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ARTICLE

Enhancing LoRaWAN Sensor Networks: A Deep Learning Approach for Performance Optimizing and Energy Efficiency

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ABSTRACT: The rapid expansion of the Internet of Things (IoT) has led to the widespread adoption of sensor networks, with Long-Range Wide-Area Networks (LoRaWANs) emerging as a key technology due to their ability to support long-range communication while minimizing power consumption. However, optimizing network performance and energy efficiency in dynamic, large-scale IoT environments remains a significant challenge. Traditional methods, such as the Adaptive Data Rate (ADR) algorithm, often fail to adapt effectively to rapidly changing network conditions and environmental factors. This study introduces a hybrid approach that leverages Deep Learning (DL) techniques, namely Long Short-Term Memory (LSTM) networks, and Machine Learning (ML) techniques, namely Artificial Neural Networks (ANNs), to optimize key network parameters such as Signal-to-Noise Ratio (SNR) and Received Signal Strength Indicator (RSSI). LSTM-ANN model trained on the "LoRaWAN Path Loss Dataset including Environmental Variables" from Medellín, Colombia, and the model demonstrated exceptional predictive accuracy, achieving an R^2 score of 0.999, Mean Squared Error (MSE) of 0.041, Root Mean Squared Error (RMSE) of 0.203, and Mean Absolute Error (MAE) of 0.167, significantly outperforming traditional regression-based approaches. These findings highlight the potential of combining advanced ML and DL techniques to address the limitations of traditional optimization strategies in LoRaWAN. By providing a scalable and adaptive solution for large-scale IoT deployments, this work lays the foundation for real-world implementation, emphasizing the need for continuous learning frameworks to further enhance energy efficiency and network resilience in dynamic environments.

KEYWORDS: LoRaWAN; performance optimization; energy efficiency; ML; DL

1 Introduction

1.1 Background and Motivation

The rapid growth of the Internet of Things (IoT) has driven the widespread deployment of large-scale sensor networks across various fields including smart cities, industrial automation, and environmental monitoring [1–3]. Among the technologies enabling IoT, the Long-Range Wide-Area Networks (LoRaWANs) have gained significant attention owing to their capability for long-range communication with low power consumption, making them ideal for battery-operated devices in wide-area sensor networks. LoRaWAN operates in unlicensed frequency bands, providing a flexible and scalable solution for IoT applications that require network infrastructure to support thousands of nodes over large geographical areas [4].

Energy efficiency (EE) and network performance optimization, both are critical for large-scale IoT deployments, as the number of connected devices continues to increase. However, ensuring long battery life for IoT devices whilst maintaining reliable network throughput and low latency poses a significant challenge [5]. A traditional approach, such as the standard Adaptive Data Rate (ADR) algorithm, often struggles to adapt to dynamic environmental and network conditions, resulting in inefficient resource allocation and excessive energy consumption [6]. Additionally, these approaches typically overlook the role of environmental variability and temporal dependencies, which are critical in large-scale deployments. These limitations highlight the need for advanced, data-driven methodologies capable of dynamically optimizing network parameters in real time while addressing environmental and operational variability. This study proposes a novel hybrid Deep Learning (DL) approach to bridge this gap, offering a scalable solution to optimize both performance and EE in LoRaWAN networks.

Recently, Machine Learning (ML) and Deep Learning (DL) have emerged as valuable tools for optimizing network performance [7]. By recognizing patterns in data and predicting key metrics, such as signal quality and energy consumption, ML/DL techniques can dynamically adjust network configurations and improve both performance and energy efficiency. These data-driven approaches offer promising solutions to the challenges faced in optimizing LoRaWAN networks, particularly in contexts where traditional algorithms have proven to be insufficient [8,9].

1.2 Research Problem

The major challenge in LoRaWAN networks is the optimization of both performance and energy efficiency. With numerous configurable parameters, such as transmission power (TP), spreading factor (SF), and bandwidth (BW), determining the optimal configuration for each device in a large-scale network becomes complex. An inadequate configuration can lead to increased packet collisions, lower throughput, and excessive energy consumption, ultimately limiting the network scalability and device battery life [10].

In addition, LoRaWAN's ADR algorithm struggles to maintain network performance in dynamic environments because it lacks the ability to adapt to fluctuating signal conditions and environmental factors. This issue is further amplified in wide-area networks where devices experience varying levels of interference, path loss, and shadowing. Consequently, there is a pressing need for advanced methodologies that can intelligently predict network behavior and optimize resource allocation in real time.

Several studies have attempted to address these challenges using ML and DL techniques [8,11–14]. For instance, Rajab et al. [15] applied Support Vector Regression (SVR) and Deep Neural Networks (DNNs) to dynamically adjust transmission parameters, such as SF and TP, achieving a 43% reduction in energy consumption compared with traditional ADR algorithms. Bernard et al. [16] demonstrated how embedding Long Short-Term Memory (LSTM) models into sensors helped reduce redundant transmissions by predicting future data points, resulting in a 40% reduction in transmission costs. However, their limitations lie in the dependency on simulation-based testing, computational constraints, and reliance on specific configurations for optimal performance. These studies utilized datasets that focus primarily on simulated or controlled environments without capturing real-world environmental variability, which is the main focus of this study.

Another method used to address dynamic environmental conditions in LoRaWAN networks is reinforcement learning (RL). RL models were used by Minhaj et al. [8] to optimize the allocation of SF and TP, considering real-time channel conditions and interference. The results showed a 25% reduction in energy consumption and improved Packet Reception Ratio (PRR). This work leveraged a custom dataset of controlled experiments, limiting its ability to generalize across diverse environments. Although RL demonstrates adaptability, its real-world scalability remains limited due to complexities in implementation.

Other studies, such as those by Kaur et al. [9], have implemented hybrid models that combine Artificial Neural Networks (ANN) with Particle Swarm Optimization (PSO) to efficiently optimize LoRa parameters.

This study demonstrated the improvements achieved by adjusting the SNR and RSSI to optimize the SF and significantly enhance the LoRa network performance in industrial scenarios. Similarly, Guerra et al. [17] used a Random Forest (RF) and Artificial Neural Networks (ANNs) to predict RSSI based on environmental factors, resulting in greater accuracy and improved energy consumption through the dynamic adjustment of network parameters. Moreover, ARIMA models have been combined with ANNs to forecast RSSI and optimize TP, particularly under adverse weather conditions. These studies demonstrate that ML/DL models can overcome the limitations of traditional ADR by adapting network parameters based on real-time data and environmental conditions. While these studies demonstrate the potential of ML and hybrid approaches to enhance LoRaWAN performance, they share common limitations, including constrained application scenarios, and challenges in scalability and real-world implementation.

Despite these advances, optimizing the performance and energy efficiency of LoRaWANs remains a complex challenge owing to the dynamic and heterogeneous nature of large-scale IoT deployment [18]. Most of the existing models are computationally intensive and may not be feasible for real-time deployment in energy-constrained IoT devices. Also, there is a lack of research that incorporates temporal dependencies and environmental variability into these models, which is essential for long-term network optimization in dynamic environments. Therefore, there is a critical need for advanced ML/DL methodologies that enable real-time context-aware network optimization, ensuring both scalability and energy efficiency in LoRaWAN networks.

