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RESEARCH ARTICLE

Enhancement in Optimal Resource-Based Data Transmission Over LPWAN Using a Deep Adaptive Reinforcement Learning Model Aided by Novel Remora With Lotus Effect Optimization Algorithm

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ABSTRACT Wireless Sensor Networks (WSN) are adopting low-power wide area networks (LPWAN), such as long-range (LoRa) wide area networks, to increase communication standards. LoRa has been used to gather sensor data for many applications, such as environmental monitoring. The existing LoRa system faces degradation in network performance because of interference and congestion with the development of Internet-of-Things (IoT) devices. More than the device parameters and algorithms must be improved in large IoT applications. In massive LoRa systems, resource allocation is effectively performed using new reinforcement learning and machine learning approaches. These approaches have proven to be quite effective. Hence, this work implements an efficient optimal resource allocation scheme for effective data transmission over the LoRa with the minor power requirement with the aid of Deep Adaptive Reinforcement Learning (DARL). The parameters required to minimize the power requirement while transmitting the data are estimated with the help of this DARL model. The variables in the DARL are optimally selected by using a new optimization algorithm named Integrated Remora with Lotus Effect Optimization Algorithm (IR-LEOA) that is executed by combining Remora Optimization Algorithm (ROA) with the Lotus Effect Optimization Algorithm (LEA). The network parameters, such as the transmission power, channel, and spreading factor, are tuned using the same IR-LEOA. The server in the LoRa is matched by the agents generated by the DARL model. Then, the transmission parameters are given to the network's terminal hub after the agents in the DARL are generated. Throughput, energy efficiency, latency, and transmission rate are analyzed using this optimization strategy. The effectiveness of the model is proved by conducting extensive experimentation.

INDEX TERMS Optimal resource allocation, data transmission, low power wide area network, integrated remora with lotus effect optimization algorithm, deep adaptive reinforcement learning, latency, transmission rate.

I. INTRODUCTION

The development of the Internet of Things (IoT) promises to connect 22 billion devices, and long-range (LoRa) will effectively manage it in 2025 [1] LoRa is effectively used in cellular networks and domains like industry and academia to

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provide better communication [2]. LoRa mechanism provides low deployment costs and low power consumption. The chirp spread spectrum strategy uses different spreading factors (SF) in LoRa with low energy consumption [3]. It is used to increase the network efficiency. In LoRa technology, the LoRa network devices use physical layer operations to improve the network performance and battery life [4]. Customization and resource allocation are the critical part of IoT. Some vital issues, such as limited shared resources, inaccurate radio connections, and limited intrinsic networks, affect resource allocation [5]. It increases the heterogeneity and quality of service (QoS) regarding hardware diversity. Coexistence issues have increased in the development of LoRa [6]. The server increases the communication power and modifies the SF by considering the signal-to-noise ratio (SNR) to enhance the energy efficiency, airtime, and data [7] transmission speed. The transmit power is changed at each stage using a centralized approach, increasing resource efficiency [8]. A wide range of IoT technology requires a lot of linked devices for resource allocation-based data transmission. A compelling resource allocation mechanism is needed to increase resource efficiency and avoid channel conflicts [9], and an intelligent resource allocation system is necessary [10].

In traditional systems, the resource allocation in LoRa suffers from high computational cost and channel utilization. The network capacity is decreased while allocating the resources to large networks [11]. The existing resource allocation strategies provide low quality of service. It degrades the robustness of the network. Several lightweight strategies for allocating SFs in dense LoRa networks are used in the literature [12]. But, it gives inaccurate reliability. The conventional system's goal is to statistically minimize the probabilities of two or more communications overlapping in frequency and time [13]. Traditional LoRa networks must improve reliability and control overhead because they are still adopted based on network size.

On the other hand, the scheduling strategy's primary goal is to improve reliability by allocating transmission slots with minimal cost [14]. However, the existing network increases the overhead and computational cost issues. Recently, other reinforcement learning and deep reinforcement learning methods have been used for resource allocation in wireless LoRa networks. The deep adaptive learning and reinforcement learning algorithms are combined to form a deep adaptive reinforcement learning (DARL) strategy. This strategy solves the high-dimensional space and selection problem [15]. The deep adaptive learning approach primarily uses artificial neural networks to solve high-dimension problems during the decision-making process [16]. Using an agent aware of the decision-making procedure to interact with its surroundings and obtain the best reward is the primary goal of the reinforcement learning algorithm. The interactions with educational settings, such as user volume, color, and service quality requirements, are issues of existing approaches [17].

Because of the above interaction, a reinforcement agent determines the best resource allocation policy in Long Range Wide Area Networks (LoRaWAN) to resolve the above interaction issue. The traditional method increases the possibility of information loss and interference when transmitting data with more devices. Additionally, the conventional method selects the best solution for large networks due to its conservative environment [18]. The conventional LoRa system suffers from low power consumption, range, limited data rate, and interference issues. Traditional methods need to address multi-objective problems. Balancing spectral efficiency, energy usage, and fairness poses a significant challenge in future WAN resource allocation. A better method using advanced learning is proposed to reduce transmission power while meeting reliability, latency, and transmission rate requirements. However, finding the best rules in the current environment takes a lot of work. Also, it's essential to understand and apply several critical theories quickly at the beginning. Hence, a novel optimal resource allocation-based data transmission scheme on the LoRa system is developed in this work. Existing research has not addressed the multi-objective resource allocation challenges in LoRa systems.

The following sections give the designed resource allocation-based data transmission objectives over LoRa networks.

- To develop a practical resource allocation-based data transmission to minimize the transmission power and maximize the transmission data rate in LoRa networks. It is used to improve wireless communications without any congestion and interference.
- To implement an efficient IR-LEOA strategy that optimizes the variables like spreading factor (SF), channel, number of iterations, and transmission power from the DARL model to improve the resource allocation effectiveness in high throughput, energy efficiency, transmission rate, and low latency.
- To design a DARL model inspired by deep adaptive reinforcement learning techniques using IR-LEOA optimization to solve resource allocation issues and increase total computing productivity in large-scale LoRa networks.
- To compare the effectiveness of the resource allocation-based scheme data transmission with several heuristic algorithms using various performance measures.

The remaining sections comprehensively examine the designed resource allocation model for data transmission over LoRa networks. They encompass the elucidation of advantages and limitations of the current resource allocation-based data transmission in Section II, followed by the presentation of the network model for the LoRa system, the motivation for resource optimization, and an explanation of the proposed framework in Section III. Additionally, Section IV delves into both conventional and suggested strategies in detail. Section V presents objective results, followed by a discussion of the reinforcement learning technique and an explanation of the developed DARL model in Section VI. Section VII concludes the designed resource allocation model-based data transmission over LoRa networks, summarizing its effectiveness and implications. Finally, Section VIII outlines future research directions, including security enhancements and optimization strategies.

II. LITERATURE SURVEY

Many researchers have explored methodologies and strategies proposed by different studies to optimize resource allocation in LoRa networks. These approaches encompass reinforcement learning, decentralized and centralized methods, game-theoretic paradigms, and mathematical models, each aiming to enhance throughput, reduce energy usage, and improve overall network performance. This comprehensive analysis sets the stage for the current research to build upon existing knowledge and propose novel solutions for effective resource management in LoRa networks; the following sections concisely describe each study discussed:

A. DISCUSSION ON RESOURCE ALLOCATION MODELS

In 2023, Rao and Sundar [19]. offered a reinforcement learning approach-based system to minimize power transmission and increase the data transfer rate in LoRa networks. The reinforcement learning technique was used to find the variables during the data transmission. Here, the transmission power was effectively minimized. In LoRa, the network resources like transmission power, spreading factor, and channel were effectively optimized. An effective hybrid coati with an energy valley strategy tuned these parameters. Many reinforcement learning agents were used to equalize the terminal hubs in the LoRa server. The tuned parameter was applied to the terminal hubs. The parameter optimization was used to enhance the throughput and reduce the energy usage. The explored system showed higher efficacy than other resource allocation systems in LoRa.

In 2023, Xu et al. [20] integrated reconfigurable intelligent surfaces (RIS) with cell-free networks to enhance network capacity. The learning-based deep distributed ADMM (D2-ADMM) network was developed based on algorithm unrolling to use parallel computing resources. Furthermore, the research introduces a monodirectional information exchange strategy with minimal signaling overhead to enhance the efficiency of D^2-ADMM in distributed base stations (BSs).

In 2023, Gava et al. [21]. offered a new resource optimization methodology in LoRas. The maintenance costs and implementation complexity were decreased using a low-cost spanning tree and Variable Neighbourhood Search (VNS) strategy. Performance investigations were carried out in LoRa using LoRa repeaters to improve the coverage. VNS strategy was used to determine the repeater's location. Total execution time and energy usage were minimized by adjusting parameters like transmission power, spreading factor, and bandwidth. The performance evaluation was conducted over various previously used data transmission frameworks.

In 2023, Minhaj et al. [22]. implemented a novel way of distributing the spreading factor (SF) and transmission power to the devices by combining a decentralized and centralized method with two independent learning methodologies. Transmission power was assigned centrally by reducing the contextual bandit issue using machine learning (ML) techniques. The reinforcement learning (RL) technique allocated the spreading factor parameter to the network devices. The designed system proved higher accuracy and low energy usage for large congested networks than current state-of-the-art algorithms.

In 2023, Garrido-Hidalgo et al. [23]. developed a new data communication framework in LoRa. It was one of the most advanced technologies in industry and academia for low-cost and low-power communications. The characteristics of LoRa were known to compromise its reliability in large-scale and high-traffic deployments. Some time-slotted techniques were proposed to schedule LoRa transmissions appropriately. The traditional resource allocation system needed to be given more effectiveness while training the real-world applications. This work effectively worked in real-life implementations and showed better efficacy for data transmission in LoRa. This research developed an effective resource allocation model using a multi-agent systems (MAS) techniques in LoRa networks, and it proved high scalability, better design, and logic implementation. The system's integration of agents led to improved network size. This work showed better node allocation and accurate time slot computation in massive LoRa networks.

In 2023, Wei et al. [24]. suggested a new resource allocation model in LoRa networks. The LoRa application services had three primary groups. That was safety, monitoring, and control. The suggested priority-based resource allocation (PB-RA) strategy increased the throughput. It decreased the average packet loss by allocating the spreading factor parameter to network devices based on the highest priority parameter. The IEEE 2668 standard was initially developed to thoroughly and quantitatively assess the coordination capabilities regarding quality of service (quality of service) effectiveness, such as throughput, latency, and packet loss rate (PLR). The best service parameters enhanced the network's HDex and device capacity using the Genetic Algorithm (GA)–based strategy.

In 2022, Xu et al. [25] presented a reconfigurable intelligent surface (RIS) based on deep reinforcement learning (DRL) in millimeter-wave (mmWave) multiple-input multiple-output (MIMO) systems. It achieved more robust performance with reduced interaction overhead and relayed on perfect channel state information (CSI). It attained average enhanced achievable rates compared to existing DRL-based methods.

In 2022, Gumaei et al. [26]. recommended a practical framework using a game-theoretic paradigm for LoRa, which aims to maximize the energy efficiency and packet delivery

TABLE 1. Features and challenges of resource-based data transmission in LPWAN using existing techniques.

Author [citation]	Methodology	Features	Challenges
Rao *et al.* [19].	RL, HC-EVOA	• It decreases the energy consumption and increases the throughput during the execution. • It reduces the time consumption while performing the resource allocation process.	• It needs to handle the complex optimization issues. • It only supports a low data rate.
Xu *et al.* [20].	RIS.	• It reduces costs and improves network efficiency. • Network performance is maximized by efficient use of computing resources.	• It needs to improve and optimize resource allocation. • It needs to manage the interference and hardware costs.
Gava *et al.* [21].	VNS and MST.	• It improves the quality of service of the LoRa networks. • The methodology maintains optimal resource use and adequate network performance by balancing energy efficiency and data-gathering time.	• Maintaining a balance between energy efficiency and data gathering takes time and effort. • Maintaining the network's stability while using various network conditions is challenging.
Minhaj *et al.* [22].	Reinforcement learning and supervised machine learning.	• This method allows dense LoRa networks higher PRR, goodput, and energy efficiency. Completing this process takes less time.	• Interference in both uplink and downlink directions is conceivable since this technique needs a proper feedback system. • It increases the packet loss ratio.
Hidalgo *et al.* [23].	MAS.	• It effectively handles the high traffic scenarios and obtains better reliability outcomes. • It effectively supports real-world applications.	• It needs to allocate resources to highly congested and large networks. • It gives low performance because of interference and congestion issues.
Wei *et al.* [24].	GA.	• It minimizes the average packet loss rate. • It increases the capacity while controlling the threshold value for every service in LoRa.	• It increases the computational load and communication latency. • It suffers from uncoordinated configuration, scalability issues, and limited channel resources.
Xu *et al.* [25].	DRL.	• Deployed the DRL technique for mmWave MIMO systems facilitated by RIS. • It provides a location-aware imitation environment.	• RIS-aided mmWave MIMO systems in facing dynamic channel challenges. • Interference management is a challenge in RIS-aided mmWave MIMO systems.
Gumaei *et al.* [26].	Game Theory	• BE-LoRa aims to make LoRa nodes more productive than the previous Adaptive Data Rate approach by improving packet delivery and energy consumption and equitably allocating power.	• Large numbers of nodes using the same channel provide scalability problems for LoRaWAN networks.
Bankov *et al.* [27].	MCSs.	• It reduces the traffic load issues. • It enhances the network capacity and quality of service during the data transmission in LoRa.	• Enhancing the model to evaluate packet loss in large network configurations with gateway constraints and SF overlaps.
Azizi *et al.* [28].	MIX-MAB.	• It requires less maintenance. • It improves the network connectivity during the data transmission.	• The computational cost is high. • Uncrewed aerial vehicles may face scalability, performance validation, and adaptability challenges.

ratio simultaneously-the ratio of throughput to transmit power defined by the LoRa node's utility function. The rational users were used to maximize the utility function. The energy allocation strategy used in this LoRa network was based on the SF and SINR parameters. The best equal LoRa (BE-LoRa) strategy was used to optimize the LoRa nodes. The suggested BE-LoRa allocation strategy improved the numerical and simulation results better than those of existing systems.

In 2019, Bankov et al. [27]. investigated an accurate mathematical model of low-power data transmission in a LoRa sensor network. It validated important quality of service metrics such as packet loss ratio and network capacity. The transmission model attempted failures brought on by channel noise, and the LoRa networks used an unlicensed spectrum. This model was effectively used in high traffic and other scenarios. Most of the existing networks were affected by the efficacy of the LoRa and quality of service parameters. They utilized the Modulation and coding schemes (MCSs) to improve LoRa's quality of service. The resource allocation was used to improve the throughput and transmission efficiency.

In 2022, Azizi et al. [28]. explored a resource allocation model using reinforcement learning techniques to allow the parameters to adjust their transmission parameters. The optimization strategy had two phases: exploitation and exploration. This strategy was used to allocate the resources in LoRa. The simulation findings proved that the implemented framework performed better than other currently used methods. The suggested solution outperformed the current schemes regarding PDR and convergence time by considering the numerical results.

B. PROBLEM STATEMENT

The conventional resource allocation-based data transmission in LoRa has many challenges, including security, server dependence, quality of service, network connectivity, coverage, limited resource capacities, coexistence, and scalability. It is hard to allocate the resources while training the massive networks. The existing systems suffer from high computational load and communication latency issues. Hence, an efficient resource-based data transmission in LoRa is needed to solve the above problems. The advantages and disadvantages of the existing optimization-based resource allocation framework in LoRa are given in Table 1. Hybrid coati with energy valley optimization algorithm (HC-EVOA) [19] decreases the energy consumption and increases the throughput during the execution. Also, it reduces the time consumption while performing the resource allocation process. It does not handle complex optimization issues but only supports low data rates. Integrating reconfigurable intelligent surfaces (RIS) [20] into cell-free systems reduces costs and enhances network efficiency by optimizing performance using computing resources. However, challenges persist in improving and optimizing resource allocation and managing interference and hardware costs. Variable Neighbourhood Search (VNS) and minimum spanning tree (MST) [21] provide low convergence rates and high packet reception ratio. Also, it improves the quality of service of the LoRa networks. However, it suffers from contextual bandit problems, and it is hard to maintain the network's stability using various network conditions. Combining reinforcement learning and supervised machine learning [22] has improved the energy efficiency, output quality, and Packet Reception Rate (PRR) of dense LoRa networks, reducing the required processing time. However, its operation necessitates a feedback system, potentially leading to uplink and downlink interference.

Yet, training the massive IoT networks requires a lot of device parameters, increasing the packet loss ratio. A multi-agent system (MAS) [23] handles the high-traffic scenarios and obtains better reliability outcomes. Also, it effectively supports real-world experiments. Yet, it suffers from allocating resources to highly congested and extensive networks and performs poorly because of interference and congestion issues. Genetic Algorithm (GA) [24] minimizes the average packet loss rate. Also, it increases the capacity while controlling the threshold value for every service in LoRa. Yet, it increases the computational load and communication latency and suffers from uncoordinated network configuration, scalability problems, and limited channel resources. The introduced deep reinforcement learning (DRL) [25] approach in reconfigurable intelligent surface (RIS)-aided millimeter-wave (mmWave) multiple-input multiple-output (MIMO) systems provides a novel solution. It creates a location-aware imitation environment and effectively reduces interaction overhead. However, challenges persist due to the dynamic nature of the wireless channel in RIS-aided mmWave MIMO systems. Dependence on accurate channel state information, which is incredibly challenging to obtain in mmWave frequencies, poses another hurdle. Additionally, interference management remains a significant challenge in such systems. Game theory [26] effectively supports multiple services in LoRa networks. Also, it provides high security and avoids economic imbalances. Yet, it suffers from server dependence and limited resource capacities and requires more maintenance services. Modulation and coding schemes (MCSs) [27] reduce the traffic load issues. Also, it enhances the network capacity and quality of service during communication in LoRa. Yet, it only supports high data rate applications and suffers from coverage, mobility, and security issues. MIX-multi-armed bandit (MIX-MAB) [28] requires less maintenance. Also, it improves the network connectivity during the data transmission. However, the computational cost is high and also, and it also increases the computational complexity. A new efficient resource-based data transmission framework in LoRa is designed based on reinforcement learning techniques to overcome the above difficulties.

III. SYSTEM MODEL OF LOW POWER WIDE AREA NETWORKS, MOTIVATION AND ARCHITECTURE OF RESOURCE OPTIMIZATION FOR BETTER DATA TRANSMISSION

A. LORA: SYSTEM MODEL

A single LoRa model comprises a half-duplex gateway and fixed LoRa end devices. The LoRa system contains three classes: A, B, and C. The end devices are evenly spaced around the gateway and are considered class A devices. Most of the time, the end devices are in sleep mode to preserve battery life. They only wake up to conduct uplink transmissions when a new packet arrives.

Additionally, each end device completes an uplink transmission during the system training process, and each end device gets a downlink acknowledgement from the gateway. They assume that the gateway transmits the acknowledgement separately from the uplink channel to prevent interference between downlink acknowledgements and uplink transmissions. The LoRa defines two receive windows, like $SY1$ and $SY2$. It is used to determine the confirmed traffic in the network. In the second receive window, $SY2$, end devices wait for an acknowledgement, which saves channel resources and energy. The symbol duration of LoRa is determined based on the bandwidth EI and the spreading factor PF. EI denotes the bandwidth, PF denotes the spreading factor. The LoRa's symbol duration U_t is calculated using Eq. 1.

$$U_t = \frac{2^{PF}}{EI} \tag{1}$$

The gateway transmits the acknowledgements to a fixed spreading factor. The high spreading factor uses transmit energy $q_t = 27\,\text{dBm}$. The term e^o represents the path loss exponent in LoRa communication range, which is determined by path loss. The path loss M_{path} is calculated using Eq. 2.

$$M_{\text{path}} = \left(\frac{4.\pi.g}{d}\right)^2 .e^o \tag{2}$$

Here, the LoRa frequency is noted by g, and the link budget M_{Bud} is measured using Eq. 3.

$$M_{\text{Bud}} = \frac{Q_{\text{Us}}}{T_{\text{s}}(\text{TG, CX})} \tag{3}$$

Here, the term Q_{Us} indicates the transmission power and the term $T_s(TG, CX)$ denotes the receiver sensitivity, which is determined by the bandwidth and spreading factor. The minimal received power for detecting the signal is receiver sensitivity. The term SNR_0 is calculated using Eq. 4.

$$\text{SNR}_0 = \frac{F_{\text{BIT}}}{O_0} \tag{4}$$

Here, O_o notes the noise power density. The parameter is assumed to be $F_{BIT} = T_S.U_{BIT}$ The received power is denoted by T_s and the bit duration is noted by U_{BIT}. The above formula is rewritten using Eq.5.

$$\text{SNR}_{(0)} = \frac{T_s \cdot 2^{TG}}{OG \cdot l \cdot U \cdot CX} \tag{5}$$

The term T_s is calculated using Eq. 6.

$$T_s = \frac{\text{SNR}_0 \cdot O \cdot l \cdot U \cdot CX}{2^{TG}} \tag{6}$$

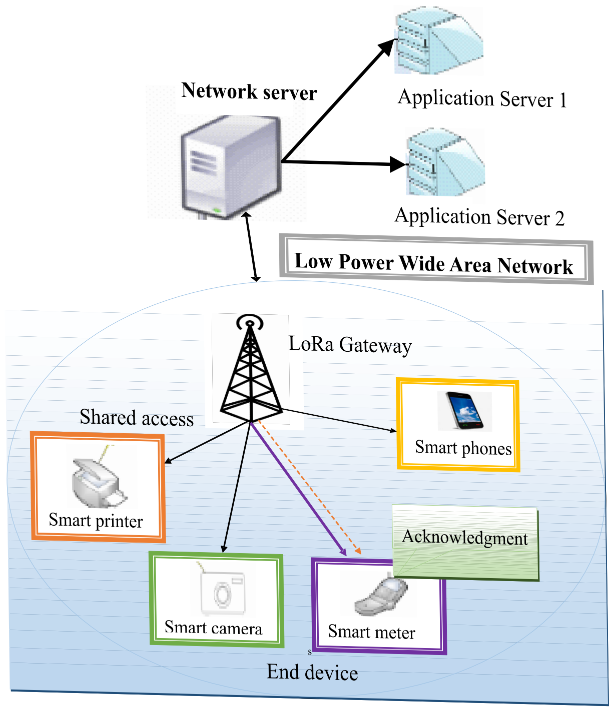


FIGURE 1. Network model of LoRa.

The receiver sensitivity $T_s(TG, CX)$ is calculated using Eq. 7.

$$\begin{aligned} T_s(TG, CX) &= \text{SNR}(TG) \cdot O_0 \\ &= \text{SNR}(TG) \cdot OG \cdot l \cdot U \cdot CX \end{aligned} \tag{7}$$

Here, the parameters Kelvin constant, noise, and temperature are indicated by l, OG and U, respectively. The term SNR(TG) is measured by Eq. 8.

$$\text{SNR}(TG) = \frac{\text{SNR}_0}{2^{TG}} \tag{8}$$

Next, the link budget equals the path loss and is used to estimate the value of the maximum communication range of the LoRa. The LoRa communication range is validated using Eq. 9.

$$e = \left(\frac{M_{\text{path}}}{\left(\frac{4 \cdot \pi \cdot g}{d}\right)^2}\right)^{\frac{1}{o}} \tag{9}$$

The high spreading factor values are used to get long LoRa ranges. Hence, the LoRa range is increased based on the spreading factor. The details of LoRa modulation and accurate radio environment are captured in the uplink transmission. Every possible LoRa parameter is used to reduce the packet loss at the uplink transmission. The LoRa parameters are bit error rate, co-SF capture effect, temporal collision, fading, wireless channel attenuation and inter-spreading factor. The network model of LoRa is shown in Fig. 1.

B. MOTIVATION BEHIND RESOURCE OPTIMIZATION

One of the challenges of the LoRa network is the near-far effect issue. Route loss, fading, and other factors affect the received power at different places during data transmission in wireless communication. In the general scenario, the receive power at the receiving end near the transmitter source is higher than the remote receiving end. This scenario impacts the LoRa network's capture effect. Hence, independent of the terminals' distance from the gateway, all terminals received power must be balanced to improve the data rate. However, most of the LoRa network's resource allocation strategy was limited to a single objective: maximizing the terminal adaptive data rate. It is concentrated on a single parameter, such as the spreading factor. Here, the primary goal of resource allocation is multi-objective optimization. It optimizes factors like the spreading factor, transmission power, channel, and time. The tools, techniques, and models for multi-objective optimization and multi-radio parameters still need to be improved. Several Lagrangian relaxation techniques and conventional approaches in LoRa suffer from dimensionality issues. The implementation of the DARL model has demonstrated better solutions.

Optimization problems are typically used in the DARL model to seek solutions that satisfy particular optimal qualities under specific conditions. A collection of objective functions, a set of constraints, and a set of decision variables are used to express these issues. Its primary benefit is that it uses well-established computational tools and several solution techniques with regulated calculation times and accuracy. In this work, the designed IR-LEOA strategy is used to optimize factors such as spreading factor, transmission power, channel, and number of iterations from the DARL model to enhance the performance of LoRa networks. The gateway manages wireless resources and then performs the resource allocation using optimized parameters from the DARL model. The motivation of this work is formulating and optimizing a solution using the designed IR-LEOA with the DARL model to achieve the lowest energy consumption and maximize the data extraction rate in the LoRa network. We contribute to providing solutions and decreasing resource allocation optimization issues for LoRa network uplink transmission. Optimal resource allocation with the lowest packet collision probability and the lowest network energy usage is the biggest challenge of the LoRa systems. This DARL approach uses the designed IR-LEOA optimization to solve the above resource allocation issue.

C. PROPOSED RL-BASED RESOURCE OPTIMIZATION IN LORA

Most conventional resource allocation-based data transmission models increase the packet loss and interference issues on LoRa systems. It provides high energy consumption, limited coverage, low transmission rate and high cost. Due to packet loss, the existing system affects the network's service quality and causes network overload issues. Many users in the existing system need more resources, such as energy and spectrum. It provides low transmission throughput. Because of the extensive range of application demands, increasing security and privacy during data transmission is challenging. It gives low adaptability and efficiency outcomes. As a result, the agent's training could be more trustworthy. A feedback mechanism is necessary for most of the system to function correctly. It suffers to reduce the uplink and downlink interference issues. In conventional systems, the resource allocation performance is decreased in terms of spectrum constraint, real-time communication, security, scalability and application-specific needs, including data rates and mobility. Thus, a new resource allocation-based data transmission system in LoRa is developed to resolve the above difficulties. The architectural illustration of the suggested resource allocation scheme for data transmission in LoRa is depicted in Fig. 2.

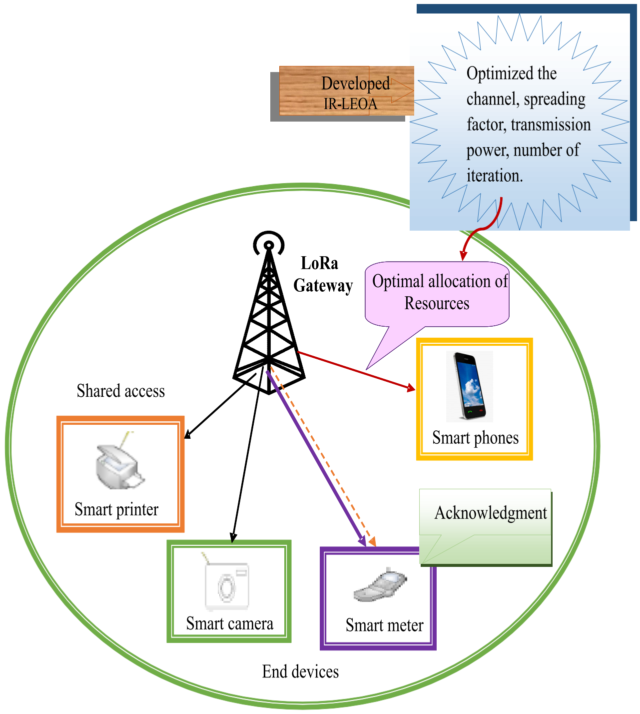


FIGURE 2. Architectural view of suggested resource allocation-based data transmission in LoRa.

A newly developed resource allocation-based data transmission scheme in LoRa is used to reduce the transmission power and effectively increase the data rate during the data transmission. It helps to enhance the wireless communication environments without interference and network congestion. Here, the DARL technique is used to identify the appropriate parameters in the LoRa system to minimize the transmission power. DARL is used to solve the LoRa challenges, and its goal is to optimize the allocation of network resources like transmission power, spreading factor, and channel. It allocates transmission power, spreading factor, and channel for IoT devices to improve quality of service requirements. Here, the LEA and ROA strategies are combined to implement an IR-LEOA strategy. It is used to select the parameters in the DARL model optimally. The

IR-LEOA is developed to tune the network resources or parameters such as channel, spreading factor, transmission power, and number of iterations from the DARL model to increase throughput, energy efficiency, and transmission rate and minimize latency. The agents produced by the DARL model match the terminal nodes in the LoRa server. The optimal transmission variables are sent to the network terminal hub when the DARL agent is generated. This optimization strategy analyses the transmission rate, latency, energy efficiency, and throughput. Performance analysis of the suggested system is conducted using existing methods and algorithms with various performance metrics and a proposed integrated Heuristic Strategy for Resource Optimization in LoRa.

D. REMORA OPTIMIZATION ALGORITHM

Remora [29]. is well-known for its propensity to swim top oceangoing whales, ships, and other marine. This behavior is not only free from enemy invasion but also labor-saving. The remora is typically found in tropical waters and can also go to colder waters. Remora primarily consumes invertebrates and other fish. it adsorbed the next host and moved on to another sea area. The ROA strategy has two behaviors. That is host feeding and eating. The remora position and individual solutions of remora are initialized in the ROA. The remora is attached to the swordfish-the position of the swordfish updates simultaneously with the remora's attachment Eq. 10. gives this mathematical behavior of position updating.

$$S_j^{u+1} = S_{\text{BEST}}^u - \left(\text{rand}(0,1)^* \left(\frac{S_{\text{BEST}}^u + S_{\text{rand}}^u}{2}\right) - S_{\text{rand}}^u\right) \tag{10}$$

Here, the number of present iterations is noted by u. The term U denotes the maximum iteration. The random position is noted by S_{rand}^u. The optimal location of the remora is effectively updated using the random parameter. It takes small steps to change the host effectively. The term S_{buu} is calculated using Eq. 11.

$$S_{\text{buu}} = S_j^u + (S_j^u - S_{\text{PR}})^* \text{rand} \tag{11}$$

Here, the term S_{PR} is the previous position of the remora. The small step is noted by S_{buu}. The active step of remora is said to be a slight global movement, represented in Eq. 12. and Eq. 13. correspondingly.

$$g(S_j^u) > g(S_{\text{buu}}) \tag{12}$$

$$g(S_j^u) < g(S_{\text{buu}}) \tag{13}$$

Here, the present solution is indicated by $g(S_j^u)$. The strived solution is noted by $g(S_{\text{buu}})$. The minimal strived solutions are used to determine the fitness function. If the fitness value of the strived solution is higher than the present solution, it returns for the host selection process.

1) EATING

In this phase, the position is updated based on the whale's position. Here, the remora is attached to the whale. This mathematical expression is measured using Eq. 14.

$$S_{j+1} = E^* f^{b*} \cos(2\pi\beta) + S_j \tag{14}$$

The calculation of β, and E are given in Eq. 15. and Eq. 17. respectively.

$$\beta = \text{rand}(0,1)^*(b-1) + 1 \tag{15}$$

The term b is determined using Eq. 16.

$$b = -\left(1 + \frac{u}{U}\right) \tag{16}$$

$$E = \left|S_{\text{BEST}} - S_j\right| \tag{17}$$

Here, the term E is the present optimal solution. It is determined based on the distance of prey and hunter. In this phase, the remora and the whale position are the same. The random value is indicated by β, and it is chosen in the interval of $[-1, 1]$.

2) HOST FEEDING

In the exploitation procedure, the host feeding is one of the subdivisions. The remora moves around the host using the small steps given Eq. 18. and Eq. 19. respectively.

$$S_j^u = S_j^u + B \tag{18}$$

$$B = C^*(S_j^u - D^* S_{\text{BEST}}) \tag{19}$$

The term C is determined through Eq. 20.

$$C = 2^* W^* \text{rand}(0,1) - W \tag{20}$$

The term W is estimated using below Eq. 21.

$$W = 2^*\left(1 - \frac{u}{\text{MAX\_}i\text{Tr}}\right) \tag{21}$$

Here, the term B is the small step. The term D is the condition assumed to be 0.1. C notes the random host. The search space is decreased during the remora feeding on the host. The iteration runs 30 times, and the best fitness solutions are effectively determined. The best solution is determined in the range of [0, 0.3]. The ROA strategy effectively reduced the computational complexity issues. The pseudocode of the suggested ROA is given in the Algorithm. 1.

E. LOTUS EFFECT OPTIMIZATION ALGORITHM

The lotus effect is referred to as leave's self-cleaning and super-hydrophobic features. This LEA [30]. strategy has two phases: extraction and exploration. In the exploration phase, the actions of insects like dragonflies and the seed-spreading activities are used. In the extraction phase, the flower buds grouped around a focal core could inspire local search strategies that use multi-populations and search parameters.

1) EXPLORATION STAGE

The dragonflies cause leaf pollination. The dragonfly algorithm is inspired to implement the LEA strategy. In the dragonfly strategy, the enemy and food behavior of the dragonfly are effectively used to determine the best solutions.

Algorithm 1 Implemented ROA

Load the position of the population.
Initialize the optimal solution.
while condition **do**
    Determine the fitness solution of remora.
    Verify the search agent space.
    Update the variables x, y, and z.
    for each agent **do**
        if condition **then**
            Determine the position using Eq. 14.
        else
            Calculate the position using Eq. 18.
        end if
    end for
    Find the current fitness value.
end while
Return the best fitness solution.

The dragonfly position is updated based on the escaping strategy from enemies and food-searching activities. The location of the individual is measured using Eq. 22.

$$T_j^u = -\sum_{k=1}^{O}\left(Y_j^u - Y_k^u\right) \tag{22}$$

Here, the term Y_j denotes the present position. The term k is the index. The current iteration is noted by u. The number of individuals is indicated by O. The alignment is measured using Eq. 23.

$$H_j^u = \frac{\sum_{k=1}^{O} Y_k^u}{O} \tag{23}$$

Here, the term Y_k^u is the velocity. The cohesion is measured using Eq. 24.

$$I_j^u = \frac{\sum_{k=1}^{O} Y_k^u}{O} - Y_j^u \tag{24}$$

Here, the term Y_j denotes the present position. The term k is the index. The current iteration is noted by u. The term Y_j indicates the position of the individual. The food-searching activities are calculated using Eq. 25.

$$G_j^u = Y_+^u - Y_j^u \tag{25}$$

Here, the term Y_+^u is the food position. It is used to determine the best fitness solution. The escaping strategy is calculated using Eq. 26.

$$Q_j^u = Y_-^u - Y_j^u \tag{26}$$

Here, the enemy position is noted by Y_-^u. It is used to determine the worst fitness solution. The dragonfly movement is measured using Eq. 27.

$$\Delta Y_j^{u+1} = (tT_j^u + hH_j^u + iI_j^u + gG_j^u + qQ_j^u) + x\Delta Y_j^u \tag{27}$$

Here, the term t is the coefficient value. The separation degree is indicated by T_j^u. The alignment coefficient is noted by b. The individual's alignment is noted by H_j^u. The term i is the cohesion coefficient. The individual's cohesion is indicated by G_j^u. The food source is indicated by g, and the enemy is noted by q. The individual's enemy is noted by Q_j^u. The term x denotes the weight, and the term u indicates the iteration. The term $Y_j^{(u+1)}$ is calculated using Eq. 28.

$$Y_j^{u+1} = Y_j^u + x\Delta Y_j^{u+1} \tag{28}$$

Here, the term Y_j^{u+1} is the location vectors. The location is updated using Eq. 29.

$$Y_j^{(u+1)} = Y_j^u + \mathrm{LEVY}(z) \times Y_j^u \tag{29}$$

Here, the term u is the present iteration. The dimension is indicated by z.The term $\mathrm{LEVY}(y)$ is calculated using Eq. 30.

$$LEVY(y) = 0.01 \times \left(\frac{S_1 \times \vartheta}{|S_2|^{\frac{1}{\theta}}}\right) \tag{30}$$

Here, the random values are noted by s_1 and s_2, respectively. The constant value is noted by θ. The term ϑ is measured using Eq. 31. and Eq. 32.

$$\vartheta = \left(\frac{\zeta(1+\theta) \times \sin\left(\frac{\pi\theta}{2}\right)}{\zeta\left(\frac{1+\theta}{2}\right) \times \vartheta \times 2 \times \left(\frac{\theta-1}{2}\right)}\right)^{\frac{1}{\theta}} \tag{31}$$

$$\zeta(y) = (y-1)! \tag{32}$$

2) EXPLOITATION STAGE

The pollination activity is used in this phase. It is also said to be the extraction stage. A coefficient specifies the size of each flower's growing area around the best-found flower in this type of pollination. This behavior is measured using Eq. 33.

$$Y_j^{(u+1)} = Y_j^u + S(Y_j^u - h^*) \tag{33}$$

Here, the term $Y_j^{(u+1)}$ is the pollen position. The best position is noted by h^*. The term S denotes the area growth, calculated by Eq. 34.

$$S = 2q^{-\left(\frac{4u}{M}\right)^2} \tag{34}$$

Here, the term M is the iteration count. The term S is utilized to balance the exploitation and exploration phases. The capacity is measured using Eq. 35.

$$i_j^u = \frac{\left(|g_j^u - g_{\mathrm{MAX}}|\right) \times Cns}{(|g_{\mathrm{MIN}} - g_{\mathrm{MAX}}|)} \tag{35}$$

Here, the term i_j^u is the capacity. g_j^u indicates the size, and g_{MAX} denotes the maximum fitness size. g_{MIN} denotes the minimum fitness size. The term SLCT_j^u is calculated by Eq. 36.

$$\mathrm{SLCT}_j^u = \frac{i_j^u}{\sum_{k=0}^{i} i_k^u} \tag{36}$$

Here, the term l is the number of pits. The term i_j^u is the capacity. The drop velocity is measured using Eq. 37.

$$W_j^{u+1} = r \times W_j^u \tag{37}$$

The position of moving drops is measured using Eq. 38. and Eq. 39.

$$W_j^{u+1} = W_j^u + \mathrm{rnd}(Y_{\mathrm{DEp}}^u - Y_j^u) \tag{38}$$
$$Y_j^{u+1} = Y_j^u + W_j^{u+1} \tag{39}$$

Here, the term Y_{DEp}^u is the present location, and the term W_j^u is the present velocity. The pseudocode of the investigated LEA is provided in the Algorithm. 2.

Algorithm 2 Designed LEA

```
Initialize the search agents, size of population, and random parameter.
Determine the best search agent.
Update the parameters and velocity.
for each agent do
    Determine the best optimal solution.
    for each agent do
        Update the position.
        if condition then
            Update the position of the new flower using Eq. 29.
        else
            Update the position using Eq. 33.
        end if
    end for
end for
Evaluate the water movement and capacity.
Return the best optimal solution.
```

F. PROPOSED IR-LEOA

The suggested Integrated Remora with Lotus Effect Optimization Algorithm (IR-LEOA) strategy is used to enhance the efficacy of the resource allocation process by optimizing the parameters. Parameters like channel, spreading factor, transmission power, and number of iterations are optimized using the deep adaptive reinforcement learning (DARL) model to maximize energy efficiency, transmission rate, and throughput and minimize latency. The implemented IR-LEOA strategy is used to enhance the computing process during resource allocation. The Remora Optimization Algorithm (ROA) optimization has high convergence accuracy and speed. It reduces the computational complexity. It does not change the host. Hence, it is easy to implement. Yet, it suffers from high-dimensional complexity issues. It requires more time for the computation. The Lotus Effect Optimization Algorithm (LEA) optimization effectively solves global optimization difficulties. It gives efficient and scalable outcomes. However, it requires more computational resources when using large-scale data. It provides low accuracy and high error rates. To solve these difficulties, the IR-LEOA strategy is implemented. In the designed IR-LEOA, the solution is upgraded based on current fitness. If the current fitness solution is greater than the mean fitness like ($CurFit > MEnFit$), the implemented IR-LEOA updates the position using the ROA. Otherwise, the position will be updated using the LEA. Here, $CurFit$ denotes the current fitness, and $MEnFit$ indicates the mean fitness. The pseudocode of the explored IR-LEOA is given in Algorithm 3. The flowchart illustration of the investigated IR-LEOA is shown in Fig. 3.

Algorithm 3 Explored IR-LEOA

```
Set the location of population.
Load the optimal fitness and best solution.
Update the position vectors and velocity.
for each agent do
    Determine the remora's fitness solution and global optimal solution.
    for each agent do
        Verify the search agent space.
        if condition then
            Update the position using LEA in Eq. 33.
        else
            Update the position using ROA in Eq. 10.
        end if
    end for
end for
Return the best fitness solution.
```

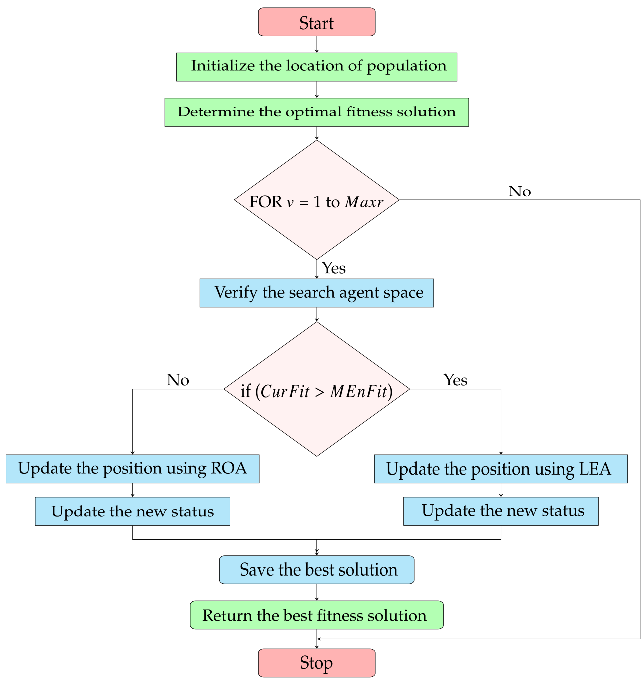


FIGURE 3. Schema chart of the developed IR-LEOA.

IV. DISTRIBUTION OF NETWORK SOURCES USING ADVANCED REINFORCEMENT LEARNING STRATEGY FOR EFFICIENT DATA TRANSMISSION IN LORA

A. REINFORCEMENT LEARNING

The reinforcement learning model [31]. Contains only one LoRa gateway and multiple counts of LoRa nodes. The number of LoRa nodes is noted by P. The term c_v denotes the network variables. The compensation parameter s_v is determined using the network variables. Reinforcement learning effectively learns the optimal decision. The Markov process is used to implement reinforcement learning. It contains action, state, discount factor, transaction, and reward function. The agent's primary goal in reinforcement learning is to improve the total reward. The total reward I_v is calculated using Eq. 40.

$$I_v = \sum_{k=v}^{v} S_{k+1} \tag{40}$$

Here, the term V denotes the time. The action phase is also said to be R-network. These two components are positioned with the grid size of 1500 × 1500. The LoRa gateway is placed in the center of the grid, and the remaining nodes are distributed throughout the grid. The nodes and the gateway adjust the spreading factor and the transmission power based on the adaptive data rate. The LoRa gateway is taken as a container for every agent node. This gateway is used in the reinforcement learning to achieve a better spreading factor and transmission power. In this case, the network has more nodes to organize with an agent. So, it easily controls the agent and their uses.

Finally, optimal resource allocation achieves a high balance between energy collection and energy consumption at sensors. It is used to maximize the future compensation and convergence rate. The Deep Q-network (DQN) structure model generates the reinforcement learning agent, which is used to identify LoRa's network parameters.

B. DARL-BASED NETWORK RESOURCE DISTRIBUTION

Reinforcement learning and deep learning technologies are used to develop a deep reinforcement learning method. The DARL technique is used to identify the appropriate parameters in the LoRa system to minimize the transmission power. DARL is used to solve the LoRa challenges, and its goal is to optimize the allocation of network resources like transmission power, spreading factor, and channel. It allocates transmission power, spreading factor, and channel for IoT devices to improve quality of service requirements. DARL can directly leverage raw state representations and train policies with efficient and effective methods for non-linear generalization and high-dimensional feature extraction for complex systems and tasks with a deep learning approach. The DARL algorithms are effectively used in the discrete action space of DQN. It estimates R-values by using a neural network with weights. DQN is different from conventional learning in that it uses the function approximation approach, which typically necessitates a large amount of manual adjustment to stabilize the learning process. That is experience replay and the target network. The term $\hat{R}$ denotes the target network. The R-network and the target network have the same architecture. The R-network weights are copied to the target network at a regular periodicity. The agent status $f_u = (t_u, b_u, s_u, t_{u+1})$ is stored in a data set with minimal time to conduct experience

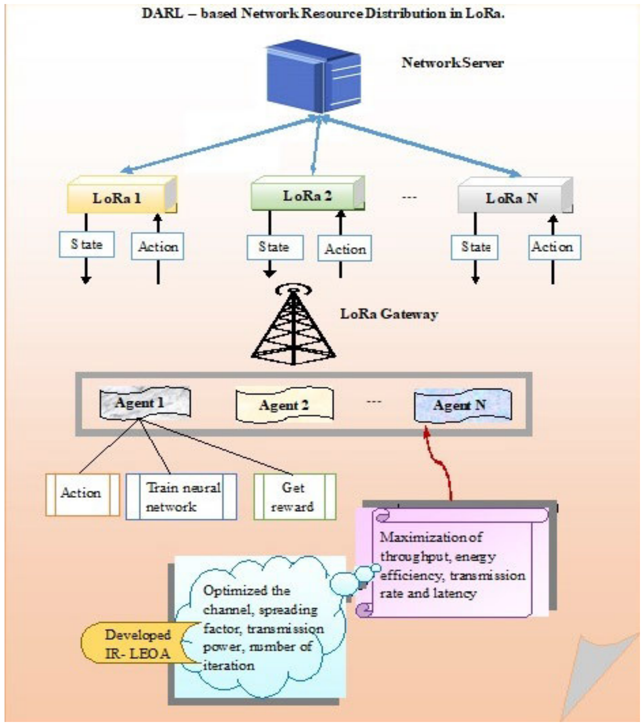


FIGURE 4. Structural illustration of the offered DARL-based network resource distribution.

replay. R-network is executed using several mini-batches and randomly taken from the parameter F. This parameter F is used to minimize the loss function and is measured using Eq. 41.

$$M_j(\varnothing_j) = F_{(t,b)\sim q}\left\lfloor \left(Z_j - R(t, b; \varnothing_j)\right)^2 \right\rfloor \tag{41}$$

Here, z_j denotes the target R-value modeled using the target network $\hat{R}$ at the iteration j. The term t denotes the state value, and the term b denotes the action value. The probability distribution (t, b) is noted by q. Stochastic gradient descent is one method for updating neural network weights, calculated using Eq. 42.

$$\nabla_{\varnothing_j} M_j(\varnothing_j) = F_{(t,b)\sim q}\left\lfloor (Z_j - R(t, b; \varnothing_j))\nabla_{Q_j} R(t, b; \varnothing_j)\right\rfloor \tag{42}$$

The DQN is used in the DARL structure to decrease the training variance and increase the data efficiency. A neural network approximation is used to construct and learn a stochastic policy based on a joint distribution of mixed random variables to maximize the discrete and continuous actions simultaneously. The suggested IR-LEOA is used in DARL training to increase the safety requirements during data transmission in LoRa networks. The suggested DARL method allows the agent to investigate safe data scheduling operations at a low cost. Hence, the DARL model allocates the resources directly to LoRa networks. The structural illustration of the offered DARL-based network resource distribution is displayed in Fig. 4.

C. OBJECTIVE FUNCTION

The suggested DARL-based resource allocation for data transmission over the LoRa network's goal is reducing power consumption and enhancing the data transmission rate. The DARL model effectively learns the optimal resource allocation using the designed IR-LEOA. Deep reinforcement learning effectively solves complicated issues with minimal training knowledge. It provides better and more stable solutions to optimize the algorithms. However, the computational cost is high and suffers from dimensionality issues. It requires large-scale data for the training. It needs to solve the overload issues of states. To overcome these issues, the DARL-based resource allocation is developed. It effectively solves the resource allocation issues. The IR-LEOA is designed to tune the network resources or parameters such as channel, spreading factor, transmission power, and number of iterations from the DARL model to increase the throughput, energy efficiency, and transmission rate and minimize the latency. The objective functions of increased throughput, energy efficiency, transmission rate, and minimized latency are given in Eq. 43.

$$\mathrm{Ob}_j = \underset{\{MR_c^{\mathrm{DARL}}, VG_s^{\mathrm{DARL}}, JM_{tp}]^{\mathrm{DARL}}, IA_i^{\mathrm{DARL}}\}}{\arg\min} \left(\frac{1}{T} + \frac{1}{E} + \frac{1}{TR} + LA \right) \tag{43}$$

Here, the value MR_c^{DARL} denotes the optimized channel, and it is selected in the range of $[1, 20]$. The parameter VG_s^{DARL} denotes the optimized spreading factor, and it is taken in the range of $[0.01, 0.99]$. The optimized transmission rate is noted by JM_{tp}^{DARL} and it is chosen in the range of $[2, 128]$. The optimized number of iterations is noted by IA_i^{DARL}, and it is selected in the range of $[10, 1000]$. The throughput T formula is provided in Eq. 44.

$$T = \frac{\sum_{l=1}^{v} T_l}{v} \tag{44}$$

Here, the term v indicates the total transmission, and the term T_l denotes the total received data. Eq. 45. measures the energy efficiency formula.

$$E = \frac{\sum_{p=0}^{p-1} T_{\mathrm{Sum},p}}{\sum_{p=0}^{p-1} U_{\mathrm{up},p}} \tag{45}$$

Here, the term p denotes the channel. $T_{\mathrm{Sum},p}$. notes the total data transmission time. The successful transmission is noted by $U_{\mathrm{up},p}$. Eq. 46. measures the transmission rate formula.

$$TR = \frac{Os - D}{Ot} \tag{46}$$

Here, Ot denotes the total number of sent data, and Os denotes the total number of received data. The number of conflicting packets is noted by D. The latency formula is given in Eq. 47.

$$LA = \frac{K^{SU}}{S_t^{SU}} \tag{47}$$

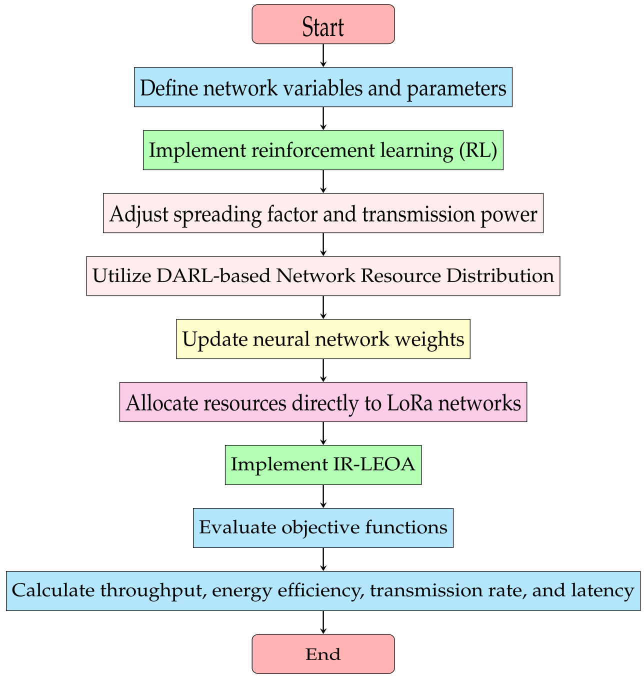


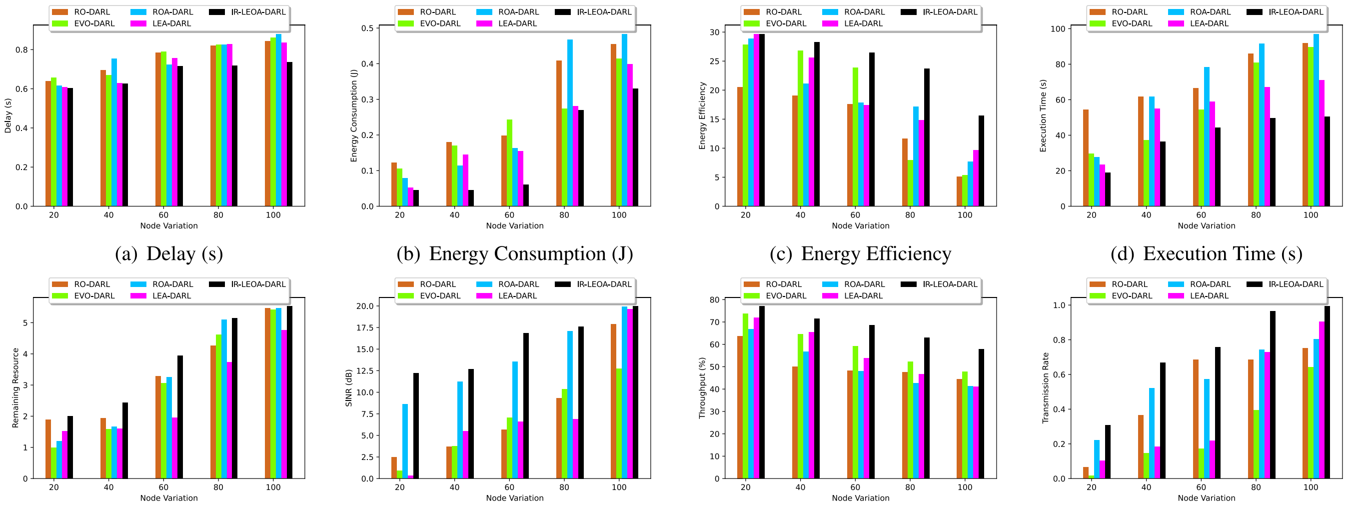
FIGURE 5. Schema chart of the developed method.

Here, the term S_t^{SU} indicates the total data transmission time. The term K^{SU} denotes the time of received data.

D. FRAMEWORK IMPLEMENTATION

This section provides a detailed, step-by-step explanation of the general resource allocation-based data transmission framework over LPWAN. The developed method's flowchart illustration is presented in Fig. 5

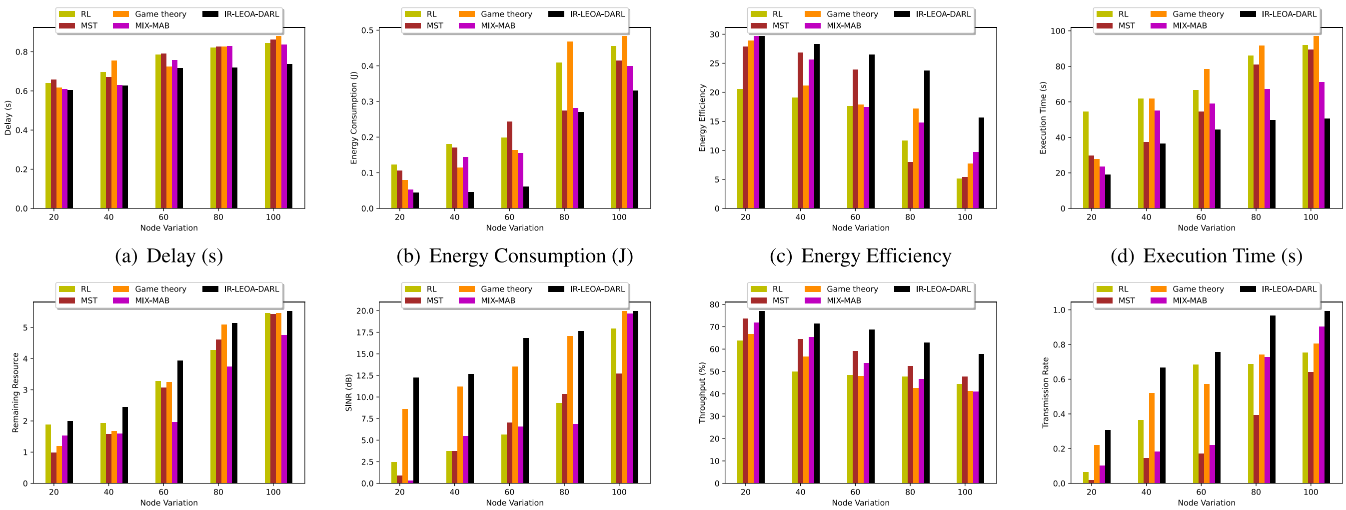
1) Configure the parameters and variables for the network.
2) Apply reinforcement learning (RL) through the Markov process:
   (i) Determine action, state, discount factor, transaction, and reward functions.
   (ii) Create RL agents by utilizing the Deep Q-network (DQN).
   (iii) Determine the overall reward by utilizing Eq. 40.
3) The spreading factor and transmission power are modified based on the adaptive data rate.
4) Employ Distributing Network Resources with DARL-based Approach:
   (i) Apply deep learning methods and deep reinforcement learning.
   (ii) Determine the optimal channel, spreading factor, and transmission power using DARL.
   (iii) Distribute network resources to enhance service quality.
   (iv) Develop training policies that utilize effective techniques for non-linear generalization.
   (v) Use a weighted neural network to estimate R-values.
   (vi) Apply mini-batches to R-network execution.
   (vii) Reduce loss function by applying Eq. 41.



(a) Delay (s) (b) Energy Consumption (J) (c) Energy Efficiency (d) Execution Time (s)

(e) Remaining Resource (f) SINR (dB) (g) Throughput (h) Transmission Rate

FIGURE 6. Performance investigation of the designed resource allocation-based data transmission in LoRa among several algorithms for (a) Delay, (b) Energy Consumption, (c) Energy Efficiency, (d) Execution Time, (e) Remaining Resource, (f) *SINR*, (g) Throughput, (h) Transmission Rate.



(a) Delay (s) (b) Energy Consumption (J) (c) Energy Efficiency (d) Execution Time (s)

(e) Remaining Resource (f) SINR (dB) (g) Throughput (h) