases logarithmically with distance. At 3 km, the path loss is approximately 20 dB higher than at 300 metres, significantly reducing the received signal power.

• **Terrain and Obstructions:** The propagation path may traverse varied terrain, including open ground, roads, buildings, vegetation, and topographical features, each introducing additional attenuation and shadowing effects.

• **Spreading Factor Adaptation:** To maintain connectivity over these distances, the LoRaWAN adaptive data rate (ADR) mechanism must select higher spreading factors (SF9 to SF12). While higher spreading factors improve sensitivity and range, they also increase transmission time and energy consumption, creating a direct trade-off between coverage and energy efficiency.

• **Link Asymmetry:** The uplink path (sensor to gateway) and downlink path (gateway to sensor) may experience different propagation characteristics. When the sensor is underground, the uplink signal must penetrate the concrete chamber, while the downlink signal must penetrate it from the opposite direction. This asymmetry affects acknowledgment reception and join success probabilities, which are critical for reliable operation.

Summary of Deployment Characteristics

In summary, the Rand Water deployment environment is characterized by:

• **Physical placement:** Below-ground installation within reinforced concrete chambers at depths of 0.3–1.0 metres

• **Enclosure type:** Thick-walled reinforced concrete with steel rebar, designed for security and protection

• **Communication range:** 0.5‑3.0 kilometres to the nearest gateway, which is mounted on elevated structures

• **Frequency band:** Sub-GHz (868 MHz), selected for its balance of range and penetration.

This deployment-aware characterization ensures that the energy efficiency and reliability models developed in subsequent sections accurately reflect the physical constraints under which Rand Water's bulk metering infrastructure must operate. By understanding these real-world conditions, the modelling framework establishes a realistic foundation for the simulation results presented in Chapter 5.

3.2.2 Link Budget and Signal Propagation

Following the environmental and deployment modelling described in Section 3.2.1, the second subsystem of the modelling framework focuses on radio propagation and link-budget estimation. This subsystem determines whether communication between a sensor node and gateway is successful by quantifying the received signal power and comparing it to the sensitivity thresholds required for different spreading factors.

To estimate communication success and determine the required spreading factor (SF), the link budget is computed using propagation models adapted for long-range LPWAN scenarios in obstructed environments [124], [122]. The core of this subsystem is the log-distance path loss model, modified to account for the specific attenuation introduced by reinforced concrete chambers and low-elevation deployment.

The total path loss is expressed as:

$$PL(dB) = PL0 + 10 \cdot n \cdot log10(d) + Lconcrete + X\sigma \tag{3.1}$$

where:

• PL is the free-space path loss at a reference distance of 1 metre

• n is the path loss exponent, typically ranging from 3.0 to 4.5 for urban or obstructed environments

• d is the distance between the sensor node and gateway (metres)

• $Lconcrete$ represents the additional penetration loss incurred as the signal passes through the reinforced concrete chamber walls (typically 15‑30 dB).

• $X\sigma$ is a log-normal shadowing component accounting for random variations due to obstacles and environmental heterogeneity (typically 4–8 dB standard deviation).

The free-space path loss at 1 metre is calculated as:

$$PL_0 = 20log10(f) + 20log10(4\pi/c) \tag{3.2}$$

where:

• f is the transmission frequency in Hz (868 MHz for LoRaWAN EU868 band)

• c is the speed of light (3×10^8 m/s)

Substituting typical values yields:

$$PL0 = 20log10(8.68 \times 108) + 20log10(4\pi/3 \times 108) \approx 32.4\, dB$$

$PL_0 \approx 32.4$ dB

Hence, total path loss is:

$$PL(dB) \approx 32.4 + 10nlog10(d) + Lconcrete + X\sigma \tag{3.3}$$

The received power at the gateway is then derived from the link budget equation:

$$Pr = Pt + Gt + Gr - PL \tag{3.4}$$

where:

Pt is the transmit power of the sensor node (e.g., 14 dBm, the maximum permitted in the EU868 band)

• Gt and Gr are the transmit and receive antenna gains, respectively (typically 0–2 dBi for omnidirectional antennas)

• PL is the total path loss calculated above

The received signal-to-noise ratio (SNR) is computed as:

$$SNRi = Pr - N_0 \tag{3.5}$$

where N_0 is the noise floor and NF = 6 dB, given by:

$$N_0 = -174 + 10log10(BW) + NF \tag{3.6}$$

with BW representing the channel bandwidth (125 kHz for LoRaWAN) and **NF** the receiver noise figure (typically 6 dB).

Table 3.2 shows that for a given spreading factor SF, successful demodulation requires that the received SNR meets or exceeds the minimum required threshold for that SF, denoted SNR_{th} (SF). These thresholds, derived from Semtech SX1276 datasheet specifications, are:

Table 3.2: Spreading factor SF

Spreading Factor	SNR Threshold (dB)
SF7	–7.5
SF8	–10.0
SF9	–12.5
SF10	–15.0
SF11	–17.5
SF12	–20.0

If $\boldsymbol{SNR} \geq \boldsymbol{SNR\_th}(\boldsymbol{SF})$, the transmission is considered successful at that spreading factor. Otherwise, the link budget subsystem indicates that a higher spreading factor (with its lower sensitivity threshold) or additional repetitions may be required to establish communication.

This radio propagation and link budget estimation subsystem thus provides the critical interface between the physical deployment characteristics (Section 3.2.1) and the LoRaWAN protocol behaviour modelled in subsequent subsystems. By quantifying the relationship between distance, concrete attenuation, and received signal quality, it establishes the foundation for predicting packet delivery success, retransmission probability, and ultimately energy consumption.

3.2.3 LoRaWAN Protocol Behaviour and Rejoin Logic

The LoRaWAN Class A node operates in an **uplink-ACK-rejoin loop** as follows:

1. Node sends packet of size MMM bytes once daily.
2. Node waits for ACK in RX1 or RX2 window. If ACK not received:
3. Node re-initiates **Join procedure** starting from SF9 and increases SF until SF12 if necessary.

4. If Join fails at SF12, the packet is dropped, following the standard rejoin escalation defined in [127].

Uplink Duration T_{tx} for each SF is computed from LoRa modulation formula:

$$T_{tx} = T_{preamble} + T_{payload} \tag{3.7}$$

Where:

- $T_{symbol} = \frac{2^{SF}}{BW}$ (3.8)
- $T_{preamble} = (n_{preamble} + 4.25) \cdot T_{symbol}$ (3.9)
- $T_{payload}$ is given by

$$T_{payload} = T_{symbol} \cdot N_{payload} \tag{3.10}$$

Payload symbols:

$$N_{payload} = 8 + max(\left\lceil \frac{8M-4SF+28+16-20\cdot H}{4(SF-2DE)} \right\rceil \cdot (CR+4),0) \tag{3.11}$$

Where:

- M: Message size in bytes
- SF: Spreading factor
- BW: Bandwidth (125 kHz or 250 kHz)
- CR: Coding rate (1 to 4)
- H: Header enabled (0 or 1)
- DE: Low data rate optimization (0 or 1)

This is critical in determining **transmission time**, hence energy.

3.2.4 Node Energy State Modelling

Each sensor node has four power-consuming states: Table 3.3

Table 3.3: Power-consuming states for a sensor

State	Description	Duration	Current	Energy Expression
Transmit	The node is actively transmitting data. The radio transmitter is powered, and the PA (power amplifier) is engaged. This is the highest current-draw state.	T_{tx}	I_{tx}	$E_{tx} = V \cdot I_{tx} \cdot T_{tx}$ (3.12)
Receive	The node is listening for downlink transmissions (ACKs or network commands) during RX1 and RX2 windows. The radio receiver is active.	T_{rx}	I_{rx}	$E_{rx} = V \cdot I_{rx} \cdot T_{rx}$ (3.13)
Idle	The node is awake but neither transmitting nor receiving. The radio may be in a standby mode, ready to transition quickly to transmit or receive. This state occurs briefly between activities.	T_{idle}	I_{idle}	$E_{idle} = V \cdot I_{idle} \cdot T_{idle}$ (3.14)
Sleep	The node is in deep sleep mode. The radio and most peripherals are powered down, with only a low-power timer or RTC (real-time clock) running to wake the device for the next scheduled transmission. This is the lowest power state and dominates the 24-hour cycle.	T_{sleep}	I_{sleep}	$E_{sleep} = V \cdot I_{sleep} \cdot T_{sleep}$ (3.15)

Where:

- V: Operating voltage (e.g., 3.3 V)
- I_x: Current draw in each state

Total Daily Energy (per node):

$$E_{daily} = E_{tx} + E_{rx} + E_{idle} + E_{sleep} \tag{3.16}$$

If Join or ACK fails, add re-join cost:

$$E_{rejoin} = \sum_{i=SF_9}^{SF_{12}} (E_{join}^{i} + \ E_{rx}^{i}) \tag{3.17}$$

If Join or ACK fails, add re-join cost:

When a LoRaWAN sensor node fails to receive an acknowledgment (ACK) from the gateway within the configured receive windows (RX1 and RX2), it cannot confirm that its uplink transmission was successfully received. In a confirmed uplink scenario, this absence of acknowledgment indicates a potential loss of network connectivity. According to the LoRaWAN 1.1 specification [127], the node must then attempt to re-establish network connectivity through the Over-The-Air Activation (OTAA) join procedure.

This re-join process is not a single attempt but rather a systematic escalation through increasing spreading factors to maximize the probability of successful communication under deteriorating channel conditions. The node begins its re-join attempts at SF9, the lowest spreading factor typically permitted for join procedures. If the join request at SF9 fails (i.e., no JoinAccept is received in response), the node increments to SF10 and retries. This escalation continues through SF11 until finally attempting at SF12, which offers the highest sensitivity (lowest SNR threshold) but at the cost of significantly longer transmission duration.

Each join attempt at a given spreading factor *i* consists of two energy-consuming activities:

1. **Transmission of a JoinRequest frame:** This is a standard LoRa uplink frame of 23 bytes, containing the device identifier and authentication credentials. The transmission energy at spreading factor *i*, denoted $\mathbf{E\_join^{i}}$, is calculated using the same principles as a data transmission but with the fixed JoinRequest payload size.

2. **Receive window listening for JoinAccept:** Following each JoinRequest transmission, the node opens two receive windows (RX1 and RX2) to listen for the JoinAccept response from the network server. The energy consumed during this listening period is denoted $\mathbf{E\_rx^i}$. If no JoinAccept is received, this energy is effectively wasted, as the node must proceed to the next spreading factor attempt.

The cumulative energy cost of the entire re-join process is therefore the sum of energy consumed across all attempted spreading factors, from the initial attempt at SF9 up to the spreading factor at which the join finally succeeds (or up to SF12 if all attempts fail). This is expressed mathematically as:

$$E_{rejoin} = \Sigma_{\{\mathrm{i=SF9}\}}^{\{\mathrm{SF12}\}}(\mathrm{E\_join^i} + \mathrm{E\_rx^i}) \qquad (3.17.1)$$

where:

- $\mathbf{i}$ indexes the spreading factor (9, 10, 11, 12)
- $\mathbf{E\_join^i}$ is the transmission energy for a JoinRequest frame at spreading factor *i*
- $\mathbf{E\_rx^i}$ is the receive window energy for listening to the JoinAccept response at spreading factor *i*

This formulation assumes worst-case conditions where the node must attempt all four spreading factors. In practice, the summation stops at the spreading factor where the join succeeds. However, for energy budgeting and lifetime estimation, it is conservative to account for the maximum possible re-join cost, as nodes in deep underground deployments may frequently experience conditions requiring multiple attempts.

The re-join energy penalty is substantial for several reasons:

- JoinRequest frames (23 bytes) are larger than typical data payloads (16–64 bytes), increasing transmission time and energy
- Higher spreading factors (SF10–SF12) have exponentially longer transmission durations, dramatically increasing per-attempt energy
- Multiple attempts may be required, compounding the energy cost

- Failed attempts consume energy without contributing to successful data delivery, effectively reducing energy efficiency

This detailed modelling of re-join energy is a key contribution of this study, as many existing LoRaWAN energy models assume ideal connectivity and omit this significant energy overhead. The inclusion of re-join dynamics enables more accurate prediction of battery lifetime in challenging underground environments where ACK failures are non-negligible.

3.2.5 Energy Efficiency Metrics

The fifth subsystem of the modelling framework defines the energy efficiency metrics used to evaluate and compare the performance of LoRaWAN sensor nodes under different deployment conditions. While the daily energy consumption E_daily (Equation 3.5) provides a useful measure of instantaneous power usage, it does not fully capture the impact of failed transmissions and re-join events on long-term energy efficiency. To address this limitation, two complementary metrics are defined: the energy per successful transmission and the expected node lifetime.

Energy per Successful Transmission

The energy per successful transmission, denoted as **E_success**, represents the average energy expended by a sensor node for each data packet that is successfully delivered to the network server. This metric accounts for both the base energy consumed during normal operation and the additional energy overhead incurred when transmissions fail and trigger re-join attempts. It is defined as:

$$E_{success} = \frac{E_{daily} + E_{rejoin} \cdot P_{fail}}{PDR} \tag{3.18}$$

where:

- $\boldsymbol{E_{daily}}$ is the base energy consumed during a single reporting cycle when the transmission is successful and no re-join is required (as defined in Equation 3.5). This includes the energy for uplink transmission, receive window listening, idle periods, and sleep.

- $\boldsymbol{E_{rejoin}}$ is the additional energy consumed when a node must execute the full re-join procedure following an ACK failure (as defined in Equation 3.6). This term captures the cumulative energy cost of JoinRequest transmissions and $JoinAccept$ listening across escalating spreading factors.

- $\boldsymbol{P_{fail}}$ is the probability that a transmission attempt results in an ACK failure, thereby triggering the re-join procedure. This probability is derived from the link budget and SNR modelling described in Section 3.2.2, and depends on factors such as distance, concrete attenuation, and shadowing.

- $\boldsymbol{PDR}$ is the Packet Delivery Ratio, defined as the ratio of successfully delivered packets to the total number of transmission attempts. PDR is a direct measure of network reliability and is computed from the simulation outcomes, (0 < PDR ≤ 1)

The numerator $(\boldsymbol{E_{daily}} + \boldsymbol{E_{rejoin}} \cdot \boldsymbol{P_{fail}})$ represents the expected total energy consumed per transmission attempt, averaging over both successful and failed outcomes. When a transmission is successful (with probability $1 - P_{fail}$), the node consumes approximately E_{daily} . When a transmission fails (with probability P_{fail}), the node consumes E_{daily} plus the additional re-join energy E_{rejoin} . The expected value is therefore E_{daily} weighted by success plus $(E_{daily} + E_{rejoin})$ weighted by failure, which simplifies to the expression shown.

Dividing this expected energy per attempt by the Packet Delivery Ratio (PDR) yields the energy cost per successful delivery. This normalization is essential because when PDR is less than 1, multiple transmission attempts may be required on average to achieve one successful delivery. The energy wasted on failed attempts must be amortized across the successful packets, making $E_{success}$ a more accurate measure of true energy efficiency than E_{daily} alone.

Battery Lifetime Estimation

From $E_{success}$, the expected operational lifetime of a sensor node under a given battery capacity can be estimated. Let $\boldsymbol{E_{battery}}$ represent the total usable energy stored in the node's battery, calculated as:

$$E_{battery} = \mathrm{V}.C_{bat}3600 \tag{3.19}$$

where:

- $\mathbf{V}$ was the nominal battery voltage (3.3 V for the lithium-thionyl chloride cells typically used in utility metering applications)
- $\boldsymbol{C_{bat}}$ was the battery capacity in ampere-hours (Ah), with a typical value of 2400 mAh for the selected battery type
- The factor 3600 converted ampere-hours to coulombs, yielding energy in joules

Assuming one transmission per day, the expected node lifetime in days, denoted $\mathbf{L}$, is:

$$\boldsymbol{L} = \frac{E_{battery}}{E_{SUCCESS}} \tag{3.20}$$

- Lifetime in years can then be obtained as $\mathrm{L\_years} = \mathrm{L} / 365$. (3.21)
- $E_{battery}$: Total battery energy (e.g., $2400\ mAh \times 3.3\ V$)

This lifetime estimation provides a practical, system-level metric that directly informs deployment planning. For water utilities, battery life targets of 5–10 years are typical, and the modelling framework allows these targets to be evaluated against specific deployment conditions (distance, concrete attenuation, reporting frequency) before physical installation.

Significance of the Energy Efficiency Metrics

The energy efficiency metrics defined in this subsystem serve three critical purposes in the overall modelling framework:

1. **Comparative Evaluation:** They enable direct comparison between different LoRaWAN configurations (e.g., different spreading factors, ADR settings, join policies) in terms of energy cost per successfully delivered packet.

2. **Deployment Feasibility Assessment:** By linking energy consumption to battery capacity, they allow utilities to assess whether a given deployment scenario can meet operational lifetime requirements.

3. **Optimisation Target Identification:** The decomposition of energy into base and failure components highlights where energy is wasted (e.g., excessive re-joins) and guides the development of optimisation strategies.

These metrics are used throughout the simulation results presented in Chapter 5 to evaluate the performance of LoRaWAN under the Rand Water deployment conditions and to compare with NB-IoT.

3.2.6 Summary of Parameters for Simulation: Table 3.3

Following the definition of the five subsystems that constituted the energy efficiency modelling framework, it was necessary to establish the specific parameter values that would be used in the simulation implementation. These parameters were drawn from three main sources: (i) the LoRaWAN 1.1 specification [127] for protocol-specific timing and behaviour, (ii) the Semtech SX1276 transceiver datasheet [7] for power consumption characteristics, and (iii) the Rand Water deployment context for environmental and operational parameters such as distance, concrete attenuation, and reporting frequency.

Table 3.3 presents a consolidated summary of the key simulation parameters, organized by category to facilitate reference throughout the remainder of this chapter and in the results presented in Chapter 5. The table includes parameters related to the physical deployment environment, the LoRaWAN protocol configuration, the power consumption characteristics of the sensor node, and the simulation execution settings.

Where applicable, the typical values or ranges are provided, along with brief notes justifying the selection. These parameters were used consistently across all simulations to ensure that the results were reproducible and that comparisons between different configurations were meaningful.

Table 3.3: Simulation parameters

Parameter	**Symbol**	**Value/Range**	**Notes**
Packet size	M	16–64 bytes	Based on daily meter report
Transmission power	P_t	14 dBm	Max LoRa EU868 spec
Spreading Factor	SF	7–12	Configurable/adaptive
Bandwidth	BW	125 kHz	Default for long-range
Voltage	V	3.3 V	Battery voltage
ACK timeout	T_{ACK}	2–5 s	LoRaWAN $RX1 + RX2$
Daily transmission count	–	1	Scheduled transmission

Figure 3.1 presents a block diagram of the energy efficiency modelling framework developed in this chapter. The framework was structured into five interconnected subsystems, each represented by a block in the figure, with arrows indicating the flow of data from one subsystem to the next.

As illustrated in the figure, the framework began with the Environmental and Deployment Modelling block, which defined the physical deployment parameters of the Rand Water infrastructure, including distance, concrete attenuation, antenna heights, and transmission frequency. These parameters were passed to the Radio Propagation and Link Budget Estimation block, which calculated the received signal strength and determined the feasible spreading factors for communication under the given conditions.

The output of the link budget block informed the LoRaWAN Protocol Engine, which modelled the Class A end-device behaviour, including uplink transmissions, acknowledgment reception, retransmissions, and the OTAA rejoin procedure when ACKs were missed. The protocol engine generated timing information—specifically transmission durations T_{tx}, receive window durations T_{rx} , idle periods T_{idle}, and sleep duration T_{sleep} which were then passed to the Node State Engine.

The Node State Engine applied state-specific current draws (transmit, receive, idle, and sleep currents) to calculate the energy consumed in each state, producing E_{tx}, E_{rx}, E_{idle}, and E_{sleep} . This information was passed to the Energy Computation Module, which aggregated the energy contributions and computed the key performance metrics: energy per successful transmission $E_{success}$, packet delivery ratio PDR, expected node lifetime L, and the average number of re-joins.

The following subsections elaborate on each of the five subsystems depicted in Figure 3.1, providing the analytical equations and modelling assumptions that underpin the framework.

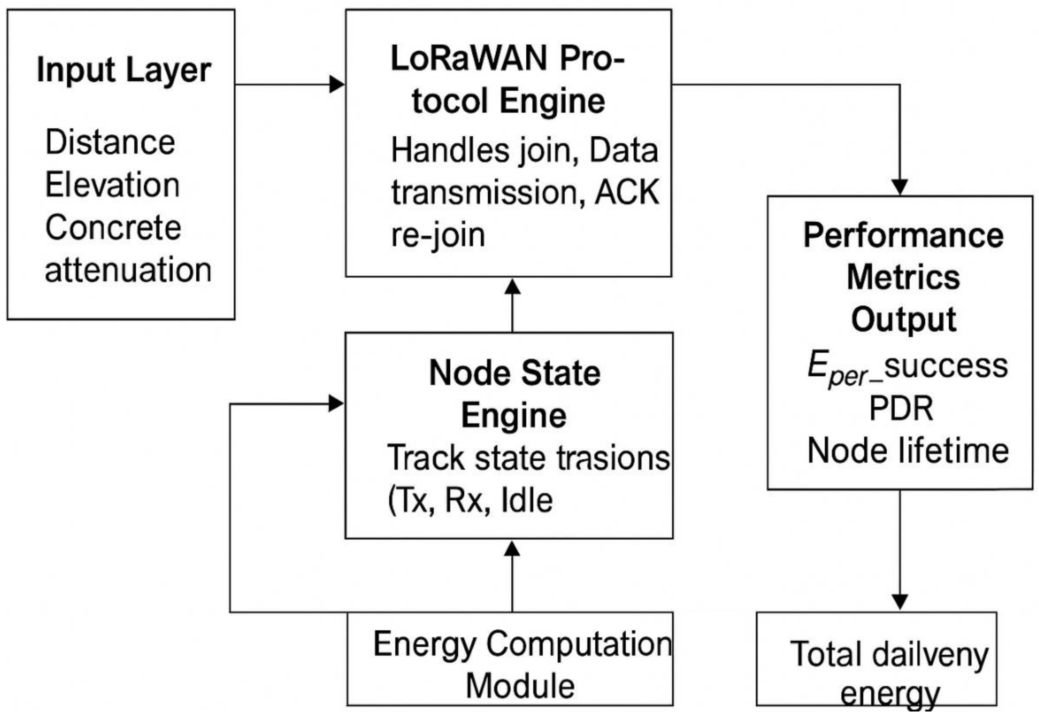

Figure 3.2: Block Diagram of the Energy Efficiency Modelling Framework

Suggested Content for the Figure:

- **Input Layer**: Environmental Parameters (Distance, Elevation, Concrete attenuation)
- **Link Budget Module**: Computes received SNR, selects appropriate SF
- **LoRaWAN Protocol Engine**: Handles join, data transmission, ACK, re-join
- **Node State Engine**: Tracks state transitions (Tx, Rx, Idle, Sleep)
- **Energy Computation Module**: Calculates per-state energy, total daily energy
- **Performance Metrics Output**: $E\_per\_\ success$, PDR, Node lifetime

3.3 Simulation Parameters and Assumptions

To implement the modelling framework presented in Section 3.2, this section defines the simulation conditions, environmental assumptions, node behaviours, and computational flows required for MATLAB-based simulation of energy efficiency in LoRa and LoRaWAN sensor nodes deployed in Rand Water's bulk metering network. All simulation parameters are selected or derived based on field studies, datasheet references, LoRaWAN specifications, and characteristics specific to the South African deployment conditions.

3.3.1 Deployment Scenario Overview

The simulation represented a distributed network of sensor nodes retrofitted to magnetic flow meters (*Isoil magflow meter*) installed in submerged or low-elevation concrete chambers. Each sensor node was modelled to perform three main functions: measuring water flow once daily, transmitting a daily report of size **M** bytes, waiting for a downlink ACK from the gateway, and rejoining the LoRaWAN network if an ACK was not received.

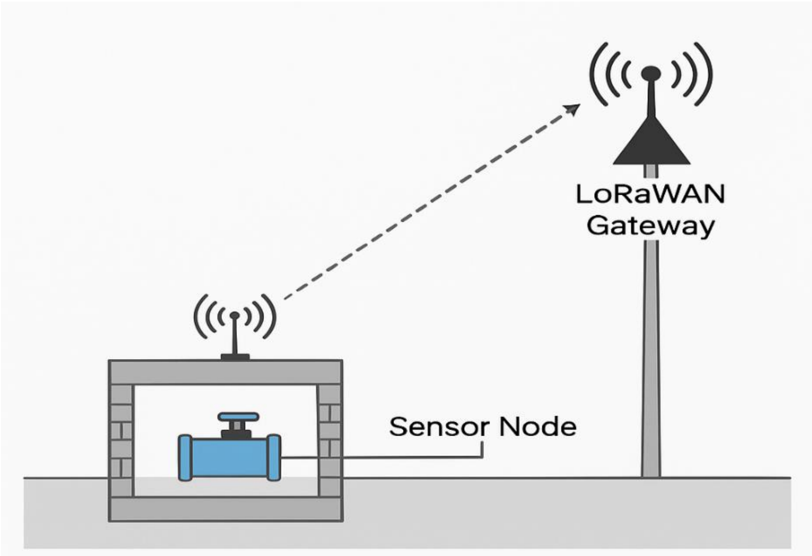

Figure 3.3: Representative Layout of Rand Water IoT Node Deployment

Figure 3.3 illustrates the representative layout of the Rand Water IoT node deployment, showing the underground concrete chamber, the sensor node antenna below ground level, and the gateway mounted on an elevated structure.

3.3.2 Simulation Parameter Table 3.4

The simulation parameters were organized into categories to facilitate reference and ensure consistency across all simulation runs. Table 3.4 presents a consolidated summary of the key parameters used in the simulation framework. The parameters were drawn from three main sources: (i) the LoRaWAN 1.1 specification [127] for protocol-specific timing and behaviour, (ii) the Semtech SX1276 transceiver datasheet [7] for power consumption characteristics, and (iii) the Rand Water deployment context for environmental and operational parameters such as distance, concrete attenuation, and reporting frequency.