1.3 Research Contribution

This study aims to apply LSTM-ANN techniques to optimize the performance and energy efficiency of LoRaWAN-based sensor networks. The contributions of this study are as follows:

- To identify the optimal configurations of the key LoRaWAN parameters that balance performance and energy consumption.
- To investigate the relationships between communication parameters and their combined impact on network performance and energy efficiency, particularly in large-scale, wide-area networks.
- To develop a novel hybrid DL model, specifically combining Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANN), that incorporate real-world environmental variability and temporal dependencies, offering a robust solution for network optimization.

1.4 Structure of the Paper

The remaining sections of this paper are organized as follows. Background information on LoRaWAN and IoT sensor networks is provided in Section 2, along with a literature review of LoRaWAN and examples of ML and DL applications in IoT Sensor Networks. Section 3 elaborates on the methodology, including data collection and preprocessing, model architecture, and model optimization. The results and discussion are presented in Section 4, followed by suggestions for future research in Section 5, which concludes the paper.

2 Background

This section provides an overview of the key technologies and challenges associated with optimizing the performance and energy efficiency of LoRaWAN-based IoT sensor networks. Section 2.1 presents the role of IoT and LoRaWAN as critical communication protocols that facilitate long-range, low-power communications. Section 2.2 describes the evaluation metrics for the performance optimization and energy efficiency of LoRaWAN networks. Finally, Section 2.3 explores advanced techniques, including ML and DL methodologies, that have been implemented to enhance network resource allocation and energy efficiency in large-scale IoT deployments.

2.1 IoT and LoRaWAN Sensor Networks

IoT is a crucial technical development that has transformed several sectors by allowing objects to exchange data and communicate over large distances. Real-time data collection, exchange, and analysis are facilitated by IoT, which boosts operational effectiveness [1,19,20]. However, to handle many connected devices, the adoption of IoT networks necessitates communication protocols that are not only scalable and dependable but also energy efficient. An important piece of technology in this field is LoRaWAN [21]. LoRaWAN operates in unlicensed frequency bands and is widely adopted in applications such as smart cities, environmental monitoring, agriculture, and industrial automation [3,22–24].

LoRaWAN is an important communication protocol in IoT because it supports long-range communication with low power consumption [12,25]. The LoRaWAN protocol stack comprises of a physical layer using Chirp Spread Spectrum (CSS) modulation and a Medium Access Control (MAC) layer that controls network communication [26]. With this, the LoRaWAN not only ensures maintenance of the sensor's battery lifetime but also reduces the cost of the device [27]. This is ideally suited for large-scale end-device (ED) communication with gateways (GWs) forwarding data to a network server (NS) [28], as shown in its star-of-stars topology (Fig. 1) [29].

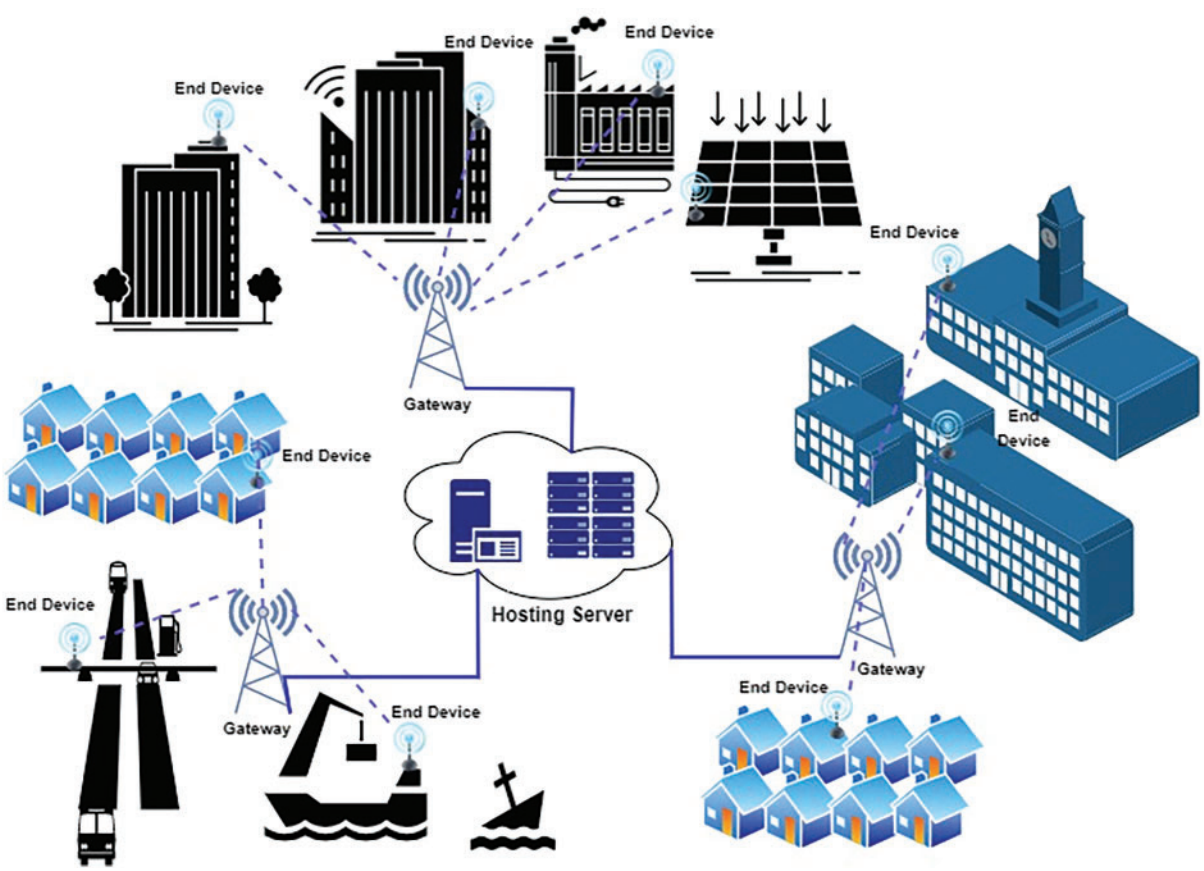

Figure 1: LoRaWAN network architecture. A typical LoRaWAN deployment includes end nodes, gateways, and hosting servers

LoRaWAN offers various communication classes designed to satisfy different latency requirements. These classes are:

- Class A (bidirectional end devices): This class is designed for minimal power consumption and is suitable for applications that require brief downlink communication after an uplink message.
- Class B: This class adds scheduled receive slots to random windows, thereby improving the predictability of the latency.
- Class C: This class keeps extra receive windows open continuously, which is ideal for IoT applications with continuous power sources.

These multiple communication classes and LoRaWAN's ability to leverage redundant reception for localization make it adaptable to a wide range of IoT application requirements [12].

