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Khalid Usman

Título: A Weighted Moving Average adaptive technique for LoRa-based networks

Juiz de Fora

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Dissertação apresentada ao Pograma de Pós-Graduação em Ciência da Computação da Universidade Federal de Juiz de Fora como requisito parcial à obtenção do título de Mestre em Ciência da Computação.

Orientador: Prof Dr. André Luiz de Oliveira

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BANCA EXAMINADORA

Prof. Dr. André Luiz de Oliveira - Orientador
Universidade Federal de Juiz de Fora

Prof. Dr. Alex Borges Vieira
Universidade Federal de Juiz de Fora

Prof. Dr. Gleiph Ghiotto de Lima de Menezes
Universidade Federal de Juiz de Fora

Profª. Dra. Kalinka Regina Lucas Jaquie Castelo Branco
Universidade de São Paulo

Juiz de Fora, 08/07/2025.

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“If one day you have to choose between the world and love,
remember: If you choose the world, you’ll be left without love, but
if you choose love, with it you will conquer the world.”
Einstein A.

RESUMO

O surgimento da tecnologia da Internet das Coisas (IoT) com uma ampla gama de aplicações inovadoras, como cidades e casas inteligentes, exige a dependência da comunicação sem fio para coletar e transmitir grandes quantidades de dados. Os recentes avanços na tecnologia sem fio, como as redes de área ampla de baixa potência (LPWAN) e os protocolos de comunicação sub-GHz, como o LoRaWAN, oferecem uma solução eficaz para a conectividade de longo alcance entre dispositivos de IoT com baixo consumo de energia e custos de implantação reduzidos. Embora a tecnologia de modulação LoRaWAN permita adaptar as transmissões com base em parâmetros, por exemplo, a relação sinal-ruído (SNR), à medida que a adoção da tecnologia de comunicação em um determinado espectro de frequência aumenta, a disputa do meio de transmissão e a intensidade da interferência também aumentam. O conceito de Rádio Cognitivo (CR) suporta o ajuste dinâmico dos parâmetros da rede LoRa para mitigar a interferência e o congestionamento da rede. Neste trabalho, é proposta a técnica Weighted Moving Average (WMA) para reduzir o congestionamento de redes de dispositivos IoT que utizam o protocolo LoRa, por meio da melhoria do SNR, minimizando a perda de pacotes. Um experimento controlado foi conduzido em um ambiente de teste de rede de uma universidade para avaliar a viabilidade da técnica de modulação WMA proposta. Os resultados demonstraram que WMA reduziu em 5.65% o tempo de reconfiguração da rede e melhorou em 39.09% o SNR em comparação com Sliding Change e LR-ADR (Long-Range Adaptive Data Rate).

Palavras-chave: Rede LoRa; Internet das Coisas; Weighted Moving Average; Relação sinal-ruído; Mudança deslizante.

ABSTRACT

The rise of Internet of Things (IoT) with a wide range of innovative applications such as autonomous vehicles, smart cities, and smart homes demands reliance on wireless communication to collect and transmit a massive amount of data. Recent advances in wireless technology, such as Low-Power Wide Area Networks (LPWAN) and Sub-GHz communication protocols (e.g., LoRaWAN) have been demonstrated to be effective in supporting long-range (LoRa) connectivity between IoT devices with low power consumption and reduced deployment costs. Although LoRaWAN signal modulation enables adapting transmissions based on parameters (e.g., Signal to Noise Ratio - SNR), as the adoption of the communication technology in a given frequency spectrum increases, the transmission medium dispute and interference also increase. The Cognitive Radio (CR) supports the dynamic adjustment of LoRa network parameters to mitigate interference and network congestion. In this master's thesis, a Weighted Moving Average (WMA) adaptation technique is proposed to reduce network congestion by improving SNR, and minimizing packet loss in LoRa-based networks of IoT devices. A controlled experiment was conducted in a university testbed network environment to evaluate the feasibility of the proposed WMA modulation technique. The results demonstrated that the proposed WMA technique reduced 5.65% the network reconfiguration time, and improved the SNR at 39.09% compared to Sliding Change and LR-ADR (Long-Range Adaptive Data Rate) state-of-the-art techniques.

Keywords: LoRa network; Internet of Things; Weighted Moving Average; Signal to Noise Ratio; Sliding Change.

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ADR	Adaptive Data Rate
BW	Bandwidth
BER	Bit Error Rate
CR	Coding Rate
CSS	Chirp Spread Spectrum
dB	Decibels
dBm	Decibels-Milliwatts
EDs	End Devices
EMA-ADR	Exponential Moving Average-based Adaptive Data Rate
FEC	Forward Error Correction
FSK	Frequency Shift Keying
(GADR)	Gaussian-Based Adaptive Data Rate
IOT	Internet of Things
IP	Internet Protocol
LoRa	Long-Range
LoRaWan	Long Range Wide Area Network
LPWAN	Low Power Wide Area Network
MAC	Medium Access Control
OSI	Open Systems Interconnection
PRR	Packet Reception Rate
RF	Radio Frequency
RSSI	Received Signal Strength Indicator
SDR	Software Defined Radio
SF	Spreading Factor
SNR	Signal to Noise Ratio
SS	Spectrum-Sensing
WMA	Weighted Moving Average

SUMMARY

1 INTRODUCTION

1.1 Context

The rise of Long-Range (LR) communication and Internet of Things (IoT) technologies enables the creation of a wide range of innovative applications in domains such as autonomous vehicles, smart cities,homes,farms, and long-range machine-to-machine communication Lima et al. [2021]. Those applications heavily rely on wireless communication technology to collect and transmit more data to a central server for further analysis. Since communication is needed for the massive adoption and deployment of IoT applications [Lima et al., 2021], recent advances in LR wireless communication technologies such as Low Power Wide Area Networks (LPWAN) have attracted the attention of researchers and companies around the world. LPWAN technologies enable IoT applications by providing high coverage with low power consumption [Silva et al., 2021]. Long-Range (LoRa®) [LoRa-Alliance, 2022] technology has been adopted due to its robustness and low power consumption, without compromising signal range and coverage. For this reason, LoRa is a promising alternative physical layer technology for ubiquitous connectivity to outdoor IoT devices Silva et al. [2023b].

LoRa physical radio frequency(RF) modulation technology relies on Chirp Spread Spectrum (CSS) modulation. LoRa modulation technology supports adapting transmissions based on parameters such as carrier frequency, channel bandwidth (BW), spreading factor (SF), coding rate (CR), and/or Signal to Noise Ratio (SNR) Silva et al. [2023b].On the other hand, LoRaWAN considers the LoRa radio as the physical layer, and defines the upper layers and the network architecture [Alliance, 2015a]. Thus, as the adoption of communication technology within a given frequency spectrum increases, the dispute for the transmission medium (i.e., concurrency) and the intensity of interference also increase. This issue reduces the packet delivery probability, and there is a need for using the frequency spectrum to increase the overall network efficiency [Figueiredo and Franco Silva, 2020].

1.2 Motivation and Research Problem

Since LoRa technology operates in three discontinuous frequency bands, specifically 433 MHz, 868 MHz, and 915 MHz, it is more challenging to adopt aggregation channel or channel shift strategies than in IEEE 802.11 networks Perahia and Stacey [2013]. Moreover, inter-symbol interference between channels within one of these frequency bands can be equally harmful to the network due to the use of a spread-spectrum modulation scheme. The concept of CR, supported by current advances in Software Defined Radio (SDR) technologies [Mitola and Maguire, 1999], allows a radio or a system to sense its operational electromagnetic environment and dynamically adjust its operating parameters to maximize throughput, reduce interference, support interoperability, and access secondary markets [Yucek and Arslan, 2009]. Due to the potential use of free spectra for opportunistic communications, which contributes to the massive adoption of IoT applications, research and development on CR technologies have grown exponentially [Mitola and Maguire, 1999; Yucek and Arslan, 2009].

CR-based technologies support adaptive and autonomous spectral awareness (spectrum sensing (SS)), detection of available channels (spectrum decision making), dynamic adjustment of radio operating parameters (spectrum mobility), and concurrent communication (spectrum sharing) Mitola and Maguire [1999] Yucek and Arslan [2009]. In this context, cognitive networks and adaptive exchanges of network operating frequencies become an enjoyable to improve the physical parameters of network quality over time [Figueiredo and Franco Silva, 2020] [Abdelfadeel et al., 2018] [Farhad et al., 2022]. It raises the following research question (**RQ**): How can cognitive radio and adaptive exchange of networks be combined to reduce inter-symbolic interference between channels in LoRa-based networks?

Previous work in this direction includes a linear regression extension of the Adaptive Data Rate (LR-ADR) [Moysiadis et al., 2021] resource allocation mechanism for the network server side to smooth the SNR per gateway and to support LoRa-enabled end devices (EDs) to regain connectivity with the network server faster. Similarly, the Instant Change [Figueiredo and Franco Silva, 2020] adaptive method improves the SNR, bit error rate (BER), and frequency change LoRa network parameters. However, Instant Change only considers the values of the most recent SNR samples of LoRa messages on the 433 MHz and 915 MHz frequencies for decision-making Silva et al. [2023b] Figueiredo and Franco Silva [2020]. We utilize these frequency bands due to the free license bands. Later, the SlidingChange algorithm [Silva et al., 2023a] was proposed to address the limitations of the Instant Change method. Sliding Change considers an average of Wn-1 (Wn represents the size of the sliding window to be used), previous measurements, and the current measurement to smooth out punctual effects and impulsive noise that can occur in the transmission environment. However, the results of the SlidingChange technique demonstrated a small gain in SNR, scoring a reduction of 39.09% on the average SNR compared to Instant Change. Although their benefits exist, existing Cognitive Radio-based techniques have limitations regarding the maintenance of the signal quality in LoRa-based networks operating under dynamic environments subject to interference (noise). Instant Change is sensitive to short-term fluctuations and often triggers unnecessary reconfigurations, degrading performance and increasing power consumption. While sliding change is more stable, it lacks flexibility in the provision of an efficient response time to changing conditions due to its fixed window weight approach. Finally, LR-ADR Moysiadis et al. [2021]operates on the server side and multiple gateways. limited to responding to SNR variations at the single gateway level.

1.3 Research Goals and Contributions

To address the limitations from related work Silva et al. [2023b] Moysiadis et al. [2021] concerning the provision of effective responses to variations in the SNR, and the environmental noise, this study introduces the master's thesis, we propose Weighted Moving Average (WMA) adaptation technique to reduce network congestion, improve SNR, and minimize packet loss in LoRa-based networks at the gateway level, thus improving the overall efficiency of IoT networks and gateways. The proposed WMA technique uses the SNR and weight to smooth short-term variations, reducing unnecessary network reconfigurations and improving availability of the lora network. We proposed the feasibility WMA technique which evaluated in an experimental study that assessed the performance concerning network parameters such as SNR, BER, BW, and frequency against SlidingChange and LR-ADR was chosen because it is another state-of-the-art cognitive radio-based technique for reconfiguring LoRa-based IoT networks. The experiment was conducted in a controlled testbed environment to measure SNR at the gateway level in a LoRaWAN-based network, packet loss rates, and network reconfiguration efficiency against SlidingChange and LR-ADR techniques.

The results demonstrated that the proposed WMA adaptive technique may contribute to improving signal quality by enhancing the average SNR received at the gateway via smoothing short-term fluctuations using a dynamically weighted approach. It also demonstrated the potential of the WMA technique in reducing the Bit Error Rate by optimizing data transmission parameters and minimizing packet loss by reducing reconfigurations of the lora network. The reduction of the number of reconfigurations also contributes to maintaining network stability by reducing the overhead.

1.4 Organization

This dissertation is organized into five chapters. Chapter 2 presents the concepts of LoRa technology, Cognitive Radio, and adaptive communication techniques, and a discussion on related work, needed for the reader to understand the contributions of this research. Chapter 3 describes the design and implementation of the Weighted Moving Average (WMA) adaptation technique. Chapter 4 describes the feasibility evaluation of the proposed WMA adaptation technique in a testbed environment of a university LoRa-based network. Chapter 5 presents the results, which include a comparative analysis of the proposed WMA technique against Sliding and LR-ADR state-of-the-art techniques. Chapter 6 highlights the research findings, their benefits, and limitations, and discusses future research directions.

2 BACKGROUND

This chapter presents the background concepts needed for the reader to understand the context of the research contributions. Section 2.1 provides an overview of LoRa (Long-Range) communication technology. Section 2.2 presents the LoRa Wide Area Network protocol and illustrates LoRaWAN applications. Section 2.3 describes LoRa modulation parameters. Section 2.4 presents the LoRaWAN architecture. Section 2.5 describes adaptive techniques in LoRa-based networks. Section 2.6 presents a discussion on related works.

2.1 LoRa Technology

LoRa is a modulation technique derived from Chirp Spread Spectrum (CSS) technology, initially developed by Cycleo of Grenoble, France, and subsequently acquired by Semtech Corporation, a notable supplier of analog and mixed-signal semiconductors. The LoRa modulation technique is pivotal in the physical layer to facilitate LoRa wireless communications networks [Cycleo, 2020]. The features of LoRa maintain communication over extended distances with minimal power consumption, making it particularly advantageous for various wireless applications Haxhibeqiri et al. [2018] Silva et al. [2023b]. LoRa technology employs a unique method known as CSS, which is combined with Forward Error Correction (FEC) to enhance the reliability and range of communications, and CSS uses chirp spread spectrum signals whose frequency increases or decreases with time [Alliance, 2025]. LoRa key features are detailed in the following:

- **Long Range Communication:** LoRa enables long-range communication, typically 15–20 km in rural areas and 2–5 km in urban environments Haxhibeqiri et al. [2018] Ramesh et al. [2020]. It is supported by the strength of CSS modulation and its low sensitivity to noise across different frequency bands.