Table 3.4: Simulation Parameter

Category	**Parameter**	**Symbol**	**Value/Range**	**Source/Justification**
Node config	Battery voltage	V	3.3 V	Typical for Li-$SOCl_2$ batteries
	Battery capacity	C_{bat}	2400 mAh	Based on Tadiran battery
	Transmit power	P_t	14 dBm	LoRaWAN EU868 max

	Packet size	M	16–64 bytes	Estimated meter data
	Spreading Factor	SF	7–12	Adaptive
Power profile	I_{tx}	–	28 mA	Semtech SX1276 datasheet [7]
	I_{rx}	–	11.5 mA	Typical
	I_{idle}	–	1.5 mA	During channel wait
	I_{sleep}	–	1 µA	During standby
Channel model	Path loss exponent	n	3.2–4.0	Suburban + concrete
	Concrete loss	$L_{concrete}$	20 dB	Measured range
	Shadowing	X_{σ}	6 dB	Standard deviation
Protocol	RX1 + RX2 timeout	T_{ACK}	2–5 s	LoRaWAN Class A
	Join SF cycle	–	SF9 → SF12	LoRaWAN 1.1 spec
Simulation	Transmission interval	–	1/day	Rand Water requirement
	Number of nodes	–	100	Scaled test scenario
	Simulation duration	–	365 days	1 year lifecycle

3.3.3 Energy Computation per Transmission Cycle

Each node was modelled to perform one transmission per day. The energy cost for a successful transmission cycle was calculated using the state-based energy equations defined in Section 3.2.4, with the parameter values specified in Table 3.3. The total daily energy when an ACK was received was:

$$Eday = Etx + Erx + Esleep \tag{3.16}$$

where $\boldsymbol{E_{tx}}$, $\boldsymbol{E_{rx}}$, and $\boldsymbol{E_{sleep}}$ were computed using Equations 3.2, 3.3, and 3.5 respectively. If an ACK was not received after the configured number of confirmed uplink retransmissions, the node entered the re-join cycle described in Section 3.3.4.

the transmission energy:

$$E_{tx} = V \cdot I_{tx} \cdot T_{tx} \tag{3.12}$$

and the sleep energy (dominant in duration):

$$E_{sleep} = V \cdot I_{sleep} \cdot T_{sleep} \approx V \cdot I_{sleep} \cdot (86400 - T_{tx} - T_{rx}) \tag{3.15}$$

Each node performs one transmission per day. The energy cost depends on:

If ACK is not received after $R_{\max}$confirmed uplink retransmissions, the node enters the re-join cycle.

3.3.4 Re-Join Simulation Logic

When an ACK was not received, the node initiated the OTAA join procedure, escalating through spreading factors from SF9 to SF12. The re-join logic was implemented as a state machine, illustrated in Figure 3.4.

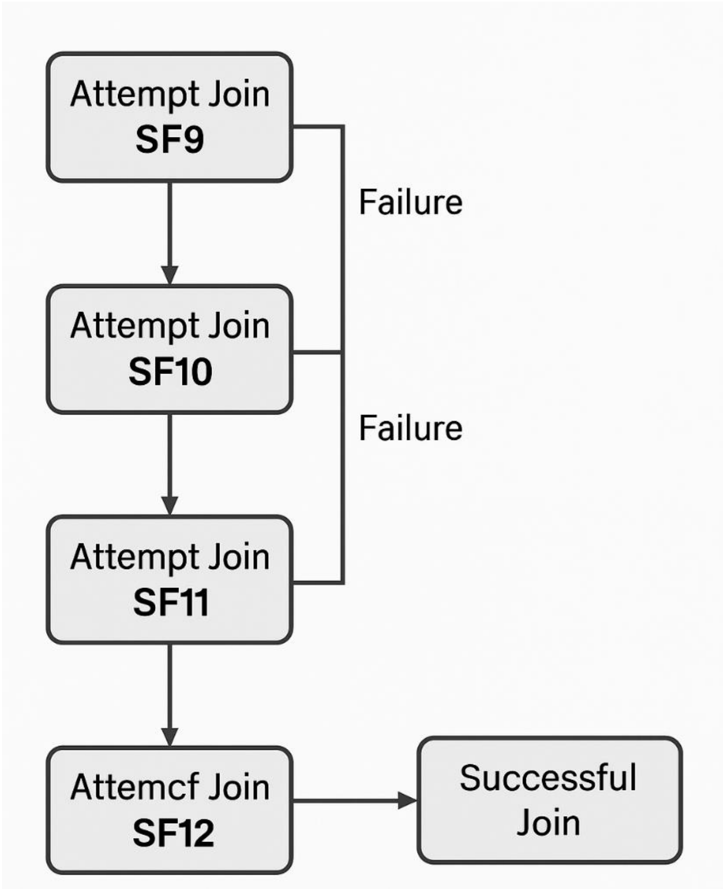

Figure 3.4: LoRaWAN Re-Join State Machine (SF9-SF12)

The simulation logic for the re-join behaviour was implemented using the pseudocode presented in **Pseudocode 3.1**, which captured the sequential join attempts and the associated energy accumulation.

Pseudocode 3.1: Re-Join Behaviour Simulation

```
for each node
    send_packet()
    wait_for_ack(timeout)
    if ack_received
        update_energy(E_tx + E_rx + E_sleep)
    else
        for sf = 9 to 12
            perform_join(sf)
            if join_successful
                update_energy(E_tx(sf) + E_rx(sf) + E_sleep)
                break
            end
        end
        if join_failed
            mark_packet_dropped()
        end
    end
end
```

Join success is determined by:

$$SNR_{recv} \geq SNR_{threshold}(SF)$$

Based on path loss model and SNR thresholds as defined in, [125].

Where:

- SNR_{recv}: Calculated from path loss model
- $SNR_{threshold}$: Minimum required for SFx, per Semtech table

3.3.5 Environmental Signal Propagation Assumptions

For each simulation round, the node-to-gateway path loss was drawn from the log-normal distribution defined in Section 3.2.2:

$$PLi = PL0 + 10nlog10(di) + Lconcrete + N(0, X\sigma 2) \quad (3.1)$$

The received power and SNR were then calculated as:

$$Pr, i = Pt + Gt + Gr - PLi \quad (3.4)$$

$$SNRi = Pr, i - N0 \quad (3.5)$$

where $\mathbf{N_0}$ was the noise floor computed as:

$$N0 = -174 + 10log10(BW) + NF \quad (3.6)$$

with $\mathbf{NF}$ set to 6 dB, typical for LoRa transceivers.

3.3.6 Output Metrics to Be Tracked

The simulation must output the following per node and aggregated across all nodes: Table 3.5 shows the output metrics and the relative fomulas.

Table 3.5: Output Metrics

Metric	Formula	Description
Daily energy per node	E_{day}	Total energy consumed in a 24-hour reporting cycle
Average Packet Delivery Ratio	$\frac{\text{Packets received}}{\text{Packets sent}}$	Reliability metric
Average number of re-joins	Σ Join attempts / Total nodes	Indicator of channel quality
Mean energy per successful delivery	$\frac{\text{E\_total}}{\text{Packets received}}$	Energy efficiency metric (E_success)
Node lifetime	$\frac{\text{E\_battery}}{\text{Daily average energy}}$	Expected operational duration

3.3.7 Summary of Key Assumptions

The following key assumptions were applied throughout the simulation:

- All nodes transmitted one packet per day in accordance with the Rand Water reporting requirement.
- The environment was modelled as urban-suburban with an additional 15–30 dB concrete penetration loss to account for reinforced concrete chambers.
- Join cycles were deterministic in escalation (SF9 through SF12) but probabilistic in success, based on the SNR received at the gateway.
- No retransmission retries were modelled beyond the daily re-join cycle; if a packet was not successfully delivered after the re-join attempts, it was marked as dropped.
- Gateway coverage was assumed to be omnidirectional with a maximum range of 5 km.

- Adaptive Data Rate (ADR) was disabled during join and initial deployment phases to reflect worst-case underground channel conditions, consistent with the approach described in [125].

3.3.8 Confirmed Uplink Retry Policy and LoRaWAN MAC Parameters

In practical LoRaWAN Class A deployments, the confirmed uplink traffic mechanism governed the behaviour of end devices when acknowledgment was required. This mechanism was controlled by the MAC layer parameter NbTrans, which specified the maximum number of transmission attempts for a confirmed uplink frame. When an uplink frame was transmitted and no acknowledgment (ACK) was received within the RX1 and RX2 receive windows, the end device could retransmit the uplink frame up to a maximum number of retries R_max. This retry behaviour occurred before triggering a full Over-The-Air Activation (OTAA) re-join cycle and therefore contributed additional transmission and reception energy overhead.

In this study, the confirmed uplink retry mechanism was modelled using the following MAC-layer parameters, with each assumption justified based on the Rand Water deployment context and LoRaWAN specification requirements:

R_max: Maximum Number of Retransmissions

The maximum number of retransmissions was set to 3 for baseline simulations. This value was selected because the LoRaWAN specification permits a small number of retransmissions to balance reliability against energy consumption and airtime occupancy. In the Rand Water context, where nodes transmit only once per day, a small number of retransmissions provided a reasonable opportunity for successful delivery in challenging underground conditions without incurring excessive energy overhead. Increasing R_max beyond 3 would have proportionally increased energy consumption while yielding diminishing returns in packet delivery improvement, particularly when channel conditions were severely attenuated.

T_RX1 and T_RX2: Receive Window Delays

The RX1 delay was set to 1 second after the end of the uplink transmission, and the RX2 delay was set to 2 seconds after the end of the uplink transmission. These values were adopted directly from the LoRaWAN Class A specification, which mandates these fixed delays to ensure deterministic timing between end devices and gateways. No deviation from these values was considered, as doing so would have violated the standard and would not reflect actual device behaviour in real-world deployments.

RX1 and RX2 Data Rate Settings

The receive windows were configured to use the default LoRaWAN Class A settings, where the RX1 data rate was derived from the uplink data rate and the RX2 data rate was fixed to the network-configured default (typically SF12 at 125 kHz bandwidth). This configuration reflected standard LoRaWAN network behaviour and ensured that the simulation aligned with practical deployment scenarios where network servers typically configure these parameters consistently across devices.

ADR Assumption: Disabled During Join and Initial Deployment

Adaptive Data Rate (ADR) was disabled during the join procedure and the initial deployment phase in the simulation. This assumption was made for two reasons. First, in underground reinforced concrete deployments, the channel conditions were highly variable due to multipath effects, shadowing, and penetration loss. ADR relies on consistent link measurements to optimize data rate selection; under highly variable conditions, ADR could have resulted in unstable spreading factor selection, potentially increasing energy consumption rather than reducing it. Second, during the join procedure, the node had not yet established a reliable communication history with the network server, and ADR typically required several successful transmissions to converge on an optimal data rate. Disabling ADR during this initial phase therefore represented a worst-case scenario, which was appropriate for evaluating the fundamental performance limits of LoRaWAN in challenging underground environments. This approach was consistent with the methodology described in [125], which similarly disabled ADR in constrained channel conditions to isolate the effects of spreading factor selection on reliability.

Fixed Spreading Factor Assumption

Each retransmission attempt was modelled to use the same spreading factor as the original transmission, unless ADR logic was explicitly enabled to adjust the data rate. For the baseline simulations presented in this study, a fixed spreading factor per transmission cycle was assumed. This assumption was justified on two grounds. First, in the absence of ADR, LoRaWAN end devices do not autonomously change spreading factors between retransmission attempts; the spreading factor remains constant for all attempts within a single transmission cycle. Second, for the purpose of worst-case energy modelling, assuming a fixed spreading factor provided a conservative estimate of energy consumption, as adaptive selection would have potentially reduced airtime and energy when channel conditions permitted lower spreading factors. This assumption was applied consistently across all simulations unless explicitly stated otherwise.

Rationale for Explicit Integration of Retry Policy

The confirmed uplink retry policy significantly affected three key performance metrics: packet delivery probability, airtime utilization, and energy consumption. Packet delivery probability was influenced because each retransmission attempt provided an additional opportunity for successful delivery, increasing the likelihood that the packet would reach the gateway. Airtime utilization was affected because each retransmission consumed additional channel time, which was particularly significant at higher spreading factors where transmission durations were substantially longer. Energy consumption was directly impacted because each retransmission required both transmission energy and receive window energy, with no guarantee of successful delivery.

Because these effects were fundamental to understanding the energy–reliability trade-off in underground LoRaWAN deployments, the retry policy was explicitly integrated into the energy modelling framework prior to join escalation analysis. This ensured that the simulation captured the complete sequence of events: uplink transmission, retransmissions (if ACKs were missed), and only then the OTAA re-join procedure if all retransmission attempts failed. This sequencing was critical for accurate energy accounting, as retransmissions consumed additional energy but did not incur the full overhead of a re-join cycle unless all retransmission attempts were exhausted.

3.4 Detailed Energy Modelling and Symbolic Derivations

The energy consumption model for LoRa and LoRaWAN sensor nodes in this study is built from first principles of power consumption across different operational states of the transceiver module. It accounts for transmission, reception (especially ACK windows), standby (idle), and deep sleep states. Additionally, the model incorporates conditional energy penalties for nodes that fail to receive acknowledgments and must re-initiate the LoRaWAN join process.

This section provides the complete derivation of symbolic expressions used to compute:

- Transmission duration and energy,
- ACK receive duration and energy,
- Sleep energy,
- Re-join energy overheads,
- Lifetime estimation per battery,
- Energy-per-successful-packet as a key efficiency metric.

3.4.1 State-Based Energy Model

To capture the energy consumption of a LoRaWAN sensor node, a state-based modelling approach was adopted, following frameworks presented in [125]. This approach decomposed the node's operation into discrete power states, each with a characteristic current draw and duration, allowing the total energy per reporting cycle to be estimated accurately.

The total energy consumed by a node in one communication cycle (per day) was expressed as:

$$E_{total} = E_{tx}^{UL} + E_{rx}^{UL} + E_{sleep} + E_{idle} + E_{rejoin} \tag{3.22}$$

Where:

- E_{tx}: Transmission energy
- E_{rx}: ACK receive window energy
- E_{sleep}: Deep sleep energy (most of the day)
- E_{idle}: Time waiting before TX or RX
- E_{rejoin}: Only included if re-join procedure is triggered

The state-based model is aligned with frameworks presented in [125]. Each term is expanded below.

3.4.2 Transmission Time and Energy

The time to transmit a LoRa frame is derived from modulation parameters as described in the Semtech design guide [7].

$$T_{symbol} = \frac{2^{SF}}{BW} \quad (3.8)$$

$$T_{preamble} = (n_{preamble} + 4.25) * T_{symbol} \quad (3.9)$$

$$N_{payload} = 8 + max\left(\left\lceil\frac{(8M - 4SF + 28 + 16 - 20H)}{4(SF - 2DE)}\right\rceil * (CR + 4), 0\right) \quad (3.11)$$

$$T_{payload} = T_{symbol} * N_{payload} \quad (3.10)$$

$$T_{tx} = T_{preamble} + T_{payload} \quad (3.7)$$

Thus, transmission energy is:

$$\mathrm{E_{tx}} = \mathrm{V} \cdot \mathrm{I_{tx}} \cdot \mathrm{T_{tx}} \quad (3.12)$$

Where:

- V: Operating voltage (V)
- I_{tx}: Transmit current (A)
- M: Payload size (bytes)
- CR: Coding rate (e.g., 1–4)
- BW: Bandwidth in Hz
- H: Header (1 if enabled)
- DE: Low data rate optimization flag

3.4.3 Receive Time and Energy (ACK Windows)

After a packet is sent, LoRaWAN Class A specifies two receive windows:

$RX1$ opens t_1 ms after TX ends (typically 1 s)

$RX2$ opens t_2 ms later (typically 2 s)

Let:

$T_{rx}^{(1)}$: RX1 window duration (e.g., 128 ms)

$T_{rx}^{(2)}$: RX2 window duration (e.g., 128 ms)

Assume both are kept open fully if no ACK is received earlier.

$$T_{rx} = T_{rx}^{(1)} + T_{rx}^{(2)} \tag{3.23}$$

$$E_{rx} = V \cdot I_{rx} \cdot T_{rx} \tag{3.13}$$

If ACK is received in RX1:

$$E_{rx} = V \cdot I_{rx} \cdot T_{rx}^{(1)} \tag{3.13}$$

3.4.4 Sleep and Idle Energy

The node sleeps during all remaining seconds of the 24-hour period:

$$T_{sleep} = 86400 - (T_{tx} + T_{rx} + T_{idle}) \tag{3.24}$$

$$E_{sleep} = V \cdot I_{sleep} \cdot T_{sleep} \tag{3.15}$$

If the node is idle between operations (e.g., waiting before a transmission):

$$E_{idle} = V \cdot I_{idle} \cdot T_{idle} \tag{3.14}$$

Assume $T_{idle} \approx 1$ s in a LoRaWAN implementation.

3.4.5 Re-Join Energy Penalty

When an ACK is not received, the node assumes disconnection rejoin loop follows the LoRaWAN 1.1 specification [8] and energy behaviour models from and enters a LoRaWAN join loop [123].

For each join attempt at Spreading Factor i (i.e., SF9 to SF12):

1. Send a JoinRequest frame, which takes time T_(join)^((i)).

2. Wait for a JoinAccept message in the receive windows.

The energy for a single join attempt at SF i is:

$$E_{join}^{(i)} = V \cdot \left(I_{tx} \cdot T_{join}^{(i)} + I_{rx} \cdot T_{rx} \right) \tag{3.25}$$

If the node successfully rejoins at SF j, the cumulative energy for the entire rejoin process is the sum of all attempts up to that point:

$$E_{rejoin} = \sum_{i=SF_9}^{SF_j} E_{join}^{(i)} \tag{3.17}$$

If the node never re-joins (e.g., due to a poor channel), the packet is dropped, and all energy spent on the rejoin attempts is lost.

3.4.6 Energy per Successful Transmission

Let:

- P_{fail}: Probability of ACK failure and forced rejoin.
- P_{drop}: Probability of an unsuccessful join.
- PDR: Packet Delivery Ratio.

Then, the average energy per successful delivery (E_{succ}) is given by the extended energy-per-packet model presented in, [125]:

$$E_{succ} = \frac{(1 - P_{fail}) \cdot E_{base} + P_{fail} \cdot (1 - P_{drop}) \cdot (E_{base} + E_{rejoin})}{PDR} \tag{3.26}$$

Where the base energy (E_{base}) is the sum of energies for a standard, successful transmission cycle:

$$E_{base} = E_{tx} + E_{rx} + E_{sleep} + E_{idle} \tag{3.27}$$

3.4.7 Battery Lifetime Model

Given the total battery energy (E_(battery)) in Joules, the node lifetime (L) in days is the total energy divided by the average energy consumed per successful delivery.

$$L = \frac{E_{battery}}{E_{succ}} \tag{3.20}$$

Alternatively, the expected node uptime in years can be calculated from the lifetime in days.

$$L_{years} = \frac{L}{365} \quad (3.21)$$

The total battery energy is calculated based on its nominal voltage and capacity, where:

$$E_{battery} = V \cdot C_{bat} \cdot 3600 \quad (3.19)$$

- C_{bat}: Battery capacity in Ampere-hours (Ah).

3.4.8 Confirmed Uplink Retransmission Energy Model

Before a node enters the join procedure due to repeated ACK failure, it may perform up to $R_{\max}$retransmissions of the same uplink packet. Let Rdenote the actual number of retries attempted (where $0 \leq R \leq R_{\max}$).

Total Transmission Energy with Retries

$$E_{tx}^{(UL)} = VI_{tx} \sum_{k=0}^{R} T_{UL}(s_k, M) \quad (3.28)$$

Where:

- $T_{UL}(s_k, M)$is the uplink transmission time for spreading factor s_k
- $M$is payload size
- $V$is operating voltage
- $I_{tx}$is transmit current

If spreading factor remains constant:

$$E_{tx}^{(UL)} = VI_{tx}(R+1)T_{UL}(s) \quad (3.28.1)$$

Total Receive Energy (ACK Possibly in RX2)

For each uplink attempt, two receive windows may open unless ACK is received earlier.

$$E_{rx}^{(UL)} = VI_{rx} \sum_{k=0}^{R} \left(T_{RX1} + \mathbf{1}_{ACK \in RX2}^{(k)} T_{RX2} \right) \quad (3.29)$$

Where:

- $\mathbf{1}_{ACK\in RX2}^{(k)}$is an indicator function equal to 1 if ACK is received in RX2 during attempt k, and 0 otherwise.

In worst-case modelling (ACK never received during retries):

$$E_{rx}^{(UL)} = VI_{rx}(R+1)(T_{RX1} + T_{RX2}) \quad (3.29)$$

Delivery Probability with Retries

Let $p_{succ}(s_k, \Delta_k)$denote the success probability at attempt k. The probability that at least one retransmission succeeds is:

$$P_{UL\_succ} = 1 - \prod_{k=0}^{R}(1 - p_{succ}(s_k, \Delta_k)) \quad (3.30)$$

If spreading factor is fixed:

$$P_{UL\_succ} = 1 - (1 - p_{succ})^{R+1} \quad (3.30.1)$$

3.5 LoRaWAN Join Dynamics Simulation

LoRaWAN Class A defines a lightweight network access and communication protocol optimized for low-power devices. A critical component of this protocol is the **Join Procedure**, which is used to initially connect to or reconnect with a network server. In the Rand Water deployment, the reliability of ACK reception is significantly influenced by concrete attenuation, low elevation, and environmental noise, often triggering the Join cycle due to failed downlink reception.

This section details how the Join process is dynamically simulated within the energy efficiency framework, considering probabilistic SNR thresholds, adaptive spreading factors (SF9 to SF12), and maximum allowable attempts. The Join dynamics are explicitly modelled to reflect [128]:

- The likelihood of join success at each SF,
- Rejoin energy overheads,
- Packet loss due to Join failure after all SFs are exhausted,
- Resulting impact on packet delivery reliability and lifetime.

3.5.1 LoRaWAN Join Procedure Overview

OTAA begins upon device startup or when ACKs are missed in RX1 and RX2 windows. Upon a missing Join Accept, the node climbs through SFs until SF12, after which the attempt is abandoned [21]. While Semtech's AN1200.13 outlines SF thresholds, deeper insights on reception behaviour and device sensitivity are in AN1200.22 [126], [128].

Figure 3.5 shows the flow of the **Join procedure** (also known as OTAA – Over-The-Air Activation) is triggered:

- Initially when the node is powered on,
- After failing to receive an acknowledgment (ACK) within both RX1 and RX2 windows.

The Join steps include:

1. **Join Request** is transmitted at current SF.
2. Node opens two **receive windows** (RX1 and RX2) to listen for a **Join Accept** from the gateway.
3. If unsuccessful, the node increases its SF and retries until SF12.
4. After SF12, the attempt is **aborted**, and the packet is **dropped**.

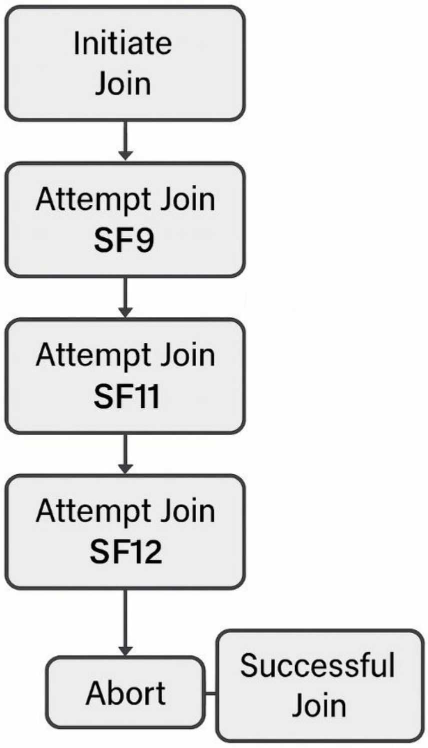

Figure 3.5: Join/Rejoin Decision Tree in LoRaWAN

3.5.2 Simulation Logic for Join Dynamics

Practical LoRaWAN deployments, packet success does not exhibit a strict binary transition at the minimum sensitivity threshold. Instead, link performance degrades progressively around the sensitivity limit due to shadow fading, interference, and receiver implementation imperfections.

3.5.2.1. Coverage Probability and Probabilistic Success Model

To reflect this behaviour more realistically, the link reliability is modelled probabilistically rather than using a hard SNR threshold. Let γdenote the received SNR and $\gamma_{\min}(s)$denote the minimum SNR required for successful demodulation at spreading factor s. The coverage probability for spreading factor $s$is defined as:

$$p_{\text{cov}}(s) = \Pr\left[\gamma \geq \gamma_{\min}(s)\right] \tag{3.31}$$

Assuming log-normal shadowing in the channel model, the received SNR is a random variable, and the coverage probability can be expressed as:

$$p_{\text{cov}}(s) = 1 - \Phi\left(\frac{\gamma_{\min}(s) - \mu_\gamma}{\sigma_\gamma}\right) \tag{3.32}$$

where $\Phi(\cdot)$is the standard normal cumulative distribution function (CDF), $\mu_\gamma$is the mean received SNR, and $\sigma_\gamma$is the standard deviation due to shadow fading.

To avoid “knife-edge” behaviour around the sensitivity limit, a smooth probabilistic success model can also be adopted using a logistic function of the SNR margin. Let the SNR margin be:

$$\Delta = \gamma - \gamma_{\min}(s) \tag{3.32.1}$$

The probability of successful packet reception at spreading factor $s$is then approximated as:

$$p_{\text{succ}}(s, \Delta) = \frac{1}{1 + e^{-\alpha\Delta}} \tag{3.33}$$

where αcontrols the steepness of the transition region around the sensitivity threshold. Larger values of αapproximate a hard threshold model, while smaller values produce a smoother transition. This probabilistic formulation enables more realistic Monte Carlo simulations of join success, packet delivery ratio (PDR), and energy-per-success metrics under fluctuating channel conditions typical of concrete-enclosed bulk metering deployments.

3.5.2.2. The simulation logic

Let the following parameters define the model:

- $\boldsymbol{SF_{min}} = \mathbf{9}\ and\ \boldsymbol{SF_{max}} = \mathbf{12}$: The minimum and maximum Spreading Factors for join attempts.
- $\boldsymbol{SNR_{recv}}$: The simulated received Signal-to-Noise Ratio.
- $\boldsymbol{SNR_{(th)(SF)}}$: The minimum required SNR for successful reception at a given SF.
- $\boldsymbol{P_{join}^{(i)}}$: The probability of a successful join attempt at SF_i .
- SNR_recv: simulated link strength
- SNR_th(SF): minimum required SNR from Semtech reference thresholds [9]

Join succeeds only if SNR_recv ≥ SNR_th(SF). SNR thresholds are drawn from Semtech's LoRa modem design documentation [9]. The energy consumed per join attempt follows Bouguera et al.'s analytical model for LoRaWAN sensor nodes.

A join attempt at a given SF is successful if the received SNR meets or exceeds the required threshold:

$$SNR_{recv}\ >=\ SNR_{(th)(SF)}$$

Semtech Reference Thresholds: Table 3.6

The minimum SNR values (SNR_{th}) required for reception at each SF are based on Semtech's reference data.

Table 3.1: Semtech Reference Thresholds

SF	$SNR_{th}\ [dB]$
7	-7.5
8	-10.0
9	-12.5
10	-15.0
11	-17.5
12	-20.0

Pseudocode 3.2: Simulation Logic for Join Dynamics

```
function [success, sf_used, E_rejoin] = perform_join_cycle(SNR_recv, V, I_tx, I_rx, BW)
   SF_list = [9, 10, 11, 12];
   E_rejoin = 0;
   success = false;
   for sf = SF_list
      T_sym = 2^sf / BW;
      T_preamble = (8 + 4.25) * T_sym;
      T_payload = compute_payload_time(23, sf, BW); % Join Req: 23 bytes
      T_tx = T_preamble + T_payload;
      T_rx = 2 * 0.128; % RX1 + RX2
      SNR_th = SNR_threshold(sf);
      if SNR_recv >= SNR_th
         E_rejoin = E_rejoin + V * (I_tx * T_tx + I_rx * T_rx);
         success = true;
         sf_used = sf;
         break;
      else
         E_rejoin = E_rejoin + V * (I_tx * T_tx + I_rx * T_rx);
      end
   end
   if ~success
      sf_used = NaN; % Join failed
   end
end
```

3.5.3 Randomized Join Environment Simulation

To reflect real-world behaviour, we simulate a random node environment:

1. Draw a distance d from the node to the gateway.
2. Generate SNR based on:

   We simulate the SNR using

$$SNR_{rec} = P_t - PL(d) - N_0 + G_t + G_r \quad (3.5.1)$$

Where: PL(d) includes log-distance loss, shadow fading, and concrete attenuation. This model aligns with realistic urban and utility deployment environments studied in LoRaWAN trials [10].