Additionally, LoRaWAN operates in two communication modes: confirmed and unconfirmed. The confirmed mode improves the reliability of data transmission because each data packet sent by an end device requires acknowledgment from the gateway [30–32]. This approach ensures successful packet delivery to the NS although it may incur higher energy consumption if required. However, the unconfirmed mode is inherently more energy efficient, as it eliminates the need for acknowledgments and retransmissions, reducing the overall energy consumption of the end devices [33,34]. By leveraging advanced communication protocols and optimization techniques, it is possible to balance the trade-offs between performance and energy efficiency in LoRaWANs. The end device (ED) employs an ADR recovery mechanism to further enhance energy efficiency by optimizing the transmission parameters based on the network conditions and the distance between the end device and the gateway [30,34].

2.2 Performance Optimization and Energy Efficiency in LoRaWAN

LoRaWAN has gained significant attention in recent years owing to its potential for enabling large-scale IoT deployments. This communication protocol offers several advantages, including low data rates, minimal power consumption, extensive coverage, and straightforward management, making it an efficient solution for a range of IoT applications [27]. However, performance optimization and energy efficiency remain key challenges, particularly in terms of resource allocation and scalability. LoRaWAN operates on open Industrial, Scientific and Medical (ISM) bands, which are shared with other technologies, leading to interference and congestion issues that further complicate the optimization of network performance [23].

The traditional ADR algorithm, which is a key mechanism for optimizing communication in IoT networks, is widely adopted for managing transmission parameters such as the SF and TP. ADR dynamically adjusts these parameters by analyzing periodic feedback from devices, which report metrics like Received Signal Strength Indicator (RSSI) and Signal-to-Noise Ratio (SNR) [35]. This adaptation process aims to enhance energy efficiency while maintaining reliable communication [6]. However, ADR has several limitations in dense networks [35]. It relies on periodic uplinks to adapt, making it slow to respond to sudden environmental changes, and its conservative approach to parameter selection often results in suboptimal performance under dynamic network conditions [35–37]. For instance, in fast-changing environments, such as industrial IoT settings or urban areas with varying interference levels, ADR's reliance on historical data hinders its ability to adjust parameters swiftly. ADR struggles particularly in high-density IoT environments, where many devices simultaneously transmit data, causing increased collisions and latency. This periodic feedback mechanism may require several transmission cycles to adjust TP, which is insufficient in fast-changing environments [10,36,38]. Moreover, in dense urban areas with fluctuating signal interference, ADR often selects suboptimal settings, exacerbating packet loss and energy consumption [39]. These inefficiencies highlight ADR's limited scalability and adaptability in dynamic IoT networks. These limitations highlight the need for improved ADR algorithms capable of real-time adaptation to dynamic environments, optimizing resource allocation, and enhancing overall network performance.

The performance of a LoRaWAN network is largely determined by metrics such as the SNR and the RSSI, which influence the reliability and energy efficiency of the network [22]. The SNR measures the clarity of the signal compared to the background noise, whereas the RSSI indicates the power level of the received signal. Both metrics play a crucial role in determining link quality, packet delivery rate, and overall network efficiency. Higher values of SNR and RSSI typically correspond to better network performance because they reduce the likelihood of retransmissions, lower the bit error rate (BER), and enhance energy efficiency by minimizing the need for excessive TP. Optimizing these parameters is critical for maintaining network performance while minimizing energy consumption, particularly for large-scale deployments with numerous sensors [26].

Several studies have explored how environmental conditions, such as temperature, humidity, and interference, affect the RSSI and SNR. Minhaj et al. [8] incorporated fading models into LoRaWAN simulations to evaluate the SNR and RSSI under various environmental conditions, demonstrating the importance of these metrics for maintaining energy efficiency in challenging network environments. SNR is particularly important in determining PRR. Their research demonstrated that higher SNR values are associated with lower bit error rates, which improves PRR and reduces the need for retransmissions, thereby conserving energy. Moreover, in a recent study by Guerra et al. [17], a hybrid model combining ARIMA with AI techniques was proposed to forecast the RSSI using weather parameters. This hybrid model, which integrated ARIMA with Artificial Neural Networks (ANN), outperformed traditional models, particularly in environments with significant weather-induced channel variations, emphasizing the importance of hybrid models in capturing both linear and nonlinear patterns.

In LoRaWAN, the SF, TP, and coding rate (CR) are often adjusted based on SNR and RSSI readings to maintain optimal performance. It has been shown that optimizing these parameters using SNR and RSSI not only enhances link quality, but also balances the trade-off between network coverage and energy consumption [9,26].

2.3 Application of ML and DL in LoRaWAN

ML has proven to be highly effective in improving SNR and RSSI prediction, leading to more efficient network management. Optimizing the SNR and RSSI has a direct impact on improving network performance and energy efficiency in LoRaWAN networks. These metrics are influenced by various environmental and network conditions such as rain and humidity [26], and ML techniques have proven to be powerful tools for improving their prediction and management.

Traditional models often fail to capture the dynamic, nonlinear nature of real-world environments. On the other hand, ML models can process a wide range of inputs, including environmental conditions and network parameters, to make more accurate predictions. For instance, Guerra et al. [17] demonstrated that Random Forests (RF) and Artificial Neural Networks (ANNs) can outperform traditional models in predicting RSSI based on environmental data, thereby significantly improving network efficiency. In addition, the application of hybrid models, such as those combining ARIMA and ANNs, further enhances the RSSI prediction accuracy by capturing both short-term and long-term patterns in time-series data. Furthermore, Kaur et al. [9] successfully combined Artificial Neural Networks (ANN) with Particle Swarm Optimization (PSO) to predict RSSI in industrial IoT environments, leading to more accurate link quality predictions and better energy management. They demonstrated that optimizing the RSSI can significantly reduce the bit error rate and enhance network reliability in both obstructive and non-obstructive environments. The use of an ANN-PSO model to optimize the TP based on RSSI readings led to improvements in energy efficiency, and demonstrating that small adjustments in these metrics can have substantial effects on the overall network performance.

Another direction to address LoRaWAN network limitations in recent studies have explored ML and reinforcement learning (RL) techniques for dynamic resource allocation, such as SF and TP, which significantly improve network throughput and energy efficiency. For example, Minhaj et al. [8] proposed a RL-based method for dynamic SF and TP allocation that considers real-time channel fading and interference, thereby improving PRR and energy efficiency. Their approach combined centralized ML-based TP allocation with decentralized RL-based SF allocation, demonstrating enhanced performance in reducing energy consumption while maintaining high PRRs. This dual strategy not only improved scalability but also alleviated congestion, making it suitable for future IoT applications. Using a Nakagami-m fading model, the RL algorithm showed superior adaptability to real-world channel variations, achieving approximately 26 times better energy efficiency than other state-of-the-art algorithms in congested networks. Furthermore, research [40] has demonstrated that by optimizing parameters such as SP and TP using the RL algorithm, the overall performance and energy efficiency of LoRaWAN networks can be significantly enhanced. Therefore, these findings demonstrate the efficacy of ML and RL-based dynamic resource allocation in enhancing the LoRaWAN network performance, paving the way for more efficient and scalable IoT deployments.