- **Low Power Consumption:** LoRa is optimized for low power consumption, facilitating to enabling devices to operate for 5 to 10 years on a single battery, an essential feature for remote applications. where frequent battery replacement is impractical Haxhibeqiri et al. [2018] Silva et al. [2023b].

- **Robustness in Adverse Conditions:** LoRa operates in unlicensed frequency bands, Such as 433 MHz and 915 MHz Alliance [2015b] Haxhibeqiri et al. [2018], providing a cost-effective solution for global wireless applications. Its intense signal penetrates through walls and buildings, ensuring reliability in dense indoor environments.

- **Scalability and Data Rate Adjustment** A key advantage of LoRa technology is its adaptable data rate, which can be tuned through parameters such as SF, BW, and CR Moysiadis et al. [2021]. Higher SF values increase communication range and reliability at the cost of reduced data rate, while lower SF values enable faster data transmission, making them suitable for time-sensitive applications Silva et al. [2023b].

2.2 LoRaWAN Protocol and its Applications

Long Range Wide Area Network (LoRaWAN) is a network protocol developed by the LoRa Alliance, built on top of the LoRa physical layer to enable scalable, low-power communication for IoT applications [Cycleo, 2020] Alliance [2015b] Haxhibeqiri et al. [2018]. LoRaWAN defines the system architecture and communication rules necessary for reliable large-scale deployments. It uses a star-of-stars topology, EDs transmit via single-hop wireless links to one or more Gateways, which forward data to a central network server over standard IP networks, as illustrated in Fig. 1.

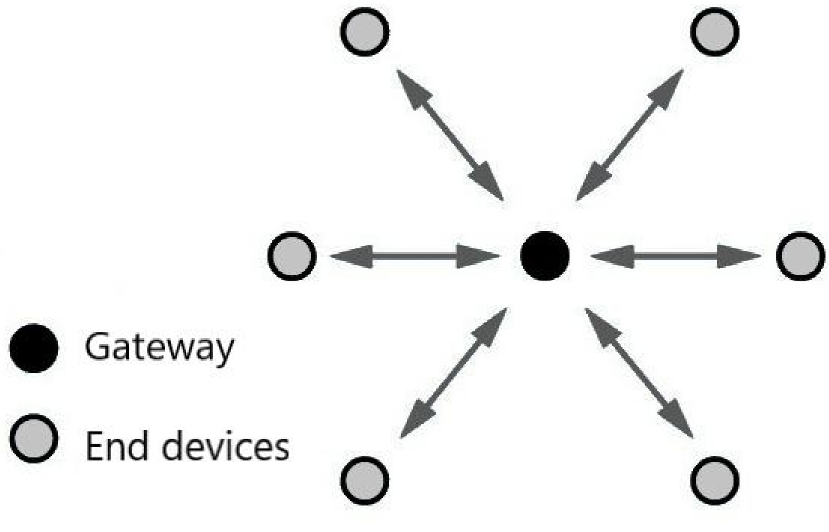

Fig.1. Star topology.

LoRaWAN supports both bi-directional communication and multicast operations, allowing remote management tasks such as over-the-air (OTA) firmware updates Alliance [2015b] Haxhibeqiri et al. [2018]. It incorporates ADR algorithms to optimize transmission power and data rates based on network conditions, significantly enhancing battery life and network capacity [Serati et al., 2022]. LoRaWAN ensures compatibility and scalability across regions. It extends the LoRa physical layer by providing a standardized framework that supports large-scale, low-power, and LoRa IoT deployments, thereby accelerating the global demands of IoT ecosystems. LoRaWAN key features include:

- **Network Structure:** LoRaWAN defines the communication protocol and network architecture, while the LoRa physical layer is responsible for establishing the wireless links Alliance [2015b] Haxhibeqiri et al. [2018]. The network uses a star-of-stars topology, in which gateways relay messages between end devices (EDs) and a central network server Ertürk et al. [2019] Haddaoui et al. [2022].

- **Battery Life:** The protocol is designed to optimize the battery life of network devices and minimize the energy required to communicate, which is achieved through efficient communication scheduling that reduces the on-air time.
- **Security:** LoRaWAN emphasizes security with end-to-end encryption, unique network keys for each device, and mutual authentication to ensure secure connections between the network server and devices.
- **Adaptive Data Rate (ADR):** This feature optimizes data rates, airtime, and energy consumption by ADR, transmission power, and repetition rates based on the network conditions or the requirements of the end device.

LoRa and LoRaWAN are widely used in IoT applications across several domains due to their long-range and low-power consumption capabilities. Some typical applications of LoRa and LoRaWAN include IoT applications across the following domains:

- **Smart Cities:** LoRa and LoRaWAN, characterized by LoRa communication and low power consumption, are fundamental to smart city infrastructure. They enable efficient street lighting, waste management, and parking systems by optimizing energy use, monitoring bin levels, and guiding drivers to available spaces. LoRa-enabled sensors facilitate real-time monitoring, while LoRaWAN enhances operational efficiency and fosters sustainable, connected urban environments.
- **Smart Homes and Buildings:** In smart homes and buildings, LoRa technology enhances building management systems by integrating sensors that monitor energy usage, environmental conditions, and security systems. These sensors can help optimize heating, ventilation, and air conditioning (HVAC) systems based on occupancy and weather conditions, improve security through window and door sensors, and manage lighting and other electrical appliances to maximize energy efficiency.
- **Agriculture:** LoRaWAN addresses the challenge of monitoring large, remote areas by enabling cost-effective communication. Key applications include soil moisture monitoring for precision irrigation, enhancing water use efficiency, and crop health monitoring to detect early signs of disease or plant stress, allowing timely interventions. LoRa also supports livestock tracking by monitoring movement and behavior, which helps improve animal well-being and reduce the risk of theft. By leveraging LoRa, farmers can increase operational efficiency, boost yields, and promote sustainability.

- **Industrial Automation:** LoRa technology plays a crucial role in industrial automation, enabling remote monitoring and predictive equipment maintenance. Sensors collect performance data, which is analyzed to predict failures and schedule maintenance, reducing downtime and costs. LoRa also monitors environmental factors such as temperature, humidity, and vibrations, ensuring optimal equipment and worker safety conditions. The remote monitoring enhances operational efficiency and supports health and safety compliance, driving innovative manufacturing advancements.

- **Smart Meters:** In the utilities sector, LoRaWAN facilitates the remote and automated reading of water, gas, and electric meters. This remote data collection capability enables utility providers to monitor consumption accurately and in real-time without requiring manual meter readings. Such applications lead to more accurate billing processes and provide consumers with detailed consumption data, encouraging energy and resource conservation.

- **Environmental Monitoring:** LoRa technology is essential for environmental monitoring, enabling LoRa tracking of air quality and water levels. LoRaWAN-equipped sensors provide continuous data from remote locations, which is crucial for early warning systems in flood-prone areas and pollution monitoring. This timely data supports disaster management planning (preparedness), pollution control, and sustainable resource management, supporting practical environmental protection efforts.

- **Healthcare:** LoRa technology is increasingly applied in healthcare for remote patient monitoring. Wearable devices with LoRaWAN track vital signs like heart rate, blood pressure, and glucose levels, transmitting data to healthcare providers for continuous monitoring, which improves chronic disease management and primary care, reducing hospital visits and healthcare costs.

- **Supply Chain and Logistics:** In the logistics sector, LoRaWAN facilitates supply chain management through asset tracking and inventory management. Sensors can monitor the conditions and locations of goods throughout the supply chain, from warehouses to transportation to final delivery. This monitoring includes tracking sensitive goods' temperature and humidity conditions, such as food and pharmaceuticals, ensuring they are stored and transported safely.

- **Utility and Infrastructure Management:** LoRaWAN supports the management of critical infrastructure bridges, roads, and railways by enabling predictive maintenance and structural health monitoring. Sensors detect and report issues such as cracks, vibrations, and structural weaknesses, facilitating timely interventions that enhance safety and reduce repair costs. The flexibility and scalability of LoRa and LoRaWAN technologies address the diverse demands of modern IoT applications, establishing their crucial role in advancing digital transformation and contributing significantly to the global IoT ecosystem.

2.3 LoRa Modulation and Key Parameters

LoRa modulation technique, developed by Semtech Corporation, is the physical layer of LoRaWAN and uses CSS technology, which offers strong resistance to interference and multipath fading Cycleo [2020] LoRa Alliance [2015]. It employs frequency-varying chirp pulses to enable low-power communication by encoding multiple bits per chirp. Compared to traditional Frequency Shift Keying (FSK), LoRa provides better transmission over long distances and low SNR conditions, making it suitable for various LPWAN applications in urban and remote areas. LoRa modulation parameters are listed in the following:

- **Spreading Factor(SF):** In LoRa modulation, the Spreading Factor determines the ratio between the symbol rate and the chip rate Silva et al. [2023a]. It directly affects the time-on-air, link budget, and communication range. A higher SF increases the duration of each symbol, thereby enhancing receiver sensitivity and improving range and robustness against interference, but at the cost of a lower data rate. However, this increase in signal duration comes with trade-offs: **Reduced Data Rate**: As the SF increases, the data rate decreases because the same amount of data requires more time to be transmitted Moysiadis et al. [2021]. This reduction in data rate limits the volume of data sent over a network in a given time; **Increased Airtime:**, A higher SF lengthens the packet transmission time, which leads to greater energy consumption and shorter battery life Ramli et al. [2020]. However, LoRa's dynamic SF adjustment enables optimization for specific conditions using higher SF for reliable communication in dense environments and lower SF for increased data rates where range is less critical. This adaptability ensures efficient spectrum use and energy management, making LoRa suitable for diverse LPWAN applications; and **Bandwidth (BW)**: In LoRa modulation, it critically influences several aspects of the communication link, including the data rate, resistance to interference, and overall network efficiency LoRa Alliance [2015]. In LoRa technology, BW refers to the frequency band width utilized during transmission. The choice of BW directly affects the modulation rate and the spectral efficiency of the channel.

  Overview of Bandwidth Settings in LoRa: In LoRa systems, common BW settings are 125 kHz, 250 kHz, and 500 kHz. Each BW setting has implications for the performance and applicability of the communication link:

  1. **125 kHz:** Using a smaller BW of 125 kHz decreases the amount of data that can be transmitted per second. This configuration improves the receiver's sensitivity due to the lower noise BW, resulting in a better SNR. This trade-off

benefits LoRa communications by prioritizing signal reliability over data rate Silva et al. [2023a] Moysiadis et al. [2021] LoRa Alliance [2015].

2. **250 kHz and 500 kHz:** Higher BW settings (e.g., 250 kHz, 500 kHz) enable higher data rates, reducing transmission time and energy consumption per bit, which is advantageous for battery-dependent applications requiring fast data transmission. However, wider BWs reduce receiver sensitivity and increase sensitivity to interference, potentially compromising communication reliability in noisy environments.

3. **Regulatory and Application Considerations**: Both regulatory constraints and application-specific requirements influence the selection of BW in LoRa modulation. High BWs support higher data rates but increase interference responsiveness, while lower BWs enhance the network sensitivity and strength, which is ideal for LoRa applications.

4. **Balancing Network Performance**: Efficient BW management is key to optimizing LoRa networks and balancing throughput, range, and power consumption. Dynamic adjustments based on environmental and application needs enhance performance, scalability, and efficiency in diverse IoT systems.

- **Coding Rate (CR):**In LoRa modulation, the CR is a key parameter that enhances the reliability of data transmission by introducing FEC, which helps detect and correct errors caused by noise or interference LoRa Alliance [2015]. This parameter configures the level of superfluity embedded into the transmitted data, enhancing the system's ability to correct errors that may occur during the transmission process due to noise, interference, or signal degradation.

  1. **Function of CR:** In LoRa technology, the CR is defined as the ratio of data bits to the total transmitted bits, which includes both data and redundancy Silva et al. [2023a] LoRa Alliance [2015]. Standard CR values range from 4/5 to 4/8. A CR of 4/5 allocates one-fifth of the transmission to overabundance, meaning one overabundance bit is added for every four data bits. In contrast, a CR of 4/8 implies that half of the transmitted bits are redundant, enhancing reliability at the cost of reduced data throughput.

  2. **Impact of CR on Transmission:**

     A higher CR introduces additional redundancy into the transmitted signal, thereby enhancing the system's error correction capability LoRa Alliance [2015]. This increased redundancy enables the receiver to more effectively reconstruct the original data, even in the presence of significant signal degradation. As a result, a higher CR is especially beneficial in challenging communication environments, such as those with high interference or substantial physical obstacles that may attenuate or delay the signal Moysiadis et al. [2021] Silva et al. [2023a].

However, increasing the CR also required certain trade-offs:

3. **Reduced Payload Throughput:** The proportion of the BW available for actual data payload decreases. This reduction in effective throughput can be detrimental in applications requiring the transmission of large volumes of data within a limited time frame.
4. **Increased Transmission Time:** More extra information leads to more extended message frames for the same data. This increase in transmission time can reduce the overall network capacity as the channel is occupied for extended periods, potentially leading to congestion in dense network deployments.
5. **Elevated Energy Consumption:** For battery-operated devices, the extended transmission times required by higher CR increase power consumption, thus reducing the operational lifespan of the device between charges.
6. **Strategic Application of CR:**

   Optimal CR selection in LoRa systems balances error resilience with data efficiency. Higher CR improves reliability under interference but reduces throughput. Therefore, CR should be customized to environmental conditions, application latency, and power constraints to ensure efficient and robust network performance.