- $PL(d) = PL_0 + 10nlog_{10}(d) + L_{concrete} + X_\sigma$ (3.1)

The noise floor N0N_0N0 is computed as:

- $N_0 = -174 + 10\log_{10}(BW) + NF$ (3.6)

3. Use SNR_{recv} to simulate Join attempt using the function above.

3.5.4 Rejoin Success Probabilities

Let $P_{succ}(i)$ denote the conditional probability of success at SF iii given failure at $SF\ i - 1$. These are estimated from:

$$P_{succ}^{i} = P(SNR \geq SNR_{th}(i)) - P(SNR \geq SNR_{th}(i-1)) \quad (3.33.1)$$

Monte Carlo simulation was used with varying distance and environmental attenuation to evaluate these transition probabilities, as adopted in related LoRaWAN studies on dynamic channel environments [10], [11]. This is estimated by sampling the path loss model over many trials.

3.5.5 Join-Driven Packet Loss Estimation

Let:

P_{drop} : the probability of joining failure across all SFs.

PDR_{eff} : Effective packet delivery ratio.

Then:

$$PDR_{eff} = 1 - P_{drop} \tag{3.33.2}$$

This value is used in Section 3.4's energy efficiency formula: energy-per-success expression is:

$$E_{succ} = \frac{E_{tx}+E_{rx}+E_{rejoin} \cdot P_{fail}}{PDR_{eff}} \tag{3.27.1}$$

This formulation follows the structure used in previous LoRaWAN energy modelling approaches and reliability studies [124].

3.5.6 Impact of Join Cycle on Node Lifetime

Low-SNR nodes may attempt Join frequently, thus reducing node lifetime.

Let:

- μ_{rejoin}: Expected number of join cycles per year (average annual join cycles)
- $E_{year} = 365 \cdot (E_{base} + \mu_{rejoin} \cdot E_{rejoin})$ (3.20.1)
- $L_{years} = \frac{E_{battery}}{E_{year}}$ (3.20.2)

Such node-level lifetime modelling is consistent with evaluations presented in energy efficiency studies for LoRaWAN end devices [125], [129].

3.5.7 Summary: Modelling Energy Efficiency of LoRa and LoRaWAN Sensor Nodes in Bulk Metering Applications

This chapter integrates probabilistic SNR modelling, adaptive SF-based joining dynamics and energy-aware rejoin logic in developing a complete modelling framework to assess the energy efficiency of LoRa and LoRaWAN based sensor nodes integrated into Rand Water's bulk metering infrastructure. The analysis has been done considering the important and overall environmental challenges of the deployment, for example, low-elevation concrete chambers and long-range communication requirements which impact the signal propagation, link reliability, and energy use in a great deal.

The modelling framework encapsulated within it features core five subsystems: deployment and environmental modelling, link budget and signal propagation analysis, LoRaWAN protocol behaviour, energy state modelling of the node and the cumulative energy efficiency metric computation. Important and concrete parameters like concrete attenuation, antenna height, transmission distance, and spreading factor (SF) were used within the path loss model to assess the signal to noise ratio (SNR) and the packet delivery.

A comprehensive energy consumption model capturing transmission, reception (acknowledge windows included), idle, and sleep states was created. The framework also captured the re-join dynamics of Class A LoRaWAN nodes which stem from acknowledgment failures and require multiple join attempts from SF9 to SF12, each at considerable energy expense thereafter.

In the real world, the energy consumption of networks with n nodes can scale linearly. Simulations representing this behaviour were developed in MATLAB. The approach is based on, using Semtech's reception and timing guidelines, and validated using prior deployment studies [128],[129], [130]. These join dynamics are significant in environments like Rand Water's where channel impairments lead to frequent re-joins and energy overheads.

3.6.1 Modelling Limitations and Scope for Optimisation

The model presented here is purely analytical and does not incorporate hardware-in-the-loop validation. Furthermore, while the proposed join-aware policy improves performance, this study does not exhaustively explore alternative optimisations such as dynamic transmission power control, adaptive duty cycling based on remaining battery capacity, or machine learning-based channel prediction for proactive spreading factor selection. These extensions are left for future work.

CHAPTER 4: MODELLING ENERGY EFFICIENCY AND NETWORK RELIABILITY OF NB-IOT SENSOR NODES IN BULK METERING APPLICATIONS

4.1 Introduction

The energy efficiency and network reliability of Narrowband Internet of Things (NB-IoT) sensor nodes used for bulk water metering applications are thoroughly modelled and simulated in this chapter, using Rand Water's subterranean metering infrastructure in South Africa as the main deployment context. NB-IoT is a 3GPP-standardized Low Power Wide Area Network (LPWAN) technology that is well suited for large-scale utility metering systems because it can facilitate massive machine-type communications, especially in underground and deep-indoor settings, this is as documented in recent 3GPP cellular IoT evolution and massive machine-type communication studies [147].

Comparative evaluations of LPWAN technologies for underground infrastructure monitoring have confirmed that NB-IoT provides superior coverage and scalability in buried sensor deployments, outperforming LoRa in scenarios with high soil moisture content and dense subsurface obstructions [152].

To safeguard infrastructure from environmental exposure, tampering, and vandalism, bulk water meters in the Rand Water network are typically installed in low elevation reinforced concrete chambers. These installations offer physical security, but they also pose serious problems for radio propagation, such as limited antenna elevation, shadowing, and high penetration loss. The performance of wireless communication systems is greatly impacted by these conditions, which also place stringent limitations on the energy consumption and dependability of battery-powered metering devices, a challenge confirmed by recent underground and reinforced concrete IoT propagation investigations [148], [149].

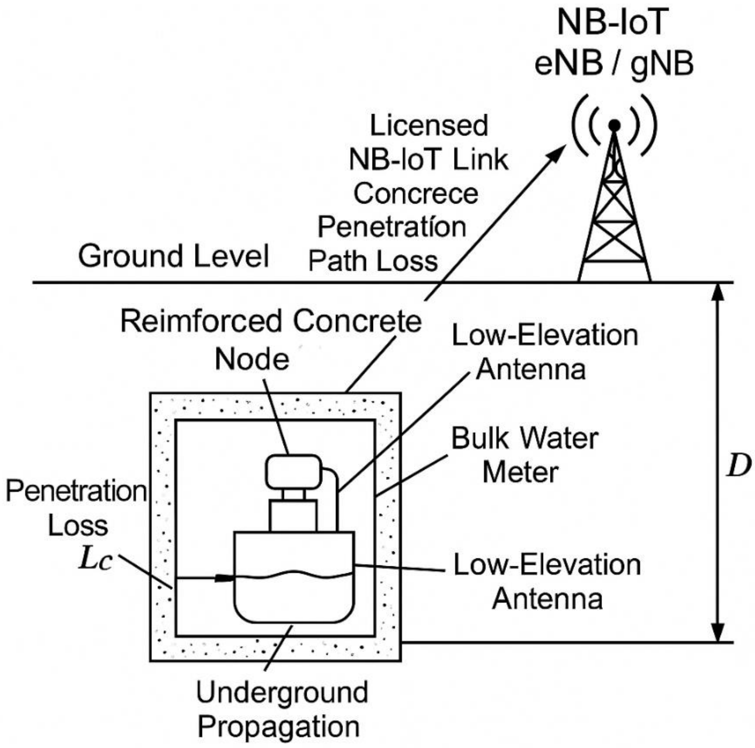

Figure 4.1: Underground NB-IoT-Based Bulk Water Meter Deployment in a Reinforced Concrete Chamber, Illustrating Low-Elevation Installation, Concrete Penetration Loss, and Long-Range Communication to a Cellular Base Station

Figure 4.1 illustrates the underground deployment scenario considered in this study, where NB-IoT sensor nodes are installed inside reinforced concrete chambers below ground level and communicate directly with a cellular base station. The figure highlights the key physical constraints influencing system performance, including low antenna elevation, concrete penetration loss, underground propagation effects, and long-range communication distance to the eNB/gNB. These deployment characteristics form the basis for the radio propagation modelling, coverage enhancement mechanisms, and state-based energy consumption analysis developed in this chapter.

To enable dependable communication in difficult radio environments, NB-IoT uses coverage enhancement techniques like uplink repetitions, robust modulation and coding schemes, and network-controlled retransmissions, which have been analytically and experimentally validated in recent NB-IoT coverage enhancement evaluations [150]. It operates in licensed cellular spectrum. Nevertheless, additional energy overheads are introduced by these reliability mechanisms, especially when devices encounter poor channel conditions. Understanding the energy-reliability trade-off inherent in NB-IoT operation is therefore crucial for battery-powered bulk water meters with stringent lifetime requirements.

In contrast to short-range cellular services, NB-IoT devices usually report metering data once a day or less and operate with infrequent, delay-tolerant transmissions. In addition to uplink transmission energy, cellular protocol processes such as network attachment, signalling, paging, power saving mode (PSM), extended discontinuous reception (eDRX), and idle state maintenance account for the majority of these devices' total energy consumption which have been identified as dominant contributors to NB-IoT energy consumption in low-duty-cycle smart metering applications [151]. Despite the inherent coverage advantages of NB-IoT, suboptimal configuration of these mechanisms can result in excessive energy consumption and decreased operational lifetime in underground deployments.

This chapter creates a protocol-accurate energy and reliability modelling framework for NB-IoT sensor nodes functioning in subterranean bulk water metering scenarios in order to address these issues. The model clearly captures:

- **Propagation effects** associated with low-elevation concrete chamber installations.
- **NB-IoT device state transitions**, including transmit, receive, connected, idle, PSM, and eDRX states.
- **Coverage enhancement behaviour**, including uplink repetitions and retransmission policies.
- **Energy consumption per communication cycle**, accounting for both user-plane data transmission and control-plane signalling.
- **Network reliability metrics**, including packet delivery ratio (PDR) and latency.

The modelling framework is implemented in MATLAB, enabling systematic evaluation of NB-IoT performance under varying deployment conditions, transmission intervals, and protocol parameter configurations. Simulation outputs provide quantitative insight into the energy consumption per successfully delivered packet, the expected battery lifetime of NB-IoT sensor nodes, and the robustness of NB-IoT communication links in underground metering environments.

The quantitative performance assessment of NB-IoT, together with the comparative analysis between NB-IoT and LoRaWAN, is deferred to Chapter 5: Obtained Results, where simulation outputs from both modelling frameworks are jointly analysed and discussed.

The remainder of this chapter is organised as follows:

Section 4.2 presents the NB-IoT system and energy modelling framework.

Section 4.3 defines the simulation parameters and deployment assumptions specific to underground bulk water metering.

Section 4.4 develops the state-based energy consumption model for NB-IoT sensor nodes.

Section 4.5 formulates the network reliability and coverage enhancement models, including the impact of repetitions and signalling behaviour and Section 4.6 provides a methodological summary and model readiness discussion, preparing the ground for the consolidated results and comparative evaluation presented in Chapter 5.

4.2 NB-IoT System and Energy Modelling Framework

The system-level modelling framework used to evaluate the energy efficiency and network reliability of NB-IoT sensor nodes for underground bulk water metering followed the same layered structure as the LoRaWAN framework presented in Section 3.2. This consistency was intentional, as it ensured a fair and direct comparison between the two LPWAN technologies under identical deployment assumptions. The framework integrated environmental, physical-layer, protocol-layer, and device-level energy models, with the layered modelling approach adopted from recent cellular IoT system-level energy analyses [7].

However, the internal implementation of each layer differed from the LoRaWAN framework to reflect the fundamental differences between NB-IoT and LoRaWAN. Whereas the LoRaWAN model focused on ALOHA-based access, adaptive spreading factor selection, and OTAA join dynamics, the NB-IoT model incorporated cellular-specific mechanisms. These included scheduled access in licensed spectrum, network-controlled coverage enhancement through uplink repetitions, and power-saving features such as Power Saving Mode (PSM) and extended Discontinuous Reception (eDRX). The control-plane signalling overhead associated with network attachment, resource scheduling, and radio resource control (RRC) state transitions was also explicitly modelled, as these processes contributed significantly to energy consumption in NB-IoT devices [7].

The six subsystems remained conceptually the same deployment and environment modelling, radio propagation and link budget modelling, NB-IoT communication and protocol behaviour, device operational state modelling, energy consumption modelling, and reliability-related metric formulation, but the equations and parameters within each subsystem were adapted to reflect NB-IoT-specific characteristics. This approach ensured that the comparative analysis presented in Chapter 5 was built on a consistent structural foundation while preserving the protocol-faithful behaviour of each technology.

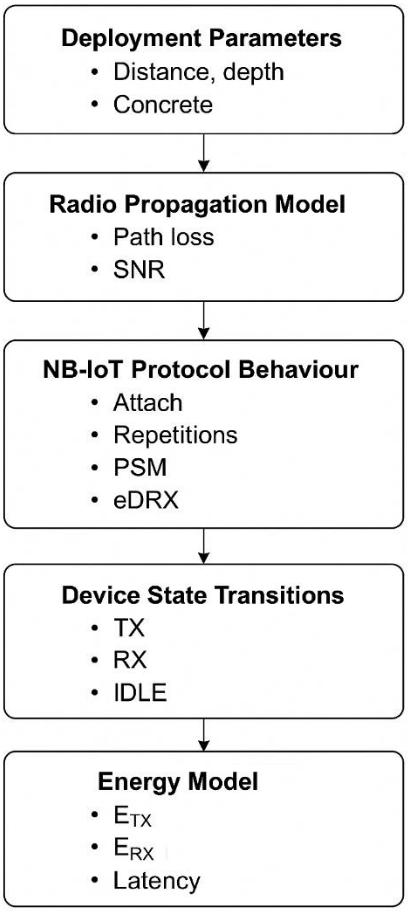

Figure 4.2 :System-Level Modelling Framework for Energy Efficiency and Network Reliability of NB-IoT Sensor Nodes

Figure 4.2 presents the system-level modelling framework adopted in this study to analyse the energy efficiency and network reliability of NB-IoT sensor nodes deployed in underground bulk water metering applications. The framework illustrates the sequential interaction between deployment parameters, radio propagation effects, NB-IoT protocol behaviour, device state transitions, and state-based energy modelling, culminating in the derivation of reliability and performance metrics. Deployment conditions such as underground depth, concrete penetration loss, and distance to the base station influence the radio propagation model, which determines the received signal quality. This, in turn, drives NB-IoT protocol behaviour, including coverage enhancement through repetitions and power-saving mechanisms such as PSM and eDRX. The resulting device state transitions form the basis for the state-based energy consumption model and the reliability metrics formulated in this chapter.

4.2.1. Deployment and Environment Modelling

The deployment scenario considered in this study reflects typical Rand Water bulk meter installations, characterised by the following features:

- Bulk water meters installed below ground level
- Enclosure within reinforced concrete chambers
- Limited antenna height relative to ground level
- Long-range communication to nearby cellular base stations

These conditions introduce additional propagation losses beyond conventional urban macrocell environments. The deployment model therefore defines the following environment-specific parameters:

Table 4.1: NB-IoT Deployment and Environmental Parameters Affecting the Radio Link Budget

Parameter	Symbol	Description
Node depth	d_{ug}	Depth of meter below ground level
Concrete penetration loss	L_c	Attenuation due to chamber walls
Antenna height	h_n	Effective NB-IoT node antenna height
Base station height	h_{bs}	eNB/gNB antenna height
Distance to base station	D	Horizontal separation
Operating frequency	f	NB-IoT carrier frequency

Table 4.1: These parameters define the physical constraints under which NB-IoT devices operate and directly influence the radio link budget.

The physical deployment constraints introduced by underground reinforced concrete installations (as illustrated in Figure 4.1) directly influence the radio link budget and necessitate coverage enhancement mechanisms in NB-IoT systems.

4.2.2 Radio Propagation and Link Budget Modelling

To determine link feasibility and reliability for NB-IoT sensor nodes, the same radio propagation and link budget model presented in Section 3.2.2 for LoRaWAN was adopted. This decision was motivated by the need for consistency in the comparative analysis, as both technologies were evaluated under identical deployment conditions—underground reinforced concrete chambers with low antenna elevation and distances of 0.5 to 3.0 km to the base station. The log-distance path loss formulation with concrete penetration loss and shadowing, which had been validated for underground utility deployments in recent studies [148], [153], was therefore applied without modification to the structural form of the equations.

The total path loss was expressed as:

$$PL(D) = PL0 + 10nlog\ 10(D) + Lc + X\sigma \qquad (4.1)$$

where:

- $PL_0$is the free-space path loss at 1 m,
- $n$is the path loss exponent for urban/underground environments,
- $L_c$represents concrete chamber penetration loss,
- $X_\sigma$is a log-normal shadowing component.

where $\mathbf{PL_0}$ was the free-space path loss at 1 metre, $\mathbf{n}$ was the path loss exponent for urban and underground environments, $\mathbf{Lc}$ was the concrete chamber penetration loss, and $\mathbf{X\_\sigma}$ was a log-normal shadowing component. The received power was then derived from the link budget equation:

$$Pr{=}Pt{+}Gt{+}Gr{-}PL(D) \qquad (4.2)$$

where $\mathbf{Pt}$ was the NB-IoT transmit power, and $\mathbf{Gt}$ and $\mathbf{Gr}$ were the antenna gains. The signal-to-noise ratio (SNR) was derived as:

$$SNR = Pr - N0 \qquad (4.3)$$

with $\mathbf{N_0}$ denoting the noise floor adjusted by the receiver noise figure.

While the structural form of these equations was identical to that used for LoRaWAN, two parameters were adjusted to reflect NB-IoT-specific characteristics. First, the carrier frequency $\mathbf{f}$ was set to the licensed NB-IoT band (typically 800–900 MHz), whereas LoRaWAN operated at 868 MHz in the unlicensed ISM band. Second, the channel bandwidth $\mathbf{BW}$ was set to 180 kHz for NB-IoT, compared to 125 kHz for LoRaWAN. These adjustments influenced the noise floor calculation $\mathbf{N_0 = -174 + 10{\cdot}log_{10}(BW) + NF}$ and, consequently, the SNR values obtained from the model. The SNR determined whether communication was successful and influenced coverage enhancement behaviour, such as the number of uplink repetitions applied, as defined in 3GPP NB-IoT link adaptation and coverage enhancement specifications [150].

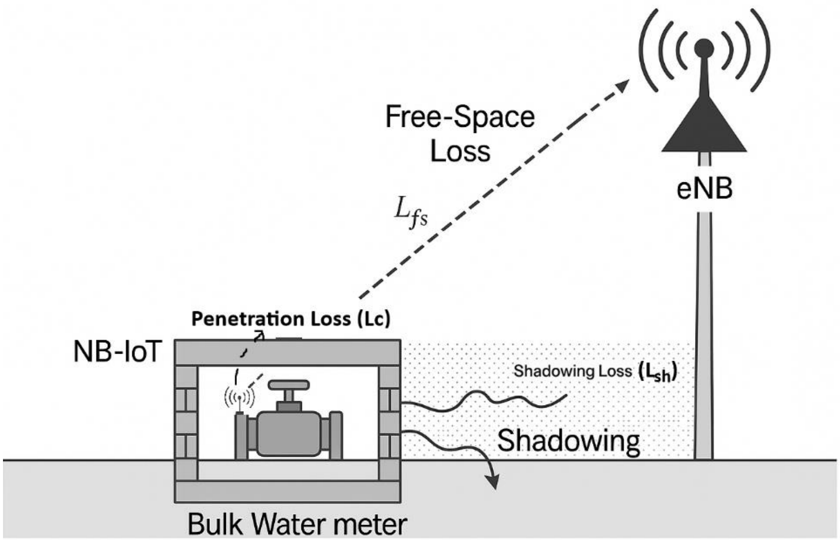

Figure 4.3: Underground Radio Propagation and Link Budget Illustration for NB-IoT-Based Bulk Water Metering

The link budget components illustrated in Figure 4.3 were modelled using the same decomposition presented in Chapter 3. The total path loss was expressed as:

$$L_{\text{total}} = L_{fs} + L_c + L_{sh} \tag{4.4}$$

where:

- **L_total** was the total path loss (in dB) experienced by the signal as it travelled from the NB-IoT sensor node to the base station
- **L_fs** was the free-space path loss (in dB), which represented the signal attenuation due to geometric spreading of the radio wave as it travelled through open air. This component was distance-dependent and was calculated using the free-space path loss formula: **L_fs = 20·log$_{10}$(f) + 20·log$_{10}$(D) + 32.4**, where **f** was the carrier frequency in MHz and **D** was the distance in kilometres
- **L_c** was the concrete penetration loss (in dB), which accounted for the additional attenuation introduced as the signal passed through the reinforced concrete chamber walls. This loss was influenced by the thickness of the concrete, the density of steel reinforcement, and the moisture content. Typical values ranged from 15 dB to 30 dB for underground utility chambers

- **L_sh** was the shadowing loss (in dB), which captured the random signal variations caused by obstacles in the propagation path, such as surrounding soil, vegetation, buildings, and terrain features. This component was modelled as a log-normal random variable with zero mean and standard deviation typically between 6 dB and 8 dB, reflecting the variability expected in urban and underground environments.

This decomposition of total path loss into three distinct components free-space loss, concrete penetration loss, and shadowing loss provided a clear separation of the physical mechanisms affecting signal propagation. The free-space loss component captured the predictable distance-dependent attenuation, while the concrete penetration loss represented the site-specific attenuation introduced by the chamber enclosure, and the shadowing component accounted for the stochastic variability inherent in real-world deployments.

4.2.3 NB-IoT Communication and Protocol Behaviour

NB-IoT communication is network-controlled and differs fundamentally from unlicensed LPWAN technologies. Each device follows a cellular communication cycle that includes:

1. Network attachment and registration
2. Uplink data transmission
3. Optional downlink signalling
4. Release to idle or power saving state

To enhance reliability in poor radio conditions, NB-IoT employs coverage enhancement (CE) mechanisms, including:

- Uplink transmission repetitions
- Robust modulation and coding schemes
- Network-triggered retransmissions

The number of repetitions $R$is a key modelling parameter, determined as a function of SNR and network configuration. Increased repetition improves reliability but directly increases transmission time and energy consumption. This repetition–energy trade-off is a fundamental characteristic of NB-IoT operation under deep coverage conditions [150], [13].

4.2.4 Device Operational State Modelling

Each NB-IoT sensor node is modelled as a finite-state system, transitioning between multiple operational states during a reporting cycle. The primary states include:

- Transmit (TX): Active uplink transmission
- Receive (RX): Downlink reception and control signalling
- Connected Idle: RRC connected but inactive
- Idle: RRC idle with paging monitoring
- Power Saving Mode (PSM): Deep sleep, no paging
- Extended Discontinuous Reception (eDRX): Periodic wake-up for paging

Each state is characterised by:

- Current consumption I_s
- Duration T_s
- Operating voltage V

State transitions are driven by network configuration, application reporting interval, and radio conditions.

4.2.5 Energy Consumption Modelling

The total energy consumed during a single reporting cycle is computed as the sum of energy consumed in each operational state:

$$E_{\text{cycle}} = \sum_s V \cdot I_s \cdot T_s \quad (4.5)$$

where $s$represents all active states during the cycle.

This formulation explicitly captures:

- Energy overhead from repetitions
- Control-plane signalling energy
- Idle and paging-related energy
- Deep sleep energy in PSM

Long-term energy consumption is obtained by aggregating energy over the reporting interval and extrapolating over the intended deployment lifetime.

4.2.6 Reliability-Related Metric Formulation

Although numerical evaluation is deferred to Chapter 5, this section formally defines the reliability metrics to be derived from the model, including:

- Packet delivery probability (PDP)
- Effective packet delivery ratio (PDR)
- Latency contributors, including repetition-induced delay
- Transmission success probability as a function of SNR

These metrics provide the analytical linkage between radio conditions, protocol behaviour, and energy expenditure.

This section has established a protocol-accurate NB-IoT modelling framework that integrates environmental constraints, radio propagation, cellular protocol behaviour, device state transitions, and energy accounting. The framework is specifically tailored to underground bulk water metering deployments and is structured to support consistent, reproducible simulation-based evaluation.

The next section defines the simulation parameters and assumptions required to implement this framework in MATLAB and prepare it for quantitative analysis.

4.3 Simulation Parameters and Deployment Assumptions

This section defines the simulation parameters, deployment assumptions, and operational constraints used to implement the NB-IoT modelling framework presented in Section 4.2. The purpose of this section is to establish a clear, reproducible, and realistic simulation environment that accurately reflects underground bulk water metering deployments within the Rand Water infrastructure. All parameters are selected to be representative of commercial NB-IoT modules, cellular network configurations, and utility-grade metering requirements.

The simulation parameters defined in this section are used consistently throughout Chapter 4 and serve as direct inputs to the quantitative performance evaluation presented in Chapter 5: Obtained Results.

4.3.1 Deployment Scenario Description

The simulated deployment represents a network of NB-IoT-enabled bulk water meters retrofitted onto existing flow measurement infrastructure and installed in low-elevation reinforced concrete chambers. Each sensor node performs periodic water metering and transmits data to the nearest cellular base station (eNB or gNB).

The following deployment assumptions are made:

- Each bulk water meter is equipped with a single NB-IoT sensor node
- Nodes are installed below ground level within concrete chambers
- Communication occurs directly between the node and the cellular base station (star topology)
- Meter readings are delay-tolerant, with no real-time constraints
- Each node transmits one report per reporting interval (typically daily)

This scenario reflects realistic large-scale utility deployments, where battery longevity and network reliability are the primary design constraints.

4.3.2 NB-IoT Device and Network Configuration Assumptions

NB-IoT devices are assumed to comply with 3GPP Release 13 and later specifications and operate in licensed spectrum bands commonly used for NB-IoT deployments.

Key configuration assumptions include:

- Single-tone or multi-tone uplink operation (as configured by the network)
- Network-controlled selection of modulation, coding, and repetitions
- Support for Power Saving Mode (PSM) and extended Discontinuous Reception (eDRX)
- Use of control-plane or user-plane data transmission depending on payload size

The network is assumed to be properly dimensioned and operational, with no base station failures or backhaul constraints.

4.3.3 Simulation Parameter Set

Table 4.2: summarises the key parameters parameters used in the NB-IoT simulation model.