Gonzalez-Palacio et al. [41] introduced an environment-aware combined path loss and shadow fading model (CPLS) for LoRaWAN networks. This model incorporates ML models, such as multiple linear regression, support vector regression, random forests, and artificial neural networks, into path loss and shadow fading models, which are used to optimize the TP and SF using an ADR algorithm. The developed models demonstrated a root mean square error (RMSE) of up to 1.566 dB and an R^2 value of 0.94, achieving a 43% improvement in energy efficiency compared to traditional ADR methods by reducing the link margin required for reliable communication.

Although LoRaWAN offers advantages in terms of long-range communication and low power consumption, it still faces performance challenges related to packet loss, collisions, and interference. A LoRaWAN gateway receiving messages from multiple IoT devices on the same channel can lead to high packet loss owing to collisions and interference, thereby impacting network scalability and efficiency [5,42]. For instance, Ojo et al. [43] proposed a deep-learning-based approach to predict and mitigate such interference. By using a Recurrent Neural Network (RNN), they were able to predict interference patterns with high accuracy, leading to improved throughput and reduced energy consumption of the LoRaWAN network. Their model showed a reduction in the estimation error to less than 5 dB compared to traditional methods.

The integration of ML and DL into IoT sensor networks has revolutionized the optimization of performance and energy efficiency, particularly in large-scale deployments [26]. In low-power wide area networks (LPWAN), such as LoRaWAN, ML and DL models are increasingly applied to address challenges such as signal degradation, interference, and energy constraints. These networks, which are widely adopted for their long-range communication and low power consumption, have critical requirements for efficient resource management, making ML and DL indispensable for real-time optimization [44]. By leveraging ML models, network parameters, such as SF and TP, can be dynamically adjusted based on network conditions, thereby significantly enhancing network performance and reducing energy consumption [12].

One case study by Rajab et al. [15] applied Support Vector Regression (SVR) and Deep Neural Networks (DNNs) to reduce power consumption in LoRaWAN devices. By adjusting transmission parameters, such as SF and TP, the authors managed to optimize the battery lifetime of sensor devices, demonstrating energy savings of up to 43% compared with traditional methods. This study highlights how ML models allow devices to operate more efficiently without compromising the data throughput by continuously learning from environmental data and network conditions.

Similarly, Bernard et al. [16] focused on embedding Long Short-Term Memory (LSTM) neural networks directly onto LoRaWAN sensors to manage compressed communication. This method reduces the transmission of redundant data by allowing sensors to predict future data points based on historical time-series data. If the predicted values closely matched the measured values, the data transmission was skipped, significantly reducing energy consumption. The results showed that this dual-prediction model achieved a 40% reduction in the transmission costs and improved the energy efficiency of the network. This approach not only highlights the potential of DL in handling complex time-series data but also demonstrates its effectiveness in reducing the overall communication burden on constrained IoT devices.

In a comparative study by Bouras et al. [14], several ML models were examined for SF selection in LoRaWAN. By simulating different network conditions and applying models such as Random Forest (RF) and Gradient Boosting (GB), the authors found that ML-based SF allocation significantly outperformed both random SF assignment and traditional ADR algorithms. Their approach led to improved delivery ratios and reduced energy consumption, demonstrating the benefits of using ML to optimize the critical communication parameters in LoRaWAN networks.

González-Palacio et al. [45] developed a ML-Assisted Transmission Power Control (TPC) system for LoRaWAN, leveraging ML models like Random Forest and ANN to predict real-time SNR values. Using six months of environmental data from Medellín, Colombia, the study achieved a 47.1% reduction in energy consumption, a 99% Packet Delivery Rate (PDR), and a 9.5% reduction in network collisions. However, its reliance on computationally intensive models and specific datasets limits its scalability to broader applications.

Similarly, Qamar et al. [46] proposed hybrid ANN-based algorithms, Reduced k-means with ANN (RkM-ANN) and Delay Bound Reduced k-means with ANN (DBRkM-ANN), to optimize mobile sink routing in Wireless Sensor Networks (WSNs). Their approach enhanced network lifespan and reduced delays, though validation was limited to simulations, lacking real-world testing. Table 1 presents a series of studies from 2020 to 2024 that implemented various ML and DL techniques to improve the performance and energy efficiency of LoRaWAN networks. These results collectively demonstrate how advanced ML/DL techniques have improved the overall performance and enhanced the energy efficiency of LoRaWAN networks. While these studies exhibit promising advancements in using ML and DL techniques to enhance LoRaWAN networks, they commonly face challenges related to scalability, real-world deployment complexities, and dependence on specific datasets and hardware configurations.

Table 1: Summary of ML/DL techniques in performance optimization and energy efficiency

Author(s)	Year	ML/DL technique	Improvement	Limitation
Khalifeh et al. [40]	2020	RL	Optimized energy consumption based on real-time conditions.	Heavily reliant on specific hardware setups.
Rajab et al. [15]	2021	SVR, DNN	Achieved a 43% reduction in energy consumption by dynamically adjusting transmission parameters.	Limited scalability for larger and more dynamic IoT environments.
Bernard et al. [16]	2021	LSTM	40% reduction in transmission costs by predicting data points and reducing redundant transmissions.	Dependency on fine-tuned thresholds for optimal compression.

(Continued)

Table 1 (continued)

Author(s)	Year	ML/DL technique	Improvement	Limitation
Bouras et al. [14]	2021	RF, GB	Improved delivery ratios and reduced energy consumption through optimized SF allocation.	Focused on simulation data with limited real-world application.
Kaur et al. [9]	2022	ANN-PSO	Enhanced LoRa network performance in industrial scenarios through SNR and RSSI optimization.	Limited to indoor industrial scenarios.
Minhaj et al. [8]	2023	RL, ML	25% reduction in energy consumption and improved PRR by optimizing TP and SF.	Complex implementation for real-world scalability.
Gonzalez et al. [41]	2023	MLR, SVR, RF, ANN	Enhanced energy efficiency by 43%, achieving RMSE of 1.566 dB and an R^2 score of 0.94, outperforming traditional ADR algorithms.	Complexity in integrating environmental variables into real-time applications.
Guerra et al. [17]	2024	RF, ANN, ARIMA	Improved RSSI prediction using environmental factors, enhancing energy consumption.	Focused on linear dependencies, with limited exploration of nonlinear patterns.
Ojo et al. [43]	2024	RNN	Improved throughput and reduced energy consumption.	Deployment in mountainous areas only.
Gonzalez et al. [45]	2024	MLR, Lasso, Ridge, GAM, ANN, SVR, RF	47.1% reduction in energy consumption and improved PDR.	High computational overhead during training.
Qamar et al. [46]	2024	ANN, hybrid RkM-ANN, DBRkM-ANN	Reduced energy consumption and improved network lifetime.	Limited generalization due to lack of real-world data validation.

