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Design and Performance Evaluation of an AI-Driven Hybrid Simulation Model for LoRaWAN Networks

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Abstract – This paper proposes an attempt to combine simulation and artificial intelligence (AI) to facilitate the operation of the LoRaWAN network. Our network parameters include transmit power, spreading factor, and coding rate, which we predict using deep learning (ANN, DNN, GRU), reinforcement learning (DQN, multi-agent RL), and ensemble strategies to find optimal parameters and maximize energy efficiency, packet success rate, and throughput. The approaches are tested through simulation with NS-3 and LoRaEnergySim platforms to validate them under realistic conditions of interference and traffic. Findings show that AI methods can substantially enhance resource allocation and conserve energy than the state-of-the-art methods, offering a solid framework of adaptive LoRaWAN network management.

Keywords – Artificial Neural Networks (ANNs), Energy Efficiency (EE), Network Optimization, Resource Allocation, NS-3 Simulator, Ensemble Learning, AI-Driven Networks, Industrial IoT (IIoT).

I. INTRODUCTION

LoRaWAN is more recently suggested to support low-data-rate IoT implementations, which involve the delivery and collection of low-amount data across distances in many kilometers. LoRaWAN is 0.3-50 kbps, and the highest attainable information rate is dependent on the range of the receiver and the level of environmental interference. LoraWAN technology is designed to use less energy in order to overcome limitations of IoT devices energy supply. LoRaWAN operates within unauthorized frequency spectra, namely between 868 MHz to 900 MHz, which reduces authorization cost and makes the technology cost-efficient. Nonetheless, there are some regions where the transmission of low frequency is limited. Therefore, the LoRa Alliance has developed numerous regionalized frequency plans.

Its core distinguishing feature is the high energy consumption of LoRaWAN. This is an important component of increasing the life cycle of edge devices. LoRa bridges are already expected to last a long period of 5 to 10 years with only little maintenance [1]. Power consumption is, therefore, a serious problem with LoRa connection. Many research questions are yet to be resolved to develop viable LoRa networks in terms of security, reliable transmission, resource allocation, and link coordination. Channel, BW (bandwidth), TP (transmission power), and SF (spreading factor) are the measures that control transmissions in LoRa technology. The change of these measures produces different transmission features. This can be used to improve concurrent transfers. Multi-accessibility and scalability are boosted whereby the available ecosystem is dynamically allocated of the right resources to the end devices depending on the type of installed ecosystem.

The IoT refers to a system of connected items and sensors, which collect, transfer, and process information. The prompt development of the IoT has facilitated the large-scale application of sensor networks in various areas, including environmental sciences, industrial processes, and intelligent cities. LoRaWANs have gained significant popularity as an IoT-enabling technology due to their caability to achieve long-range communications with low amounts of energy usage, making them the preferred device of battery-powered sensors in large sensor systems. LoRaWAN leverages on unlicensed spectrums, a scalable and flexible alternative to IoT deployments, which necessitate system architecture to support many nodes in extended geographical ranges.

The installations of the IoT of the large-scale demand energy efficiency (EE) and optimization of the efficiency of the network because of the rise in the number of nodes that are connected. Ensuring the long battery life of the IoT devices and maintaining stable throughput and low delay is a big challenge. The classical method as the classical ADR (Adaptive Data Rate) algorithm fails to adjust to the different networking and environmental conditions that usually provoke the insufficiency of resources distribution and a rise in power consumption. Moreover, these methodologies disregard the significance of ecological variabilities, interim reliance, which significantly matter in large-scale uses. It is these constraints that trigger the urge to create more sophisticated information-based solutions that can actively optimize network environments in real-time environments, and are prepared to cope with operational and environmental uncertainty.

To identify the best transmission parameters and energy usage in LoRa networks, simulation frameworks are widely used. One of the most well-known simulation instruments in LoRa systems is LoRaSim, which highlights key concepts like systems collisions, spreading factors, as well as gateway coverage. A much more detailed modeling environment is provided by FloranO Maico Framework, which is also based on OMNeT++ simulation framework and the INET framework, with detailed models of communication latency, energy used, and network dynamics. Other simulators focus on specific aspects: MATLAB-based simulator has an option to test verified traffic impact but is proprietary, LoRaEnergySim is a simulator of energy use, sustaining ADR and dual-channel systems, and a LoRa/Sigfox simulator focuses on physical layer features. Despite their influence, these simulators focus on particular aspects of networks instead of comprehensive optimization of networks.