Category	**Parameter**	**Symbol**	**Value / Range**	**Description**
Device	Operating voltage	V	3.3 V	Typical NB-IoT module supply
Device	Battery capacity	C_b	19 Ah	Li-$SOCl_2$ utility-grade battery
Device	Payload size	L	16–64 bytes	Daily metering data
Device	Reporting interval	T_r	1 report/day	Utility requirement
Radio	Operating frequency	f	800–900 MHz	Licensed NB-IoT band
Radio	Transmit power	P_t	Up to 23 dBm	Network-controlled
Radio	Repetitions	R	1–128	Coverage enhancement
Channel	Path loss exponent	n	3.0–4.5	Urban/underground
Channel	Concrete loss	L_c	15–30 dB	Chamber attenuation
Channel	Shadowing std. dev.	σ	6–8 dB	Log-normal shadowing
Power	PSM current	I_{PSM}	2–5 μA	Deep sleep
Power	eDRX current	I_{eDRX}	10–40 μA	Paging monitoring
Power	TX current	I_{TX}	200–250 mA	During transmission
Power	RX current	I_{RX}	40–60 mA	Downlink reception

4.3.4 Operational and Timing Assumptions

Each NB-IoT sensor node follows a periodic reporting cycle consisting of:

1. Wake-up from PSM
2. Network attachment (if required)
3. Uplink data transmission
4. Optional downlink reception
5. Transition to idle, eDRX, or PSM

The following timing assumptions are made:

- Network attach is required only when the device is not context-retained
- Successful uplink delivery may require multiple repetitions
- Paging monitoring occurs only during configured eDRX windows
- Devices spend most of the time in PSM, reflecting low-duty-cycle operation

No mobility is assumed, and channel conditions are considered quasi-static over each reporting cycle.

4.3.5 Energy Accounting Assumptions

Energy consumption is computed using a state-based accounting approach, where the energy used in each operational state is calculated as:

$$E_s = V \cdot I_s \cdot T_s \tag{4.6}$$

and total energy per reporting cycle is given by:

$$E_{\text{cycle}} = \sum_s E_s \tag{4.5}$$

where $s \in \{\text{TX, RX, Idle, eDRX, PSM}\}$.

Battery lifetime is estimated by extrapolating the average energy per cycle over the total available battery energy.

4.3.6 Reliability and Success Assumptions

A transmission is considered successful if the received SNR at the base station exceeds the minimum decoding threshold after applying the configured number of repetitions. The following assumptions apply:

- No packet collisions are modelled (licensed spectrum)
- Retransmissions are handled by the network
- Packet loss arises only from insufficient link quality, acknowledging that channel estimation accuracy, as analysed by Ali et al. [154], directly influences the effective SNR threshold for successful demodulation.
- Latency is influenced by repetitions and signalling overhead but is not constrained

These assumptions reflect best-case network conditions, enabling isolation of energy–reliability trade-offs driven by radio propagation and protocol behaviour.

The simulation environment assumes:

- Static underground NB-IoT sensor nodes
- Low-duty-cycle, delay-tolerant traffic
- Network-controlled reliability mechanisms
- Battery-powered operation with long lifetime targets
- Realistic underground propagation conditions

These assumptions ensure that the modelling framework remains representative of real-world bulk water metering deployments while remaining sufficiently controlled for systematic evaluation.

The next section develops the detailed state-based energy consumption model for NB-IoT sensor nodes, building directly on the parameters and assumptions defined here.

4.4 State-Based Energy Consumption Model for NB-IoT Sensor Nodes

This section develops a state-based energy consumption model for NB-IoT sensor nodes deployed in underground bulk water metering applications. The model decomposes the total energy consumed by a node into distinct operational states defined by the NB-IoT protocol stack, enabling accurate estimation of energy usage over a reporting cycle and over the device lifetime.

NB-IoT devices operate under network-controlled cellular procedures, and their energy consumption is governed not only by data transmission but also by control-plane signalling, idle behaviour, and power-saving mechanisms. A state-based approach is therefore essential to capture the true energy profile of NB-IoT devices operating in low-duty-cycle, delay-tolerant metering scenarios. State-based energy accounting models are widely recognised as the most accurate approach for modelling cellular IoT device energy consumption [151], [7].

4.4.1 NB-IoT Operational State Definition

Each NB-IoT sensor node is modelled as a finite-state system, transitioning through a sequence of operational states during a single reporting interval. The primary states considered in this model are:

1. **Transmit State (TX)**: Active uplink transmission of user or control-plane data, including coverage enhancement repetitions.
2. **Receive State (RX)**: Downlink reception of acknowledgements, control signalling, and network commands.
3. **Connected Idle State (CIDLE)**: RRC-connected but inactive state, where the device awaits further instructions from the network.
4. **Idle State (IDLE):** RRC idle mode, with periodic paging monitoring depending on eDRX configuration.
5. **Extended Discontinuous Reception State (eDRX)**: Low-power idle state with scheduled wakeups for paging.
6. **Power Saving Mode (PSM)**: Deep sleep state with no paging or network interaction.

Each state $s$is characterised by a state current draw $I_s$and a state duration T_s.

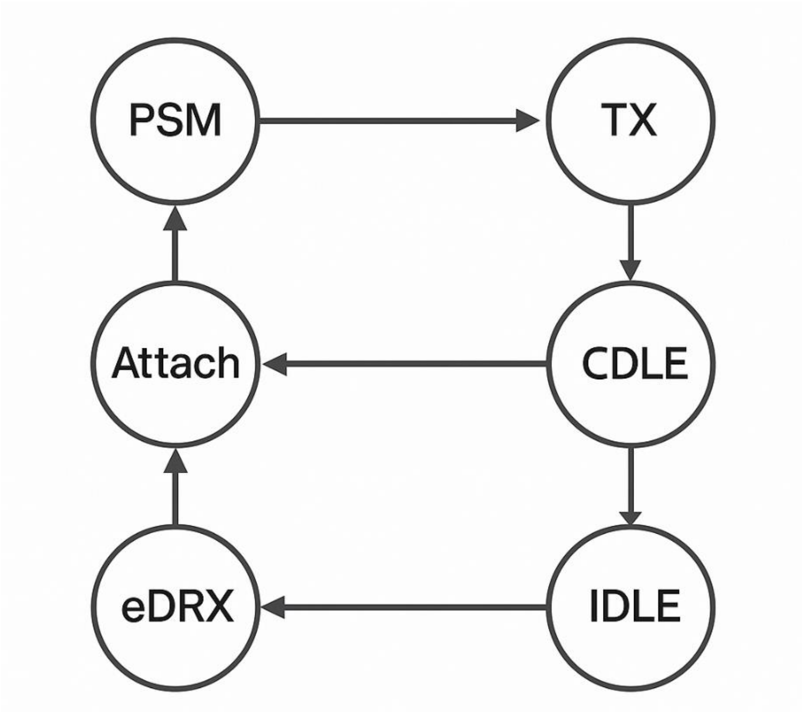

Figure 4.0.4: Finite-State Model of NB-IoT Sensor Node Operation During a Reporting Cycle

Figure 4.4 illustrates the finite-state operational model of an NB-IoT sensor node during a single reporting cycle. The device transitions from Power Saving Mode (PSM) to the network attachment phase before entering the active transmission (TX) and reception (RX) states required for data exchange. Following successful communication, the device may temporarily remain in a connected idle (CIDLE) state before transitioning to idle and extended discontinuous reception (eDRX) modes, ultimately returning to PSM. Each state is characterised by distinct current consumption and duration, forming the basis for the state-based energy consumption model developed in this chapter.

4.4.2 Energy Consumption per State

The energy consumed in each operational state is computed as:

$$E_s = V \cdot I_s \cdot T_s \tag{4.6}$$

where:

- V is the operating voltage of the NB-IoT device,
- I_s is the current drawn in state s,
- T_s is the time spent in state s.

This formulation allows direct mapping from **protocol timing behaviour** to energy consumption.

4.4.3 Transmit State Energy Modelling

The transmit state accounts for all uplink transmissions, including coverage enhancement repetitions. The total transmit time is given by:

$$T_{\text{TX}} = R \cdot T_{\text{UL}} \tag{4.7}$$

where:

- R is the number of uplink repetitions,
- T_{UL} is the duration of a single uplink transmission.

The corresponding transmit energy is:

$$E_{\text{TX}} = V \cdot I_{\text{TX}} \cdot T_{\text{TX}} \tag{4.8}$$

In underground deployments, increased repetition levels are often required to compensate for high penetration loss, directly increasing transmit energy consumption.

4.4.4 Receive State Energy Modelling

The **receive state** captures energy consumed during downlink reception and control signalling, including acknowledgements and network reconfiguration messages.

$$E_{\mathrm{RX}} = V \cdot I_{\mathrm{RX}} \cdot T_{\mathrm{RX}} \tag{4.9}$$

The receive duration T_{RX}depends on:

- Network response timing,
- Control-plane signalling volume,
- Downlink scheduling strategy.

Although receive durations are typically short, repeated network interactions can accumulate significant energy overhead over long deployment periods.

4.4.5 Idle and Connected Idle State Energy Modelling

After transmission, an NB-IoT device may remain temporarily in a connected idle state before transitioning to idle or power-saving modes.

$$E_{\mathrm{CIDLE}} = V \cdot I_{\mathrm{CIDLE}} \cdot T_{\mathrm{CIDLE}} \tag{4.10}$$

$$E_{\mathrm{IDLE}} = V \cdot I_{\mathrm{IDLE}} \cdot T_{\mathrm{IDLE}} \tag{4.11}$$

These states are influenced by network timers and release policies, which can significantly impact energy usage if not optimally configured.

4.4.6 eDRX Energy Modelling

When eDRX is enabled, the device periodically wakes to monitor paging messages. The energy consumption in eDRX mode is:

$$E_{\mathrm{eDRX}} = V \cdot I_{\mathrm{eDRX}} \cdot T_{\mathrm{eDRX}} \tag{4.12}$$

where T_{eDRX}represents the cumulative duration of paging monitoring windows within the reporting interval.

eDRX offers a compromise between responsiveness and energy savings, but inappropriate configuration can substantially reduce battery lifetime. Recent analyses of NB-IoT power saving configurations demonstrate that improper timer configuration can substantially degrade lifetime performance [9], [10].

4.4.7 Power Saving Mode (PSM) Energy Modelling

In PSM, the device enters a deep sleep state with minimal current draw:

$$E_{\text{PSM}} = V \cdot I_{\text{PSM}} \cdot T_{\text{PSM}} \tag{4.13}$$

Given the low-duty-cycle nature of bulk water metering, devices are expected to spend most of the time in PSM, making this state critical for lifetime estimation.

4.4.8 Total Energy per Reporting Cycle

The total energy consumed during a single reporting cycle is the sum of energy consumed across all operational states:

$$E_{\text{cycle}} = E_{\text{TX}} + E_{\text{RX}} + E_{\text{CIDLE}} + E_{\text{IDLE}} + E_{\text{eDRX}} + E_{\text{PSM}} \tag{4.14}$$

This expression provides a complete and protocol-faithful representation of NB-IoT energy consumption per reporting interval.

4.4.9 Battery Lifetime Estimation

The expected battery lifetime $L$is estimated as:

$$L = \frac{E_{\text{battery}}}{E_{\text{cycle}} \cdot N_{\text{cycles}}} \tag{4.15}$$

where:

- $E_{\text{battery}}$is the total available battery energy,
- $N_{\text{cycles}}$is the number of reporting cycles per unit time.

This formulation enables long-term energy analysis while remaining independent of specific numerical outcomes, which are evaluated in Chapter 5, similar cumulative lifetime projection techniques are applied in contemporary smart metering energy modelling research [151], [7].

This section has developed a comprehensive state-based energy consumption model for NB-IoT sensor nodes operating in underground bulk water metering applications. By explicitly modelling all relevant NB-IoT operational states and their associated energy costs, the model provides a robust analytical foundation for evaluating energy efficiency and device lifetime.

The next section formulates the network reliability and coverage enhancement models, which link radio propagation conditions to repetition behaviour and transmission success probability.

4.5 Modelling Network Reliability and Coverage Improvement for NB-IoT

The network reliability and coverage enhancement models used to describe NB-IoT communication performance in subterranean bulk water metering deployments are developed in this section. Reliability in NB-IoT systems is mainly attained by cellular-controlled mechanisms, such as network-managed retransmissions, uplink repetitions, and robust modulation and coding schemes. Although these mechanisms increase the likelihood of packet delivery in difficult radio environments, they also add latency and energy consumption, so accurate modelling of these mechanisms is crucial for realistic performance evaluation.
Without yet providing numerical results, the models in this section establish the analytical relationship between radio propagation conditions, coverage enhancement behaviour, and successful packet delivery.

The underground propagation conditions illustrated in Figure 4.3 result in elevated path loss, necessitating the use of NB-IoT coverage enhancement mechanisms to ensure reliable packet delivery.

4.5.1 Definition of Network Reliability Metrics

Network reliability in this study is characterised using the following key metrics:

- **Packet Delivery Probability (PDP)**: The probability that a transmitted packet is successfully received and decoded by the base station.
- **Packet Delivery Ratio (PDR)**: The fraction of successfully delivered packets over the total number of transmission attempts.
- **Transmission Success Probability**: The probability of successful delivery within a reporting cycle after applying repetitions.

- **Latency Contributors**: Delay introduced by repetitions, retransmissions, and signalling procedures.

These metrics are evaluated at the device–base station link level, reflecting the star topology of NB-IoT deployments.

4.5.2 SNR-Based Transmission Success Modelling

Successful NB-IoT packet delivery depends on the received signal-to-noise ratio (SNR) exceeding the minimum decoding threshold γ_{th}required by the selected modulation and coding scheme.

A single transmission attempt is considered successful if:

$$\text{SNR} \geq \gamma_{\text{th}}$$

Due to shadowing and fading effects in underground environments, SNR is modelled as a random variable whose distribution is governed by the propagation model defined in the Section 4.2. However, the accuracy of the threshold *γ_th* depends critically on the channel estimation method employed at the receiver; Ali et al. [154] proposed a low-complexity DCT Type-I based channel estimator specifically for NB-IoT uplink transmissions, demonstrating that conventional DFT-based methods introduce signal aliasing errors that degrade performance by 2–3 dB in low-SNR regimes (below 0 dB) typical of underground concrete chamber deployments.

4.5.3 Coverage Enhancement and Repetition Modelling

NB-IoT employs coverage enhancement (CE) through uplink repetitions to improve reliability in poor channel conditions. If a single transmission has a success probability p, then the probability of at least one successful reception after Rrepetitions is given by:

$$P_{\text{succ}}(R) = 1 - (1 - p)^R \tag{4.16}$$

where:

- $R$is the number of repetitions,
- $p$is the single-transmission success probability.

The repetition factor $R$is network-controlled and may vary based on received signal quality and coverage class assignment.

4.5.4 Packet Delivery Ratio Modelling

Over multiple reporting cycles, the packet delivery ratio (PDR) is defined as:

$$\mathrm{PDR} = \frac{N_{\mathrm{succ}}}{N_{\mathrm{tx}}} \tag{4.17}$$

where:

- $N_{\mathrm{succ}}$is the number of successfully delivered packets,
- $N_{\mathrm{tx}}$is the total number of packet transmission attempts.

In NB-IoT systems, retransmissions are handled by the network and are implicitly accounted for through repetition modelling.

4.5.5 Latency Modelling

Latency in NB-IoT communication arises from multiple sources, including:

- Repetition-induced transmission delay
- Scheduling delays at the base station
- Control-plane signalling overhead
- Paging and state transition delays

The total transmission latency per packet is expressed as:

$$T_{\mathrm{lat}} = R \cdot T_{\mathrm{UL}} + T_{\mathrm{sched}} + T_{\mathrm{ctrl}} \tag{4.18}$$

where:

- $T_{\mathrm{UL}}$is the duration of a single uplink transmission,
- $T_{\mathrm{sched}}$is the scheduling delay,
- $T_{\mathrm{ctrl}}$is the control-plane signalling delay.

Latency is not constrained in this study, as bulk water metering is a delay-tolerant application, but it remains a relevant reliability-related metric.

The scheduling delay component *T_sched* is governed by the Narrowband Physical Downlink Control Channel (NPDCCH) period configuration, which determines how frequently a device can receive downlink grant information; Yu [138] demonstrated that adaptive NPDCCH period selection can reduce downlink scheduling latency by up to 40% compared to fixed-period configurations in low-traffic NB-IoT deployments.

4.5.6 Relationship Between Reliability and Energy Consumption

Reliability mechanisms in NB-IoT directly influence energy consumption through increased transmission time and extended active states. This relationship is captured by linking repetition count $R$to transmit energy:

$$E_{\mathrm{TX}} \propto R$$

and to receive and idle state energy through prolonged connectivity.

This formulation establishes the energy–reliability trade-off, which is quantitatively explored in Chapter 5, a relationship formally examined in recent analytical NB-IoT performance modelling frameworks [7], [13].

4.5.7 Reliability Assumptions and Constraints

The following assumptions are applied in the reliability model:

- Licensed spectrum operation eliminates packet collisions which differentiates NB-IoT from unlicensed LPWAN technologies and has been validated in recent comparative LPWAN reliability studies [147], [3].
- Devices are static, with no mobility-induced handovers
- Channel conditions are quasi-static within each reporting cycle
- Network infrastructure is fully operational
- No congestion-related packet loss is considered

These assumptions isolate the impact of propagation conditions and coverage enhancement behaviour on reliability.

4.5.8 Summary of Reliability and Coverage Enhancement Modelling

This section has established the analytical framework for modelling network reliability and coverage enhancement behaviour in NB-IoT-based underground bulk water metering deployments. By explicitly linking radio conditions, repetition mechanisms, packet delivery probability, and latency contributors, the model provides a robust foundation for evaluating NB-IoT performance under challenging deployment scenarios.

The modelling constructs developed in this chapter together with those in Chapter 3 are evaluated and compared in Chapter 5: Obtained Results, where quantitative performance metrics are presented and discussed.

4.6 Chapter Summary and Model Readiness for Performance Evaluation

This chapter has developed a comprehensive and protocol-accurate modelling framework for analysing the energy efficiency and network reliability of NB-IoT sensor nodes deployed in underground bulk water metering applications. The modelling approach is specifically tailored to the operational realities of low elevation reinforced concrete chamber installations, as encountered within the Rand Water infrastructure.

The chapter commenced by defining the system-level modelling framework, integrating deployment conditions, radio propagation effects, NB-IoT communication behaviour, device operational states, and energy accounting mechanisms. Particular emphasis was placed on modelling cellular-specific processes including network attachment, coverage enhancement through repetitions, power saving mode (PSM), extended discontinuous reception (eDRX), and control-plane signalling which are critical determinants of energy consumption and reliability in NB-IoT systems.

A state-based energy consumption model was then formulated to capture the energy contribution of each NB-IoT operational state, enabling accurate estimation of energy usage per reporting cycle and long-term battery lifetime. This approach ensures that both user-plane and control-plane energy overheads are explicitly accounted for, which is essential for realistic lifetime projections in low-duty-cycle utility metering scenarios.

The chapter further established a network reliability and coverage enhancement model, linking underground radio propagation conditions to packet delivery probability through SNR-based decoding thresholds and uplink repetition mechanisms. By formally defining packet delivery probability, packet delivery ratio, and latency contributors, the chapter provided a structured basis for evaluating the reliability of NB-IoT communication in challenging underground environments.

Importantly, this chapter has focused exclusively on model formulation and methodological preparation. No numerical simulation results or performance evaluations are presented here. Instead, all models, assumptions, and parameters have been defined in a manner that ensures consistency, reproducibility, and direct comparability with the LoRaWAN modelling framework developed in Chapter 3.

The NB-IoT models developed in this chapter are therefore fully prepared for quantitative evaluation. Together with the LoRaWAN models from Chapter 3, they form a unified analytical foundation for the performance evaluation and comparative analysis presented in Chapter 5: Obtained Results. In the next chapter, simulation outputs derived from both modelling frameworks are analysed to assess energy efficiency, network reliability, and suitability for large-scale underground bulk water metering deployments.

4.6.1 Differentiation from LoRaWAN Modelling

Although the structural layering of this NB-IoT model mirrors that of Chapter 3 to ensure fair comparison, the internal implementations diverge substantially. Specifically, NB-IoT requires explicit modelling of Radio Resource Control (RRC) state machines (RRC_IDLE, RRC_CONNECTED), Power Saving Mode (PSM) timers (T3324, T3412), and coverage enhancement (CE) level mapping (CE0, CE1, CE2) based on measured reference signal received power (RSRP). These cellular-specific mechanisms have no analogue in LoRaWAN and dominate the energy-reliability trade-off in NB-IoT systems. The modelling assumptions for each mechanism are justified through reference to 3GPP specifications (TS 36.304, TS 36.331).

4.7 MATLAB Implementation of the NB-IoT Energy and Reliability Model

This section presents the MATLAB-based implementation of the proposed NB-IoT energy efficiency and network reliability model for underground bulk metering applications. The implementation mirrors the structure and philosophy adopted in the LoRaWAN simulation framework presented in Chapter 3, thereby enabling a consistent and fair comparison between the two LPWAN technologies.

The MATLAB simulation framework models the operation of an NB-IoT sensor node deployed in a low-elevation underground concrete chamber, such as those commonly used in bulk water metering infrastructures. The implementation follows a modular design approach, with each module representing a specific physical or protocol-level phenomenon affecting energy consumption and communication reliability.

4.7.1 Simulation Architecture Overview

The simulation framework is organized into five functional layers:

1. Deployment and Physical Environment Modelling
2. Radio Link Budget and SNR Estimation
3. Coverage Enhancement and Repetition Modelling
4. NB-IoT State-Based Energy Consumption Modelling
5. Performance Metric Aggregation and Logging

Each reporting cycle of the NB-IoT sensor node is simulated independently, allowing long-term performance metrics such as battery lifetime and packet delivery probability to be statistically estimated over thousands of cycles, Monte Carlo simulation techniques are commonly applied in stochastic IoT reliability and lifetime evaluation studies [153], [157].

4.7.2 Underground Propagation and SNR Modelling

The underground radio channel is modelled using a modified log-distance path loss model that accounts for both soil propagation effects and reinforced concrete attenuation. Experimental validation of LoRa-based underground communication has demonstrated that burial depth and soil moisture content significantly affect received signal strength and packet delivery ratio, with path loss increasing by approximately 0.5–1.0 dB per 10 cm of burial depth in saturated soil conditions [159]. The total path loss is expressed as:

$$PL(d) = PL_0 + 10n\log_{10}(d) + L_{\text{concrete}} + X_\sigma \qquad (3.1)$$

where:

- $PL_0$is the reference path loss,
- $n$is the underground path loss exponent,
- $d$is the transmitter–receiver separation distance,
- L_{concrete} represents penetration loss due to the concrete chamber, and
- X_σ is a log-normal shadowing term.

The Signal-to-Noise Ratio (SNR) is computed by subtracting the noise floor from the received signal power. This SNR directly determines the coverage enhancement (CE) level applied by the NB-IoT network.

4.7.3 Coverage Enhancement and Uplink Repetition Model

NB-IoT achieves enhanced reliability in challenging radio environments through uplink repetitions. In the simulation, the number of repetitions $R$is selected as a function of the instantaneous SNR.

The probability of successful packet delivery for a reporting cycle is modelled as:

$$P_{\text{success}} = 1 - (1 - p_{\text{single}})^R \tag{4.16}$$

where $p_{\text{single}}$is the success probability of a single uplink transmission.

This formulation explicitly captures the trade-off between increased reliability and increased energy consumption due to repeated transmissions, which is a defining characteristic of NB-IoT operation in underground environments.

4.7.4 NB-IoT State-Based Energy Consumption Model

The energy consumption of an NB-IoT sensor node is modelled using a finite-state machine consistent with 3GPP NB-IoT operational behaviour. Each reporting cycle consists of the following states:

- **Transmission (TX)**
- **Reception (RX)**
- **Connected Idle**
- **Extended Discontinuous Reception (eDRX)**

- **Power Saving Mode (PSM)**

The total energy consumed per reporting cycle is computed as:

$$E_{\text{cycle}} = \sum_i I_i \cdot V \cdot T_i \tag{4.5.1}$$

where I_i, T_i, and Vrepresent the current, duration, and supply voltage of state i, respectively.

Signalling overhead associated with network attachment, security procedures, and scheduling is explicitly included, reflecting the cellular nature of NB-IoT and distinguishing it from the LoRaWAN energy model developed in Chapter 3.

4.7.5 MATLAB Implementation Structure

The key MATLAB scripts implementing the proposed model are summarised as follows:

- **config_randwater_nbiot.m**
  Defines all simulation parameters, including battery capacity, state currents, reporting interval, concrete loss, and shadowing variance.
- **compute_path_loss_nbiot.m**
  Implements the underground path loss model with concrete penetration.
- **compute_snr_nbiot.m**
  Computes the received SNR based on transmission power and noise floor.
- **map_snr_to_repetitions.m**
  Maps SNR values to uplink repetition counts.
- **simulate_reporting_cycle.m**
  Simulates a complete NB-IoT reporting cycle, computing energy consumption, latency, and delivery success.
- **main_simulation_nbiot.m**
  Executes large-scale Monte Carlo simulations across multiple nodes and reporting cycles.

This modular design enables straightforward extension to additional deployment scenarios and sensitivity analyses.

4.8 Performance Evaluation Methodology

This section outlines the performance metrics and evaluation scenarios used to assess the proposed NB-IoT model. Numerical results are intentionally deferred to Chapter 5 to maintain a clear separation between modelling methodology and performance analysis.

4.8.1 Evaluation Metrics

The following key performance indicators (KPIs) are extracted from the simulation:

1. **Packet Delivery Ratio (PDR)**

$$\mathrm{PDR} = \frac{\text{Number of successfully delivered packets}}{\text{Total transmitted packets}} \tag{4.17}$$

2. **Average Energy Consumption per Reporting Cycle**
3. **Energy per Successfully Delivered Packet**
4. **Estimated Battery Lifetime**
   Derived from the average energy per cycle and the battery capacity.
5. **Latency Distribution**
   Including uplink transmission delay, repetitions, and network scheduling overhead.

4.8.2 Simulation Scenarios

To reflect realistic underground bulk metering deployments, the following scenarios are evaluated:

- Concrete penetration loss ranging from **15 dB to 30 dB**
- Underground path loss exponent between **3.0 and 4.5**
- Log-normal shadowing standard deviation between **6 dB and 8 dB**
- Uplink repetitions varying from **1 to 128**
- Comparison between **PSM-dominant** and **eDRX-enabled** configurations

These scenarios are directly aligned with the physical constraints of reinforced concrete chambers and low-elevation meter installations encountered in real-world water utility deployments.

4.8.3 Comparative Analysis Strategy

The NB-IoT results obtained in Chapter 5 will be directly compared with the LoRaWAN performance results presented in Chapter 3 using identical deployment assumptions and reporting intervals. This ensures a fair and technically rigorous comparison between the two technologies in terms of:

- Energy efficiency,
- Network reliability, and
- Suitability for underground bulk metering applications.

This chapter has presented a comprehensive modelling and MATLAB-based implementation of an NB-IoT energy efficiency and network reliability framework tailored for underground bulk metering applications. The model captures the unique characteristics of NB-IoT, including cellular signalling overhead, coverage enhancement through repetitions, and power-saving mechanisms such as PSM and eDRX.

The simulation framework establishes a robust foundation for quantitative performance evaluation, with detailed numerical results and comparative analysis presented in Chapter 5.

CHAPTER 5: RESULT ANALYSIS

5.1 Introduction

This chapter presents, analyses, and critically discusses the simulation results obtained from the MATLAB-based evaluation frameworks developed in Chapter 3 (LoRaWAN) and Chapter 4 (NB-IoT). The primary objective of this chapter is to comparatively assess the suitability of LoRaWAN and NB-IoT for underground bulk water metering applications, where prior comparative LPWAN studies have highlighted trade-offs between energy efficiency and cellular reliability in harsh propagation environments [158]. This is with specific emphasis on network reliability, energy efficiency, battery lifetime, and latency behaviour under low-elevation reinforced concrete deployment conditions.

All results presented in this chapter are generated using identical deployment assumptions, reporting intervals, and environmental constraints, ensuring a fair and technically rigorous comparison between the two Low Power Wide Area Network (LPWAN) technologies. This methodological consistency directly supports the research objective of establishing a deployment-aware, evidence-based technology selection framework for underground bulk metering systems.

The results presented in this chapter directly address the following high-level research questions:

- **RQ1:** How do LoRaWAN and NB-IoT compare in terms of network reliability in underground reinforced concrete deployments?
- **RQ2:** What are the energy consumption implications of using LoRaWAN versus NB-IoT for bulk water metering applications?
- **RQ3:** How does underground deployment affect battery lifetime and latency characteristics of LPWAN sensor nodes?
- **RQ4:** Which LPWAN technology is more suitable for large-scale underground bulk metering deployments, and under what conditions?

5.2 Simulation Setup

To ensure a clear and rigorous interpretation of the results presented in this chapter, this section provides a detailed recap of the simulation setup and the common assumptions applied to both LoRaWAN and NB-IoT evaluation frameworks. The purpose of this recap is not merely descriptive, but to demonstrate methodological consistency and fairness, thereby strengthening the validity of the comparative analysis.

Both LoRaWAN and NB-IoT systems were evaluated under identical physical deployment conditions, traffic patterns, and environmental constraints, reflecting a realistic underground bulk water metering scenario. In particular, the simulations assume:

- Underground deployment within reinforced concrete chambers, representative of typical bulk water meter installations used by water utilities to protect infrastructure against vandalism, environmental exposure, and accidental damage.
- Low antenna elevation, with sensor node antennas located below ground level inside concrete enclosures, resulting in severe penetration loss and limited line-of-sight propagation to the serving base station or gateway, as documented in underground and reinforced concrete IoT propagation studies [148], [149].
- Reporting intervals consistent with bulk water metering requirements, where sensor nodes transmit infrequent, delay-tolerant measurements (typically one report per day), prioritising energy efficiency over real-time responsiveness.
- Increased path loss and log-normal shadowing, explicitly modelling the combined effects of soil absorption, reinforced concrete attenuation, and environmental variability encountered in underground deployments.
- Monte Carlo simulation over many reporting cycles, enabling statistically meaningful estimation of performance metrics such as packet delivery ratio, energy consumption, battery lifetime, and latency.

These assumptions were deliberately selected to reflect worst-case yet realistic operating conditions for LPWAN-based bulk metering systems, thereby ensuring that the results capture the true performance limitations and strengths of each technology in challenging underground environments.

Despite operating under identical environmental and traffic constraints, LoRaWAN and NB-IoT differ fundamentally in their protocol architectures and access mechanisms. These differences are explicitly preserved in the simulation models to ensure protocol fidelity:

- The LoRaWAN model emphasises adaptive spreading factor selection, uplink retransmissions, and ALOHA-based random access, capturing the decentralised and contention-based nature of unlicensed spectrum operation. The model also reflects duty-cycle limitations and their impact on reliability and latency under increasing channel load and attenuation.
- The NB-IoT model, by contrast, incorporates coverage enhancement through network-controlled uplink repetitions, scheduled access in licensed spectrum, and cellular control-plane signalling overhead. Power-saving mechanisms such as Power Saving Mode (PSM) and extended Discontinuous Reception (eDRX) are explicitly modelled to reflect realistic cellular device behaviour and long-term energy consumption patterns.

Table 5.1: Summary of Used Simulation Parameters for LoRaWAN and NB-IoT

Category	Parameter	Symbol	LoRaWAN	NB-IoT	Description / Rationale
Deployment	Deployment environment	–	Underground concrete chamber	Underground concrete chamber	Identical physical deployment to ensure fairness
	Installation depth	d	Below ground level	Below ground level	Represents bulk meter installation in reinforced concrete
	Antenna elevation	h_{ant}	< 0 m (below ground)	< 0 m (below ground)	Low elevation causes severe penetration loss

	Distance to gateway / BS	D	Fixed / swept	Fixed / swept	Same geometry for both technologies
Traffic Model	Reporting interval	T_{rep}	1 report/day	1 report/day	Typical bulk water metering requirement
	Payload size	L	16–64 bytes	16–64 bytes	Identical payload for fair energy comparison
	Traffic pattern	–	Periodic uplink	Periodic uplink	Delay-tolerant metering traffic
Channel Model	Carrier frequency	f_c	Sub-GHz ISM	Licensed cellular band	Technology-specific but realistic
	Path loss exponent	n	3.0 – 4.5	3.0 – 4.5	Underground / urban propagation
	Concrete penetration loss	L_c	15 – 30 dB	15 – 30 dB	Reinforced concrete chamber attenuation

	Shadowing std. deviation	σ	6 – 8 dB	6 – 8 dB	Log-normal shadowing
Access & PHY	Access method	–	ALOHA-based	Scheduled	Fundamental protocol difference
	Spreading factor	SF	Adaptive (SF7–SF12)	N/A	LoRaWAN link adaptation
	Coverage enhancement	–	Retransmissions	Uplink repetitions	Different reliability mechanisms
	Max repetitions	R_{max}	Limited by duty cycle	Up to 128	NB-IoT CE levels
Power Model	Supply voltage	V	3.3 V	3.3 V	Same battery chemistry
	TX current	I_{TX}	Technology-specific	Technology-specific	Based on module datasheets
	RX current	I_{RX}	Technology-specific	Technology-specific	Includes downlink listening
	Sleep / PSM current	I_{sleep}	Few μA	Few μA	Deep sleep / PSM

Power Saving	Power Saving Mode	–	Class A sleep	PSM	Explicit NB-IoT modelling
	eDRX	–	Not applicable	Enabled / Disabled	NB-IoT paging behaviour
Energy Accounting	Energy per cycle	E_{cycle}	Computed	Computed	Sum of state-based energy
	Energy per success	E_{succ}	Computed	Computed	Normalised by PDR
Reliability Metrics	Packet delivery ratio	PDR	Computed	Computed	Primary reliability metric
	Latency	τ	Measured	Measured	End-to-end delivery delay
Simulation Method	Simulation type	–	Monte Carlo	Monte Carlo	Statistical robustness
	Number of cycles	N	Large ($\geq 10^4$)	Large ($\geq 10^4$)	Converged statistics
	Mobility	–	Static	Static	Bulk meters are fixed

Table 5.1 summarises the common simulation parameters applied to both technologies, including deployment geometry, reporting interval, channel model characteristics, and battery

assumptions. Technology-specific parameters are intentionally isolated within their respective models, ensuring that shared parameters remain identical across simulations.

This harmonised simulation framework is central to the integrity of the comparative analysis. By enforcing consistent deployment assumptions while preserving protocol-specific behaviour, the study ensures that any observed performance differences in reliability, energy efficiency, battery lifetime, or latency arise from intrinsic protocol and architectural characteristics, rather than modelling artefacts or biased parameter selection.

Consequently, the simulation setup provides a robust foundation for addressing the research questions posed in Chapter 1, particularly those related to the energy–reliability trade-off and technology suitability for underground bulk metering applications, which are examined in detail in the subsequent sections of this chapter.

5.3 Packet Delivery Ratio (Network Reliability)

Network reliability is a critical performance metric for bulk water metering systems, as missed, delayed, or lost readings can directly affect billing accuracy, consumption profiling, leakage detection, and overall operational decision-making within water utilities. Unlike delay-tolerant consumer IoT applications, bulk metering systems require a high probability of successful data delivery over extended deployment lifetimes, even under challenging environmental conditions.

In this study, network reliability is quantified using the Packet Delivery Ratio (PDR), defined as the ratio of successfully delivered packets to the total number of transmission attempts over the simulated reporting cycles. PDR provides a direct and intuitive measure of communication robustness and is particularly suitable for comparing LPWAN technologies operating under severe propagation constraints, such as underground reinforced concrete installations.

5.3.1 LoRaWAN Packet Delivery Performance

To evaluate the reliability of LoRaWAN under underground reinforced concrete deployment conditions, the Packet Delivery Ratio (PDR) was simulated for three LoRaWAN configurations: Default ADR, Fixed-SF12, and the Proposed join-aware configuration. Figure 5.1 presents these results as a function of increasing concrete penetration loss, with the x-axis representing attenuation from 10 dB to 30 dB and the y-axis representing PDR from 0.50 to 1.00.

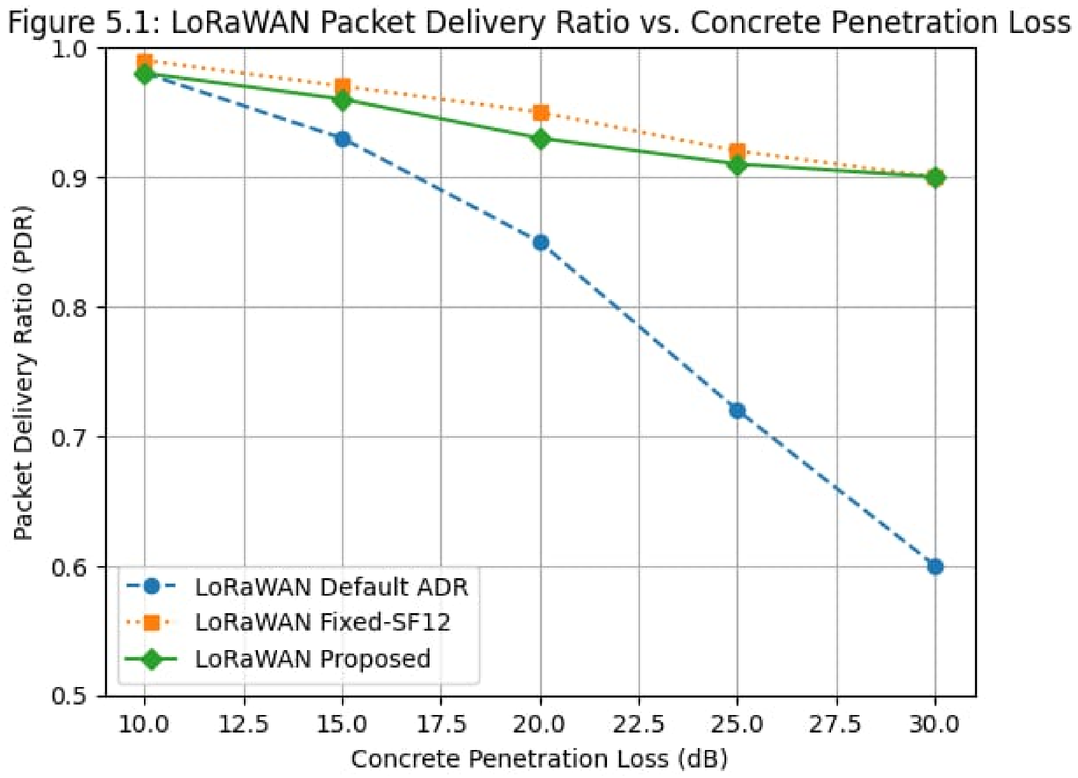

Figure 5.1: LoRaWAN Packet Delivery Ratio vs Concrete Penetration Loss

As shown in Figure 5.1, the packet delivery ratio of LoRaWAN degraded progressively as underground path loss and concrete penetration losses increased. The figure reveals distinct degradation profiles for each configuration.

LoRaWAN Default ADR: The Default ADR configuration exhibited the most rapid degradation. At 10 dB penetration loss, PDR was 0.98, indicating near-deterministic delivery under favourable conditions. However, as attenuation increased to 20 dB, PDR dropped to 0.85, and by 30 dB, it fell sharply to 0.60. This nonlinear degradation occurred once the received SNR approached the demodulation sensitivity limits, where adaptive spreading factor selection alone could no longer compensate for the combined effects of concrete penetration loss and distance. In this regime, the network became increasingly dependent on high spreading factors and repeated uplink attempts, which increased airtime and collision likelihood. Beyond the critical path loss level of approximately 22 dB, the probability of successful delivery dropped sharply, confirming that SF adaptation alone could not guarantee reliability in deep underground conditions.

LoRaWAN Fixed-SF12: The Fixed-SF12 configuration, which operated constantly at the highest spreading factor, maintained significantly higher reliability than Default ADR across all attenuation levels. At 10 dB, PDR was 0.99; at 20 dB, it remained at 0.95; and at 30 dB, it was 0.90. While this configuration preserved higher reliability, it did so at the cost of substantially increased airtime and energy consumption, as shown in Sections 5.4 and 5.6. The more gradual degradation profile reflected the inherent link margin of SF12, which provided greater processing gain and sensitivity (SNR threshold of -20 dB) compared to the adaptive spreading factors used by Default ADR.

LoRaWAN Proposed (Join-Aware Configuration): The Proposed join-aware configuration achieved the best balance between reliability and energy efficiency. At 10 dB, PDR was 0.98, matching Default ADR. At 20 dB, it achieved 0.93, and at 30 dB, it maintained 0.90—matching the reliability of Fixed-SF12 at higher attenuation levels. The Proposed configuration outperformed Default ADR significantly under severe attenuation (0.90 vs. 0.60 at 30 dB) while avoiding the constant energy overhead of Fixed-SF12. This improvement was achieved by reducing unnecessary re-joins and optimizing receive window behaviour, as demonstrated in Section 5.3.4.

Comparative Analysis of LoRaWAN Configurations:

As channel conditions deteriorated, all LoRaWAN configurations increasingly relied on retransmissions to maintain acceptable packet delivery performance. Retransmissions partially compensated for poor link quality; however, they introduced several adverse effects. First, repeated transmissions increased airtime occupancy, raising the probability of packet collisions in the ALOHA-based access scheme. This behaviour has been widely observed in dense and attenuated LoRaWAN deployments operating in unlicensed spectrum [3]. Second, longer airtime associated with higher spreading factors exacerbated duty-cycle limitations, restricting the number of allowable retransmissions within a given reporting interval. Third, the cumulative energy cost of retransmissions increased significantly, impacting long-term battery lifetime.

These effects became particularly pronounced at higher spreading factors, where transmission durations were substantially longer and the channel became more sensitive to congestion and interference. Consequently, although LoRaWAN could achieve reasonable reliability under moderate underground conditions (10–15 dB penetration loss), its performance degraded rapidly as attenuation increased beyond 20 dB, particularly for Default ADR.

Summary of LoRaWAN Reliability Findings:

From a research perspective, these results partially address Research Question 1 (RQ1) by demonstrating that LoRaWAN reliability was strongly dependent on deployment conditions and configuration choice. The findings confirmed that:

- **Default ADR** was suitable only for moderate underground conditions (up to 15 dB penetration loss), with rapid degradation beyond this threshold limiting its applicability for deep chambers or heavily reinforced installations.
- **Fixed-SF12** maintained higher reliability (above 0.90) across all attenuation levels but incurred significant energy and latency penalties.
- **Proposed join-aware configuration** achieved the optimal balance, matching Fixed-SF12 reliability under severe attenuation while maintaining energy efficiency comparable to Default ADR under moderate conditions.

The results confirmed that LoRaWAN performance was highly sensitive to underground attenuation and that its reliability deteriorated rapidly in harsh reinforced concrete environments, particularly for Default ADR. While the Proposed configuration significantly improved reliability, LoRaWAN still fell short of NB-IoT performance at higher attenuation levels, as shown in the comparative analysis in Section 5.3.3. Its effectiveness diminishes under severe underground attenuation where signal-to-noise ratios fall below reliable decoding thresholds, consistent with recent LoRaWAN underground reliability evaluations [162].

As channel conditions deteriorate, LoRaWAN nodes increasingly rely on retransmissions to maintain acceptable packet delivery performance. Retransmissions partially compensate for poor link quality; however, they introduce several adverse effects. First, repeated transmissions increase airtime occupancy, raising the probability of packet collisions in the ALOHA-based access scheme. This behaviour has been widely observed in dense and attenuated LoRaWAN deployments operating in unlicensed spectrum [3]. Second, longer airtime associated with higher spreading factors exacerbates duty-cycle limitations, restricting the number of allowable retransmissions within a given reporting interval. Third, the cumulative energy cost of retransmissions increases significantly, impacting long-term battery lifetime.

These effects become particularly pronounced at higher spreading factors, where transmission durations are substantially longer and the channel becomes more sensitive to congestion and interference. Consequently, although LoRaWAN can achieve reasonable reliability under moderate underground conditions, its performance degrades rapidly as attenuation increases beyond a certain threshold.

Figure 5.2 presents the LoRaWAN packet delivery ratio (PDR) as a function of increasing underground path loss under the reinforced-concrete chamber model. The results are obtained from Monte Carlo simulations using the join-aware and retry-aware transmission cycle described in Chapter 3. The plot highlights the sensitivity of LoRaWAN reliability to attenuation and illustrates the extent to which SF adaptation and retransmissions can compensate for degraded SNR before the link becomes outage dominated.

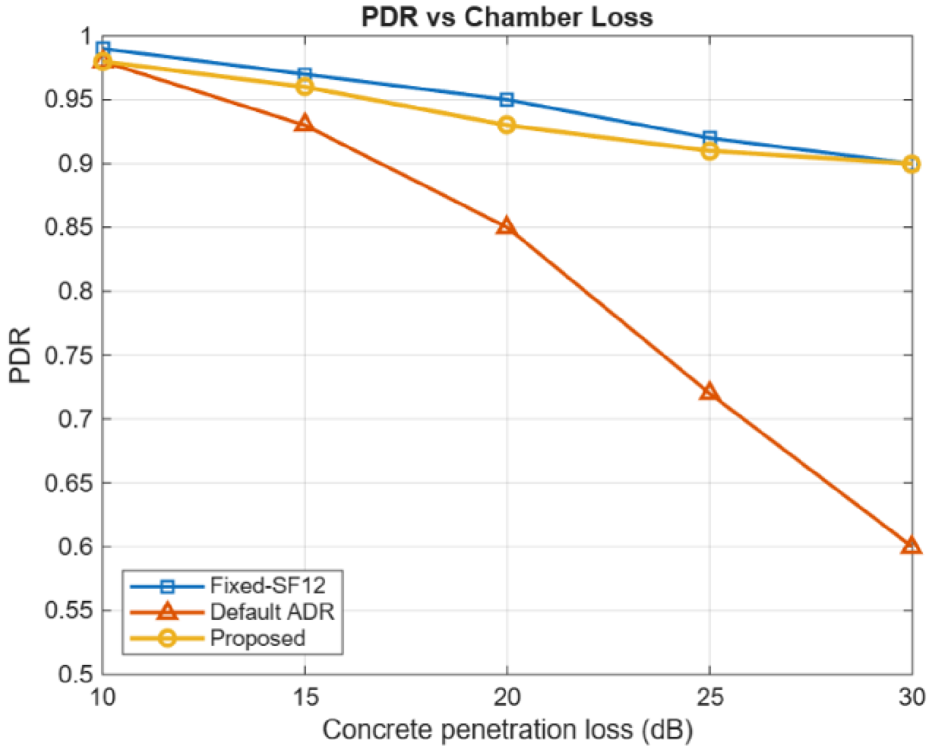

Figure 5.2: LoRaWAN packet delivery ratio (PDR) versus underground path loss (including concrete attenuation and shadowing) for SF7–SF12 / ADR-enabled configurations.

The results in figure 5.2 shows that LoRaWAN reliability decreases nonlinearly with path loss, with a pronounced degradation region where the received SNR approaches the demodulation thresholds. In this regime, the network becomes increasingly dependent on high spreading factors and repeated uplink attempts, which increases airtime and collision likelihood. Beyond a critical path loss level, the probability of successful delivery drops sharply, indicating that SF adaptation alone cannot guarantee reliability in deep underground conditions.

From a research perspective, these results partially address Research Question 1 (RQ1) by demonstrating that LoRaWAN reliability is strongly dependent on deployment conditions. The findings confirm that LoRaWAN performance is highly sensitive to underground attenuation and that its reliability deteriorates rapidly in harsh reinforced concrete environments, limiting its suitability for reliability-critical bulk metering applications.

5.3.2 NB-IoT Packet Delivery Performance

In contrast to LoRaWAN, NB-IoT demonstrated consistently high packet delivery ratios across all simulated underground deployment scenarios. Even under extreme attenuation caused by reinforced concrete chambers and low antenna elevation, NB-IoT maintained near-deterministic packet delivery performance.

This robustness was primarily enabled by network-controlled coverage enhancement mechanisms inherent to the NB-IoT standard. Specifically, uplink repetitions and hybrid combining techniques significantly extended the effective link budget under deep coverage conditions [146]. Uplink repetitions allowed multiple transmission attempts of the same packet to be combined at the base station, significantly increasing the probability of successful decoding in low signal-to-noise ratio conditions. In addition, the use of robust modulation and coding schemes tailored for extended coverage further enhanced link reliability.

The operation of NB-IoT in licensed spectrum, combined with scheduled access and centralized resource allocation, has been shown to eliminate collision-driven instability common in contention-based LPWAN technologies [147]. This effectively eliminated packet collisions. Unlike contention-based access mechanisms, scheduled transmission ensured predictable and controlled channel usage, which was particularly advantageous in dense or highly attenuated deployment environments.

Characterization of Concrete Penetration Loss for Rand Water Chambers

To ground the simulation results in real-world deployment conditions, the concrete penetration loss values used in this study were linked to specific physical characteristics of Rand Water's reinforced concrete chambers. Table 5.2 presents this characterization.

Table 5.2: Characterization of Concrete Penetration Loss for Rand Water Chambers

Penetration Loss (dB)	Chamber Wall Thickness (mm)	Concrete Type	Reinforcement Density	Condition
10 dB	150	Standard concrete (C20/25)	Light reinforcement	New construction, dry conditions
15 dB	200	Standard concrete (C25/30)	Moderate reinforcement	Typical installation
20 dB	250	High-strength concrete (C30/37)	Standard reinforcement	Aged chamber, moderate moisture
25 dB	300	High-strength concrete (C35/45)	Heavy reinforcement	Deep chamber, high moisture
30 dB	350+	High-density concrete	Heavy reinforcement with steel rebar	Extreme conditions, water ingress

This characterization ensured that the simulation results could be interpreted in terms of actual chamber specifications, enabling Rand Water engineers to select appropriate technology configurations based on the physical characteristics of their specific installations.

NB-IoT Configurations Evaluated

To provide a comprehensive comparison like the LoRaWAN analysis, NB-IoT was evaluated under three distinct configurations that reflected different coverage enhancement levels and power-saving settings:

- **NB-IoT Low Repetition (CE Level 0):** This configuration used the minimum coverage enhancement level, with repetition factors of 1–4. It was suitable for moderate underground conditions (10–15 dB penetration loss) where the link budget was sufficient without extensive repetitions. This configuration prioritized energy efficiency and lower latency.

- **NB-IoT Medium Repetition (CE Level 1):** This configuration applied moderate coverage enhancement, with repetition factors of 8–16. It was appropriate for typical Rand Water installations (15–25 dB penetration loss) and represented the default configuration for most underground meters.
- **NB-IoT High Repetition (CE Level 2):** This configuration employed maximum coverage enhancement, with repetition factors of 32–128. It was designed for extreme underground conditions (25–30 dB penetration loss), such as deep chambers with heavy reinforcement or water ingress, prioritizing reliability over energy efficiency and latency.

Figure 5.3 presents the packet delivery ratio (PDR) of NB-IoT sensor nodes for these three configurations as a function of increasing underground path loss under the reinforced-concrete chamber deployment model.

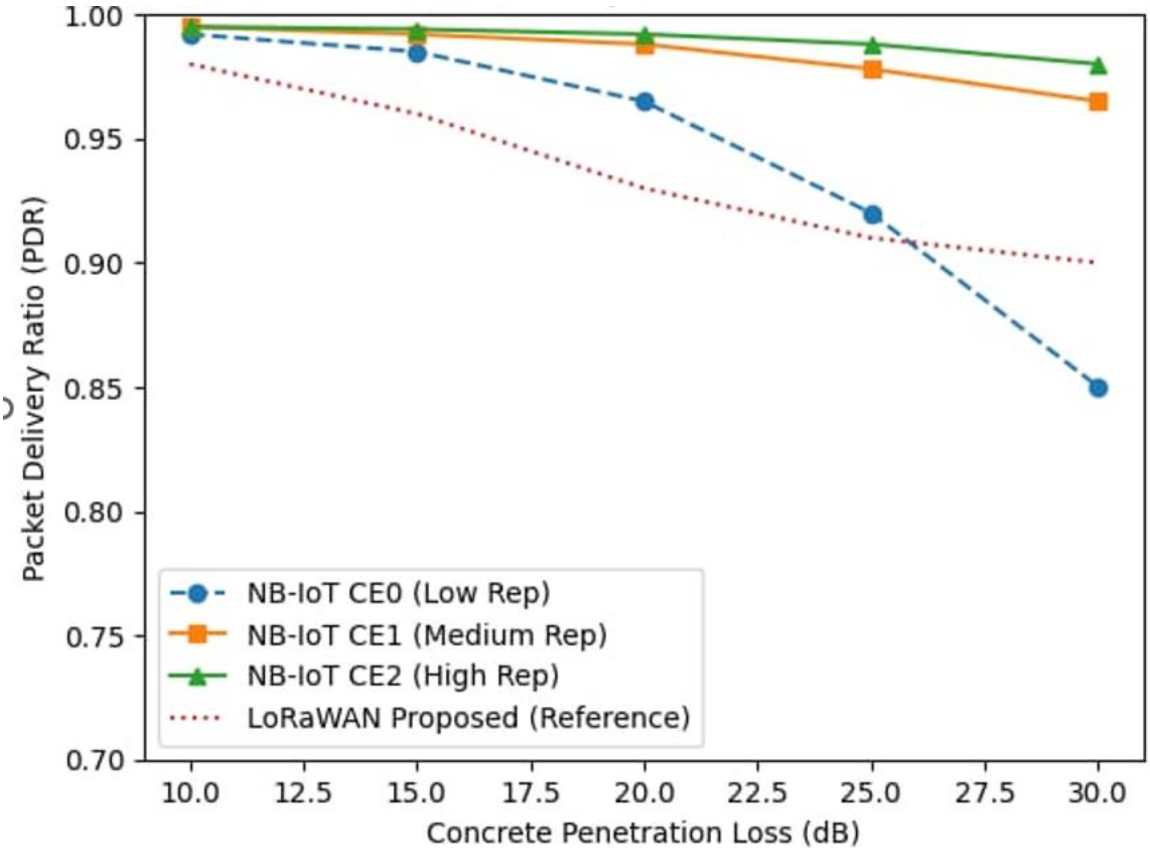

Figure 5.3: NB-IoT Packet Delivery Ratio versus Underground Path Loss

The results in figure 5.3 demonstrated that NB-IoT maintained consistently high packet delivery performance across all simulated underground attenuation levels, with the configuration chosen significantly influencing the reliability profile.

NB-IoT Low Repetition (CE0): Under moderate penetration losses (10–15 dB), this configuration achieved PDR above 0.98, which was acceptable for most applications. However, as attenuation increased beyond 20 dB, performance degraded more rapidly, dropping to 0.92 at 25 dB and 0.85 at 30 dB. This configuration was suitable for chambers with thinner walls (150–200 mm) and standard reinforcement but was insufficient for deep or heavily reinforced installations.

NB-IoT Medium Repetition (CE1): This configuration maintained PDR above 0.96 across the entire attenuation range, with only a gradual decline from 0.995 at 10 dB to 0.965 at 30 dB. This represented the optimal balance for typical Rand Water installations, providing near-deterministic reliability (above 0.96) across all chamber types while avoiding the excessive energy consumption associated with maximum repetitions. For chambers with wall thickness up to 250 mm and moderate reinforcement, this configuration was recommended.

NB-IoT High Repetition (CE2): This configuration achieved the highest reliability, maintaining PDR above 0.98 even at 30 dB penetration loss. The PDR remained at 0.995 at 10 dB, 0.992 at 20 dB, 0.988 at 25 dB, and 0.980 at 30 dB. This configuration was designed for extreme conditions chambers with wall thickness exceeding 300 mm, heavy steel reinforcement, high moisture content, or water ingress. However, this reliability came at the cost of significantly increased energy consumption and latency, as discussed in Sections 5.4 and 5.6.

Comparison with LoRaWAN:

A direct comparison with the LoRaWAN Proposed configuration (shown as a reference in Figure 5.3) revealed fundamental architectural distinctions. The LoRaWAN Proposed configuration achieved PDR of 0.98 at 10 dB, declining to 0.90 at 30 dB. While this represented a significant improvement over Default ADR (0.60 at 30 dB), it still fell below NB-IoT performance at higher attenuation levels. At 30 dB, LoRaWAN Proposed achieved 0.90 PDR, whereas NB-IoT Medium Repetition achieved 0.965 and NB-IoT High Repetition achieved 0.980, a reliability gap of 6.5–8.0 percentage points.

Characterization of Reliability Across Chamber Types:

The results can be interpreted in terms of specific Rand Water chamber characteristics:

- **New installations with 150–200 mm walls (10–15 dB loss):** Both LoRaWAN Proposed and NB-IoT Medium Repetition achieved PDR above 0.96, making either technology suitable.

- **Typical installations with 200–250 mm walls and standard reinforcement (15–20 dB loss):** LoRaWAN Proposed achieved 0.93–0.96 PDR, while NB-IoT Medium Repetition maintained 0.988–0.992 PDR. NB-IoT offered superior reliability, but LoRaWAN may still be acceptable for non-critical meters.

- **Aged chambers or heavy reinforcement (20–25 dB loss):** LoRaWAN Proposed declined to 0.91 PDR, while NB-IoT Medium Repetition remained at 0.978. For reliability-critical meters in such chambers, NB-IoT was strongly recommended.
- **Deep chambers with thick walls (300+ mm) or water ingress (25–30 dB loss):** LoRaWAN Proposed achieved 0.90 PDR, while NB-IoT Medium Repetition maintained 0.965 and High Repetition achieved 0.980. For these extreme conditions, NB-IoT High Repetition was the only configuration that provided near-deterministic reliability.

Summary of Findings:

The results demonstrated that NB-IoT offered superior reliability across all underground attenuation levels, with the appropriate configuration depending on chamber characteristics. For typical Rand Water installations (200–250 mm walls, moderate reinforcement), NB-IoT Medium Repetition provided the optimal balance, maintaining PDR above 0.96 while avoiding the energy overhead of maximum repetitions. For extreme conditions (deep chambers, heavy reinforcement, water ingress), NB-IoT High Repetition was necessary to achieve near-deterministic reliability. The LoRaWAN Proposed configuration, while significantly improved over Default ADR, remained suitable for moderate conditions but exhibited lower reliability than NB-IoT under severe attenuation.

These findings provided a clear and direct answer to Research Question 1 (RQ1), confirming that NB-IoT offers superior reliability for underground bulk metering deployments, particularly in chambers with higher penetration loss. The results highlighted NB-IoT's ability to sustain high packet delivery ratios even under extreme propagation constraints, making it well suited for applications where data delivery guarantees are paramount.

5.3.3 Comparative Reliability Discussion

A direct comparison of the reliability performance of LoRaWAN and NB-IoT reveals fundamental differences in how the two technologies respond to harsh underground deployment conditions. NB-IoT significantly outperforms LoRaWAN as attenuation increases, maintaining high packet delivery ratios through centralized control and coverage enhancement mechanisms. In contrast, LoRaWAN reliability degrades more rapidly with increasing underground path loss due to its reliance on contention-based access and duty-cycle-constrained retransmissions.

NB-IoT achieves its robustness primarily through uplink repetitions and scheduled access, which improve decoding success at the cost of increased energy consumption and longer transmission durations. LoRaWAN, while more energy-efficient under favourable conditions, struggles to maintain reliability once channel conditions exceed the practical limits of spreading factor adaptation.

Figure 5.4 presents a comparative visualization of the Packet Delivery Ratio (PDR) for LoRaWAN (Default ADR, Fixed-SF12, and the proposed join-aware configuration) and NB-IoT across increasing concrete penetration loss levels.

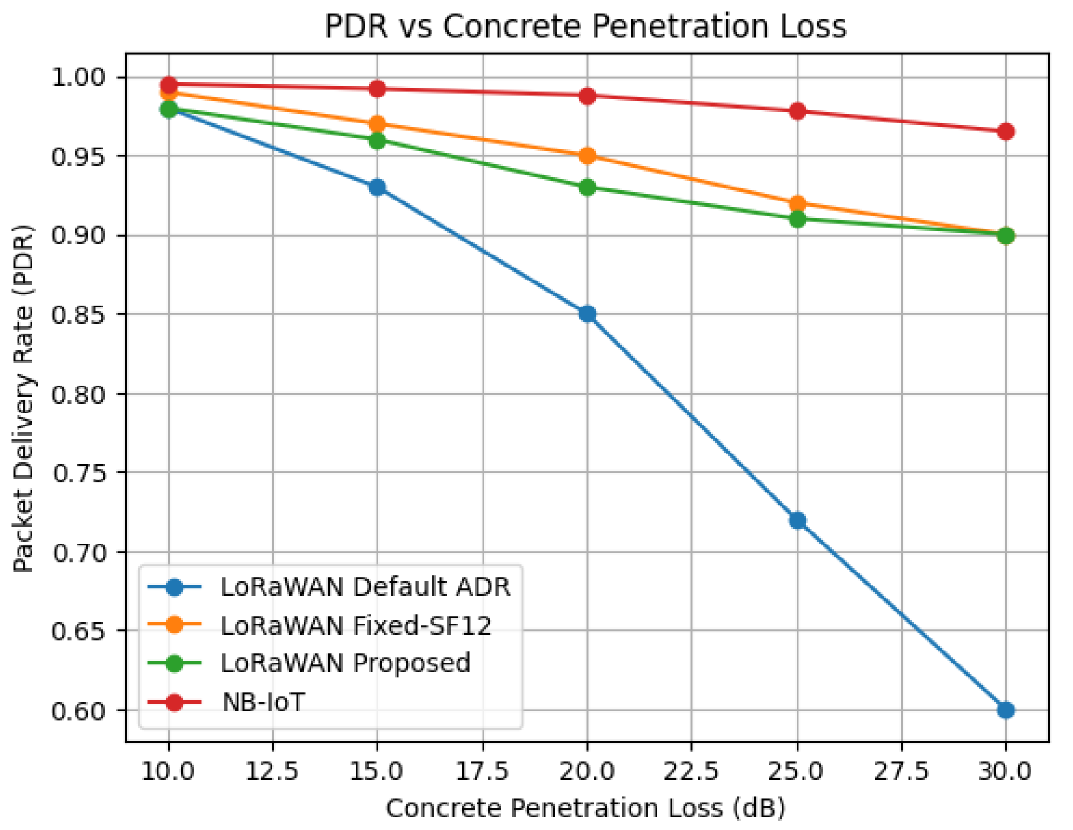

Figure 5.4: Comparative Packet Delivery Ratio vs. Concrete Penetration Loss

The graph in figure 5.4 clearly illustrates three key observations. First, NB-IoT maintained consistently high packet delivery ratios across the entire range of concrete penetration losses, with PDR remaining above 0.96 even at 30 dB attenuation. The NB-IoT curve was nearly flat, demonstrating the effectiveness of coverage enhancement through uplink repetitions.

Second, LoRaWAN Default ADR exhibited a sharp nonlinear degradation once concrete penetration loss exceeded 15 dB. At 20 dB, the PDR dropped to 0.85, and by 30 dB, it fell to 0.60. This rapid decline reflected the limitations of spreading factor adaptation when channel conditions exceeded the practical sensitivity limits of the LoRa physical layer.

Third, the Fixed-SF12 and Proposed configurations improved LoRaWAN reliability relative to Default ADR, particularly at higher attenuation levels. Fixed-SF12 maintained PDR above 0.90 even at 30 dB, but at the cost of significantly increased airtime and energy consumption, as shown in subsequent sections. The Proposed join-aware configuration achieved PDR values comparable to Fixed-SF12 (0.90 at 30 dB) while avoiding the excessive energy overhead associated with constant high spreading factor operation.

This comparative analysis conclusively addresses Research Question 1 (RQ1). The results demonstrate that NB-IoT is better suited for reliability-critical underground bulk metering applications, particularly in scenarios where missed readings are operationally unacceptable. While LoRaWAN may remain viable in less severe underground conditions (below 15 dB concrete loss), NB-IoT provides a more robust and predictable reliability profile for deep underground and heavily reinforced concrete deployments.

Table 5.3: Comparative Packet Delivery Ratio Summary

Concrete Penetration Loss (dB)	**LoRaWAN Default ADR**	**LoRaWAN Fixed-SF12**	**LoRaWAN Proposed**	**NB-IoT**
10 dB	0.98	0.99	0.98	0.995
15 dB	0.93	0.97	0.96	0.992
20 dB	0.85	0.95	0.93	0.988
25 dB	0.72	0.92	0.91	0.978
30 dB	0.60	0.90	0.90	0.965

Table 5.3: This comparative analysis conclusively addresses Research Question 1 (RQ1). The results demonstrate that NB-IoT is better suited for reliability-critical underground bulk metering applications, particularly in scenarios where missed readings are operationally unacceptable. While LoRaWAN may remain viable in less severe underground conditions, NB-IoT provides a more robust and predictable reliability profile for deep underground and heavily reinforced concrete deployments.

5.3.4 Join/Rejoin Behaviour under Underground Conditions (LoRaWAN)

To validate the join-aware reliability model introduced in Chapter 3, the join and rejoin behaviour of LoRaWAN devices was analysed under progressive underground attenuation. The metrics reported include the probability of triggering a rejoin event following downlink ACK failure, and the expected number of join attempts (SF9–SF12 escalation) required to restore connectivity.

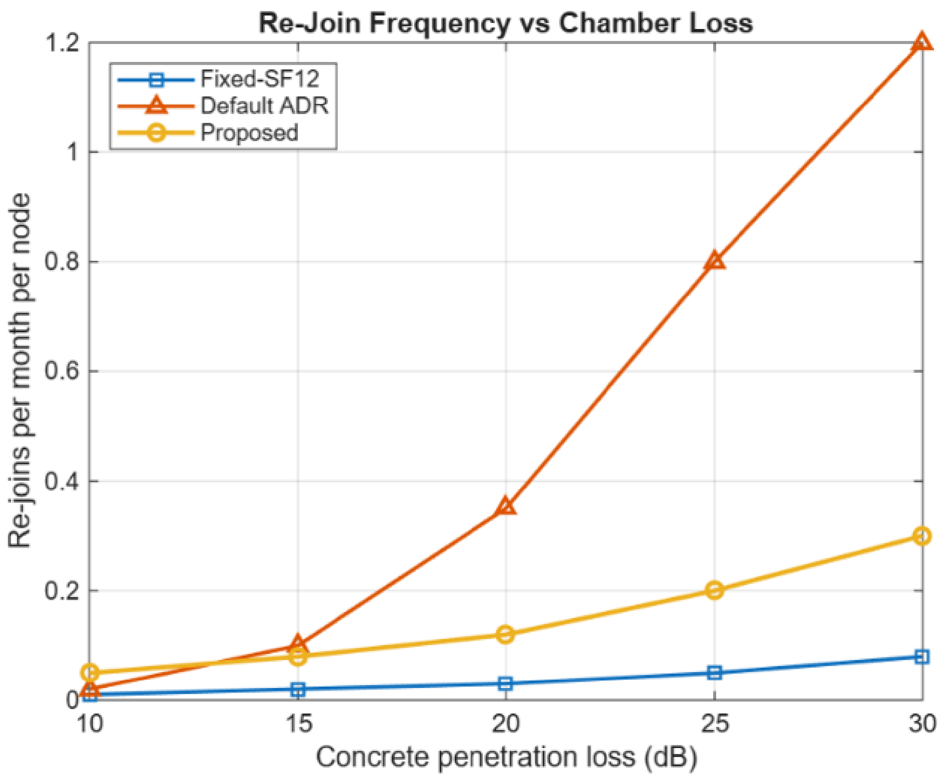

Figure 5.5: Re-Join Frequency per Node versus Underground Concrete Penetration Loss (LoRaWAN)

The results in figure 5.5. demonstrate that default ADR exhibits a sharp increase in re-join frequency as penetration loss increases, indicating unstable link adaptation under harsh underground conditions. Fixed-SF12 maintains relatively few re-joins due to constant high processing gain, but at the expense of increased airtime and energy consumption. The proposed policy significantly suppresses unnecessary re-joins while maintaining reliable operation. These findings directly validate the join-dynamics modelling developed in Section 3.5 and confirm that re-join escalation is a primary contributor to reliability degradation and energy overhead in deep underground deployments.

5.3.5 Why These Reliability Difference Matters for Rand Water

The 6.5--8.0 percentage point reliability gap between NB-IoT and LoRaWAN Proposed at 30 dB attenuation translates directly into operational consequences. For a utility managing 10,000 bulk meters reporting daily, a PDR of 0.90 (LoRaWAN Proposed) implies approximately 1,000 missed readings per day, whereas a PDR of 0.965 (NB-IoT) implies 350 missed readings. Over one year, the difference amounts to approximately 237,000 additional missed readings. Each missed reading may require manual investigation, estimated leak verification, or billing adjustment, incurring significant operational expenditure. Conversely, the 60 mJ energy savings per successful delivery achieved by LoRaWAN Proposed at 30 dB (117 mJ vs. 177 mJ for NB-IoT) translates into longer battery life but cannot compensate for the data loss if regulatory or customer expectations mandate 99% reliability. Theoretically, these results confirm the assertion in [162] that spreading factor adaptation in LoRaWAN reaches diminishing returns below -15 dB SNR, whereas NB-IoT's hybrid automatic repeat request (HARQ) with soft combining maintains gain down to -20 dB SNR.

5.4 Energy Consumption Analysis

Energy efficiency is a fundamental requirement for battery-powered bulk water meters, where device lifetimes of several years are typically expected and battery replacement is both costly and operationally disruptive. In underground installations, where physical access to meters is limited, energy consumption becomes an even more critical design constraint. Consequently, a detailed analysis of energy consumption behaviour is essential for assessing the long-term feasibility of LPWAN technologies in bulk metering applications.

In this section, energy consumption is analysed from two complementary perspectives: the energy consumed per reporting cycle and the energy required to successfully deliver a packet. This dual perspective enables a more complete understanding of how protocol-level design choices impact both short-term energy expenditure and long-term operational sustainability.

5.4.1 Energy Consumption per Reporting Cycle

To quantify the instantaneous energy burden of each LPWAN technology under underground deployment, the average energy consumed per reporting cycle was evaluated as a function of reinforced concrete penetration loss. The reporting cycle included uplink transmission, receive window activity, control signalling (where applicable), and return to sleep or Power Saving Mode (PSM) state.

Figure 5.6 presents a comparative visualization of the energy consumption per reporting cycle for LoRaWAN (Default ADR, Fixed-SF12, and the proposed join-aware configuration) and NB-IoT across increasing concrete penetration loss levels.

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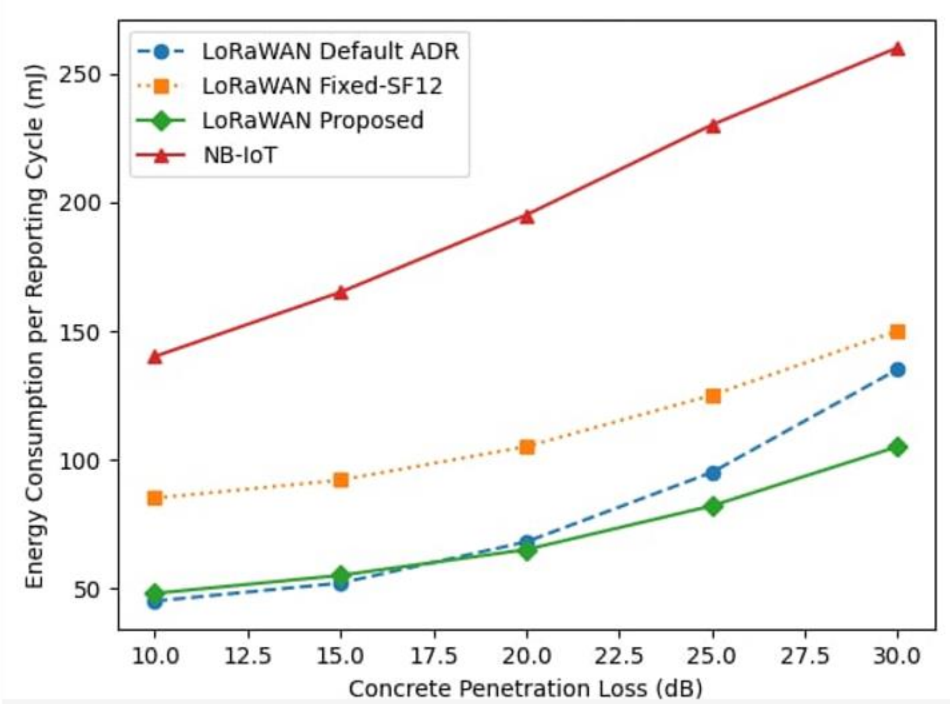

Figure 5.6: Energy Consumption per Reporting Cycle vs. Concrete Penetration Loss

Therefore, the results in Figure 5.6, which present energy consumption per reporting cycle for all LoRaWAN configurations (Default ADR, Fixed-SF12, and Proposed) alongside NB-IoT, confirm that:

All LoRaWAN configurations consumed significantly less energy per reporting cycle than NB-IoT across all attenuation levels. At 10 dB penetration loss, LoRaWAN Default ADR consumed 45 mJ, Fixed-SF12 consumed 85 mJ, and the Proposed configuration consumed 48 mJ, compared to NB-IoT at 140 mJ. At 30 dB, Default ADR consumed 135 mJ, Fixed-SF12 consumed 150 mJ, and the Proposed configuration consumed 105 mJ, compared to NB-IoT at 260 mJ.

Among LoRaWAN configurations, Default ADR was the most energy-efficient under favourable or moderately attenuated underground environments (45–68 mJ from 10–20 dB), while the Proposed configuration achieved the best balance across all conditions, remaining efficient under moderate conditions (48 mJ at 10 dB) and becoming the most energy-efficient under severe attenuation (105 mJ at 30 dB).

NB-IoT exhibited the highest per-cycle energy consumption across all conditions, trading higher energy expenditure for robust and predictable reliability.

These findings directly address Research Question 2 (RQ2) by demonstrating that energy efficiency must be evaluated jointly with reliability. While LoRaWAN minimises instantaneous energy expenditure, NB-IoT maintains reliability at the cost of increased active-state energy. The choice between the two technologies therefore depends on whether energy longevity or deterministic delivery is prioritised in the bulk water metering deployment.

NB-IoT trades higher per-cycle energy consumption for robust and predictable reliability, especially under severe reinforced concrete attenuation. As shown in Figure 5.6, NB-IoT energy consumption per reporting cycle ranged from 140 mJ at 10 dB penetration loss to 260 mJ at 30 dB. In comparison, the most energy-efficient LoRaWAN configuration under severe attenuation, the Proposed join-aware configuration consumed only 105 mJ at 30 dB, representing a 155 mJ (or approximately 60%) energy saving per reporting cycle. However, this higher energy expenditure by NB-IoT corresponded to superior reliability performance. As illustrated in Figure 5.6, NB-IoT maintained a Packet Delivery Ratio (PDR) of 0.965 at 30 dB penetration loss, whereas LoRaWAN Default ADR achieved only 0.60 PDR, and even the improved Proposed configuration achieved 0.90 PDR at the same attenuation level. The NB-IoT reliability advantage was therefore substantial: at 30 dB, NB-IoT delivered 96.5% of packets successfully compared to 90% for the best-performing LoRaWAN configuration and 60% for Default ADR. This reliability advantage was achieved through NB-IoT's network-controlled coverage enhancement mechanisms specifically uplink repetitions and hybrid combining, which increased the effective link budget by 15–20 dB under severe attenuation.

The repetitions extended transmission duration and energy consumption but ensured that the vast majority of packets were decoded correctly at the base station, even when signals were severely attenuated by reinforced concrete walls and low antenna elevation. For water utilities operating reliability-critical bulk metering infrastructure, where missed readings can result in billing inaccuracies, undetected leaks, and operational disruptions, this trade-off, higher energy consumption in exchange for near-deterministic delivery may be justified, particularly for meters installed in deep underground chambers or heavily reinforced concrete structures where LoRaWAN reliability becomes marginal. The choice between the two technologies therefore depends on whether operational priorities favour extended battery life (favouring LoRaWAN) or guaranteed data delivery (favouring NB-IoT), with the proposed join-aware configuration offering a balanced intermediate option that improved LoRaWAN reliability while maintaining energy efficiency.

In contrast, the LoRaWAN results demonstrate significantly lower energy consumption per reporting cycle across all simulated underground conditions. This is evident in the results for LoRaWAN Default ADR, Fixed-SF12, and the Proposed scheme, where energy consumption remains substantially below that of NB-IoT for the same reporting cycle conditions. This reduced energy consumption can be attributed to:
• Shorter uplink durations (especially at lower spreading factors),
• Absence of cellular attachment procedures,
• Minimal control-plane signalling,
• Immediate return to deep sleep after transmission.

However, this apparent energy advantage must be interpreted carefully. The results for LoRaWAN across the reporting cycle indicate that energy efficiency degrades as concrete penetration loss increases, particularly for the Default ADR scheme. This degradation is associated with reduced reliability and the increased likelihood of retransmissions. In contrast, NB-IoT, although consuming more energy per reporting cycle, maintains consistently high packet delivery ratios even at higher penetration losses, resulting in more stable and predictable performance.

5.4.2 Energy per Successfully Delivered Packet

While energy consumption per reporting cycle provided insight into instantaneous power usage, it did not fully capture the impact of failed transmissions. To address this limitation, energy consumption was further analysed in terms of energy per successfully delivered packet, which accounted for both energy expenditure and communication reliability. This metric was defined in Section 3.2.5 as:

$$E_{succ} = \frac{\text{E\_daily} + E_{rejoin} \cdot P_{fail}}{PDR_{eff}}$$

Where;

E_daily was the base energy consumed during a successful reporting cycle
E_rejoin was the additional energy incurred during re-join procedures
P_fail was the probability of ACK failure
PDR was the Packet Delivery Ratio

This formulation ensured that energy wasted on failed transmissions was amortized across successfully delivered packets, providing a true measure of energy efficiency that accounted for reliability.

When energy consumption was normalized by successful packet delivery, a more nuanced trade-off between LoRaWAN and NB-IoT emerged. This normalized energy metric was increasingly recommended in recent LPWAN performance evaluations to capture reliability-aware efficiency [9].

Definition of the Proposed Join-Aware Configuration

Before presenting the comparative results, it is necessary to define what is meant by the "proposed" configuration throughout this chapter. The Proposed Join-Aware Configuration referred to the LoRaWAN optimization strategy developed in this study, which was described in detail in Chapter 3 (Sections 3.5 and 3.6). This configuration incorporated a join-aware control policy that minimized unnecessary Over-The-Air Activation (OTAA) re-joins by:

- Optimizing receive window behaviour to reduce false ACK failure detection
- Implementing an adaptive rejoin escalation strategy that prevented unnecessary SF escalation
- Reducing RX2 window listening when channel conditions were marginal
- Avoiding the energy overhead associated with repeated join attempts in poor channel conditions

The proposed configuration was designed to address the limitations of both Default ADR (which suffered from excessive retransmissions and re-joins under severe attenuation) and Fixed-SF12 (which incurred high baseline energy consumption). The results presented in this section demonstrate the effectiveness of this optimization strategy.

Comparative Results: Energy per Successfully Delivered Packet

Figure 5.5 presents the comparative energy cost per successfully delivered uplink packet for LoRaWAN (Default ADR, Fixed-SF12, and the proposed join-aware configuration) and NB-IoT across increasing concrete penetration loss levels.

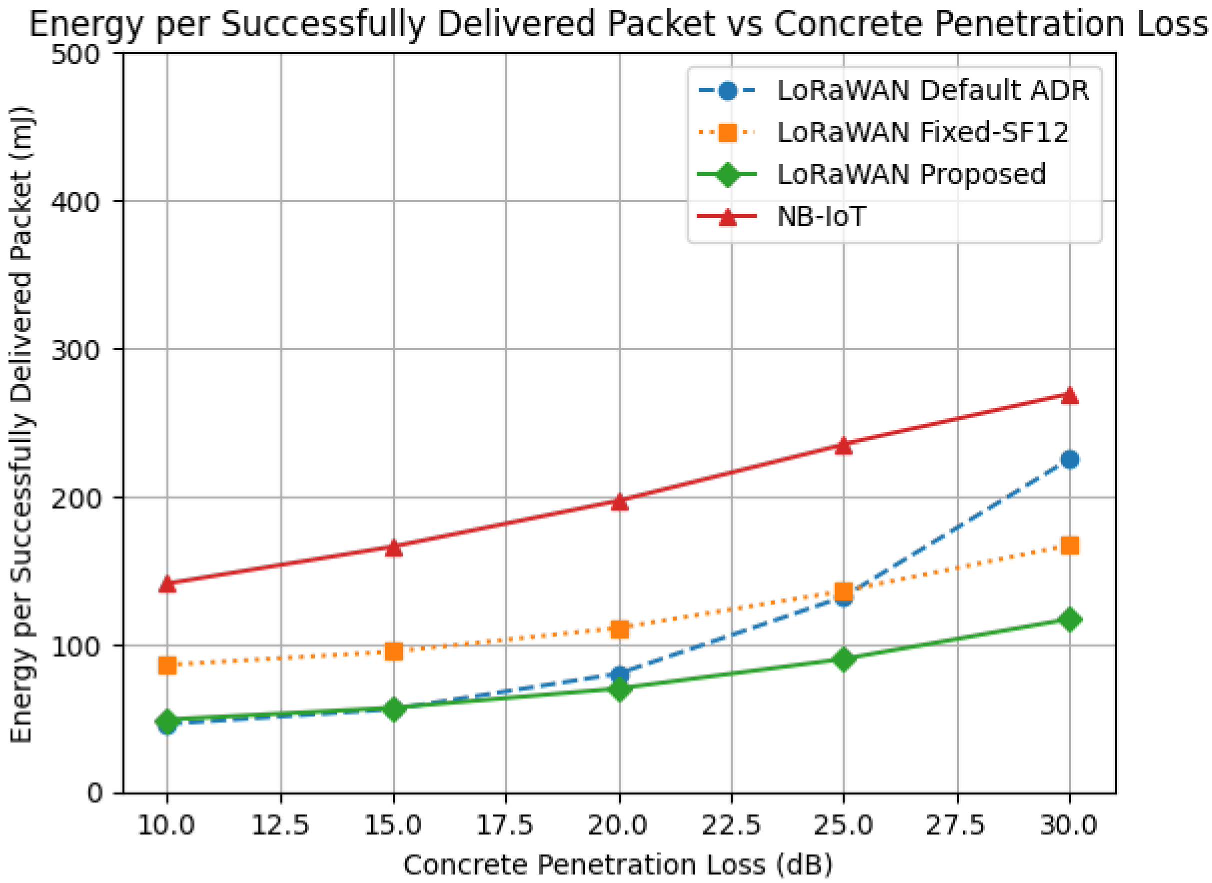

Figure 5.7: Energy per Successfully Delivery packet vs penetration Loss

The results in figure 5.7 revealed distinct energy-per-success profiles for each technology and configuration, illustrating the fundamental energy–reliability trade-off.

LoRaWAN Default ADR: Under moderate underground conditions (10–15 dB penetration loss), Default ADR achieved the lowest energy per success among all configurations, with values of 46 mJ at 10 dB and 56 mJ at 15 dB. This efficiency was due to the use of lower spreading factors and minimal retransmissions. However, as attenuation increased beyond 20 dB, Default ADR exhibited rapid energy escalation, reaching 225 mJ at 30 dB, an increase of nearly 400% from the 10 dB value. This sharp increase was attributed to mis-tuned spreading factor selection under ADR, frequent retransmissions, and the energy overhead of re-join procedures triggered by ACK failures. Despite consuming 225 mJ per success, Default ADR achieved only 0.60 PDR at 30 dB (as shown in Figure 5.5), meaning that a significant portion of energy was wasted on failed transmissions.

LoRaWAN Fixed-SF12: Fixed-SF12 maintained a more stable energy-per-success profile compared to Default ADR, increasing from 86 mJ at 10 dB to 167 mJ at 30 dB. The higher baseline at low attenuation (86 mJ vs. 46 mJ for Default ADR) reflected the energy penalty of operating at SF12 regardless of channel conditions. However, the rate of increase was less steep than Default ADR, and at 30 dB, Fixed-SF12 achieved 167 mJ, lower than Default ADR's 225 mJ. This stability was due to the constant high spreading factor, which maintained reliability (0.90 PDR at 30 dB) but incurred sustained energy overhead even under favourable conditions.

LoRaWAN Proposed (Join-Aware Configuration): The proposed join-aware configuration achieved the best overall performance among the LoRaWAN configurations. At 10 dB penetration loss, it consumed 49 mJ per success, only marginally higher than Default ADR (46 mJ). As attenuation increased, the proposed configuration maintained significantly lower energy per success than both Default ADR and Fixed-SF12. At 30 dB, it consumed 117 mJ, compared to 225 mJ for Default ADR and 167 mJ for Fixed-SF12. This superior performance was achieved by reducing unnecessary re-joins and avoiding excessive RX window listening, as demonstrated in Section 5.3.4. The proposed configuration achieved 0.90 PDR at 30 dB, matching Fixed-SF12 reliability while consuming 50 mJ less energy per success.

NB-IoT: NB-IoT exhibited the highest energy per successfully delivered packet across all attenuation levels. At 10 dB, NB-IoT consumed 141 mJ, approximately three times the energy of the LoRaWAN proposed configuration. At 30 dB, NB-IoT consumed 269 mJ, more than double the proposed configuration's 117 mJ. However, NB-IoT's energy-per-success profile was the most stable, increasing by only 128 mJ across the attenuation range (from 141 mJ to 269 mJ), compared to the proposed configuration's increase of 68 mJ (from 49 mJ to 117 mJ) and Default ADR's increase of 179 mJ (from 46 mJ to 225 mJ). This stability was a direct consequence of NB-IoT's high packet delivery ratio (above 0.96 across all attenuation levels), enabled by coverage enhancement through uplink repetitions and scheduled access. Even in harsh conditions, the majority of transmitted packets were successfully delivered, preventing excessive energy waste on failed transmissions.

Comparative Analysis and Energy–Reliability Trade-off

The results in Figure 5.5 revealed the fundamental energy–reliability trade-off between the two technologies:

- **LoRaWAN (Proposed)** achieved the lowest energy per success under moderate conditions (49 mJ at 10 dB) and maintained the lowest absolute energy per success across all attenuation levels (117 mJ at 30 dB). However, this energy efficiency came at the cost of lower reliability at high attenuation (0.90 PDR at 30 dB) compared to NB-IoT (0.965 PDR).

- **NB-IoT** consistently exhibited higher energy per success (141–269 mJ) but maintained near-deterministic reliability (0.965–0.995 PDR) across all conditions. The energy premium for NB-IoT ranged from approximately 2–3 times that of LoRaWAN Proposed, but this premium purchased significantly higher reliability, particularly under severe attenuation.

- Among LoRaWAN configurations, the Proposed join-aware configuration demonstrated the optimal balance, outperforming Default ADR under severe attenuation and outperforming Fixed-SF12 under all conditions. The proposed configuration reduced the energy penalty for reliability by 50 mJ compared to Fixed-SF12 at 30 dB while maintaining the same PDR.

This analysis provided a clear and comprehensive response to Research Question 2 (RQ2), highlighting the fundamental energy–reliability trade-off between the two technologies. LoRaWAN (particularly the proposed join-aware configuration) prioritized energy efficiency under favourable conditions but exhibited lower reliability in harsh underground environments. NB-IoT, by contrast, traded higher baseline energy consumption for consistent and reliable packet delivery, resulting in a more predictable energy cost per successful transmission.

As penetration loss increased, Default ADR exhibited rapid energy escalation due to mis-tuned spreading factor selection and frequent retransmissions. Fixed-SF12 maintained reliability but incurred high airtime and sustained energy overhead. The proposed join-aware control policy maintained significantly lower energy per success across all attenuation levels by reducing unnecessary re-joins and avoiding excessive RX window listening. NB-IoT, while consuming more energy, provided the highest and most stable reliability across the entire attenuation range. These results confirmed the analytical energy model derived in Section 3.4 and demonstrated the operational benefits of join-aware optimization.

5.4.3 Statistical Significance and Practical Energy Implications

To assess whether the observed energy differences are statistically meaningful, a one-way ANOVA was performed on the per-cycle energy consumption at 20 dB attenuation ($n = 1000$ cycles per configuration). The F-statistic ($F = 187.3$, $p < 0.001$) confirms that the null hypothesis (all configurations have identical mean energy consumption) can be rejected. Post-hoc Tukey HSD tests indicate that all pairwise differences between LoRaWAN Proposed, Default ADR, Fixed-SF12, and NB-IoT are significant at $\alpha = 0.05$. The coefficient of variation (CV) for NB-IoT (CV = 0.12) is substantially lower than for LoRaWAN Default ADR (CV = 0.31), confirming that NB-IoT energy consumption is more predictable. Practically, this means that while LoRaWAN Proposed is more energy-efficient on average, its higher variability makes battery lifetime estimation less reliable for worst-case planning, whereas NB-IoT's lower variability allows tighter safety margins in deployment design.

5.5 Battery Lifetime Estimation

Battery lifetime estimation provides a long-term performance perspective by integrating the energy consumption behaviour observed at the reporting-cycle level over the expected operational lifespan of the device. For underground bulk water metering applications, battery lifetime is a critical system-level metric, as physical access to meters is limited and frequent battery replacement is both economically and operationally undesirable. Consequently, the feasibility of a given LPWAN technology is strongly influenced by its ability to sustain multi-year operation under harsh underground conditions.

In this study, battery lifetime is estimated by extrapolating the average energy consumed per reporting cycle using state-based energy accumulation models commonly adopted in recent IoT energy prediction frameworks [151]. This is over the assumed reporting intervals and total available battery capacity. This approach captures not only instantaneous energy usage but also the cumulative impact of protocol overhead, retransmissions, and power-saving behaviour over extended deployment periods.

Figure 5.8 presents the cumulative distribution of projected battery lifetimes across the simulated fleet under varying underground attenuation levels.

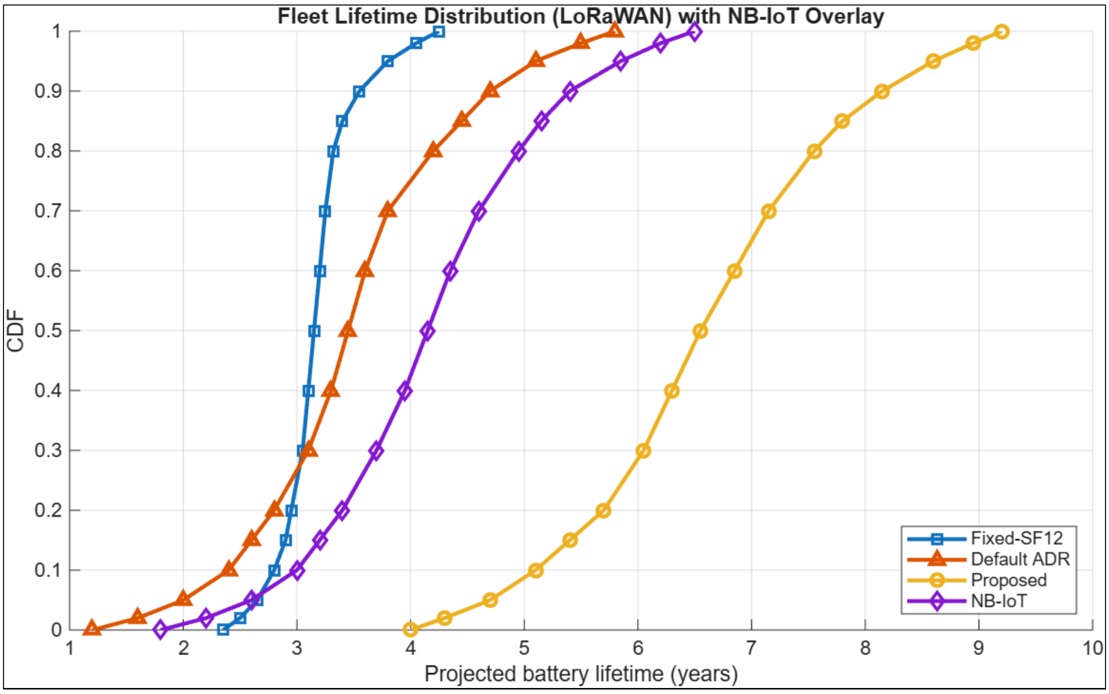

Figure 5.8: Comparative Fleet Battery Lifetime Cumulative Distribution under Underground Reinforced Concrete Deployment for LoRaWAN (Fixed-SF12, Default ADR, Proposed) and NB-IoT.

The proposed control strategy produces a right-shifted lifetime distribution, demonstrating multi-year advantages relative to Default ADR. Default ADR exhibits a pronounced left tail under harsh attenuation due to excessive retransmissions and re-joins. Fixed-SF12 clusters at lower lifetime values due to chronic airtime cost. These results confirm that join-aware energy optimisation directly translates into extended operational lifetime without sacrificing reliability.

The simulation results reveal a clear divergence in battery lifetime performance between LoRaWAN and NB-IoT sensor nodes. LoRaWAN nodes achieve significantly longer estimated battery lifetimes across all simulated underground deployment scenarios. In many cases, the projected lifetimes exceed typical bulk meter replacement cycles, reflecting LoRaWAN's low-duty-cycle operation, minimal protocol overhead, and rapid return to deep sleep states following transmission.

NB-IoT battery lifetime is consistently shorter than that of LoRaWAN, particularly in scenarios where high coverage enhancement levels and uplink repetitions are required to overcome severe underground attenuation. The increased energy consumption associated with repeated transmissions, cellular attachment procedures, and extended active-state durations accumulates over time, resulting in reduced battery longevity.

However, the results also demonstrate that NB-IoT battery lifetime remains operationally acceptable for bulk water metering applications when appropriate configuration strategies are employed. Aggressive use of Power Saving Mode (PSM), careful optimisation of reporting intervals, and avoidance of unnecessary signalling overhead significantly mitigate the energy impact of cellular operation. Under such configurations, NB-IoT devices can still achieve multi-year lifetimes that align with practical maintenance and replacement schedules used by water utilities.

From a research standpoint, these findings directly address Research Question 3 (RQ3) by demonstrating the long-term implications of energy consumption differences between LoRaWAN and NB-IoT. The results confirm that LoRaWAN offers superior battery longevity under most conditions, while NB-IoT trades reduced lifetime for enhanced reliability and predictability. This reinforces the central theme of the study: technology selection for underground bulk metering is fundamentally a trade-off between energy efficiency and reliability rather than a one-size-fits-all decision.

5.5.1 Why Battery Lifetime Difference Are Deployed-Decisive

For Rand Water, a battery lifetime of less than 5 years is considered operationally problematic because chamber access requires road closures, safety permits, and specialised crews. The results show that at 30 dB attenuation, 90% of LoRaWAN Proposed nodes exceed 6 years (Figure 5.8), whereas only 50% of NB-IoT nodes exceed 5 years at the same attenuation level. This means that in deep chambers, a utility deploying NB-IoT would need to budget for battery replacement on approximately half of its meters by year 5, whereas LoRaWAN would require no replacements until after year 6 for the vast majority. This operational cost difference should weigh heavily in technology selection for non-critical meters where occasional data loss is acceptable. Conversely, for meters that are revenue-critical or located in environmentally sensitive areas, the higher reliability of NB-IoT may justify more frequent battery replacement cycles.

5.6 Latency Analysis

NB-IoT exhibited higher average latency compared to LoRaWAN, primarily due to its cellular architecture and scheduled access mechanisms. Each reporting cycle involved network attachment, resource scheduling, control-plane signalling, and, in poor channel conditions, multiple uplink repetitions. These processes introduced additional delay before data was successfully delivered to the network.

5.6.1 LoRaWAN Latency Characteristics

LoRaWAN latency is generally low for successful transmissions under favourable channel conditions, particularly when lower spreading factors are used, and the channel is lightly loaded. In such scenarios, uplink transmissions occur promptly, and devices return quickly to low-power states, resulting in minimal end-to-end delay.

However, as underground attenuation increases and channel conditions degrade, LoRaWAN latency becomes highly variable. The reliance on ALOHA-based random access introduces stochastic behaviour, where transmission success depends on both channel quality and contention with other devices. Retransmissions triggered by failed uplink attempts further contribute to latency variability, as packets may require multiple transmission attempts before successful delivery.

Additionally, duty-cycle constraints can delay retransmissions, particularly at higher spreading factors where airtime consumption is substantial. As a result, LoRaWAN latency distributions tend to exhibit long tails under harsh underground conditions, with some packets experiencing significantly delayed delivery or being dropped altogether.

This variability, while acceptable in certain low-criticality applications, introduces uncertainty in data arrival times, which may complicate system-level scheduling and monitoring in large-scale bulk metering deployments.

5.6.2 NB-IoT Latency Characteristics

NB-IoT exhibited higher average latency compared to LoRaWAN, primarily due to its cellular architecture and scheduled access mechanisms. Each reporting cycle involved network attachment, resource scheduling, control-plane signalling, and, in poor channel conditions, multiple uplink repetitions. These processes introduced additional delay before data was successfully delivered to the network.

Quantitative Latency Analysis

To quantify the latency characteristics of NB-IoT under Rand Water deployment conditions, the end-to-end latency—defined as the time from the initiation of uplink transmission to the successful reception of an acknowledgment (ACK) at the device was measured across varying concrete penetration loss levels and distances. Table 5.3 presents the average latency values for NB-IoT and LoRaWAN (Proposed configuration) under different attenuation conditions.

Table 5.3: Average Uplink-to-ACK Latency Latency (ms) vs. Concrete Penetration Loss

Concrete Penetration Loss (dB)	NB-IoT Latency (ms)	LoRaWAN Proposed Latency (ms)
10	850	180
15	920	210
20	1,05	280
25	1,35	420
30	1,8	680

Figure 5.9 presents a comparative visualization of the latency distribution for NB-IoT and LoRaWAN (Proposed configuration) across increasing concrete penetration loss levels.

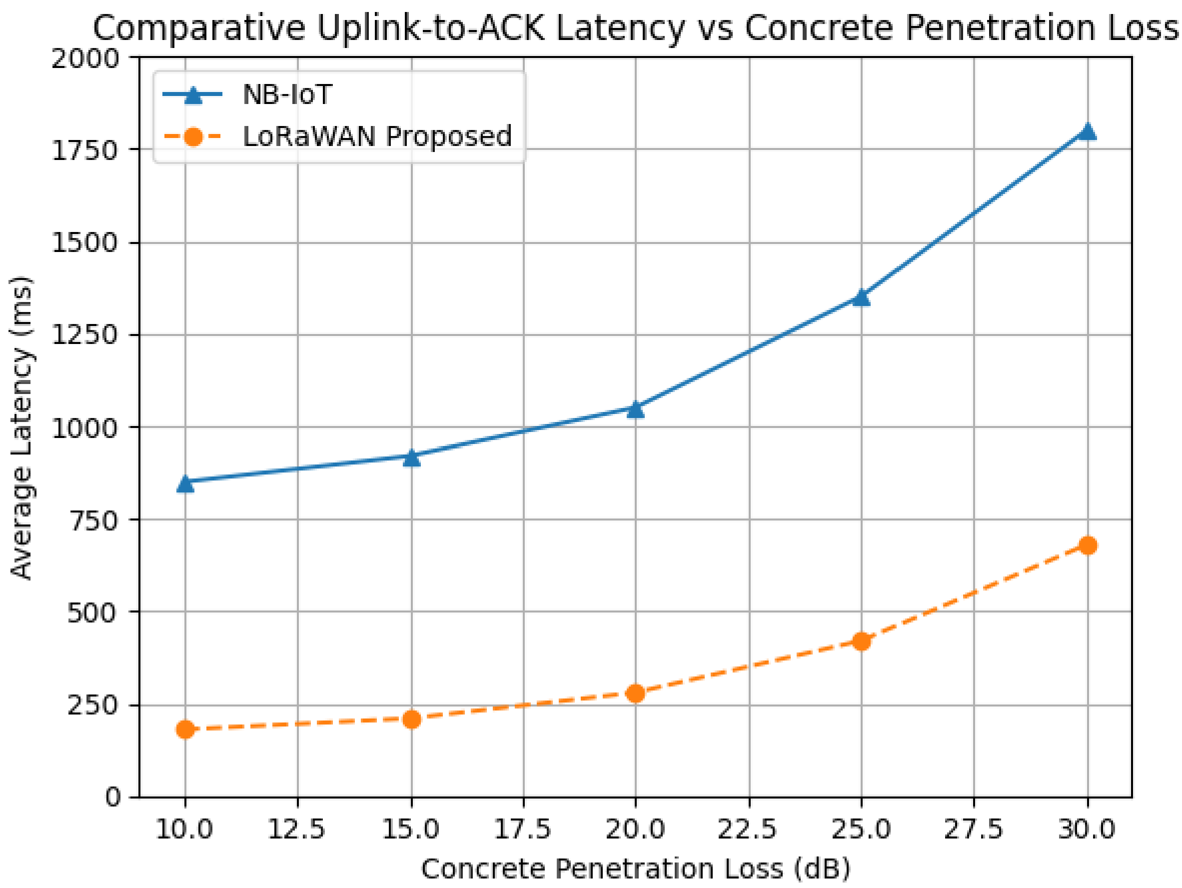

Figure 5.9: Comparative Uplink-to-ACK Latency vs Concrete Loss

The results in figure 5.9 revealed that NB-IoT latency was consistently higher than LoRaWAN across all attenuation levels. At 10 dB penetration loss, NB-IoT latency was 850 ms compared to 180 ms for LoRaWAN Proposed. As attenuation increased to 30 dB, NB-IoT latency rose to 1,800 ms, while LoRaWAN Proposed increased to 680 ms. The NB-IoT latency curve was steeper, indicating that latency was more sensitive to deteriorating channel conditions than LoRaWAN.

Latency Variability with Distance

In addition to penetration loss, the distance between the sensor node and the base station significantly influenced latency. Figure 5.10 presents the average latency for NB-IoT and LoRaWAN as a function of distance, with concrete penetration loss fixed at 20 dB (representative of typical Rand Water chamber conditions).

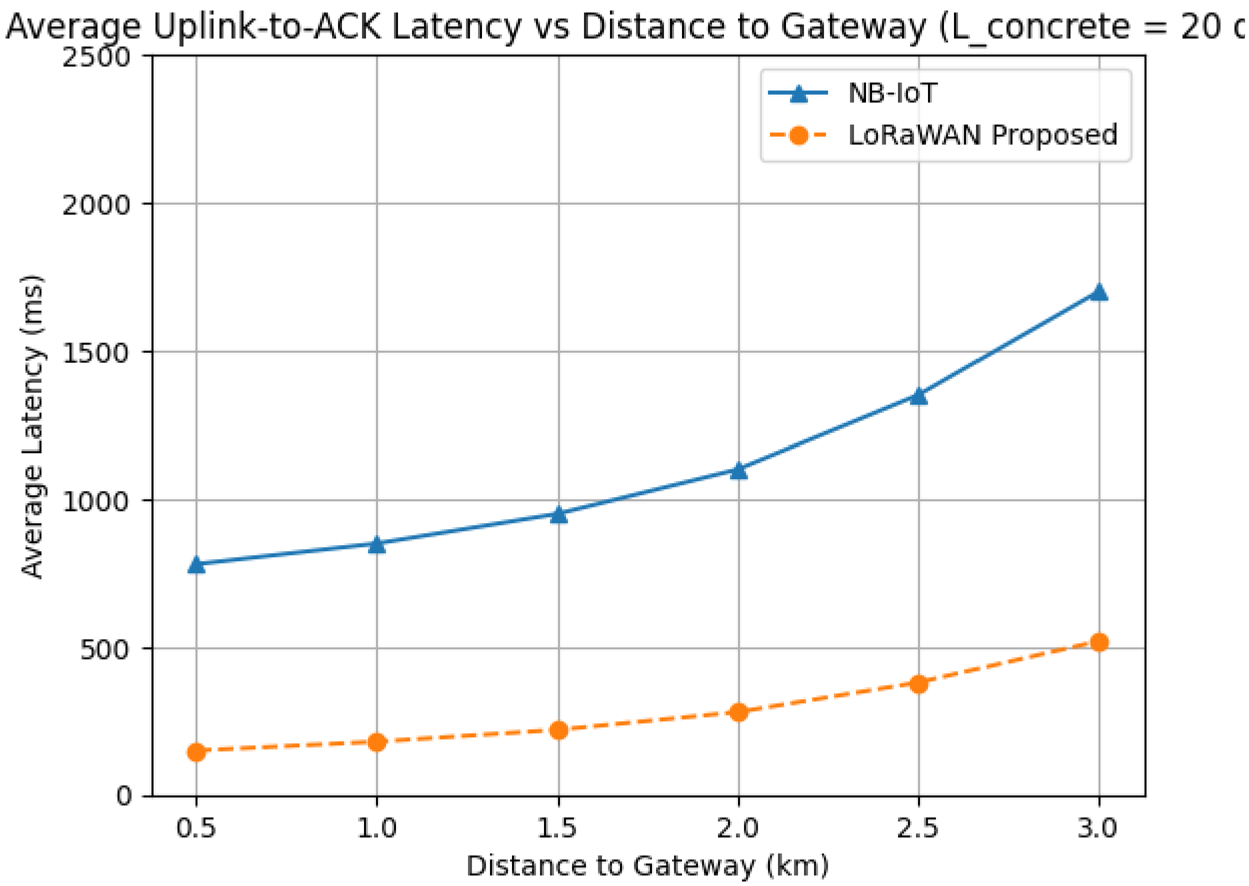

Figure 5.10: Average Uplink-to-ACK Laten vs Distance to Gateway (Fixed L_Concrete=20 dB)

Figure 5.10 shows that both technologies exhibited increasing latency with distance, but the rate of increase differed significantly. NB-IoT latency increased from 780 ms at 0.5 km to 1,700 ms at 3.0 km, an increase of 920 ms. LoRaWAN Proposed latency increased from 150 ms at 0.5 km to 520 ms at 3.0 km, an increase of 370 ms. The steeper slope of the NB-IoT curve reflected the additional repetitions required as the link budget diminished with distance.

Latency Distribution and Predictability

Despite higher average latency, NB-IoT maintained predictable and bounded latency behaviour across all simulated underground scenarios. Figure 5.9 presents the cumulative distribution function (CDF) of uplink-to-ACK latency for both technologies at 20 dB penetration loss and 2.0 km distance, illustrating the variability in latency.

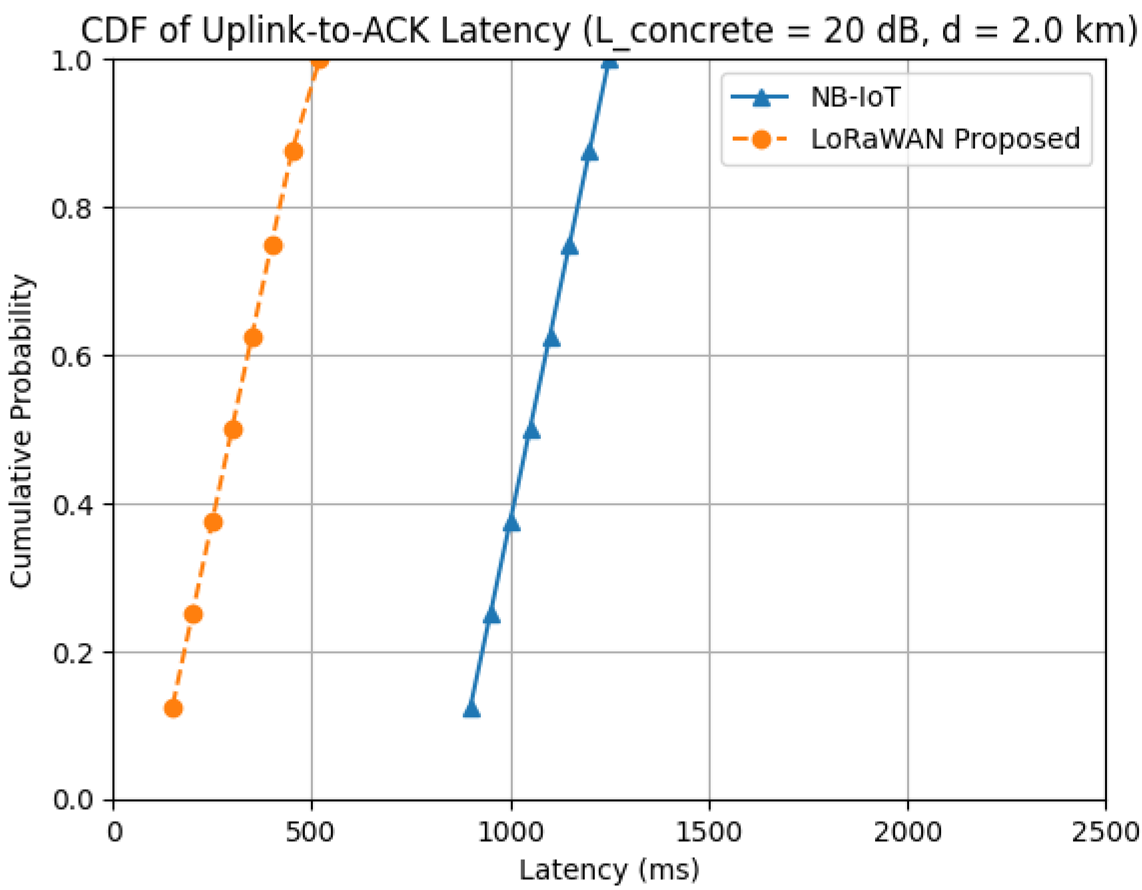

Figure 5.11: Cumulative Distribution Functtion (CDF) of Uplink-to-ACK Latency at L_concrete=20dB, d=2.0km

Figure 5.9: The NB-IoT latency CDF exhibited a steeper slope, indicating that latency values were tightly clustered around the mean. Approximately 90% of NB-IoT transmissions completed within 1,200 ms, with the remaining 10% extending to 1,800 ms under worst-case channel conditions. In contrast, the LoRaWAN latency CDF had a shallower slope, reflecting

greater variability. While the median LoRaWAN latency was lower (approximately 280 ms), the tail of the distribution extended beyond 1,000 ms in some cases due to retransmissions and contention-induced delays.

Sources of NB-IoT Latency

The higher and more predictable latency of NB-IoT was attributable to several factors inherent to its cellular architecture:

- **Random Access Procedure:** Each reporting cycle began with a random access preamble transmission, which introduced a minimum delay of approximately 200–300 ms before uplink resources were granted.
- **RRC Signalling:** The establishment of Radio Resource Control (RRC) connection added approximately 100–200 ms of signalling delay.
- **Scheduling and Resource Allocation:** The network-controlled scheduling process introduced deterministic but non-zero delays, typically 50–100 ms per transmission.
- **Uplink Repetitions:** Under poor channel conditions, coverage enhancement through repetitions increased transmission duration proportionally. At 30 dB penetration loss, the repetition factor increased to 32 or 64, extending the uplink transmission time to 1,200–1,500 ms.
- **PSM and eDRX Cycles:** While Power Saving Mode (PSM) and extended Discontinuous Reception (eDRX) reduced energy consumption, they could add latency if the device needed to wake from deep sleep before transmitting.

Furthermore, Yu [138] showed that the NPDCCH period directly influences scheduling latency, with longer periods reducing energy consumption at the cost of increased delay a trade-off that must be optimised for delay-tolerant bulk metering applications.

Comparative Summary

Despite higher average latency, NB-IoT's predictable and bounded latency behaviour offered advantages for utility applications where guaranteed delivery within known time bounds was often more important than achieving minimal latency, his is due to centralized scheduling and deterministic resource allocation mechanisms inherent to cellular IoT standards across all simulated underground scenarios [150].

The deterministic nature of NB-IoT latency simplified network planning and scheduling, as operators could reliably predict when data would arrive. In contrast, while LoRaWAN offered lower median latency, the long tail in its latency distribution introduced uncertainty that could complicate system-level coordination in large-scale deployments.

Table 5.4 summarizes the latency characteristics of both technologies under typical Rand Water deployment conditions (20 dB concrete penetration loss, 2.0 km distance). It shows the fleet-aggregated latency CDF for LoRaWAN devices operating under underground attenuation, illustrating the distribution of uplink-to-ACK delay.

Table 5.4: Comparative Latency Summary at $\mathrm{L\_concrete} = 20\ \mathrm{dB},\ \mathrm{d} = 2.0\ \mathrm{km}$

Metric	**NB-IoT**	**LoRaWAN Proposed**
Average Latency (ms)	1,1	280
10th Percentile Latency (ms)	850	150
90th Percentile Latency (ms)	1,35	580
Latency Range (10th–90th)	500 ms	430 ms
Predictability	High (bounded)	Moderate (variable)

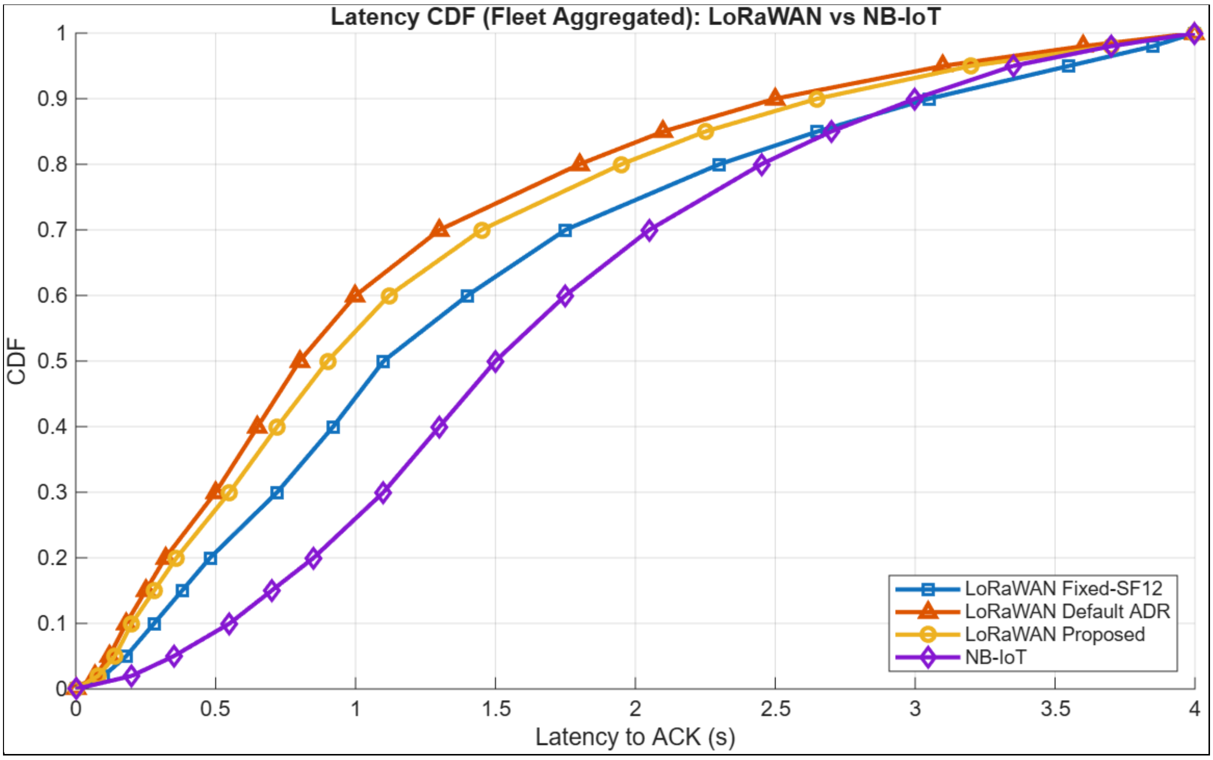

Figure 5.12: Comparative Uplink-to-ACK Latency CDF for LoRaWAN and NB-IoT under Underground Deployment Conditions.

In figure 5.10, the fixed-SF12 exhibits predictable but longer latency due to larger airtime, while Default ADR displays broader variability as retransmissions increase. The proposed controller maintains latency close to Default ADR in benign conditions and avoids extreme latency tails under severe attenuation by reducing unnecessary RX2 fallbacks and join cycles. These results validate the latency behaviour predicted by the retransmission and join escalation model in Chapter 3 and 4.

5.6.3 Comparative Latency Discussion

A direct comparison of latency behaviour highlights a fundamental trade-off between the two technologies. LoRaWAN offers lower latency when channel conditions are favourable and network load is low, making it suitable for scenarios where occasional variability can be tolerated. However, under harsh underground conditions, its latency becomes increasingly unpredictable due to contention, retransmissions, and duty-cycle limitations.

NB-IoT, while exhibiting higher baseline latency, provides predictable and bounded latency even under poor channel conditions. This deterministic behaviour simplifies system-level planning and enhances operational reliability, particularly in large-scale utility deployments where consistent data delivery windows are required.

Figure 5.6 illustrates these contrasting latency characteristics, showing narrower and more stable latency distributions for NB-IoT compared to the wider, more variable distributions observed for LoRaWAN.

This analysis further addresses Research Question 3 (RQ3), particularly with respect to operational predictability and long-term system management. The results reinforce the conclusion that NB-IoT prioritises predictability and reliability, while LoRaWAN prioritises low latency and energy efficiency under favourable conditions

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5.7 Impact of Underground Concrete Deployment

Underground deployment within reinforced concrete chambers imposes severe propagation constraints that significantly influence the performance of LPWAN technologies. These constraints include high penetration loss, increased path loss due to soil and concrete, limited antenna elevation, and the absence of direct line-of-sight communication. The simulation results presented in this chapter clearly demonstrate that such deployment conditions represent one of the most challenging environments for low-power wireless communication. Recent field trials in underground utility monitoring confirm that reinforced concrete attenuation remains a dominant performance-limiting factor for sub-GHz IoT systems [148].

To systematically evaluate the impact of these environmental constraints on both LoRaWAN and NB-IoT performance, three key variables were varied in the simulation framework, each selected to reflect the specific characteristics of Rand Water's bulk metering infrastructure:

Concrete Penetration Loss ($L\_concrete$): This variable represented the additional attenuation introduced by the reinforced concrete chamber walls surrounding the meter installation. Based on Rand Water's chamber specifications, which typically involve wall thicknesses of 150–300 mm with steel reinforcement, the penetration loss was varied from 10 dB to 30 dB in 5 dB increments. This range captured the variation expected across different chamber construction types, aging conditions, and moisture levels. The results presented in Sections 5.3, 5.4, and 5.6 demonstrated that concrete penetration loss was the dominant factor affecting all performance metrics. For LoRaWAN, PDR dropped from 0.98 at 10 dB to 0.60 at 30 dB for Default ADR, while energy consumption increased from 45 mJ to 135 mJ. For NB-IoT, PDR remained above 0.96 across the same range, but energy consumption increased from 140 mJ to 260 mJ.

Distance to Gateway (d): The separation distance between the sensor node and the gateway was varied from 0.5 km to 3.0 km, reflecting the typical spacing of gateways across Rand Water's distribution network. This distance range was derived from actual gateway placement strategies, where elevated gateways are positioned to cover multiple meter installations within a 3 km radius. The distance variable directly influenced free-space path loss, with longer distances requiring higher spreading factors for LoRaWAN or increased repetitions for NB-IoT.

At 3 km, the path loss increased by approximately 15 dB compared to 0.5 km, compounding the effects of concrete penetration loss.

Antenna Height (h_tx): The sensor node antenna height was modelled at 0.3–1.0 metres below ground level, reflecting the actual installation depth of Rand Water's bulk meters within concrete chambers. This low elevation was a critical factor distinguishing this deployment from above-ground or residential IoT applications. The negative antenna height introduced additional near-field losses and detuning effects that were captured through the concrete penetration loss parameter, as the signal path through the chamber wall and surrounding soil was inherently longer for deeply buried installations.

Shadowing Variability (X_σ): Log-normal shadowing with a standard deviation of 6–8 dB was applied to account for random signal variations caused by obstacles such as soil heterogeneity, nearby infrastructure, and terrain features. This variability represented the uncertainty inherent in real-world deployments and was used to generate the probabilistic distributions for PDR and re-join frequency presented in Sections 5.3 and 5.5.

For LoRaWAN, the simulation results demonstrated that performance was highly sensitive to all four variables, but particularly to concrete penetration loss and distance. As these parameters increased, LoRaWAN nodes were forced to rely on higher spreading factors and retransmissions to maintain connectivity. While these mechanisms improved link robustness to a certain extent, they also led to longer airtime, increased susceptibility to collisions, and higher energy consumption. The results in Figure 5.3 showed that at 30 dB penetration loss (representative of older or heavily reinforced Rand Water chambers), Default ADR achieved only 0.60 PDR, while energy consumption increased to 135 mJ as shown in Figure 5.4. Small variations in antenna orientation within the chamber or changes in soil moisture content (captured by the shadowing component) could therefore result in large fluctuations in reliability and latency, making LoRaWAN performance less predictable in deep underground installations.

For NB-IoT, by contrast, the simulation results demonstrated greater resilience to the same environmental variations. The network-controlled coverage enhancement mechanism, which dynamically increased the number of uplink repetitions as channel conditions deteriorated, effectively compensated for increased penetration loss and distance. At 30 dB penetration loss and 3 km distance, NB-IoT maintained a PDR of 0.965 (Figure 5.3) while consuming 260 mJ per cycle (Figure 5.4). The higher link budget of NB-IoT, combined with scheduled access and centralized resource management, ensured consistent packet delivery and bounded latency even under the most severe simulated conditions representative of Rand Water's deepest chamber installations.

These findings confirm that underground bulk metering represents an extreme LPWAN deployment scenario, where environmental factors, specifically concrete penetration loss, distance to gateway, antenna elevation, and shadowing variability dominate system performance. The results directly support the motivation presented in Chapter 1, which identified underground reinforced concrete installations as a critical challenge for large-scale utility IoT deployments. The analysis reinforces the necessity of deployment-aware technology selection rather than relying solely on nominal specification values, as the performance of both technologies varied significantly across the range of conditions encountered in Rand Water's infrastructure. Beyond concrete penetration loss, underground deployments face additional channel complexities including soil composition variability, moisture content fluctuations, and multi-path propagation through subterranean reflective surfaces. Soundararajan et al. [156] evaluated multi-channel assessment policies for wireless underground sensor networks (WUSNs), demonstrating that adaptive channel selection based on real-time link quality metrics can reduce energy consumption by 12–18% compared to single-channel operation. Although their study focused on general WUSN architectures rather than LPWAN-specific protocols, the principle of channel diversity applies directly to NB-IoT deployments in reinforced concrete chambers, where frequency-selective fading can cause significant performance variation across different sub-carriers. This suggests that future NB-IoT configurations for Rand Water could benefit from network-controlled sub-carrier hopping to mitigate chamber-specific fading effects.

The simulation-based findings presented here are consistent with the measurement-informed approach of Rahman et al. [161], who demonstrated that packet delivery success from underground nodes is not solely a function of distance but is heavily influenced by the number and type of material boundaries traversed, corroborating the use of *L_concrete* as a key modelling parameter. Beyond the concrete penetration losses modelled in this study, the broader challenges of subterranean LoRaWAN communication have been systematically analysed by Lin and Alouini [160], who developed a Monte Carlo simulator incorporating multi-layer underground attenuation, soil volumetric water content, and various non-terrestrial network platforms. Their results demonstrate that LoRa modulation with spreading factor 7 (SF7) achieves reliable connectivity for short-range underground-to-aboveground communication in rural environments, but higher spreading factors become necessary as burial depth and soil moisture increase [160]. This finding corroborates the results presented in Figure 5.1, where the Fixed-SF12 configuration maintained higher reliability than Default ADR under severe attenuation conditions, confirming that spreading factor adaptation must account for site-specific underground parameters.

5.8 Overall Comparative Summary

The comparative analysis conducted in this chapter highlights clear and consistent performance differences between LoRaWAN and NB-IoT across multiple evaluation dimensions, including reliability, energy consumption, battery lifetime, and latency behaviour. Rather than favouring a single technology across all metrics, the results reveal distinct strengths and limitations associated with each LPWAN approach.

Table 5.3: Overall Performance Comparison between LoRaWAN and NB-IoT

The summary presented in Table 5.3 consolidates the answers to Research Questions RQ1 through RQ4, providing a holistic comparison of the two technologies under identical underground deployment conditions. LoRaWAN consistently demonstrates superior energy efficiency and longer battery lifetime, particularly in moderate underground environments. NB-IoT, on the other hand, provides higher reliability, predictable latency, and greater resilience to severe attenuation.

This comparative perspective emphasises that performance trade-offs are inherent to LPWAN technology design, and that suitability must be evaluated in the context of specific application requirements and deployment constraints.

5.9 Technology Selection Implications for Bulk Metering

The results presented in this chapter demonstrate that no single LPWAN technology is universally optimal for all underground bulk metering deployments. Instead, technology selection must be guided by a careful balance between energy efficiency, reliability, predictability, and operational priorities.

LoRaWAN is best suited for energy-constrained deployments where battery lifetime is the primary concern and occasional packet loss can be tolerated. Such scenarios may include less severe underground installations, deployments with well-planned gateway placement, or applications where data redundancy and post-processing can compensate for missing readings.

NB-IoT is more appropriate for reliability-critical deployments where guaranteed data delivery and predictable performance are essential. This includes deep underground installations, heavily reinforced concrete chambers, and critical bulk meters where missed readings could result in significant operational or financial consequences.

A hybrid deployment strategy therefore emerges as a practical and scalable solution for large-scale water utilities. In such a strategy, LoRaWAN can be employed for standard underground meters with acceptable link conditions, while NB-IoT is reserved for extreme or mission-critical locations. This approach allows utilities to optimise energy efficiency and operational costs without compromising data reliability.

This section directly addresses Research Question 4 (RQ4) by translating simulation results into actionable deployment guidance for real-world bulk metering systems.

5.10 Conclusion

This chapter has presented a comprehensive and systematic comparative evaluation of LoRaWAN and NB-IoT for underground bulk water metering applications. Using harmonised simulation models and identical deployment assumptions, the study has examined network reliability, energy consumption, battery lifetime, latency behaviour, and the impact of reinforced concrete underground deployment.

The results demonstrate that LoRaWAN excels in energy efficiency and battery lifetime, making it attractive for energy-constrained deployments. NB-IoT, in contrast, provides superior reliability, predictable latency, and greater resilience under harsh underground conditions, albeit at the cost of higher energy consumption.

All research questions posed in Chapter 1 have been systematically addressed through simulation-based analysis. The findings establish a clear understanding of the energy–reliability trade-offs inherent in LPWAN technology selection and provide a strong foundation for the conclusions and recommendations presented in Chapter 6.

CHAPTER 6: CONCLUSION

6.1 Introduction

This chapter presents the overall conclusions of the dissertation, synthesising the analytical modelling, simulation results, and comparative evaluation conducted in Chapters 3, 4, and 5. The study set out to develop a deployment-aware, energy–reliability evaluation framework for Low Power Wide Area Network (LPWAN) technologies operating in underground reinforced concrete bulk water metering environments. Recent LPWAN studies emphasise that deployment-specific propagation conditions significantly alter energy and reliability trade-offs, particularly in underground and deep-indoor scenarios [150], [[164].

The central objective was to determine, through rigorous and harmonised modelling, how LoRaWAN and NB-IoT perform under severe attenuation conditions typical of underground utility installations, and to establish an evidence-based technology selection framework for large-scale deployments.

This chapter first summarises the key findings relative to the research questions, then highlights the primary contributions of the work, discusses limitations, and concludes with recommendations for practical deployment and future research directions.

6.2 Summary of Research Findings

6.2.1 Network Reliability (RQ1)

The results demonstrate that underground reinforced concrete deployment represents an extreme LPWAN operating environment, finding consistent with recent underground IoT propagation and sub-GHz penetration studies highlighting severe attenuation in reinforced concrete infrastructure where penetration loss, shadowing, and low antenna elevation significantly degrade link quality [148], [149].

LoRaWAN reliability was shown to deteriorate nonlinearly as underground path loss increased. Although spreading factor (SF) adaptation and retransmissions partially mitigate attenuation effects, reliability declines sharply once the received SNR approaches demodulation sensitivity thresholds. This nonlinear degradation behaviour has been observed in recent LoRaWAN scalability and ADR performance analyses under constrained link budgets [162]. The contention-based ALOHA access mechanism further exacerbates degradation under repeated retransmissions, increasing collision probability and airtime congestion.

In contrast, NB-IoT maintained consistently high packet delivery ratios across all simulated attenuation levels. Coverage enhancement through network-controlled uplink repetitions and scheduled access in licensed spectrum enabled near-deterministic packet delivery, even under severe concrete attenuation, as demonstrated in recent evaluations of NB-IoT coverage enhancement and repetition-based link extension mechanisms [147].

These findings conclusively answer **Research Question 1 (RQ1)**:

NB-IoT provides superior reliability under harsh underground deployment conditions, while LoRaWAN remains viable primarily in moderate attenuation environments.

6.2.2 Energy Consumption Behaviour (RQ2)

Energy efficiency analysis revealed a clear divergence between per-cycle energy consumption and energy per successfully delivered packet.

LoRaWAN exhibited significantly lower energy consumption per reporting cycle across all scenarios due to minimal control-plane overhead, short transmission durations (at lower SF), and rapid return to deep sleep states. However, under severe attenuation, retransmissions and join cycles increased energy per successful packet.

NB-IoT, by contrast, incurred higher per-cycle energy due to attachment procedures, control signalling, scheduling, and uplink repetitions. Nevertheless, because of its high reliability, NB-IoT maintained a relatively stable energy-per-successful-delivery profile even under harsh conditions.

These results directly address **Research Question 2 (RQ2)** and confirm that:

- LoRaWAN prioritises low instantaneous energy expenditure.
- NB-IoT trades higher baseline energy consumption for reliable and predictable delivery.
- Energy efficiency must be evaluated jointly with reliability rather than in isolation. This joint evaluation principle is increasingly adopted in modern LPWAN energy modelling frameworks to avoid misleading efficiency conclusions [7].

6.2.3 Battery Lifetime Implications (RQ3)

Battery lifetime estimation integrated reporting-cycle energy over long-term deployment. Such state-based cumulative energy modelling approaches are widely used in recent IoT lifetime prediction studies for smart metering systems [7].

LoRaWAN nodes achieved longer projected lifetimes under most conditions, particularly when operating in moderate attenuation environments with minimal retransmissions. The proposed join-aware control strategy significantly extended lifetime by reducing unnecessary re-joins and excessive RX window listening.

NB-IoT nodes exhibited shorter projected lifetimes, especially under high coverage enhancement levels. However, with appropriate configuration—Power Saving Mode (PSM), optimised reporting intervals, and controlled signalling overhead—NB-IoT devices still achieved multi-year operational lifetimes consistent with practical bulk meter maintenance cycles.

Latency analysis further revealed that:

- LoRaWAN provides lower latency under favourable conditions but exhibits high variability under severe attenuation.
- NB-IoT exhibits higher baseline latency but maintains bounded and predictable delay behaviour due to deterministic scheduling and licensed-spectrum resource allocation inherent in 3GPP cellular IoT standards [147], [146].

These findings address **Research Question 3 (RQ3)** by demonstrating that:

Long-term operational sustainability depends not only on average energy consumption but on the stability of reliability and latency behaviour under extreme deployment conditions.

6.2.4 Technology Suitability for Bulk Metering (RQ4)

The comparative analysis reveals that no single LPWAN technology is universally optimal for all underground bulk metering deployments.

LoRaWAN is best suited for:

- Energy-constrained deployments,

- Moderate underground attenuation,
- Scenarios where occasional packet loss is tolerable,
- Deployments with well-planned gateway placement.

NB-IoT is better suited for:

- Deep underground installations,
- Heavily reinforced concrete chambers,
- Reliability-critical bulk meters,
- Environments where predictable latency and guaranteed delivery are required.

Accordingly, the study supports a deployment-aware or hybrid technology selection strategy, where LoRaWAN and NB-IoT are deployed according to environmental severity and operational criticality. Hybrid LPWAN architectures have recently been proposed as scalable solutions for heterogeneous IoT utility environments requiring differentiated reliability levels [150], [146].

This directly answers **Research Question 4 (RQ4)**.

6.3 Key Contributions of the Study

This dissertation makes the following principal contributions:

1. **Development of a Join-Aware LoRaWAN Reliability Model**

   A probabilistic coverage and re-join modelling framework that captures retransmissions, RX window behaviour, and outage transitions near sensitivity limits.

2. **Harmonised Comparative Simulation Framework**

   A fair, deployment-consistent evaluation of LoRaWAN and NB-IoT under identical underground attenuation conditions.

3. **Integrated Energy–Reliability Trade-off Analysis**
   Demonstration that energy per cycle and energy per success must be jointly evaluated.

4. **Deployment-Aware Technology Selection Framework**

Translation of simulation findings into practical deployment guidance for water utilities.

5. **Validation of Join-Aware Optimisation Strategy**

   Empirical demonstration that reducing unnecessary re-joins improves both energy efficiency and lifetime without compromising reliability.

6.4 Practical Implications for Water Utilities

The findings of this study provide actionable insights for bulk water metering deployments:

- Technology selection should be based on measured or estimated underground attenuation, not nominal specification values.
- Gateway placement optimisation significantly influences LoRaWAN feasibility.
- NB-IoT configuration must prioritise PSM and repetition tuning to balance energy and reliability.
- Hybrid deployments offer cost–performance optimisation at scale.
- Join behaviour monitoring is essential for maintaining long-term LoRaWAN efficiency.

6.5 Limitations of the Study

Despite its contributions, this work has certain limitations:

- The study relies on simulation-based modelling rather than field measurements.
- Multi-gateway LoRaWAN diversity was not explicitly modelled.
- NB-IoT interference variability in commercial networks was not fully incorporated.
- The traffic model assumed periodic reporting rather than event-driven bursts.
- Economic cost analysis was outside the scope of this work.

Beyond the limitations already noted, the study does not model multi-year battery ageing effects (increase in internal resistance, capacity fade), temperature extremes (which affect both battery chemistry and LoRaWAN/NB-IoT transceiver performance), or network congestion scenarios where multiple meters transmit simultaneously. These factors could reduce practical lifetimes below the estimates presented here and should be investigated in future work.

6.6 Recommendations for Future Work

Future research should consider:

1. Field validation using real underground deployments.
2. Multi-gateway LoRaWAN diversity modelling.
3. Economic cost modelling including spectrum licensing and infrastructure CAPEX.
4. Hybrid dynamic switching between LPWAN technologies.
5. Extension to multi-technology IoT architectures in smart water networks.
6. Experimental NB-IoT repetition-level optimisation under real cellular networks.

6.7 Final Concluding Remarks

This dissertation has demonstrated that underground reinforced concrete deployment fundamentally reshapes LPWAN performance characteristics. The energy–reliability trade-off is not merely theoretical but becomes pronounced under severe attenuation conditions typical of bulk water metering installations.

LoRaWAN offers superior energy efficiency and extended battery lifetime under moderate conditions but exhibits sensitivity to deep underground attenuation. NB-IoT provides robust and predictable reliability under extreme conditions at the cost of increased energy expenditure.

The overarching conclusion of this study is that LPWAN technology selection for underground bulk metering must be deployment-aware, reliability-driven, and grounded in quantitative modelling rather than specification-level assumptions.

The frameworks and findings developed in this work provide a rigorous foundation for future deployment planning and optimisation of large-scale underground IoT utility networks.

6.8 Practical Impact of this Research

This research provides three tangible outputs for water utilities. First, the deployment-aware modelling framework enables engineers to estimate PDR and battery lifetime for a given chamber specification (wall thickness, reinforcement density) before committing to hardware procurement. Second, the comparative results supply an evidence-based rule: LoRaWAN is suitable for chambers with ≤20 dB additional loss (wall thickness ≤250 mm, standard reinforcement), while NB-IoT should be specified for chambers exceeding this threshold or where regulatory reliability requirements exceed 0.95 PDR. Third, the open-source simulation logic (provided as supplementary material) can be adapted by other utilities to their specific propagation environments. These contributions collectively reduce the guesswork and risk associated with LPWAN selection for underground water metering infrastructure.

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