The range of models employed demonstrates a consistent trend towards more dynamic data-driven optimization of transmission parameters, leading to significant reductions in energy consumption and improved network performance. As the field progresses, it is evident that hybrid approaches integrating multiple ML/DL models, as seen in recent studies, hold great promise for further advancements in network optimization, particularly in adapting to real-time conditions and environmental factors.

Various models have been employed in similar contexts, ranging from simple linear regression to complex neural networks. Linear regression models assume a linear relationship between the input variables and target variable, making them suitable for straightforward prediction tasks [47,48]. However, they may struggle to capture the nonlinear patterns in complex datasets. Nonetheless, neural networks, particularly DL architectures [8], have gained popularity owing to their ability to learn intricate patterns and relationships within data. These models can automatically extract relevant features and handle high-dimensional inputs, rendering them versatile for a wide range of applications.

Advanced models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have also demonstrated remarkable performance in time-series forecasting tasks [12,49]. These recurrent neural network architectures are designed to capture long-term dependencies in sequential data, making them particularly effective in predicting future values based on historical patterns. LSTMs and GRUs can overcome the vanishing gradient problem that plagues traditional recurrent neural networks, allowing them to learn and retain information over extended time horizons [50]. Hybrid approaches that combine multiple model types or incorporate domain-specific knowledge, have also been developed to leverage the strengths of different techniques and improve overall forecasting accuracy [17,51].

To address these challenges, advanced methods are required to dynamically optimize key network parameters such as RSSI and SNR. This study proposes a hybrid LSTM-ANN model capable of predicting network conditions and adjusting configurations in real-time, mitigating the impact of interference, improving scalability, and enhancing energy efficiency in complex and dynamic environments.

3 Methodology

LoRaWAN networks frequently encounter congestion and interference, particularly in large-scale IoT deployments, which can critically impair overall network performance and energy efficiency. Traditional methods, such as the standard ADR algorithm, fail to quickly adapt to dynamic environmental changes, resulting in poor network throughput and energy inefficiency. This study aims to optimize the performance and energy efficiency of a LoRaWAN-based IoT sensor network by predicting key performance metrics such as SNR using hybrid ML/DL models. Specifically, the approach combines Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs) to capture both temporal dependencies and non-linear relationships within the data. In Section 3.1, we describe the data collection and pre-processing steps. In Section 3.2, we present the model architecture, provide details of the chosen model, and introduce a mathematical formula. In Section 3.3, we discuss early stopping and model optimization techniques.

3.1 Data Collection and Preprocessing

This study leverages the LoRaWAN Path Loss Dataset including Environmental Variables [52], which was created to enhance the understanding of how environmental factors influence the performance of LoRaWAN networks. The dataset was collected through a comprehensive measurement campaign conducted in Medellín, Colombia, which spanned over four months. The dataset includes over 930,000 observations, capturing a wide range of variables, including the RSSI, SNR, and path loss, along with environmental factors, such as temperature, relative humidity, barometric pressure, and particulate matter.

The dataset is particularly valuable for its inclusion of environmental variables, which are often overlooked in traditional path loss models. These variables are crucial for developing more accurate models that reflect the real-world performance of LoRaWAN networks under varying environmental conditions. By incorporating these factors, the dataset allows the hybrid LSTM-ANN model to identify and learn the relationships between environmental variables and key performance metrics like RSSI and SNR, which are vital for optimizing LoRaWAN networks. Data was collected using a network of four ENs and one GW, with the ENs strategically placed to ensure line-of-sight communication across different urban scenarios (Fig. 2). The collected data includes both geometric parameters, such as distance and antenna height, and radio parameters, such as TP and frequency.

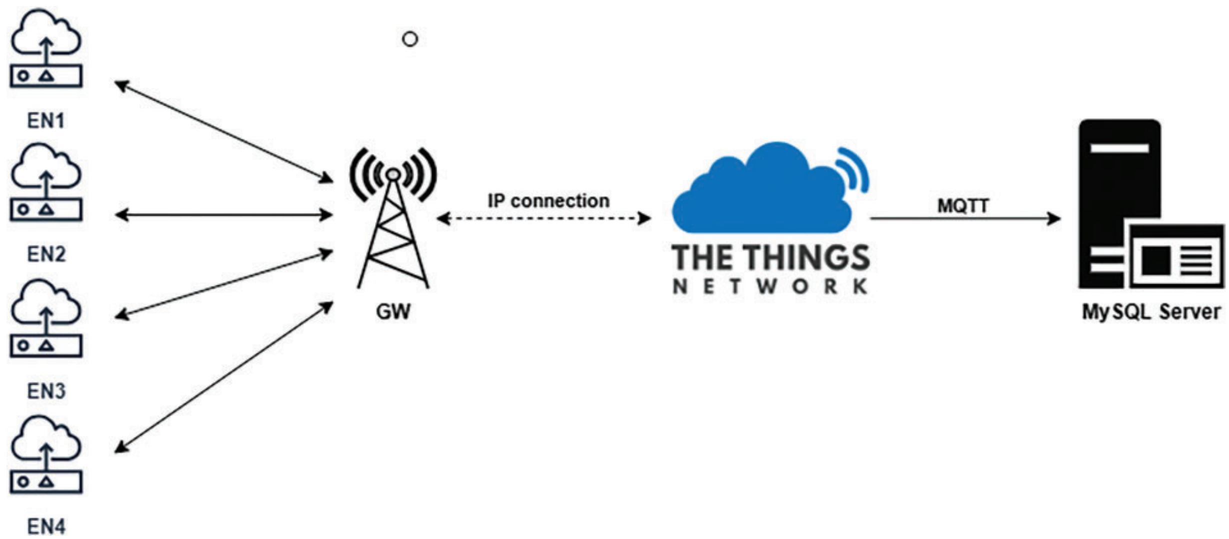

Figure 2: LoRaWAN deployment showing ENs, GW, and data flow to TTN and MySQL server [41]

Preprocessing of the dataset involved several steps to ensure its quality and suitability for DL applications. The dataset was split into training and testing sets using a uniform random split, with an 80–20 split, to facilitate model validation and prevent overfitting.

3.2 Model Architecture

3.2.1 LSTM Model

Long Short-Term Memory (LSTM) networks are a specialized form of Recurrent Neural Networks (RNNs) designed to process and learn from sequential data. Unlike traditional RNNs, which encounter difficulties in learning long-term dependencies owing to the vanishing gradient problem, LSTM networks are equipped with memory cells that store information over extended sequences [53,54]. These cells possess three gates—input, forget, and output—that regulate the flow of information, enabling the network to retain relevant information over longer periods while discarding unnecessary details.

LSTMs are particularly well suited for problems involving time-series data or sequential inputs, making them an appropriate choice for predicting performance metrics such as SNR, which can change over time depending on environmental factors and network conditions [50]. In this study, the LSTM model is used to capture the temporal dependencies between consecutive measurements of environmental factors (e.g., temperature, humidity) and radio metrics (e.g., RSSI, SNR). The ability to learn from sequential patterns makes LSTMs ideal for optimizing resource allocation in LoRaWAN networks, where communication performance is influenced by prior states of the network.

3.2.2 ANN Model

Artificial Neural Networks (ANNs) are computational models inspired by the neural networks of the human brain and consist of layers of interconnected neurons. ANNs are widely used for learning nonlinear relationships between input features and outputs, which are critical when dealing with complex datasets involving environmental factors and wireless communication metrics [55]. An ANN typically includes an input layer, one or more hidden layers, and an output layer, with each neuron applying a non-linear activation function to the weighted sum of its inputs.

In the context of this study, the performance of LoRaWAN (measured by SNR) is influenced by both linear and nonlinear interactions between environmental variables (e.g., temperature and humidity) and network parameters (e.g., TP and distance) [56,57]. While the LSTM model captures temporal dependencies, the ANN model learns nonlinearities that may not be immediately apparent from sequential data alone [41]. By integrating ANN layers into the model, this study ensures that complex relationships between the input features and the target variable are accounted for, improving the model's ability to predict network performance accurately.

3.2.3 Details of Chosen Model

The hybrid model combines the temporal modeling strengths of Long Short-Term Memory (LSTM) networks with the ability of Artificial Neural Networks (ANNs) to capture nonlinear relationships between input and output variables. This combination addresses the multifaceted challenges of optimizing LoRaWAN network performance.

The LSTM component is designed to process sequential data, such as time-varying environmental and network factors. Its ability to retain information over long sequences enables the model to capture temporal dependencies critical for predicting performance metrics like SNR and RSSI. These metrics often exhibit patterns influenced by prior network states and environmental changes, making LSTMs particularly well-suited for modeling time-series data in LoRaWAN. For instance, the LSTM identifies how fluctuations in environmental variables, such as humidity or temperature, propagates through time to impact network performance.

In contrast, the ANN component is adept at learning complex, nonlinear interactions between variables. ANN layers account for the intricate relationships between environmental factors (e.g., temperature, humidity) and network parameters (e.g., TP, distance) that influence LoRaWAN performance. These nonlinear patterns are often not immediately apparent but are crucial for understanding the interplay of environmental and network factors. For example, the ANN component identifies how combinations of temperature and distance influence SNR under varying environmental conditions.

By integrating these two components, the hybrid LSTM-ANN model leverages these complementary strengths. The LSTM focuses on capturing time-dependent patterns, while the ANN ensures that nonlinear dependencies between variables are accurately modeled, resulting in improved predictive accuracy and robustness. This dual approach enables the model to dynamically optimize key network parameters and adapt to changes in environmental and operational conditions.

The hybrid architecture consists of an input layer for features (such as SNR, RSSI, and environmental variables), followed by an LSTM layer for sequential processing. This is succeeded by a dropout layer for regularization, several dense layers with LeakyReLU activation to capture nonlinear relationships, and an output layer that predicts SNR. The inclusion of environmental variables into the input feature set ensures that the model accounts for their significant impact on network performance, enhancing its ability to make accurate and reliable predictions in diverse IoT scenarios. The architecture is depicted in Fig. 3.

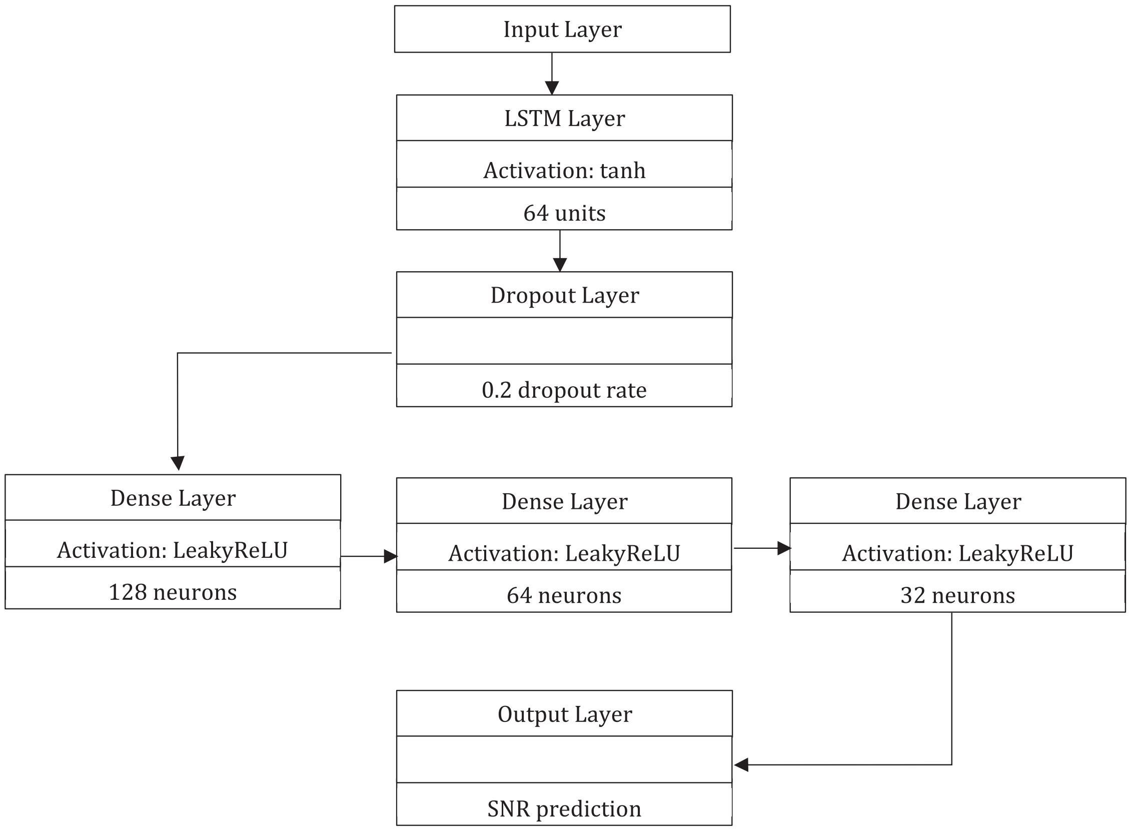

Figure 3: The hybrid LSTM-ANN model architecture

- **LSTM Layer:** The LSTM layer includes 64 units with a hyperbolic tangent activation function. This layer is crucial for capturing the sequential patterns in the data, especially given the temporal nature of wireless communication metrics. To further enhance the performance and interpretability of the model, an attention mechanism was considered.
- **Dropout Layer:** To prevent overfitting, a dropout layer with a rate of 0.2 was applied after the LSTM layer. Dropout randomly sets a fraction of input units to zero during training, which helps in regularizing the model.
- **Dense Layers:** The output from the LSTM layer was fed into a series of fully connected dense layers. These layers included 128, 64, and 32 neurons, respectively, each using the LeakyReLU activation function to introduce nonlinearity into the model, allowing it to capture more complex patterns in the data.
- **Output Layer:** A final dense layer with a single neuron and a linear activation function was used to output the predicted SNR value.

3.2.4 Mathematical Formula

Stage 1: LSTM Auto-Encoder Encoding

The LSTM autoencoder was used to encode the input data into a latent representation. The mathematical operations in the auto-encoder are defined as follows:

1. Input layer:

$$Input = X \, \varepsilon \, R^{n*t*d}$$

where n denotes the number of samples, t denotes the number of timestamps, and d denotes the number of features.

2. Auto-encoder (LSTM layer)

- The first LSTM layer transforms the input as follows:

$$H_1(t) = LSTM(X; W_1, b_1) \in R^{n\times t\times h_1}$$

where W_1 and b_1 are the weight and bias, respectively, and $h_1 = 128$ is the hidden state size.

- Attention mechanism.

$$A(t) = Attention(H_1, H_1) \in R^{n\times t\times h_1}$$

- The second LSTM layer further processes the attention output.

$$H_2(t) = LSTM(A; W_2, b_2) \in R^{n\times h_2}$$

where h_2 is the hidden state size.

- Decoder (Reverse LSTM layer).
  - Reconstruct the input using the decode latent representation.

$$\hat{X} = LSTM_{decoder}(H_2; W_d, b_d) \in R^{n\times t\times d}$$

  - Time distributed dense layer to match the original input dimension.
- Autoencoder loss.

$$L_{autoencoder} = \frac{1}{n}\sum_{i=1}^{n}\left|X_i - \hat{X}_i\right|^2$$

The auto-encoder minimizes the MSE between the original input and reconstructed input.

After training, the auto-encoder was used to extract the latent representation H_2 for further use in the LSTM-ANN model.

Stage 2. LSTM-ANN regression model

The encoded features H_2 were used to train the complex LSTM and ANN models to predict the SNR target variables.

1. Input layer:

$$Input: H_2 \in R^{n\times h_2}$$

2. First LSTM layer:

The first LSTM layer processed the encoded data.

$$H_3(t) = LSTM(H_2; W_3, b_3) \in R^{n\times t\times h_3}$$

where $h_3 = 128$.

3. Second LSTM layer:

A second LSTM layer reduces dimensionality.

$$H_4 = LSTM(H_3; W_4, b_4) \in R^{n\times h_4}$$

where $h_4 = 64$.

4. Dense layer:

The encoded output from the LSTM layer passes through a series of dense layers with a LeakyReLU activation function.

$$D_1 = LeakyReLU(Dense\,(H_4; W_5, b_5)) \in R^{n\times d_1}$$

where $d_1 = 128$.

5. Similarly, for subsequent dense layer:

$$D_2 = LeakyReLU(Dense\,(D_1; W_6, b_6)) \in R^{n\times d_2}$$

where $d_2 = 64$.

$$D_3 = LeakyReLU(Dense\,(D_2; W_7, b_7)) \in R^{n\times d_3}$$

where $d_3 = 32$.

6. Output layer:

The final output layer predicts the target variable (SNR) as follows:

$$\hat{y} = Dense\,(D_3; W_{out}, b_{out}) \in R^{n\times 1}$$

7. Loss function:

The LSTM-ANN model was trained to minimize the MSE/RMSE between the predicted and actual SNR values.

$$L_{LSTM-ANN} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|^2$$

3.3 Model Optimization and Evaluation

To mitigate overfitting and enhance the model's generalization to unseen data, an early stopping technique was implemented [58]. Ali et al. [59] highlight the risks of overfitting in deep learning-based crack detection models and emphasize the importance of optimizing training epochs to maintain a balance between accuracy and generalization. Early stopping is a regularization technique that continuously monitors validation loss during training. If no improvement was observed for ten consecutive epochs, the training process would be halted. The model was then restored to the state where it achieved the best validation performance. This approach ensures that the model does not overfit the training data and improves its generalization to the unseen data. Additionally, early stopping optimizes the computational efficiency by reducing unnecessary training time [60].

Model optimization was performed using the Adam optimizer, which combines the strengths of the Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). The Adam optimizer was selected because of its effectiveness in handling sparse and nonstationary gradients. The learning rate was set to 0.001, and additional hyperparameters, such as the number of LSTM units and dense neurons, were fine-tuned using grid and random search techniques.

4 Results and Discussion

4.1 Interpretation of Key Findings

The performance of the model is evaluated using widely recognized metrics, namely R-squared (R^2), Mean Squared Error (MSE), Mean Absolute Error (MAE), and the Root Mean Squared Error (RMSE). R^2 measures the proportion of variance in the observed data explained by the model, with values closer to 1 indicating better explanatory power. Mean Squared Error (MSE) quantifies the average squared differences between predicted and actual values, emphasizing larger errors due to squaring. Mean Absolute Error (MAE) calculates the average of the absolute differences between predicted and actual values, treating all errors equally. Finally, Root Mean Squared Error (RMSE) provides an error metric in the same units as the original data, making it easier to interpret. Together, these metrics offer a comprehensive view of model accuracy and error distribution. These metrics are calculated using the following equations:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

where y_i is the actual value of the i-th observation, $\hat{y}_i$ is the predicted value of the i-th observation, $\overline{y}$ is the mean of the actual values and n is the total number of observations.

The results of this study demonstrate the effectiveness of advanced ML and DL techniques for optimizing the performance and energy efficiency of LoRaWAN-based sensor networks. The hybrid LSTM-ANN model significantly outperformed traditional models, achieving an R^2 score of 0.999 and low error metrics such as MSE of 0.041, MAE of 0.167, and RMSE of 0.203.

Achieving an R^2 score of 0.999 is particularly notable because it indicates that 99.9% of the variance in the observed data is explained by the model. This level of accuracy is rarely achieved in traditional regression models, where R^2 values between 0.7 and 0.9 are typically considered satisfactory, especially for datasets with significant noise or complexity. The low RMSE (0.203) and MAE (0.167) values indicate that the hybrid LSTM-ANN model consistently makes highly accurate predictions with minimal deviations from the actual values. RMSE, being sensitive to larger errors, confirms that significant prediction errors are rare, showcasing the robustness of the model. MAE, which treats all errors equally, making sure that the average prediction error is small across all instances. These metrics confirm the model's ability to consistently produce accurate predictions i.e., accuracy, and its robustness in minimizing prediction errors across all observations i.e., reliability. This ensures that the model can be trusted for real-world applications where precision and consistency are critical.

To provide a clearer visual representation of the model's performance, Fig. 4 presents a graphical comparison of key metrics (R^2, RMSE) between the proposed hybrid LSTM-ANN model and the models from two previous studies that utilized the same dataset [41,52]. Additionally, Table 2 compares the performance of our hybrid LSTM-ANN model with two previous studies, illustrating its superior accuracy (R^2 = 0.999) and significantly lower error metrics (MSE, MAE, RMSE), further highlighting its robustness and applicability. The hybrid LSTM-ANN model's superior performance is attributed to its ability to capture both temporal dependencies and nonlinear relationships within the data. Unlike traditional regression models, which often struggle with these complexities, the LSTM-ANN model leverages advanced DL architectures to optimize predictions of critical network parameters such as RSSI and SNR. These results demonstrate the potential of the hybrid model to improve the performance and energy efficiency of LoRaWAN-based sensor networks, significantly advancing state-of-the-art in this field. Compared to traditional models, which often struggle with these complexities, the LSTM-ANN model optimizes both accuracy and efficiency. While the DL components increase computational demands compared to basic regression models, the trade-off is justified by the significant improvement in predictive performance, as shown by the high R^2 value (0.999) and low RMSE (0.203).

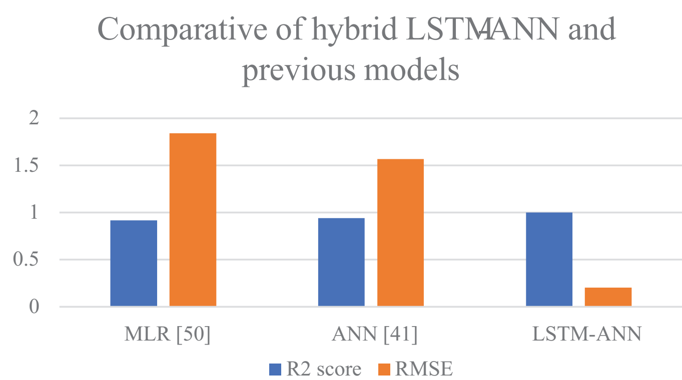

Figure 4: Comparative of hybrid LSTM-ANN and previous models [41,50]

Table 2: Comparison of hybrid LSTM-ANN and previous models

Model	MSE	MAE	R^2 score	RMSE
MLR [52]	–	–	0.917	1.84
ANN [41]	–	–	0.94	1.566
LSTM-ANN	0.041	0.167	0.999	0.203

4.2 Comparison with Existing Literature

The results of this study align with and expand upon prior research in the field. For instance, similar to the work of Rajab et al. [14], whose study demonstrated that applying DL techniques such as DNN can lead to substantial reductions in power consumption, with reported energy savings of over 40%. The use of LSTM in our work also supports the findings of Bernard et al. [15], who showed that LSTM models can reduce redundant transmissions by predicting future data points, thereby optimizing network performance and reducing energy consumption.

Our study extends this body of work, though, by including environmental variables—like temperature and humidity—into the model, which has often been overlooked in conventional research. The hybrid LSTM-ANN model was able to maximize the performance of the LoRaWAN network under various real-world circumstances by utilizing data on environmental parameters. This approach enhances the robustness and adaptability of the model, offering a more comprehensive solution compared to previous works, such as those by Kaur et al. [8], which primarily focused on industrial scenarios.

Recent studies, such as Qamar et al. [46], used hybrid approaches like k-means clustering with ANNs to optimize routing and extend network lifetime. Similarly, González-Palacio et al. [45] developed an ML-based Transmission Power Control (TPC) framework for LoRaWAN, achieving energy savings of up to 47% by integrating environmental variables. While these studies focus on specific aspects, such as routing or TP, our hybrid LSTM-ANN model captures both temporal and nonlinear relationships between environmental and network factors, offering a more comprehensive solution for optimizing LoRaWAN performance.

4.3 Practical Implications

The implications of these findings are significant for real-world IoT applications. Optimizing the energy efficiency of LoRaWAN networks is crucial for ensuring the long-term sustainability of battery-operated devices, particularly in large-scale sensor deployments such as smart cities, environmental monitoring, and industrial automation. The reduced energy consumption achieved by the ML and DL models suggests that these techniques can extend the battery life of devices, reduce operational costs, and reduce environmental impact.

Furthermore, the adaptability of the models to dynamic environmental conditions enhances the resilience and reliability of LoRaWAN networks. In real-world environments where signal conditions fluctuate owing to interference, weather, and other factors, the ability to adjust network parameters in real time can lead to more stable and efficient communications. ML and DL are valuable tools for the next generation of IoT networks, where scalability and efficiency are critical concerns.

The proposed hybrid LSTM-ANN model has significant implications for real-world IoT applications. For instance, smart agriculture networks can benefit from dynamic configuration adjustments to maintain reliable communication for monitoring soil moisture, weather conditions, and crop health [61,62]. In industrial IoT systems, the model can enhance predictive maintenance by ensuring uninterrupted data transmission in environments prone to interference. Additionally, urban environmental sensing applications, such as monitoring air quality and noise pollution, can utilize this approach to optimize communication in dense urban settings. These examples demonstrate the practical applicability of the proposed model in diverse domains requiring scalable and efficient LoRaWAN-based networks [63,64].

5 Conclusions and Future Directions

This study offers a comprehensive exploration of optimizing the performance and energy efficiency of LoRaWAN sensor networks through advanced DL techniques, addressing the limitations of traditional methods, such as the ADR algorithm. This emphasizes the crucial role of data-driven approaches in enhancing network performance in dynamic environments. The innovative use of LSTM networks and ANNs effectively captures temporal dependencies and nonlinear data relationships. The proposed models significantly surpass traditional path loss models, achieving a high predictive accuracy of SNR with an R^2 score of 0.999 and low error metrics: MSE, MAE, and RMSE of 0.041, 0.167, and 0.203, respectively. These findings underscore the potential of DL models to improve key performance metrics, such as SNR and RSSI, while optimizing the energy consumption in large-scale IoT deployments.

However, this study had several limitations. While the hybrid LSTM–ANN model demonstrated superior predictive accuracy, its significant computational resource requirements pose challenges for resource-constrained IoT devices. To address this, future research could explore model compression techniques or develop lightweight alternatives that maintain high accuracy while reducing computational overhead. Furthermore, reliance on historical data may limit the model's ability to respond to sudden and extreme changes in network conditions. Incorporating transfer learning techniques could enable quicker adaptation to new environments without extensive retraining, which is particularly advantageous for IoT applications involving frequently relocated devices.

Moreover, the dataset has certain limitations. Its geographical specificity to Medellín, Colombia, means that the environmental and network characteristics reflected in the data may not generalize seamlessly to other regions with different climates and urban structures. Additionally, the temporal scope of the dataset, spanning four months, might not capture seasonal variations, which could impact the performance of LoRaWAN networks over longer periods. Future studies could address these limitations by integrating datasets from diverse regions and extending temporal coverage to improve the generalizability and robustness of the model. Future studies should also evaluate the model's generalizability by experimenting with alternative datasets from diverse IoT domains, such as healthcare, transportation, and industrial monitoring. Investigating advanced algorithms, such as Transformer-based models or ensemble learning techniques, could further enhance the ability to handle complex temporal and nonlinear dependencies. Additionally, hybrid approaches combining time-series forecasting with environmental awareness, such as integrating GRU with autoencoders, may provide more robust solutions. Such integration could facilitate automatic detection and adjustment to unexpected events, improve resilience, and reduce energy consumption, ultimately making the model more practical and effective for real-world IoT systems.

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Availability of Data and Materials: The dataset analyzed during the current study are available in the GitHub repository, https://github.com/magonzalezudem/MDPI_LoRaWAN_Dataset_With_Environmental_Variables (accessed on 6 February 2025).

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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