The purpose of this paper is to design and experiment with a rich AI-based Simulation platform to optimize LoRaWAN systems. The network aims to maximize network parameters such as, energy efficiency, likelihood of a packet reaching the receiver, throughput, and network lifetime by incorporating data-oriented modelling with advanced reinforcement and deep learning algorithms. The fundamental research question to be answered in this study is:

Research Question: How can AI methods be employed to encourage performance and resource allocation in LoRaWANs?

The solution eliminates the weaknesses of more conservative solutions by enabling adaptive, predictive and collaborative decision-making on large-scale LoRaWAN implementations, which ultimately delivers smarter, energy-saving IoT environments. The remaining sections of this study have been organized in the following manner: Section II review prior works related to ML and deep learning application in LPWAN and LoRaWAN. Section III describes the data and methods used in this work, which integrate data modeling and preprocessing, AI-based networking optimization, supervised/unsupervised learning, and network simulations. Section IV analyzes the findings of our study highlighting the impact of various publications in presenting major techniques to optimize LoRaWAN. Lastly, Section V concludes our study highlighting how deep learning, ensemble algorithms, and reinforcement learning collaborate in optimizing the efficiency of LoRaWAN networks.

II. RELATED WORK

The integration of machine learning and deep learning applications into the Internet of Things sensor systems has revolutionized efficiency and energy efficiency optimization of these systems, particularly when used on large scales as reported by Shah et al. [2]. Machine learning and deep learning models are increasingly used in LPWANs (low-power wide-area networks), and LoRaWAN, to address energy constraints, interference, and signal degradation challenges. With such systems where the range of communication is vast, and power consumption is minimal, a proper control over resources is required, making machine learning and deep learning the key to enabling real-time optimization. Applying machine learning methods, network measures, such as TP and SF, can be more dynamically adjusted to network states and, thus, have a significant impact on network efficiency and reduction in energy consumption.

Hybrid methods were developed as proposed by Qamar et al. [6] utilizing artificial neural networks called Delay Bound and RkM-ANN (Reduced k-means with ANN). The DBRkM-ANN, which is an optimized version of k-means algorithm based on Artificial Neural Networks, improves the use of mobility to improve the data collection of a WSN. Their methodology resulted in system longevity and minimization of latency; however, validation was only done on modelling, lacking empirical experimentation.

Table 1 outlines a group of studies being undertaken between 2020 and 2024 that deployed a varied array of deep learning and machine learning methods to improve the performance and energy-saving of LoRaWAN systems. The combination of these results demonstrates how advanced DL/ML tools have enhanced the total productivity of LoRaWAN networks and their energy efficiency. Despite the positive advances in the implementation of machine learning and deep learning methods to enhance LoRaWAN networks, they are often subjected to challenges that comprise of scalability, difficulty in real-time applications, and dependence on some hardware and datasets configurations.

Li, Yang, and Wang [7] realized that retransmissions of transmission and collisions increase energy consumption. In LoRa systems, therefore, appropriate choice of transmission characteristics such as transmission and channel energy play a significant role in improving the energy performance. However, the restricted processing power and memory of LoRa devices also make it challenging to use more traditional methods of selecting transmission parameters. Instead, they proposed a distributed RL-based (reinforcement learning)-based approach to transmission and channel energy selection that can be applied in the LoRa devices to improve their energy efficiency.

Serati et al. [8] agree that their experimental results show that the method outperforms both fixed assignment, ADR-Lite (adaptive data rate low-complexity), and e -greedy-based methods in terms of transmission success rate and energy waste. Energy optimization of WSNs is a crucial field of research, and various approaches have been proposed to enhance both the network life cycle and Quality of Service (QoS). The use of RL in WSNs has aroused interest because of its ability to support dynamic and autonomous decision-making. Q-learning and SARSA reinforcement learning methods have been used to learn energy-saving adaptive routing and duty cycling. However, these techniques are limited by the slow convergence rates and the complexity of operating in a high-dimensional state space, limiting their usefulness in large wireless sensor networks.