- **Bit Error Rate (BER):**

  BER is a key performance indicator in LoRaWAN, reflecting the accuracy of data transmission. A low BER ensures reliable communication over long distances and in challenging environments, minimizing retransmissions, conserving energy, and enhancing overall network efficiency, which is productive for IoT applications.

  Several key factors impact the BER in a LoRaWAN system:

  1. **SNR:** SNR is a primary factor influencing BER in LoRaWAN. Higher SNR typically results in lower BER by reducing noise interference. LoRa's LoRa capability is primarily attributed to its resilience in low-SNR environments, enabled by robust modulation and coding schemes.
  2. **SF:** In LoRa modulation, the SF affects both the transmission range and the data rate. Higher SF increases the signal's strength against noise and interference, effectively lowering the BER but at the cost of decreased data rates.
  3. **BW:** BW affects the data rate by determining how much information can be transmitted per unit of time, while also impacting the noise level due to the

relationship between BW and signal sensitivity LoRa Alliance [2015] Figueiredo and Franco Silva [2020]. Moreover, BWs reduce the data rate but improve sensitivity and potentially lower the BER by reducing the noise in the network signals.

4. **CR:**In LoRaWAN, the CR introduces additional redundancy into the transmitted data, which enhances the receiver's ability to detect and correct errors. A higher CR increases the strength of the transmission, thus lowering the BER Figueiredo and Franco Silva [2020] Silva et al. [2023a].

Measuring and Reducing BER in LoRaWAN:

1. **Measurement:** BER is typically measured during field tests or simulations to assess the communication quality in different environments and under various network conditions. This measurement helps understand how well the network can handle data transmissions and is crucial for planning and optimization.
2. **Reducing Strategies:**
   a) **ADR:** LoRaWAN employs ADR to optimize data rate, transmission power, and SF according to the network conditions. ADR adjusts these parameters to balance power consumption, range, and BER optimally.
   b) **Error Correction:** Utilizing reliable FEC techniques helps correct errors at the receiver without retransmissions, thereby improving the effective BER.
   c) **Optimal Gateway Placement:** Placing Gateways strategically can enhance coverage and improve signal quality, directly benefiting BER performance.

BER serves as a key factor for assessing LoRaWAN network reliability. Effective management of influencing SNR, SF, BW, and CR ensures data integrity and increases network efficiency, supporting strong and sustainable IoT deployments.

- **SNR:** SNR is a key parameter that quantifies the ratio of signal power to background noise power, usually expressed in decibels (dB). A higher SNR signifies a clearer, more distinguishable signal, which improves transmission quality Silva et al. [2023a] Figueiredo and Franco Silva [2020]. SNR critically impacts link quality in LoRaWAN communication systems, which are optimized for low-power LoRa data transmission. It guarantees the receiver's ability to extract information from the networks in noisy environments. Higher SNR improves decoding accuracy and minimizes BERs, contributing to reliable network operation.

  Communication becomes challenging in a noisy environment, like a crowded room, mirroring low SNR conditions. In contrast, quiet settings enable clearer exchange, similar to high SNR, which illustrates SNR's important role in ensuring reliable, energy-efficient LoRaWAN communication, especially in noisy or remote areas.

  Implications of SNR on Network Dynamics:

  1. **Coverage and Communication Distance:**
     The SNR in LoRaWAN systems is directly correlated with communication range; higher SNR values generally allow for more extended coverage Figueiredo and Franco Silva [2020]. Higher SNR levels enable longer transmission distances,

expanding network coverage, which is critical in environments with limited gateway placement options due to geographical or infrastructural constraints.

2. **Data Rate and Modulation Parameters:**
   LoRaWAN supports variable data rates by adjusting the SF, BW, and CR based on the observed SNR Ratio Silva et al. [2023a]. When the SNR is low, a higher SF is used to enhance signal robustness, which reduces the data rate but improves communication reliability in diverse IoT network conditions.

3. **Energy Consumption:** The operational efficiency of LoRaWAN devices depends on SNR. A low SNR increases the airtime required for transmission, leading to higher energy consumption, whereas a higher SNR reduces airtime, conserving energy and prolonging the device's lifespan Silva et al. [2023a]
   .

SNR Measurement and Network Optimization Strategies:

– **Measurement Techniques:** In LoRaWAN networks, SNR is measured at the gateways receiving signals from IoT devices Silva et al. [2023a] Figueiredo and Franco Silva [2020]. It represents the ratio of signal power to noise power, reflecting the quality of the communication link. These measurements enable optimization of transmission parameters to ensure reliable data delivery. Additionally, they provide valuable insights into individual device performance, aiding network management and troubleshooting.

– **Optimization of Network Infrastructure:** Strategic placement of Gateways based on SNR mapping across the network can optimize overall communication quality and efficiency. Such strategic deployments can enhance the network's SNR, minimizing weak signal areas and maximizing the strength of data transmissions.

SNR in LoRaWAN affects the quality of individual transmissions by influencing signal reliability Figueiredo and Franco Silva [2020]. It also guides network design decisions and operational strategies. Thus, SNR plays a crucial role in both local communication and overall network performance. Effective management and optimization of SNR are necessary for ensuring that LoRaWAN networks deliver reliable and efficient communication capabilities essential for the diverse array of IoT applications they support.

2.4 LORAWAN Architecture

LoRa utilizes a radio frequency modulation technique at the physical layer (Layer 1) of the Open Systems Interconnection (OSI) model for LoRa, low-power communication.

At the same time, LoRaWAN operates at the Medium Access Control (MAC) layer (Layer 2), managing access to the shared communication medium for efficient data transmission. Together, they provide a comprehensive solution for wireless IoT networks. The LoRaWAN network topology follows a star-of-stars configuration, consisting of three key components: (i) network servers, (ii) Gateways, and (iii) end nodes. End nodes communicate with network servers via Gateways, using LoRa or FSK modulation to support various data rates and channel allocations. Network servers manage Gateways via IP, processing data frames sent by end nodes, which are received by Gateways and routed through the server [Alliance, 2015b]. An overview of the LoRaWAN architecture is shown in Fig. 2.

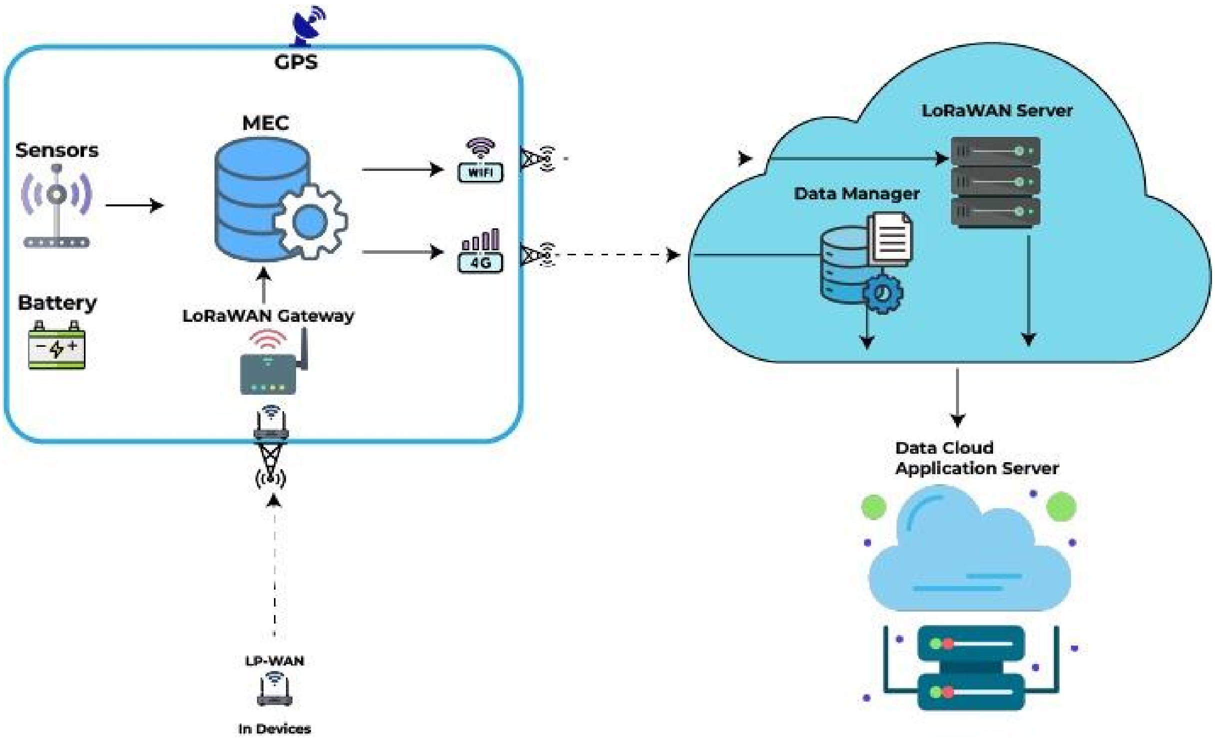

Fig. 2. Architecture of the LoRaWan network.

LoRaWAN is a MAC layer protocol designed to address medium management challenges and reduce network congestion within LPWANs. Devices that implement the LoRaWAN protocol can control a range of advanced features provided by the standard, including:

- **Channel management:** efficient allocation and utilization of frequency resources to improve network performance and minimize interference.
- **Energy Efficiency:** optimized communication schemes that reduce power consumption, extending the operational lifespan of battery-powered EDs.

- **Adaptive Data Rate:** dynamic adjustment of data transmission rates based on prevailing network conditions and link quality, ensuring optimal throughput and reliable communication.
- **Security:** strong cryptographic mechanisms for data security, integrity, and authentication, protecting networks against unauthorized access and cyber attacks.
- **GPS-Free Geolocation:** location tracking and geolocation services that function without relying on GPS signals, enabling effective positioning in environments where satellite-based systems may be unavailable or impractical.

LoRaWAN offers low-power communication for IoT with a scalable star-of-stars topology, which is ideal for managing thousands of battery-powered sensors across large areas. Its energy efficiency improves through ADR and flexible channel management, optimizing power while ensuring the reliability of the network. EDs' connections extend battery life, which is essential for remote IoT applications in industrial, agricultural, and urban settings.

LoRaWAN supports bidirectional communication for real-time control network systems [Haddaoui et al., 2022], with security features like encryption, device authentication, and session key management. Its GPS-free geolocation expands its use in areas where satellite systems are challenging to implement, as shown in Fig. 3.

LoRaWAN's architectural features and operational capabilities align well with the core requirements of IoT networks, such as extensive coverage, low power consumption, scalability, and strong security, making it an essential technology for large-scale deployments in areas like smart agriculture, industrial automation, urban infrastructure, and asset tracking, facilitating cost-effective implementation of interconnected smart devices.

2.5 Adaptive Techniques in LoRa Networks

Adaptive techniques are essential in LoRa networks to improve communication efficiency, reliability, and scalability, particularly in dynamic and heterogeneous environments Silva et al. [2023a] Moysiadis et al. [2021] Figueiredo and Franco Silva [2020]. These methods, such as ADR, instant change, sliding change, and WMA, optimize network performance by addressing signal quality, interference, and device density variations.

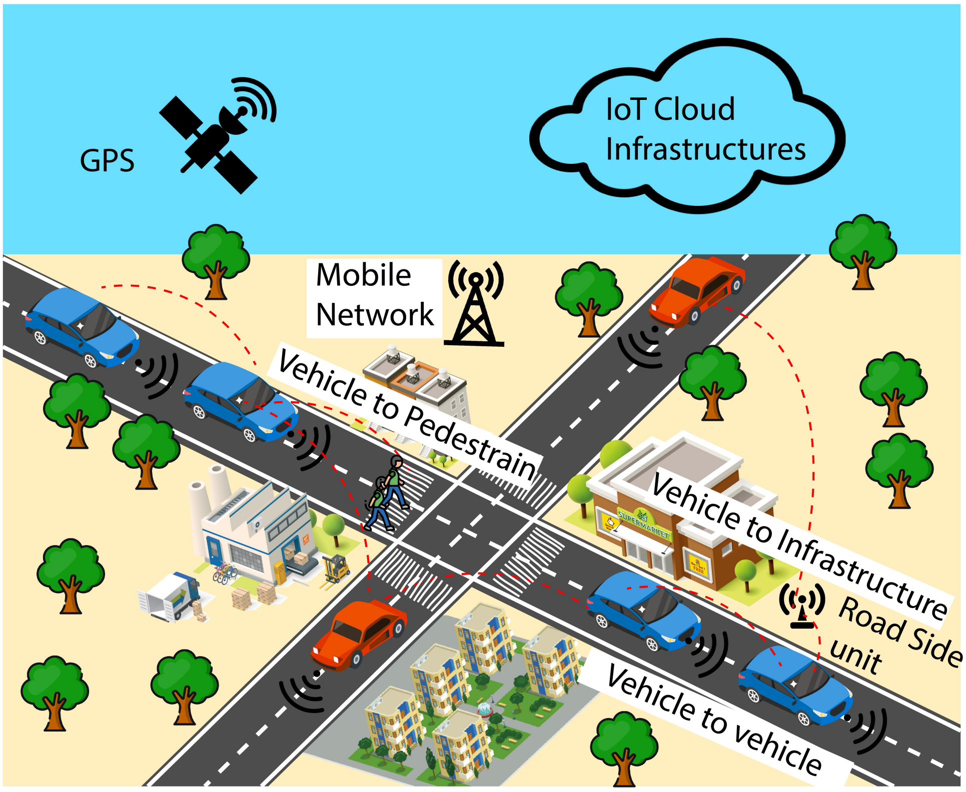

Fig. 3. Sensor network of IOT in the Smart city

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2.5.1 Adaptive Data Rate (ADR)

Adaptive Data Rate (ADR) is a mechanism designed to optimize data transmission rates, reduce airtime utilization, and minimize energy consumption within LoRa networks Moysiadis et al. [2021]. The ADR mechanism controls the following transmission parameters of an end device: SF, BW, and Transmission power.ADR in LoRaWAN reduces energy consumption by adjusting transmission power and data rates according to the distance between a device and the gateway Moysiadis et al. [2021] Figueiredo and Franco Silva [2020]. Closer devices use less power and higher data rates, while distant devices require more power and lower data rates to maintain connectivity. Devices near Gateways use lower SF and higher data rates, while those farther away use higher SF to maintain link quality [Ilarizky et al., 2021]. ADR is effective for static devices under stable Radio Frequency conditions, optimizing power and data rates. However, if Radio Frequency conditions become unstable (e.g., due to device mobility), ADR should be disabled. In LoRaWAN, the choice to enable ADR is made by the end device itself, rather than being controlled by the network or application Moysiadis et al. [2021]. This gives the device autonomy to decide whether ADR is suitable for its operating conditions. The network collects measurements from recent uplink messages to optimize data rates. For example, The Things Stack records the 20 most recent uplinks, including frame counter, SNR, and the number of Gateways [Networks, 2025]. When ADR is disabled, these measurements are discarded, and new ones are collected when ADR is re-enabled. The SNR is calculated as the difference between the measured and required SNR guides adjustments to data rate and transmission power, ensuring efficient communication in lora network [Networks, 2025].

2.5.2 InstantChange

The InstantChange algorithm is an adaptive cognitive technique designed to dynamically adjust LoRa network parameters in real time Figueiredo and Franco Silva [2020]. By rapidly responding to variations in network conditions such as interference, traffic load, or signal quality, it optimizes communication performance without requiring manual reconfiguration. InstantChange adjusts key transmission parameters, frequency, SF, and BW based on the current SNR. The method evaluates network conditions at each moment without relying on historical data Silva et al. [2023a]. After transmitting a set number of packets, it sends control packets to measure SNR for different configurations Silva et al. [2023a]. The configuration that yields the highest SNR is selected for future transmissions. The primary objective of the InstantChange algorithm is to maximize SNR, enhance communication quality, and adapt quickly to changing network conditions. The functional steps of the InstantChange algorithm are detailed in the following:

- **Data Collection:** Continuous monitoring and immediate evaluation of SNR for each received packet to detect deviations from acceptable performance thresholds.
- **Evaluation and Decision Making:** If the SNR drops below a predetermined threshold, indicative of suboptimal communication quality, the algorithm adjusts the transmission parameters.
- **Parameter Adjustment:** Increasing the SF to improve signal validity at the cost of reduced data rate. Switching the operating frequency to a less congested channel. Modifying the BW to adapt the data throughput to current network conditions.

Changes are implemented immediately, affecting all subsequent transmissions, thus ensuring that the device operates under optimal settings given the current environmental conditions. **Technical Analysis: Advantages:** High responsiveness to immediate changes in environmental conditions is crucial in highly dynamic settings where delay in adaptation can lead to communication failures. **Disadvantages:** Frequent reconfigurations may result in elevated power consumption and network instability, as continuous parameter adjustments introduce persistent fluctuations Silva et al. [2023a] Figueiredo and Franco Silva [2020].

Comparative Analysis: In contrast to other state-of-the-art approaches, employing a sliding window approach smooths short-term fluctuations, reducing the need for frequent reconfigurations. This instant change adaptive approach, responds immediately to real-time SNR variations, making it highly suitable for volatile environmental conditions. However, its rapid adjustments may compromise long-term stability when compared to more conservative algorithms. The choice between Instant Change and other adaptive strategies depends on the balance between responsiveness and stability. Future research may explore hybrid models with predictive adjustments based on historical trends to optimize the immediate and long-term performance of LoRaWAN networks.

2.5.3 SlidingChange

Sliding Change, a cognitive mechanism designed to optimize performance parameters in LoRa-based networks, enhances stability and efficiency. Introducing a sliding window approach smooths short-term fluctuations, reducing the need for frequent reconfigurations Silva et al. [2023a]. Sliding Change was evaluated against Instant Change, which makes decisions based solely on immediate data.

The dynamic reconfiguration of network parameters is a critical aspect of SlidingChange. Based on the analysis performed by the sliding window algorithm, SlidingChange can determine the optimal settings for:

– Carrier Frequency: Adjustments in carrier frequency can help avoid interference and optimize the network's frequency use.

– Spreading factor: Modifying the spreading factor affects the data transmission rate and range, balancing throughput with signal robustness.

– Bandwidth: Changing the Bandwidth influences the rate at which data is transmitted, affecting both power consumption and data rate.

These adjustments aim to maintain or improve the SNR, thereby ensuring high-quality communication within the network.By optimizing communication parameters, SlidingChange effectively minimizes packet loss and error rates, both of which are critical for applications that depend on reliable real-time data transmission Silva et al. [2023a].

Performance Evaluation: The effectiveness of SlidingChange is measured against several performance metrics:

– **SNR Improvement:** SNR is a primary indicator of the communication channel quality. Higher SNR values indicate more transparent communication and reduced noise interference.

– **Reduction in Reconfiguration Rates:** By decreasing the frequency of adjustments needed, SlidingChange enhances network stability and reduces the operational overhead associated with reconfigurations.

– **Error Rates:** Monitoring BERs and packet loss rates provides insights into the overall availability of the network. Improvements in these areas indicate more reliable communication capabilities.

Sliding Change outperforms both Instant Change and LR-ADR. While Instant Change risks instability due to its highly reactive nature, Sliding Change applies a sliding window methodology that averages data over time, enabling more consistent parameter adjustments and improving both stability and efficiency Silva et al. [2023a]. Additionally, it reduces overhead and enhances communication reliability in dynamic LoRa IoT networks, leading to improved network performance.

2.6 Related Work

This section provides an overview of existing adaptive techniques applied to LoRa-based networks. The goal is to identify their strengths and limitations in dynamic environments. By analyzing methods such as SlidingChange Silva et al. [2023a] and LR-ADR Moysiadis et al. [2021], we highlight gaps in current approaches. Related research on this topic comprises empirical studies that evaluate the performance and quality attributes of resource allocation strategies in LoRa-based networks.

Related research on this topic comprises (i) empirical studies that evaluate performance and other quality attributes of resource allocation strategies. Ramesh et al. [2020]; Zaman et al. [2024]; Cengiz et al. [2025]; Slabicki et al. [2018]. (ii) proposals of research allocation strategies Valach and Macko [2021]; Silva et al. [2023a]; Moraes et al. [2021]; Ramli et al. [2020] techniques Jeon and Jeong [2020] and Moysiadis et al. [2021]. And (iii) studies reporting both proposals for resource allocation strategies and empirical evaluation results. Valach and Macko [2021]; Figueiredo and Franco Silva [2020]; Moraes et al. [2021]; Perahia and Stacey [2013] and Moysiadis et al. [2021]. The contributions of these studies and a comparative analysis are detailed below.

Research on LoRa-based networks is an active area of study. Focusing on a range of characteristics from scalability to reliability. This research is particularly appropriate in the context of innovative city applications, where these attributes are critical to the effective deployment and operation of IoT systems Ramesh et al. [2020]; Zaman et al. [2024]; Cengiz et al. [2025].

The study by Valach and Macko [2021] introduces a machine learning approach for adapting LoRa parameters to enhance communication efficiency in IoT networks. The study integrated the adaptation of the LoRa@FIIT algorithm, proposed to improve the efficiency for IoT communication. Simulations demonstrate reduced packet collisions, lower energy consumption, and improved reliability, enabling dynamic responses to varying network conditions for enhanced energy efficiency. Experimental results also indicate a substantial reduction in packet collisions among mobile nodes, resulting in decreased channel congestion.

The study by Moraes et al. [2021] proposes an adaptive resource allocation framework based on mixed-integer linear programming (MILP) to identify optimal LoRaWAN parameter configurations, with the objective of minimizing channel occupancy while maximizing packet delivery rates. The proposed framework was benchmarked against heuristic-based resource allocation strategies, which employ practical rules and approximations to allocate resources efficiently, rather than computing exact optimal solutions. Evaluation results confirmed the efficacy of the heuristics, as they achieved performance metrics closely approximating those of the MILP-derived optimal solution, demonstrating their suitability for practical, near-optimal resource allocation in LoRaWAN environments.

Jeon and Jeong [2020] proposed an adaptive mechanism that dynamically adjusts both transmission power and uplink data rate based on real-time performance indicators and observed enhancements in uplink channel conditions. Ramli et al. [2020] proposed an adaptive network to switch between LoRaWAN and IEEE 802.11ac Perahia and Stacey [2013] protocols in situations of lower or higher data transmission demands, respectively. However, their study did not suggest that LoRa's parameters were enhanced in performance. The authors noted that the Packet Error Rate (PER) is considerably higher for IEEE 802.11ac transmissions compared to LoRa. PER quantifies the proportion of data packets that are incorrectly received, serving as a key indicator of communication reliability. In contrast, LoRa's medium- and long-range transmissions exhibit lower PER, ensuring more stable and dependable communication for distant or resource-constrained IoT devices. This observation highlights LoRa's advantage in maintaining reliable data delivery over extended distances relative to IEEE 802.11ac.

The study by Moysiadis et al. [2021] proposes a Linear Regression extension of the Adaptive Data Rate (LR-ADR) resource allocation mechanism for the network server side to smooth SNR per gateway and to support LoRa-enabled EDs to regain connectivity with the network server faster. They conduct an empirical study to evaluate the performance of LR-ADR compared to ADR, EMA-ADR (Exponential Moving Average ADR), and G-ADR (Gradient-based ADR) resource allocation mechanisms. The results indicate that LR-ADR outperforms the other approaches for example instant change, achieving a higher Packet Delivery Ratio (PDR) and lower Energy Consumption per Packet Delivered (ECPD). This means that LR-ADR delivers more packets successfully while using less energy, making it a more reliable and efficient solution compared to ADR, EMA-ADR, and G-ADR. The resource allocation mechanism proposed in this work enables dynamic adjustment of LoRa network performance parameters using a Weighted Moving Average (WMA), which smooths short-term variations, minimizes unnecessary reconfigurations, and optimizes SNR. Our solution primarily targets improvements in SNR, Bit Error Rate (BER), and the number of frequency switches. In contrast, LR-ADR Moysiadis et al. [2021] and EMA-ADR focus mainly on enhancing the Packet Delivery Ratio (PDR) and reducing energy consumption per packet delivered (ECPD). So, both resource allocation mechanisms can be seen as complementary. A comparison between our proposal and LR-ADR is presented in the results section to enrich this article.

In Jeon and Jeong [2020], the authors propose a novel hybrid approach that uses an adaptive network architecture, dynamically switching between LoRaWAN and IEEE 802.11ac protocols to optimize connectivity and improve overall network efficiency. This architecture leverages the distinct characteristics of each protocol, dynamically selecting the most suitable one based on prevailing network conditions and specific application requirements. Integrating these protocols facilitates a seamless adaptation mechanism that significantly improves data transmission reliability and throughput. This methodical integration ensures that the network remains robust and efficient, particularly suitable for diverse IoT environments where varying communication demands require flexible and adaptive network solutions. Slabicki et al. [2018] introduces two distinct algorithms, the Gaussian-based Adaptive Data Rate (GADR) and the Exponential Moving Average-based Adaptive Data Rate (EMA-ADR). The evaluation of these algorithms demonstrates promising results, showing significant improvements in packet success ratio, energy consumption, and convergence time.

The study in Figueiredo and Franco Silva [2020] proposes a practical method to improve LoRa network efficiency by leveraging the orthogonality of multiple frequency carriers. Their algorithm periodically measures the SNR values from the 433 MHz and 915 MHz bands, enabling a primary node to decide whether to switch the frequency band for all network nodes or maintain the current one based on comparative SNR values. However, experimental results from the Figueiredo and Franco Silva [2020] indicated only a marginal improvement, with an average SNR gain of 4.68%, accompanied by a high frequency of carrier changes. The high frequency of change is a consequence of the decision-making strategy based on the instant measurements of SNR on both bands. During measurement time, an impulsive noise (i.e., caused by another transceiver) could result in a low, distorted SNR value compared to the historical average. In this scenario, the proposed WMA algorithm may produce suboptimal decisions due to impulsive noise present in the communication channel.

Finally, Silva et al. [2023a] introduces “SlidingChange”, a cognitive mechanism developed to optimize performance parameters in LoRa-based networks, thereby improving both network stability and overall efficiency. The SlidingChange approach effectively smooths out fluctuations caused by short-term network variations, reducing the frequency of network reconfigurations. SlidingChange was evaluated against “InstantChange”, which relies on immediate data for decision-making, and a linear regression-based method. In a controlled testbed evaluation, SlidingChange achieved an average SNR improvement of 37%, significantly outperforming InstantChange, which yielded only a 4.6% increase. This demonstrates that SlidingChange’s which uses sliding window methodology more effectively, reduces short-term network fluctuations, resulting in more stable and optimized transmission parameters. Moreover, Sliding Change decreased the frequency of network reconfigurations by 16%, underscoring its ability to stabilize operational performance. During their analysis, they inferred that under the tested outdoor conditions, inter-node distances of approximately 400m are sufficient to demonstrate the necessity of node-aware parameter adjustments to enhance SNR. Table 1 summarizes the limitations found in related work and their future research directions.

Table 1 – Limitations and Future Work in LoRa Adaptive Techniques

Related Study	**Limitations**	**Future Work Directions**
Perahia and Stacey (2013)	High Packet Error Rate (PER) with IEEE 802.11ac for long-range communication; LoRa parameters not optimized.	Consider hybrid architectures combining LoRa with Wi-Fi for different traffic profiles.
Slabicki et al. (2018)	It considers only packet success ratio, energy consumption, and convergence, without accounting for environmental variability or the effects of noise.	Apply GADR/EMA-ADR in real-world noisy environments and compare against cognitive techniques.
Ramesh et al. (2020)	Lacks adaptive mechanisms for dynamic environments.	Investigate adaptive methods tailored for smart city deployments.
Ramli et al. (2020)	No enhancement of LoRa parameters; IEEE 802.11ac suffers higher PER over long distances.	Explore parameter tuning and hybrid protocol switching techniques.
Jeon and Jeong (2020)	Limited focus on SNR improvement and frequency switching.	Extend method to integrate SNR-aware decisions and frequency selection.

Study (Year)	**Limitations**	**Future Work Directions**
Figueiredo and Franco Silva (2020a)	High number of frequency changes due to impulsive noise and instant SNR decisions.	Introduce smoothing filters or historical weighting to reduce reconfiguration frequency.
Valach and Macko (2021)	Based on simulations only; lacks real-world validation.	Validate ML-based adaptation in real-world urban IoT deployments.
Moraes et al. (2021)	High complexity of MILP; real-time deployment not discussed.	Optimize MILP heuristics for real-time feasibility and scalability.
Moysiadis et al. (2021)	Prioritizes PDR and energy but lacks SNR and frequency reconfiguration control.	Combine LR-ADR with SNR-aware strategies for balanced performance.
Silva et al. (2023a) — Sliding-Change	Only considers fixed window sizes; moderate SNR gain; lacks weight adaptation.	Incorporate weighted history (e.g., WMA) for better smoothing and adaptability.

3 WEIGHTED MOVING AVERAGE TECHNIQUE

This chapter introduces the Weighted Moving Average (WMA) adaptive technique to improve LoRa performance in dynamic environments. WMA was designed to optimize Signal-to-noise ratio, spreading factor, bandwidth, and carrier frequency in LoRa-based networks. The goal is to enhance network availability, reduce packet loss, and improve energy efficiency.

The Weighted Moving Average (WMA) approach is based on the principle that adaptive parameters such as SNR, Spreading Factor (SF), Bandwidth (BW), and carrier frequency should be managed to balance data rate, network congestion, availability, range, and energy consumption. A higher SNR enhances transmission accuracy and network reliability, while SF controls the trade-off between communication range and throughput. BW affects both data rate and power usage, and the carrier frequency influences signal propagation and resilience to noise. Algorithms such as LR-ADR and SlidingChange dynamically adjust these parameters, thereby improving scalability, availability, and energy efficiency in IoT applications. The artifacts used in the evaluation are available on GitHub[1].

3.1 WMA Adaptive Parameter

The WMA technique improves existing adaptive algorithms such as InstantChange and SlidingChange by enabling real-time parameter adjustment while incorporating the influence of historical data. WMA balances responsiveness with stability and availability, optimizing LoRa network performance under varying environmental and operational conditions. WMA calculates a weighted average, prioritizing recent data with weights between 0 and 1 while preserving context from earlier measurements. This approach dynamically adjusts critical parameters, including Signal-to-Noise Ratio (SNR), Bit Error Rate (BER), Coding Rate (CR), Bandwidth (BW), Spreading Factor (SF), and carrier frequency, to reduce short-term fluctuations and prevent unnecessary network reconfigurations. Specifically, SNR and BER help maintain reliable data transmission, CR balances error correction and throughput, BW influences data rate and energy usage, SF controls the trade-off between range and transmission time, and carrier frequency affects signal propagation and noise resilience. Together, these adjustments improve overall network reliability and energy efficiency.

In contrast to conventional averaging methods like LR-ADR, InstantChange and SlidingChange. The weighted approach provides more accurate tracking of network

[1] `https://github.com/Khalid681/WMA-project.git`

dynamics, ensuring efficient and stable communication is crucial in IoT applications that require consistent transmission quality Peterson et al. [2023]. Overall, WMA enhances adaptive performance at the LoRaWAN Gateway level, contributing to the scalability and availability of IoT communication systems.

3.2 WMA Mathematical Formulation

In LoRa-based networks, the proposed WMA technique dynamically adjusts key transmission parameters to smooth short-term fluctuations. This approach enhances SNR, improves signal reliability, and reduces unnecessary reconfigurations, boosting overall network performance and energy efficiency. The WMA technique focuses on the LoRa parameters, e.g., SNR, carrier frequency, BW, SF, and CR. The WMA equation is used to calculate the average value of a given parameter, such as SNR (*meansnr*), over a dataset. This method assigns greater weight to more recent measurements, allowing the system to smooth short-term fluctuations while reflecting the latest network conditions, as shown in Equation 3.1.

$$AvgLen = (1 - Weight) \times meansnr + Weight \times newsnr \tag{3.1}$$

The iterative WMA process dynamically refines LoRa parameters, such as SNR, by weighting historical values “meansnr” and new inputs “newsnr”. Initially, *meansnr* is derived from the generated LoRaWAN dataset, which was generated from an over testbed environment. Each iteration is updated using the latest *newsnr*, enabling adaptive modulation over time. This recursive update captures global data trends, allowing SNR to adjust in response to network performance, thereby improving transmission reliability and efficiency in IoT systems.

WMA EQUATION :

The WMA technique adaptively adjusts SNR in LoRa-based networks by integrating historical “meansnr” and recent “newsnr” values through an adjustable weight of 0 to 1. AvgLen represents the updated SNR value computed at each iteration, reflecting the most recent network conditions while smoothing short-term fluctuations. balancing responsiveness and stability to manage frequency shifts and reduce congestion.

Assigning higher weights in the WMA increases responsiveness to recent changes, while lower weights emphasize stability by giving more importance to past observations. By smoothing short-term SNR fluctuations, WMA improves efficiency, conserves energy, and minimizes disruptions. Experimental analysis demonstrates that the proposed approach outperforms SlidingChange, achieving higher SNR and a reduced number of parameter shifts, called reconfiguration, thereby improving both network stability and performance. WMA thus offers a reliable solution for energy-efficient IoT communication in dynamic environments.

3.3 WMA Algorithm

The dynamic nature of modern systems demands efficient SNR evaluation by integrating historical and real-time data. This algorithm uses an adjustable weight; the WMA technique addresses this need by combining past and current SNR values collected from the LoRaWAN network at UFJF. This approach ensures both responsive and stable estimation, making it suitable for real-time wireless communication, control systems, and data analytics applications. The Algorithm 1. illustrates the WMA computation process.

Algorithm 1 Weighted Sum Calculation

Initialize the result variable to 0
Calculate the weighted sum of *meansnr* and *newsnr* by multiplying each quantity by its corresponding weight:
$weighted\_meansnr \leftarrow meansnr \times (1 - Weight)$
$weighted\_newsnr \leftarrow newsnr \times Weight$
Add the weighted sums to get the final result:
$result \leftarrow weighted\_meansnr + weighted\_newsnr$
Return the result.

The variables used in the Algorithm 1 “meansnr” represent the WMA of the SNR, “newsnr” is the current SNR estimate, and “Weight” is a coefficient between 0 and 1 that adjusts the influence of new data. The weight parameter, which sets the time constant of the running average low-pass filter, is chosen based on the trade-off between gateway responsiveness and stability, offering guidance for selecting an appropriate value. The update process is shown in Figure 4, with a detailed explanation provided in Section 3.2.

This approach prioritizes recent SNR measurements while maintaining historical data to stabilize SNR estimates. The WMA technique enhances the accuracy of SNR estimation by mitigating the effects of noise and data anomalies, as well as reducing the number of reconfigurations, known as frequency shifts, in LoRa-based systems with higher SNR variability.

3.4 Visual Representation of WMA Solution

The WMA process in LoRaWAN networks prioritizes recent SNR values to enable quick adaptation to network changes, such as congestion. WMA enhances communication efficiency, reduces reconfiguration called shifts, and improves SNR

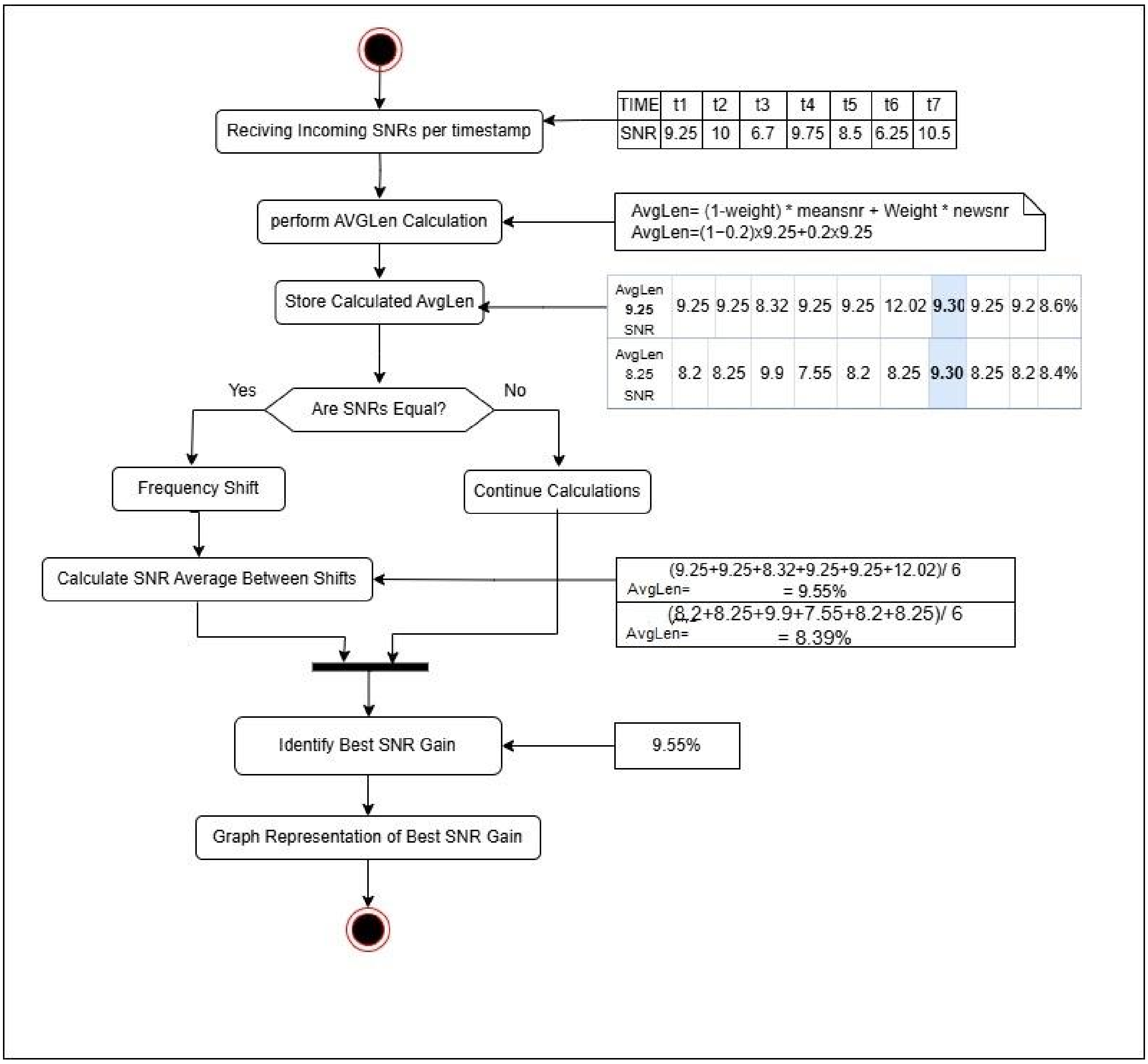

Fig. 4. WMA data-flow diagram.

performance. A visual representation of the application of WMA steps is illustrated in Fig. 5.

Step 1: Incoming SNRs per timestamp

Time	t_1	t_2	t_3	t_4	t_5	t_6	t_7
SNR	9.25	10	6.7	9.75	8.25	6.25	10.5

Step 2: WMA Calculation

Weight	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Final AvgLen
AvgLen 9.25 SNR	9.25	9.25	8.32	9.25	9.25	12.02	9.30	9.25	9.2	9.45%
AvgLen 8.25 SNR	8.2	9.05	9.9	7.55	8.2	8.25	9.30	8.25	8.2	8.4%

Step 3: SNR Average between Shifts

SNR	9.25	8.25
Frequency	915	433
SNR Average between Shifts	8.39%	9.55%

Step 4: Best SNR gain between shifts

9.55%

Step 5: Graphical Representation of best SNR and frequency shifts

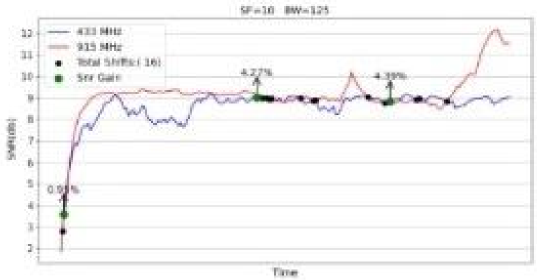

Fig. 5. Visual representation of WMA.

Fig. 5. demonstrates the WMA technique for improving SNR in LoRa networks using historical data. The process begins with an incoming dataset of SNR values, recorded at specific timestamps. These values are the input for calculating the WMA, which is applied iteratively to adjust SNR based on past and present measurements. Subsequently, for each SNR per timestamp stored in the dataset, we apply the WMA Equation 3.1 to calculate "newsnr" and highlight shifts.

1. **Step 2:** from Fig 5 illustrates the application of the WMA equation considering the following SNRs from the dataset: 9.25 and 8.25. The weight in Equation

3.1 should be greater than zero and less than 1. The WMA equation can be iteratively applied several times to the same SNR sample, using weights within this range. It determines the time constant for the running average low-pass filter. The weight parameter, which sets the time constant of the running average low-pass filter, is chosen based on the trade-off between gateway responsiveness and stability, offering guidance for selecting an appropriate value. The user can randomly define the weight values. In the example illustrated in step 2 from Figure. 5, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 were assigned to calculate the WMA to identify similar SNR values that indicate the need for frequency shifts.

A frequency shift (reconfiguration) occurs when the current and previous SNR values are the same, as highlighted in the column labeled '0.7' in step 2 (see Fig. 5).

2. **Step 3:** The average SNR between these shifts is generated to reduce short-term fluctuations and to emphasize longer-lasting patterns. The example shows only one frequency shift between 9.25 and 8.25 SNR samples from the dataset.

3. **Step 4:** Fig. 5 involves selecting the optimal SNRs that offer the most significant performance improvement. In this case, the signal frequency shifts from 915 MHz to 433 MHz to avoid interference with the medium, improving the SNR. Finally, the analysis results in the graphical representation of the SNRs being generated.

4. **Step 5:** In the Fig 5, Step 5 presents a graph that highlights the effectiveness of the WMA technique in enhancing signal analysis and interpretation.

3.5 Optimizing LoRa Network Through Adaptive WMA Integration

Adapting WMA for LoRa networks requires integrating its statistical principles with LoRa's low-power, IoT-specific characteristics. The dynamic wireless environment introduces challenges such as fluctuating signal quality, interference, and congestion, which affect performance and necessitate reconfigurations, commonly referred to as shifts. The adaptive WMA technique addresses challenges such as fluctuating signal quality, interference, congestion, and the need for frequent reconfigurations, allowing the network to respond promptly to environmental variations and thereby improving both availability and overall efficiency.

The WMA technique assigns varying weights to data points from the LoRaWAN network implemented at UFJF University [Silva et al., 2023b], with recent observations receiving higher weights, thereby enabling responsiveness to recent changes, which is essential for applications requiring timely adaptations. In LoRa networks,

key metrics like SNR, RSSI, and Packet Reception Rate (PRR) are crucial for assessing link quality and network performance. Applying the WMA to these metrics allows dynamic adjustment of transmission parameters to optimize performance.
The implementation of WMA in LoRa networks involves several critical steps:

1. **Data Collection::** Continuous collection of BW, SF, and SNR data from EDs is essential. This real-time data serves as the foundation for subsequent analysis and decision-making processes.

2. **Weight Assignment:** Assigning higher weights to more recent data points ensures that the WMA calculation reflects current network conditions. The weight parameter, which sets the time constant of the running average low-pass filter, is chosen based on the trade-off between gateway responsiveness and stability, offering guidance for selecting an appropriate value. The user can randomly define the weight values.

3. **WMA Calculation:** The weighted average is computed by multiplying each data point by its assigned weight, summing these products, and then dividing by the sum of the weights. This means that by applying the weighted average, the result reduces the impact of short-term fluctuations in the data while giving more importance to recent measurements. As a result, the computed value better reflects the current condition of the network, rather than being overly influenced by older or outdated data points.

4. **Parameter Adjustment:** The results of the WMA are utilized to inform adjustments in network parameters, such as transmission power, data rates, BW, SF, and SNR. For instance, a declining WMA of SNR might indicate the need to increase transmission power or adjust the SF to maintain reliable communication.

5. **Continuous Monitoring and Adaptation:** Regular updates to the WMA calculations with new data ensure that the network adapts promptly to any changes in the environment or network usage patterns. This ongoing process helps maintain optimal performance and energy efficiency.

Implementing WMA in LoRa networks enables the system to dynamically adapt to environmental variations, thereby improving both network availability and operational efficiency. By integrating recent and historical data, the network can make informed decisions, such as reconfiguring parameters to improve communication quality and reduce energy consumption. This adaptability is crucial in dynamic environments with mobile devices or variable interference. WMA strengthens network stability by facilitating proactive adjustments, ensuring consistent performance and energy efficiency. As IoT deployments expand, adaptive methodologies like WMA are crucial for managing the complexities of large-scale, dynamic networks in applications such as smart cities and industrial control systems.

4 FUNDAMENTALS

This chapter introduces the fundamental components and the experimental framework employed to evaluate the performance of the proposed WMA technique in LoRa-based networks. It provides a comprehensive overview of the simulation environment, network architecture and configuration, adaptive parameter adjustment mechanism, and the configuration of the experimental real-world testbed experiments. Additionally, this chapter introduces the metrics and tools used for performance evaluation and comparison with existing adaptive methods.

4.1 SIMULATION ENVIRONMENT

The WMA technique experiment systematically investigates an adaptive technique designed to enhance the efficiency and stability of LoRa-based IoT networks at the gateway level. The method dynamically adjusts critical network parameters, such as SNR, to respond to changing conditions. This approach minimizes packet loss and reduces unnecessary reconfigurations, improving energy efficiency. Overall, it optimizes network performance, ensuring more reliable and efficient communication in variable environments. The simulation framework, experimental setup, and empirical validation of the WMA approach are presented in the Results section.

4.2 NETWORK ARCHITECTURE AND CONFIGURATION WITHIN LORAWAN

LoRaWAN's star topology provides the network foundation for implementing the WMA algorithm technique, enabling efficient IoT communications through integrated nodes/ sensors, Gateways, network servers, and application servers Ertürk et al. [2019]. The WMA algorithm dynamically tunes SNR, SF, BW, and CR to optimize transmission reliability. It systematically reduces interference while balancing trade-offs among range, data rate, and error correction. These adaptive adjustments enhance network availability and promote energy-efficient, robust operation in IoT environments.

4.3 ADAPTIVE PARAMETER ADJUSTMENT VIA THE WMA TECHNIQUE

Conventional methods, such as the Sliding Change, Instant Change, and LR-ADR techniques, primarily consider recent data. The WMA technique incorporates both historical and real-time SNR measurements to dynamically optimize network parameters, ensuring more stable and efficient communication. This approach enables smoother and more stable configuration transitions, thereby reducing frequency shifts and improving overall network availability and stability.

4.4 SIMULATION ENVIRONMENT FOR THE WMA TECHNIQUE

The WMA algorithm is evaluated in a controlled experimental testbed using ESP32 microcontroller-based clients and LoRa SX1276/SX1278 transceiver modules, operating at frequencies of 433 MHz and 915 MHz. ESP32 is a low-power, Wi-Fi and Bluetooth-enabled microcontroller commonly used in IoT applications, while SX1276/SX1278 are LoRa transceivers that support long-range, low-power wireless communication. In our experiment, communication between nodes is tested over distances ranging from 500 to 700 meters, allowing us to evaluate the performance of the WMA algorithm under realistic conditions and observe its impact on signal quality and network reliability. This setup enables precise assessment of SNR improvements, network stability, and network availability across diverse conditions.

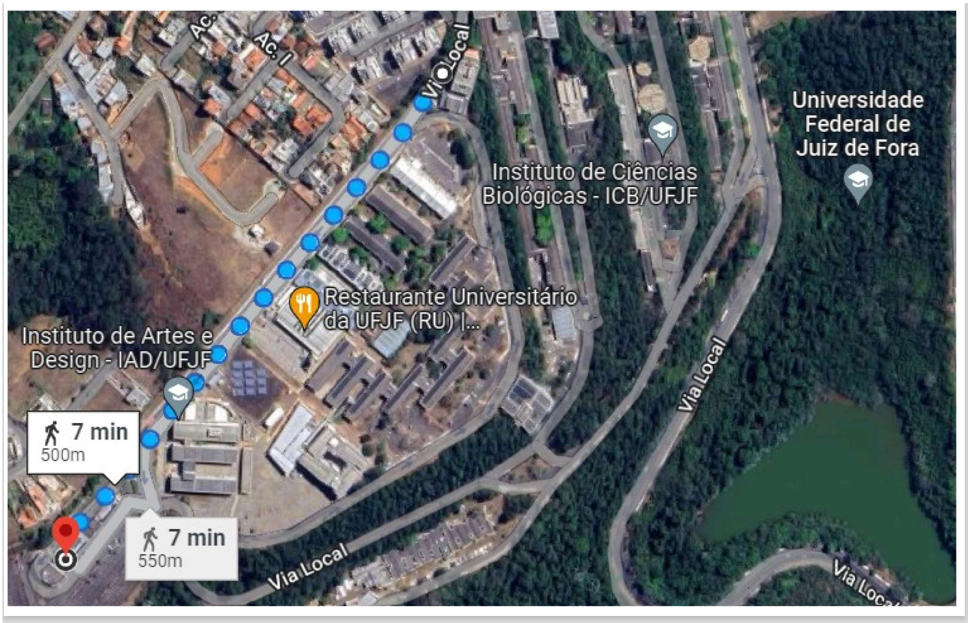

Fig. 6. Experimental testbed scenario for the LoRa-based network from Computer Science Dept. to CRITT technological and innovation center [Silva et al., 2023b].

4.5 DATA COLLECTION AND ANALYSIS FOR NETWORK PERFORMANCE EVALUATION

A mobile application is utilized for network management, allowing real-time configuration of parameters and continuous performance monitoring, as illustrated in Fig. 7. It facilitates data collection across various spreading factors and bandwidth settings, supporting the evaluation of the WMA technique's impact on SNR improvements and reconfiguration frequency, as illustrated in Fig. 8.

Fig. 7. Remote control screen on mobile app

Fig. 8. Settings screen on mobile app.

4.6 EMPIRICAL EVALUATION OF THE WMA TECHNIQUE

The WMA technique significantly outperforms existing methods such as Sliding-Change and LR-ADR, enhancing network availability and SNR. Empirical results show a 39.09% improvement in SNR and a 5.65% reduction in reconfiguration frequency, referred to as shifts as compare to Sliding Change Silva et al. [2023a]. Detailed results and analysis of the WMA performance are presented in Section 5. These outcomes demonstrate the effectiveness of the WMA algorithm in managing network adjustments and enhancing network availability.

4.7 COMPARATIVE ANALYSIS WITH EXISTING TECHNIQUES

Comparative analyses Silva et al. [2023a]; Moysiadis et al. [2021] demonstrate that the WMA technique reduces network reconfigurations (shifts) and enhances SNR, providing significant benefits for IoT systems and improving overall network performance. By integrating historical and recent data, WMA enables more stable network adjustments. In LoRa-based IoT networks, WMA enhances transmission reliability, minimizes packet loss, and optimizes SNR. These findings support the broader application of WMA for improved network performance and stability, facilitating future research and advancements in IoT network efficiency.

4.8 TESTBED SETUP FOR REAL WORLD EXPERIMENTS

The testbed environment illustrated in Fig. 6. Shows a practical setup deployed at the UFJF University campus between the Computer Science Department and the CRITT Technological and Innovation Center. It is designed to evaluate the performance of the WMA technique in a real-world scenario.

4.9 COMPONENTS OF THE TESTBED

1. **ESP32 Client:** This device functions as a client or end node in the LoRa network, equipped with LoRa communication modules such as the SEMTECH SX1276 or SX1278, which are known for their LoRa and low-power performance in IoT applications. The ESP32 transmits data packets to assess the WMA technique's impact on communication reliability and efficiency.

2. **Gateway:** The gateway, equipped with similar LoRa modules, acts as the communication hub, receiving data from the ESP32 client. It aggregates and forwards the data to a central server for processing and analysis. At this point, the effectiveness of the WMA technique in managing SNR and packet loss can be directly evaluated at the gateway level.

4.10 CONFIGURATION DETAIL

1. **Configuration Details:** The use of both 433 MHz and 915 MHz bands allows for testing under different frequency conditions, which is essential for assessing the WMA's adaptability and performance across various spectral environments that may affect propagation characteristics and interference patterns.

2. **Distance:**The nodes are placed 500–700 meters apart to evaluate the range and robustness of LoRa communication. This distance is sufficiently large to challenge signal integrity, allowing the WMA technique to demonstrate its effectiveness in improving signal strength and overall network performance.

3. **Antennas:** Different antenna types are utilized to examine how variations in design influence signal transmission and reception. These differences can substantially affect overall system performance, particularly regarding SNR and the network's capability to manage packet loss effectively.

   The testbed evaluates the improvements of the WMA technique over traditional methods, such as Sliding Change, by comparing SNR enhancements and reduced network reconfigurations (shifts). Fig. 6 shows the setup, including the ESP32 client, gateway, communication path, and campus environment, ensuring the study's relevance to real-world IoT networks.

4.11 METRICS FOR PERFORMANCE EVALUATION

The dataset enables the evaluation of adaptive techniques, such as WMA, through key metrics. "Meansnr" calculates the average SNR across transmissions, reflecting network performance and the impact of dynamic adjustments. The "Packet Loss Ratio" measures lost packets relative to total transmissions, indicating network reliability. The"Reconfiguration Rat" quantifies parameter adjustments, with higher rates indicating frequent adaptations and lower rates indicating stability. "RSSI" trends track signal strength variations, identifying environmental impacts on performance, while frequency shift analysis examines transitions between 915 MHz and 433 MHz to optimize channel allocation.

The analysis of adaptive parameter changes demonstrates how WMA optimizes LoRa networks in real-time. By assessing SNR, packet loss, BW, and SF, the dataset provides valuable insights into network performance and availability. Metrics like "meansnr", "reconfiguration rate (shifts)", and "packet loss ratio" provide quantitative evidence of the impact of dynamic adjustments on stability. This dataset aids research in optimizing LoRa networks for enhanced performance and resilience in IoT applications.

5 EXPERIMENTAL RESULTS

This Experimental Results chapter presents the empirical evaluation of the WMA technique in enhancing SNR, reducing network reconfigurations, and improving availability in LoRa-based IoT networks. Experiments were conducted in a controlled testbed simulating real-world conditions, as explained in the previous Fundamentals Chapter 4. The WMA method is compared against SlidingChange and LR-ADR Silva et al. [2023a]; Moysiadis et al. [2021], demonstrating superior signal quality and network stability. These results validate the effectiveness of WMA in dynamic IoT environments.

5.1 EXPERIMENTAL OVERVIEW

The experimental evaluation assessed the effectiveness of the WMA technique in optimizing SNR, reducing network reconfigurations (shifts) in LoRa-based IoT networks, and improving network availability compared to the Sliding Change and LR-ADR methods. The study was conducted in a controlled testbed environment in real IoT deployment scenarios, and improvements in SNRs and frequency shift reduction were measured. The artifacts used in the evaluation are available on GitHub[1].

5.2 SNR PERFORMANCE AND COMPARATIVE ANALYSIS

SNRs were the primary metric for evaluating network efficiency, which directly correlates with signal quality and interference resilience. The results from Table 2 demonstrated that the WMA-based solution reduced by 5.65% the network reconfiguration (i.e., the number of frequency switches) as compared to the Sliding Change and also improved the SNR by 39.09% Silva et al. [2023a] . The WMA technique obtained an SNR average gain of 4.86% while SlidingChange configurations achieved 2.89%, 3.61%, 4.34%, and 4.60%, and LR-ADR 3.05%, respectively (see Table 2). We focused on SlidingChange instead of LR-ADR. Each configuration, WMA, SlidingChange, and LR-ADR, was executed three times to ensure the reliability of the results and to account for potential variations in network conditions, such as SNR fluctuations and interference.

The change/shift points for the WMA technique, considering 10, 11, and 12 SFs, and 125 kHz, 250 kHz, and 500 kHz BWs, are highlighted in the line graphs shown in Figures 9–17, where the three most significant SNR improvements are marked

[1] `https://github.com/Khalid681/WMA-project.git`

with arrows, presenting the detailed graphs for WMA measurements. The WMA, SlidingChange, and LR-ADR configuration results are detailed in Table 2.

Table 2 – Summary of the three biggest SNR gains for each setup and their respective averages

Window	Experiment	BW 125 kHz SF 10	125 kHz 11	125 kHz 12	250 kHz 10	250 kHz 11	250 kHz 12	500 kHz 10	500 kHz 11	500 kHz 12	Average
	1	4.01%	3.22%	4.14%	3.10%	4.37%	2.92%	2.98%	2.21%	3.78%	
LR-ADR	2	3.92%	2.75%	3.33%	3.34%	2.54%	2.88%	2.34%	2.02%	2.09%	3.05%
	3	4.03%	4.04%	3.17%	3.16%	2.43%	2.88%	2.03%	2.45%	2.13%	
	1	5.88%	9.79%	7.85%	5.90%	3.33%	5.29%	9.33%	3.31%	5.17%	
W=10	2	4.48%	5.11%	4.49%	3.73%	2.65%	4.91%	4.50%	2.81%	3.98%	4.60%
	3	4.03%	4.64%	3.90%	3.36%	1.97%	4.90%	2.59%	2.40%	3.80%	
	1	6.42%	4.09%	11.89%	3.00%	3.32%	5.04%	8.14%	3.33%	8.20%	
W=20	2	4.66%	4.04%	5.50%	2.50%	2.89%	4.81%	2.54%	2.67%	5.06%	4.34%
	3	3.92%	3.09%	4.07%	2.02%	2.68%	4.35%	2.30%	2.22%	4.36%	
	1	4.10%	4.32%	5.09%	5.90%	4.74%	4.83%	4.26%	5.39%	4.36%	
W=30	2	3.21%	3.70%	4.67%	2.84%	1.47%	4.51%	2.99%	5.33%	4.17%	3.61%
	3	1.92%	2.48%	3.83%	1.96%	1.44%	3.64%	2.30%	2.80%	1.1%	
	1	3.21%	5.91%	7.39%	4.50%	2.56%	3.53%	2.97%	4.49%	2.60%	
W=40	2	2.06%	3.125	4.01%	2.17%	1.46%	3.21%	2.96%	2.31%	2.29%	2.89%
	3	1.29%	2.58%	1.72%	1.31%	1.39%	3.02%	1.45%	2.26%	2.24%	
	1	0.95%	4.01%	3.56%	4.24%	3.96%	4.15%	4.99%	5.54%	5.79%	
WMA	2	4.27%	4.12%	5.88%	5.85%	4.30%	4.16%	6.05%	5.84%	6.12%	**4.86%**
	3	4.39%	4.05%	6.01%	6.99%	4.23%	4.04%	6.12%	5.86%	6.33%	

The line graphs in Figures 9–17 display the obtained SNRs using the WMA technique with 10, 11, and 12 SFs, as well as 125 kHz, 250 kHz, and 500 kHz bandwidths (BW).

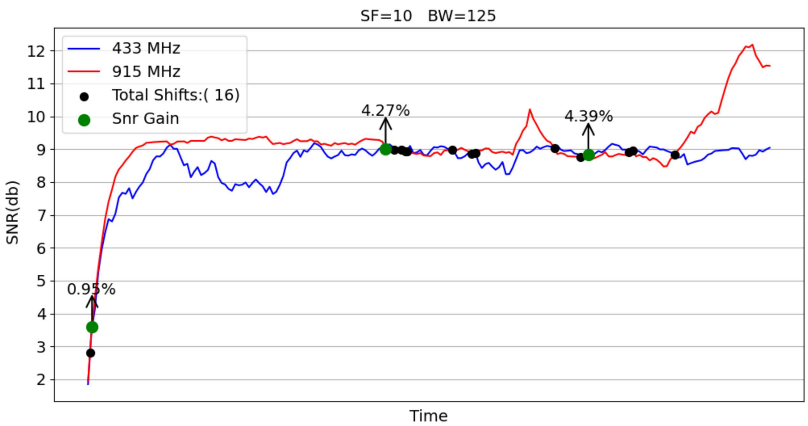

Fig.9 WMA for $SF = 10$ and $BW = 125kHz$.

Fig. 9 for SF=10, BW=125 kHz shows that the WMA-based technique achieves SNRs of 0.95%, 4.27%, and 4.39%, represented by the green dots and arrows, with a total of 16 frequency reconfigurations, or shifts, for the Timestamp. Comparing this with SlidingChange and LR-ADR, which shows at the Table 2, SlidingChange and LR-ADR required more frequent reconfigurations/shifts as compared to WMA for the same input of data from the generated dataset details shown in [Silva et al. [2023a], Moysiadis et al. [2021]], whereas WMA maintained fewer shifts while achieving higher SNR improvements.

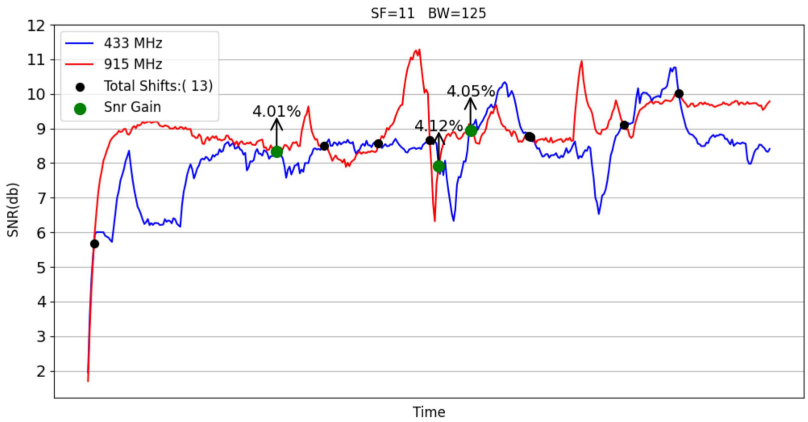

Fig.10 WMA for $SF = 11$ and $BW = 125kHz$.

Fig. 10 for SF=11, BW=125 kHz shows that the WMA-based technique achieves SNRs of 4.01%, 4.12%, and 4.05%, represented by green dots and arrows, with a total of 13 frequency shifts concerning the Timestamp, marked with black dots. The red line shows a 915 MHz frequency, and the blue line shows a 433 MHz frequency. Comparing this with Sliding Change and LR-ADR, the results are presented in Table 2.

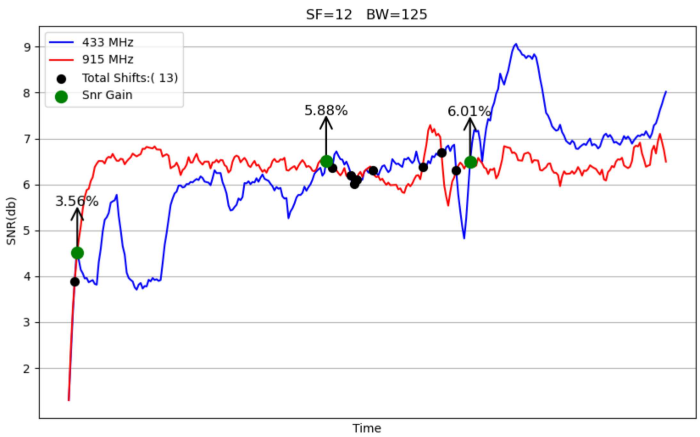

Fig.11 WMA for $SF = 12$ and $BW = 125kHz$.

Fig. 11 for SF=12, BW=125 kHz shows that the WMA-based technique achieves SNRs of 3.56%, 5.88%, and 6.01%, represented by the green dots and arrows, with a total of 13 frequency shifts concerning the Timestamp, marked with black dots. The red line shows a 915 MHz frequency, and the blue line shows a 433 MHz frequency. Comparing this with SlidingChange and LR-ADR, which are shown in Table 2.

Fig. 12 for SF=10, BW=250 kHz shows that the WMA-based technique achieves SNRs of 4.22%, 5.85%, and 6.99%, represented by green dots and arrows, with a total of 9 frequency shifts concerning Timestamp, marked by black dots. The red line

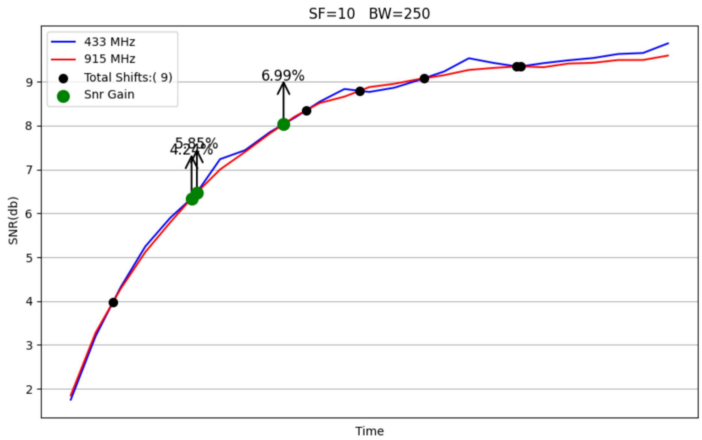

Fig.12 WMA for $SF = 10$ and $BW = 250kHz$.

shows a 915 MHz frequency, and the blue line shows a 433 MHz frequency. Comparing this with SlidingChange and LR-ADR, which are shown in Table 2. Sliding Change and LR-ADR required more frequent reconfigurations than WMA at this point. WMA enhances SNR performance while reducing network reconfigurations, making it a more efficient and stable adaptation method for LoRa networks.

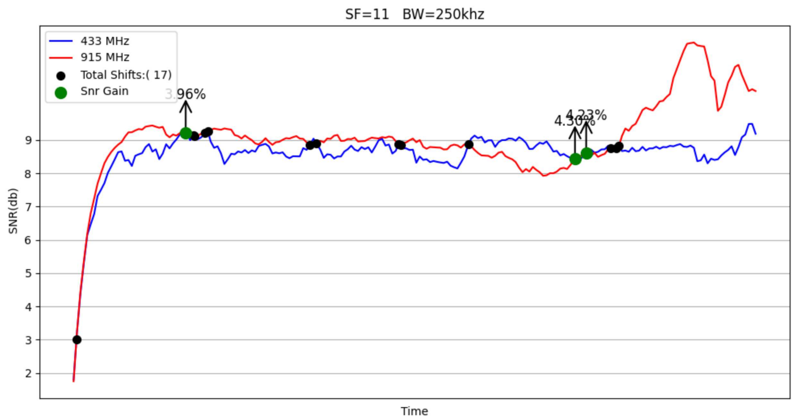

Fig.13 WMA for $SF = 11$ and $BW = 250kHz$.

Fig. 13 for SF=11, BW=250 kHz shows that the WMA-based technique achieves SNRs of 3.96%, 4.30%, and 4.23%, represented by green dots and arrows, with a total of 17 frequency shifts concerning Timestamp, marked by black dots. The red line shows a 915 MHz frequency, and the blue line shows a 433 MHz frequency. Comparing this with SlidingChange and LR-ADR, which are shown in Table 2. The SlidingWindow technique had lower SNRs, with the highest not exceeding 4.09% for SF=11 and BW=250 kHz. WMA maintained fewer shifts while achieving comparable or higher SNR improvements.

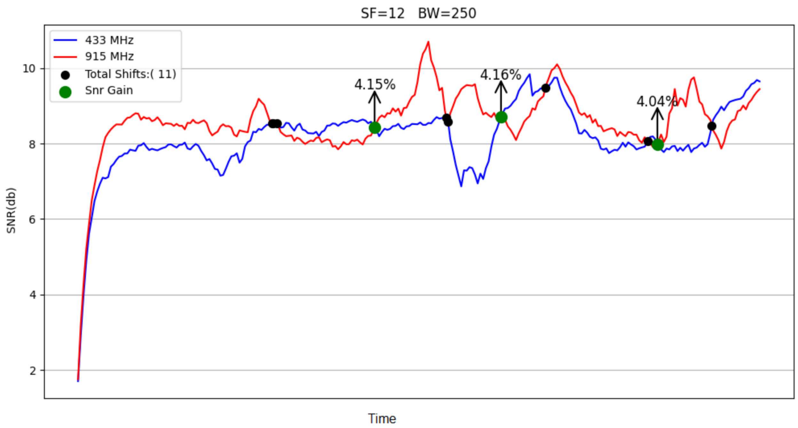

Fig.14 WMA for $SF = 12$ and $BW = 250kHz$.

Fig. 14 for SF=12, BW=250 kHz shows that the WMA-based technique achieves SNRs of 4.15%, 4.16%, and 4.04%, represented by green dots and arrows, with a total of 11 frequency shifts concerning Timestamp, marked by black dots. The red line shows a 915 MHz frequency, and the blue line shows a 433 MHz frequency. Comparing this with SlidingChange and LR-ADR, which are shown in Table 2.

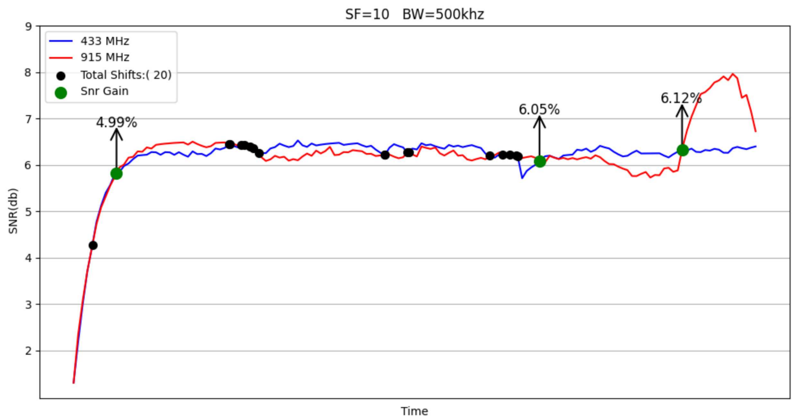

Fig.15 WMA for $SF = 10$ and $BW = 500kHz$.

The fig. 15 for SF=10, BW=500 kHz shows SNRs of 4.99%, 6.05%, and 6.12%, which represent green dots and arrows, with 20 frequency shifts concerning Timestamp, with black dots—comparing this with SlidingChange and LR-ADR, which shows at Table 2.

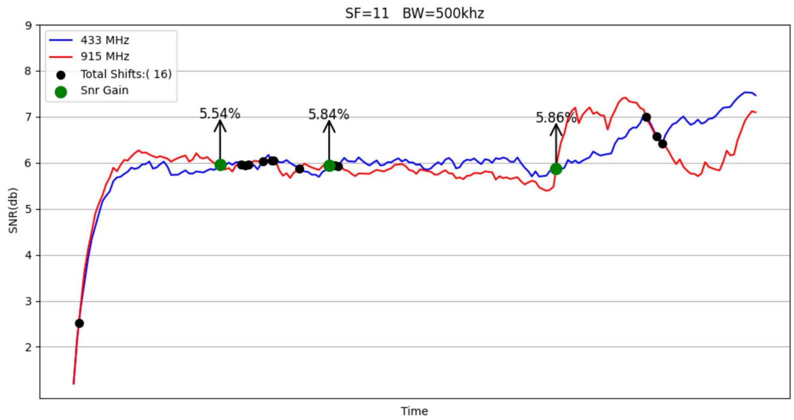

Fig.16 WMA for $SF = 11$ and $BW = 500kHz$.

The fig.16 for SF=11, BW=500 kHz shows SNRs of 5.54%, 5.84%, and 5.86%, which represent green dots and arrows, with 16 frequency shifts concerning Timestamp, with black dots—comparing this with SlidingChange and LR-ADR which shows at the Table 2,

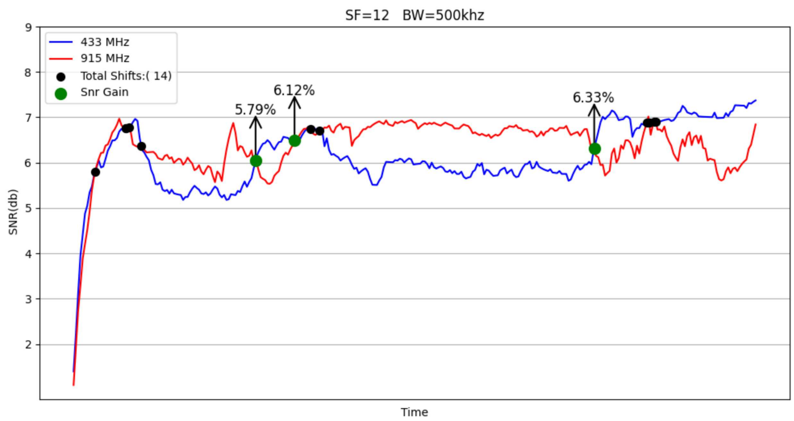

Fig.17 WMA for $SF = 12$ and $BW = 500kHz$.

The fig 17 for SF=12, BW=500 kHz shows SNRs of 5.79%, 6.12%, and 6.33%, which represent green dots and arrows, with 14 frequency shifts concerning Timestamp, with black dots—comparing this with SlidingChange and LR-ADR, which are shown in Table 2.

The reduction in network frequency reconfigurations “5.65%” in the WMA technique, is related to the algorithm’s capability to analyze trade-offs between network availability at gateway levels and communication response time. It is essential to highlight that the WMA technique reduced the number of frequency shifts across different BW and SF configurations compared with slidingChange, LR-ADR, and other state-of-the-art methods [Silva et al. [2023a], Moysiadis et al. [2021]]. Even operating under low shift frequencies, the WMA algorithm achieves an average SNR improvement of 4.86%, resulting in environments with reduced interference. This result demonstrated the feasibility of the proposed WMA-based adaptive technique in improving SNR and reducing frequency shifts in LoRa-based networks (answering the research question), which can be used in realistic IoT applications and Gateways, where conditions vary significantly.

Sensitivity analysis of WMA weights 0.1 to 0.9 reveals that higher values enhance responsiveness to SNR fluctuations but increase reconfiguration rates. In contrast, lower weights reduce reconfigurations to stabilize performance at the cost of delayed adaptation and increased energy demand. Subsequently, WMA strengthens LoRa network availability by maintaining communication consistency, reducing congestion, optimizing SNR, and enhancing security through adaptive parameter control. These findings demonstrate the cognitive radio capabilities of LoRa networks and encourage ongoing research on utilizing adaptive WMA-based algorithms to optimize SNR and other network parameters in diverse operational scenarios.

5.3 NETWORK RECONFIGURATION AND STABILITY

A critical advantage of the WMA technique is its ability to minimize network reconfigurations, measured as frequency shifts between the 433 MHz and 915 MHz bands. WMA reduced reconfiguration frequency by "5.65%" as compared to slidingChange Silva et al. [2023a]. The WMA algorithm's weighting mechanism ($Weight \in (0, 1)$) played an essential role in balancing stability and availability. 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 were assigned to calculate the WMA to identify similar SNR values that indicate the need for frequency reconfiguration/shifts. The WMA technique effectively reduces the frequency reconfigurations, known as shifts, by "5.65%" compared to the "SlidingChange" method. This reduction enhances network stability and availability, minimizing unnecessary adaptations and optimizing overall LoRa network performance.

6 CONCLUSION

This thesis presented a WMA-based adaptive technique aimed at enhancing SNR and overall network performance in LoRa-based IoT deployments. The proposed WMA approach leverages both historical and real-time SNR measurements to dynamically adjust critical network parameters, including spreading factor, BW, CR, and carrier frequency. By doing so, it effectively addresses challenges inherent in LoRa communication, such as intersymbol interference, environmental fluctuations, and packet loss, while minimizing unnecessary network reconfigurations, commonly referred to as shifts. Unlike traditional methods, such as SlidingChange and other state-of-the-art techniques that rely predominantly on immediate measurements, WMA systematically weighs recent and past data to produce a consistent, accurate representation of network conditions, thereby enhancing both stability and reliability. The primary advantage of the WMA technique lies in its ability to smooth short-term fluctuations without compromising responsiveness to meaningful changes in network conditions. Sudden variations in SNR caused by transient interference, fading, or congestion are effectively reduced, preventing erratic adjustments that could destabilize network performance. This capability reduces energy consumption by limiting unnecessary reconfigurations, thereby prolonging the operational lifetime of battery-powered IoT devices. Simultaneously, WMA ensures that the network adapts efficiently to genuine environmental changes, maintaining high signal quality and robust communication links.

Empirical evaluation was performed in a controlled experimental testbed, comprising ESP32 microcontroller-based clients and LoRa SX1276/SX1278 transceiver modules operating at 433 MHz and 915 MHz. Communication distances between nodes were set between 500 and 700 meters to replicate real-world deployment scenarios and challenge signal propagation. Each configuration, WMA, SlidingChange, and LR-ADR, was executed three times to ensure reliability and account for potential variations such as interference, multipath fading, and traffic fluctuations. Real-time monitoring and configuration were facilitated through a dedicated mobile application, allowing accurate measurement of SNR, network availability, and reconfiguration frequency.

The evaluation demonstrated that the WMA technique consistently outperforms existing approaches, including SlidingChange and LR-ADR. Specifically, WMA achieved a 4.86% improvement in SNR and a measurable reduction in the frequency of reconfigurations compared to SlidingChange. These improvements directly translate into enhanced transmission reliability, reduced packet loss, and improved network stability, which are critical for IoT applications requiring continuous and dependable communication. The weighted averaging of recent and historical measurements allows WMA to maintain high network availability while effectively reducing interference and accommodating varying traffic patterns.

Moreover, WMA provides a robust mechanism for dynamic network parameter adaptation. By continuously monitoring SNR trends and adjusting SF, BW, CR, and carrier frequency accordingly, WMA eliminates the need for manual configuration or static parameter settings. This capability is particularly valuable for large-scale IoT networks, where heterogeneous devices, variable densities, and environmental variability can cause rapid and unpredictable changes in network conditions. In such scenarios, frequent reconfigurations may introduce instability, degrade performance, and increase energy consumption; WMA addresses these issues by balancing responsiveness and stability, ensuring reliable and energy-efficient operation.

The study also highlights the benefits of integrating historical data into adaptive decision-making. Techniques like SlidingChange, which rely exclusively on immediate measurements, may overreact to transient disturbances, leading to unnecessary shifts and network instability. In contrast, WMA's incorporation of both short-term and long-term trends enables a more comprehensive assessment of network conditions, optimizing SNR, reducing packet loss, and enhancing overall reliability. This approach is especially advantageous in complex IoT environments where multiple interference sources and variable traffic patterns are common.

These findings have important implications for real-world IoT deployments. Improved SNR and reduced reconfigurations not only enhance data reliability and throughput but also facilitate energy-efficient operation, which is crucial for battery-powered sensors and devices. In applications such as industrial automation, environmental monitoring, smart cities, and precision agriculture, WMA-based adaptation can provide consistent, high-quality communication even under challenging conditions. By mitigating the effects of interference and fluctuations, WMA ensures that critical data is transmitted reliably, supporting timely decision-making and system stability.

Despite the promising results, further research is needed to validate WMA under more complex, real-world scenarios. While the controlled testbed provided meaningful insights, deployment in industrial, urban, or highly dense IoT environments may introduce additional challenges, such as cross-technology interference, dynamic traffic patterns, and mobility. Future work should focus on industrial-scale testbeds to evaluate WMA's performance under such conditions, including heterogeneous device types and multi-gateway architectures. Additionally, comparative studies with a broader set of cognitive radio and adaptive LoRa techniques would strengthen the evidence of WMA's superiority, particularly in terms of scalability, energy efficiency, and resilience.

Future extensions of this work may also explore the integration of WMA with machine learning or predictive models, enabling proactive adjustment of network parameters based on anticipated environmental changes. Such hybrid approaches could further enhance network stability, reduce energy consumption, and optimize SNR in highly dynamic environments. By combining WMA with intelligent prediction or reinforcement learning techniques, IoT networks could achieve self-optimizing, autonomous operation, supporting large-scale deployments with minimal human intervention.

In conclusion, the WMA-based adaptive technique introduced in this thesis represents a significant advancement in the design of efficient, reliable, and energy-conscious LoRa networks. By incorporating both historical and real-time measurements, dynamically adjusting transmission parameters, and reducing unnecessary reconfigurations, WMA achieves higher SNR, improved network stability, and increased availability compared to traditional methods. Empirical results confirm the technique's effectiveness in mitigating packet loss, optimizing transmission quality, and providing robust performance in dynamic IoT environments. These outcomes demonstrate that WMA is a promising foundation for future IoT networks, offering a pathway toward adaptive, resilient, and energy-efficient communication systems capable of meeting the demands of diverse real-world applications.

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