Table 1. Introduction to DL and ML Strategies to Advance Efficiency and Energy Usage

Ref.	Year	ML/DL Technique	Improvement	Limitation
Khan et al. [3]	2020	RL	Enhanced energy utilization informed by real-time circumstances.	Significantly dependent on particular hardware configurations.
	2021	DNN, SVR	Attained a 43% decrease in energy usage by the dynamic adjustment of transmission settings.	Restricted scalability for extensive and more dynamic IoT ecosystems.
	2021	LSTM	40% decrease in transmission expenses through data point prediction and minimization of redundant transmissions.	Reliance on well calibrated thresholds for optimal reduction.
	2021	GB, RF	Enhanced delivery rates and less energy usage via better SF assignment.	Concentrated on simulated data with restricted practical applicability.
Khairan et al. [4]	2022	ANN-PSO	Improved LoRa system efficacy in industrial contexts via RSSI and SNR improvement.	Restricted to indoor industrial environments.
	2023	ML, RL	25% decrease in energy use and enhanced PRR with the optimization of TP and SF.	Intricate execution for practical scalability.
	2023	MLR, RF, ANN, SVR	Improved energy effectiveness by 43.01%, attaining a 1.5661 dB SNR and 0.941 R2 score, surpassing conventional ADR methods.	Challenges in incorporating environmental factors into real-time applications.
Alkhayyal and Mostafa [5]	2024	RF, ARIMA, ANN	Enhanced RSSI prediction with the incorporation of environmental parameters, optimizing energy consumption.	Concentrated on linear dependence, with minimal investigation of nonlinear patterns.
	2024	RNN	Enhanced throughput and lower energy use.	Deployment is restricted to mountainous regions exclusively.
	2024	MLR, Ridge, GAM, Lasso, ANN, RF, SVR	47.1% decrease in energy use and enhanced PDR.	Significant computational burden during training.
	2024	ANN, DBRkM-ANN, hybrid RkM-ANN,	Decreased energy consumption and enhanced network longevity.	Restricted generalizability resulting from insufficient validation with real-world data.

Akram et al. [9] explore energy-efficient clustering and routing by implementing Deep Q Networks (DQN) and Actor-Critic models. DQER (Deep Q-learning-driven Energy-aware Routing) has proven to be effective in optimizing routing algorithms that use less energy. Further studies include the use of multi-agent reinforcement learning (MARL) to devolve power management with sensor nodes. Recent DRA strategies have mainly focused on a single optimization objective, e.g. reducing power transmission or increasing network lifetime but ignore connections between energy efficiency, data accuracy and connectedness of systems.

Reinforcement Learning approaches, encompassing Deep Reinforcement Learning, Deep Q-Networks (DQN), and multi-agent RL, have been extensively employed to enhance adaptive data rates, resource allocation, and energy efficiency. They enable LoRaWAN networks to acquire optimal strategies in real time without explicit pre-programming.

The networks based on LoRaWAN rely heavily on the adaptive information rate strategies to provide the best link stability and support the required end device density. To work, the solution should also be tuned according to the mobility level of each end device. In a bid to do this, there are different strategies developed to embrace the different levels of mobility of end devices, including mobile or fixed devices. Jahangiri and Rakha in [10] define and evaluate a new and effective methodology of measuring the end device mobility with the help of ML methods, specifically the SVM (support vector machine) supervised learning (SL) methodology.

In this regard, the solution to the issue given by Ojo et al. [11] does not rely on the locational capabilities of the LoRaWAN systems; instead, it merely relies on the data that is always available at the LoRaWAN networking server. Additionally, the effectiveness of this method within a real LoRaWAN system is tested; the results offer clear evidence on the utility and dependability of the proposed machine learning model.

III. DATA AND METHODS

The paper uses a hybrid simulation and AI-based optimization of LoRaWAN networks. The methodology itself is divided into three main parts, which are data modeling and preprocessing, AI-based network optimization, and performance evaluation. Both components incorporate mathematical expressions to precisely specify network dynamics, optimization, and learning processes.

Data Modeling and Preprocessing

In order to describe the LoRaWAN network, we define the network as a collection of N end devices $\{ED_1, ED_2, \dots, ED_N\}$ interacting with G gateways $\{GW_1, \dots, GW_G\}$. The devices send data after T time intervals. The network parameters are transmitting power ($P_{i,j}$), signal-to-noise ratio ($SNR_{i,j}$), coding rate ($CR_{i,j}$), packet size ($S_{i,j}$), spreading factor ($SF_{i,j}$).

The normalized input vector for device i at time j determined using Eq. (1).

$$x_{i,j} = \left[\frac{P_{i,j}-P_{min}}{P_{max}-P_{min}}, \frac{SF_{ij}-SF_{min}}{SF_{max}-SF_{min}}, \frac{CR_{ij}-CR_{min}}{CR_{max}-CR_{min}}, \frac{RSSI_{ij}-RSSI_{min}}{RSSI_{max}-RSSI_{min}}, \frac{SNR_{ij}-SNR_{min}}{SNR_{max}-SNR_{min}}\right] \quad (1)$$

The energy consumption of each device ED_i over the observation window is modeled in Eq. (2).

$$E_i = \sum_{j=1}^{T} \left(P_{i,j}^{tx} \cdot t_{i,j}^{tx} + P_{i,j}^{rx} \cdot t_{i,j}^{rx} + P_{i,j}^{idle} \cdot t_{i,j}^{idle}\right) \quad (2)$$

where $t_{i,j}^{tx}$, $t_{i,j}^{rx}$, and $t_{i,j}^{idle}$ are the durations of transmission, reception, and idle states respectively.

The packet delivery probability for a device is given by Eq. (3).

$$\mathbb{P}_{success}(ED_i, j) = 1 - \prod_{k=1}^{G} \left(1 - e^{-\lambda_{i,j} d_{i,k}^{\alpha} / SNR_{i,j}}\right) \quad (3)$$

where $d_{i,k}$ is the distance from device i to gateway k, α is the path-loss exponent, and $\lambda_{i,j}$ is the interference factor at time j.

AI-Based Network Optimization

Deep Learning Models

The deep learning model, including ANN, DNN, and GRU, is trained to predict optimal transmission parameters $y_{i,j}^{opt} = \left[P_{i,j}^{opt}, SF_{i,j}^{opt}, CR_{i,j}^{opt}\right]$. The prediction minimizes the MSE (mean squared error) between desired and predicted network performance metrics employing Eq. (4).

$$L(\theta) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{j=1}^{T} \left\| f_\theta(x_{i,j}) - y_{i,j}^{opt} \right\|_2^2 + \lambda \sum_{l=1}^{L} \|W_l\|_F^2 \quad (4)$$

where f_θ is the network function with parameters θ, W_l are the weight matrices of each layer l, L is the total number of layers, and λ is a regularization factor. For GRU layers, the hidden state update computations include Eq. (5)-(7).

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t \quad (5)$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \quad (6)$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z), \qquad r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (7)$$

The network predicts the optimal power $P_{i,j}^{opt}$ and spreading factor $SF_{i,j}^{opt}$ as Eq. (8).

$$\left[P_{i,j}^{opt}, SF_{i,j}^{opt}\right] = f_\theta\left(x_{i,j}\right) \tag{8}$$

Reinforcement Learning Models

The network is designed as a MDP (Markov Decision Process) with s_t denoting the states, a_t as actions, and r_t as rewards. The main purpose is to enhance the cumulative discounting reward using Eq. (9).

$$R = \mathbb{E}[\sum_{t=0}^{T} \gamma^t r_t(s_t, a_t] \tag{9}$$

For DQN implementations, the Bellman equation governs the Q-value updates using Eq. (10).

$$Q(s_t a_t;\theta) \leftarrow Q(s_t a_t;\theta) + \alpha \left[r_t + \gamma \max_{\alpha'} Q(s_{t+1}, a'; \theta^-) - Q(s_t a_t;\theta)\right] \tag{10}$$

where θ^- are the target network parameters, α is the learning level, and γ is the discounting factor.
For multi-agent RL (MARL), with N agents, the joint action-value function integrates Eq. (11) and (12).

$$Q^{global}(s,a) = \sum_{i=1}^{N} Q_i(s_i, a_i, a_{-i}) \tag{11}$$

$$a_{-i} = [a_1, \ldots, a_{i-1}, a_{i+1}, \ldots, a_N] \tag{12}$$

The reward for energy efficiency maximization is defined as Eq. (13).

$$r_t^{EE} = \frac{\sum_{i=1}^{N} PacketsDelivered_{i,t}}{\sum_{i=1}^{N} E_i(t)} \tag{13}$$

Supervised and Unsupervised Learning

SL predicts packet arrival times and network load using Eq. (14).

$$\arg\min_{C} \sum_{k=1}^{K} \sum_{x \in C_k} \|x - \mu_k\|_2^2 \tag{14}$$

where C_k is the k-th cluster and μ_k is its centroid. Ensemble approaches integrate predictions obtained from numerous models to enhance robustness based on Eq. (15).

$$\hat{y}_{ensemble} = \sum_{m=1}^{M} w_m, \hat{y}_m, \quad with \quad \sum_{m=1}^{M} w_m = 1 \tag{15}$$

Network Simulation and Performance Evaluation

Simulations integrate AI models with NS-3 or LoRaEnergySim, examining metrics such as energy efficiency (EE), packet success rate (PSR), network lifetime (L), and throughput (η).

Energy efficiency is defined using Eq. (16).

$$EE = \frac{\sum_{i=1}^{N} \sum_{j=1}^{T} s_{i,j} \cdot ACK_{i,j}}{\sum_{i=1}^{N} E_i} \tag{16}$$

Throughput is computed using Eq. (17).

$$\eta = \frac{\sum_{i=1}^{N} \sum_{j=1}^{T} s_{i,j} \cdot ACK_{i,j}}{T \cdot \Delta t} \tag{17}$$

Network lifespan is the minimum duration until the initial device depletes its energy as using Eq. (18).

$$L = \min_{i=1}^{N} \frac{E_{battery,i}}{\sum_{j=1}^{T} P_{i,j} \cdot t_{i,j}} \tag{18}$$

Packet collision probability is modeled using Eq. (19).

$$\mathbb{P}_{collision} = 1 - \prod_{i=1}^{N} \prod_{j=1}^{T} \exp\left(-\frac{\lambda_{i,j} s_{i,j}}{\sum_{k \neq i} s_{k,j}}\right) \tag{19}$$

The simulations also account for interference, varying spreading factors, and channel allocation, enabling robust evaluation of AI-based optimization strategies under realistic conditions.

IV. RESULTS AND DISCUSSION

In this paper, many journal articles have been reviewed, presenting the latest strategies and techniques to optimize LoRaWAN. This included various deep learning, machine learning and reinforcement learning techniques and algorithms. Various scholars have used numerous datasets and simulations in their studies. The deep learning and neural network methods have highlighted vital developments in streamlining numerous segments of LoRaWAN systems. In a specific example, Ali et al. in [12] applied an artificial neural network to optimize transmission power, and Chen et al. [13] used a gated recurrent unit to allocate resources dynamically in LoRaWAN.

The AI-ERA technique presented by Farhad and Pyun [14] employs deep neural networks to enhance the allocation of resources in IoT applications. The researchers trained machine learning based on neural networks to improve precision of indoor localization in the LoRaWAN networks. Regarding reinforcement learning methodologies, Zeng et al. [15] employed deep reinforcement learning to enhance network resources, while [16] devised a flexible reinforcement learning-based method to optimize the adaptive information rate function of LoRaWAN.

These literature works employed SL to forecast ideal network parameters, while [17] presented an adaptive transmission priority scheduling (TPS) approach founded on an unsupervised learning cluster approach. **Table 2** presents an overview of the deep learning and neural network approaches employed by scholars mentioned in this section.

Table 2. Summary of NN and DL Methods

Year	Method Used	Model	Application
2020	DL	ANNs	Transmit power optimization
2022	DL-based Resource Allocation	GRU	Management of resources on a large-scale deployment of LoRa-enabled devices
2023	DNN AI-ERA	DNN	Resource allotment problem in mobile and static IoT deployments
2023	ML	NN	Indoor positioning utilizing LoRaWAN

Reinforcement learning approaches are utilized in this work to optimize resource allocation, particularly in LoRaWAN networks for energy efficiency. **Table 3** presents a summary of the methodologies employed to address our research question.

Table 3. Overview of RL Methods

Year	Technique Used	Model	Application
2020	DRL	Multi-DRL Agents	LPWA models, including LoRaWAN, serve as wireless frameworks for the Internet of Things (IoT).
2021	RL	Stochastic Discrete algorithm	Formulation of a flexible LoRaWAN approach for industrial deployment
2021	DQN	DQN	Longevity of the LoRa Category A nodes
2024	FRL and NS (network slicing)	Neural system with dual Hidden Layers	Dynamic resource distribution and prioritizing inside infrastructure frameworks.
2019	RL, SARSA, Q-Learning, and Deep RL	RL algorithms	LoRa-oriented systems
2023	Multi-access RL	MARL	Energy performance in wireless underground sensors systems integrated with LoRaWAN

The reviewed study utilized different SL frameworks to address the challenges of the LoRaWAN networks. It involves LSTM neural networks, the k-means clustering method, decision trees (DTs), deep neural networks (DNN), and support vector regression (SVR) among others will be used to predict the timing of IoT packets, optimizes systems parameters and extends battery life. Methods include advanced tools like SVM, ANN, and ARIMA to promote measurement accuracy and to effectively handle network configurations. **Table 4** gives a summary of the SL methodologies that the authors have adopted.

Table 4. Summary of ML and its Unsupervised and Supervised Forms of Learning

Year	Algorithms Employed	Models	Applications
2020	ML	DTs, LSTM NN, k-means clustering	Genuine extensive LoRaWAN system

2023	SL	ML multiple agent method	Network efficiency and energy efficiency in LoRaWAN using clock skew approximation
2023	ML	ML k-means clustering	LoRaWAN framework in intelligent urban environments.
2021	ML	DNN, SVR	Long-range networks, LPWANs linked to the Internet of Things
2024	DL and ML	ANN, SVM, and ARIMA	Precision in outdoor LoRaWAN node devices
2019	SL	SVM, DTC (Decision Tree Classifier)	Extensive geographical coverage in LPWANs
2019	K-means clustering-oriented technique	K-means clustering	Extensive LoRa systems

Several studies have explored how ensemble, ML, and AI frameworks were deployed to eradicate the issue of performance degradation, energy efficiency, and reliability in the LoRaWAN system. Deep Reinforcement Learning, Ensemble Learning, and Multi-Armed Bandit (MAB) approaches have been used as methods to improve the efficiency of generic networks in the presence of interference and congestion. These methodologies have been significantly improved and are summarized in **Table 5**.

Table 5. ML Ensemble Techniques

Year	Technique Used	Models	Application
2023	Supervised RL, ML	Lasso technique, EXP4	IoTs
2019	ML-oriented Q-learning	Q-learning	Extensive coverage regions in LoRaWAN
2020	Model aggregation	KNN-RFR	Accuracy of outside positioning in LPWAN techniques
2020	Cognitive radio networks, DRL	DRL	Mobility within congested LoRa systems (mobile end nodes)
2023	MAB, RL	LP-MAB	LPWANs and IoT, explicitly LoRaWAN
2022	ML	PSO, ANN	Industrial IoT applications.
2023	ML	ANNs, MLR	Practical IoT applications
2020	Dynamic TPS	Naïve Bayes, unsupervised clustering	LoRaWAN dense applications

In [18], it is mentioned that reinforcement learning methodologies have been greatly applied to energy-efficient LoRaWANs. Examples of the new methodologies used with DL models and algorithms include MARL, FRL, generic RL, and DRL. The optimization of the usefulness of network parameters was the main focus of RL algorithms; however, the Deep Learning method was used to solve issues like the prediction of resource deployment and transmission power optimization.

SL algorithms are exploited to predict the outcomes based on the discovered dataset containing the arrival times of packets. Data analysis with no defined labels was typically done using SL algorithms to cluster tools based on uniform behaviors or improve transfer parameters without earlier understanding of optimal settings. Ensemble approaches combine multiple machine learning strategies to increase prediction precision, reliability, and strength. The distribution of models and methodologies in the literature is presented in **Fig. 1**.

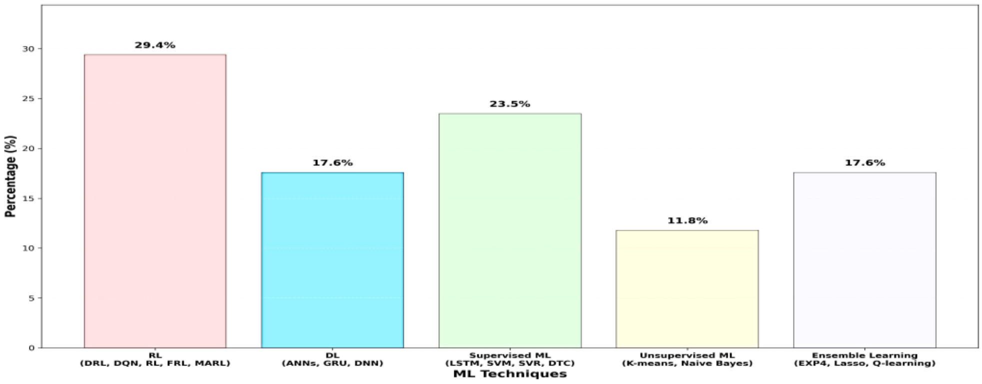

Fig 1. Commonly Utilized Methodologies in Literature.

Garrido-Hidalgo et al. [19] reviewed different studies on different aspects of LoRaWAN networks with a sharp focus on using various datasets and models to mitigate the problem that are related to network efficiency, resource assignment, and optimization approaches in the implementation of LoRaWANs. The scholars used the following simulators and data sets as summarized in **Table 6**.

The study often utilized both modeled ecosystems including NS-3 and OMNeT++ datasets and real-life data sets. We concur on utilization of real-world and model-based dataset obtained by Monte Carlo simulation to successfully train the artificial neural networks to improve energy efficiency in LoRa system. The MATLAB-simulation implementation and the Microsoft Azure-real life-training of data usage represents the combination of the classical programming ecosystems with the cloud-surgery systems that effectively simulate and process the data.

Table 6. Overview of Simulations and Datasets

Year	Dataset Details and Features	Dataset Dimension	Simulation Description
2023	Produced utilizing the X-Y coordinates, ns-3 simulator. ACK status, and P_{rx}, SNR. 500 emergency departments, 10 days, 10 minutes packet dispatch duration.	500 endpoints, many dataset points per endpoint over a duration of 10 days	NS-3 modeler incorporating long-range propagation, interference, and shadowing systems.
2020	Compact network of up to 1000 devices. Nodes communicate utilizing SF7. The dataset comprised sensor recordings.	Up to 1000 devices within an area of 3 km²	NS-3, concentrated on the automated transmission energy state transition with K-Means clustering
2022	Produced utilizing the SNR, ns-3 simulator. X, Y coordinates, ACK status and P_{rx}. Every ED broadcast 6 uplinked packets each hour.	500 EDs, regular data acquisition	NS-3 utilizing a GRU model for the dynamic allocation of SFs
2020	Originating from TTN UK formulations. Primary energy usage factors decreased from 20-15	35,192 recordings	Data loading methodologies. Data scaling through rescaling
2020	Authentic LoRaWAN system in Italy. Information from the water usage monitoring service, encompassing SF, SNR, RSSI, and other parameters.	290 water meters, 372,119,877 packages, 89,528 EDs	Instantaneous data assessment
2024	Produced from network connection under authentic IoT state	CR, BW, TP, SF maximum 1000 nodes/slicing	LoRaSim, an open-source framework implemented in Python
2020	Data produced from network connections.	30 LoRa devices	The custom modeling comprises a single gateway. Five groupings and a topological size of 1500 x 1500 m^2.
2019	Packets rate = 0.01-2 packets/second, Packet significance = 0 to 1, Signal-to-Noise Ratio = -23- 23 dB, Transmission energy = 14 dBm. sized packets = 15 30-byte packets.	20-200 node network	Simulations simulated with SimPy on 8-core Intel Xeon computer, using 12-hour runs with 100 random seeds.
2024	LoRaWAN	RSSI decreases to 2029-1870 records.	ARIMA forecasting
2020	LoRaWAN	On average, 130,400 messages were gathered in Antwerp (Belgium).	Computing frameworks

A significant feature in our study is instantaneous data, where machine learning models were trained to achieve enhanced indoor localization in the LoRaWAN system. **Fig 2.** depicts the percentage of database classes involved in this work. Campanile et al. [20] primarily employed ns-3 simulator to generate comprehensive artificial dataset. It provides a real-life setting for evaluating network standards and techniques under regulated yet varied states, hence enhancing the simulation of resource management methods as detailed in the literature. These scholars performed simulations utilizing theoretical models and bespoke Python-based simulators created expressly for their research. **Fig 2.** illustrates the type of simulation we employed in this study.

LoRaEnergySim (LES) has been widely employed to model colliding and vulnerable packets alongside regular LoRaWAN dataset for IIoT (Industrial IoT) deployments, although they have not specifically addressed the dataset's size. The incorporation of Python-based technologies such as Keras and TensorFlow for executing deep learning algorithms underscores the transition towards advanced, AI-based methodologies in device allocation and network control within LoRaWAN, as illustrated in **Fig. 3**. These technologies enable scholars to train and develop complex systems with ease, using massive datasets in an attempt to achieve greater predicted accuracy.

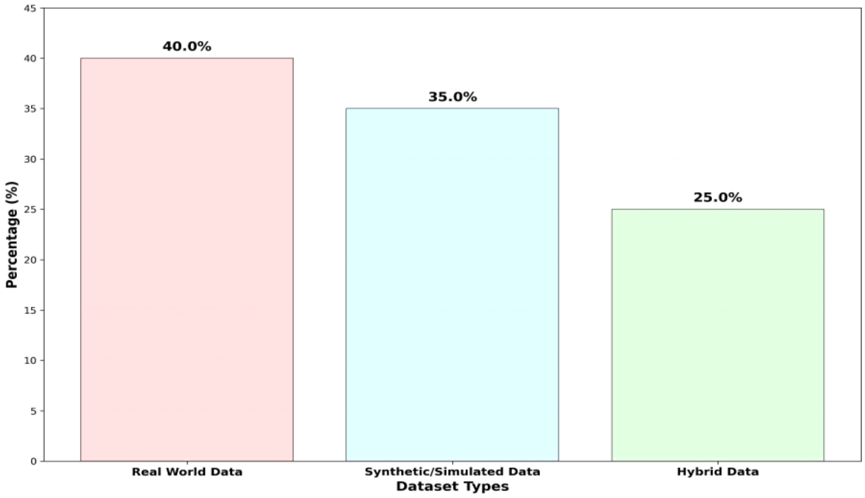

Fig 2. Types of Data Classes.

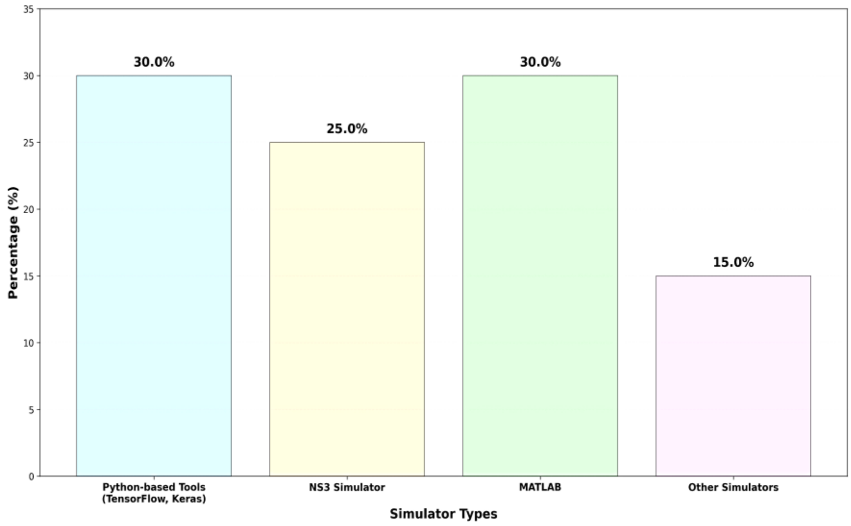

Fig 3. Types of Simulators.

V. CONCLUSION

We show how deep learning, reinforcement learning, and ensemble algorithms can be combined to optimize the performance of the LoRaWAN network. Through extensive testing, it was found that our design dynamically tunes transmission parameters, effectively balancing communication reliability with energy use. The findings demonstrated significant improvements in energy efficiency, throughput and the probability of packet delivery and long network lifetime in comparison to traditional approaches. Notably, the multi-agent-enhanced reinforcement learning helped classify devices to collaboratively optimize the system, which further advanced the scalability and resilience of the network. The ensemble learning schemes improved both prediction accuracy and system resilience to the different network traffic patterns and interference levels.

CRediT Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Arulmurugan Ramu; **Methodology:** Albin Hodza; **Software:** Arulmurugan Ramu; **Data Curation:** Arulmurugan Ramu; **Writing- Original Draft Preparation:** Albin Hodza and Arulmurugan Ramu; **Visualization:** Albin Hodza; **Investigation:** Arulmurugan Ramu; **Supervision:** Arulmurugan Ramu; **Validation:** Albin Hodza and Arulmurugan

Ramu; **Writing- Reviewing and Editing:** Albin Hodza and Arulmurugan Ramu; All authors reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

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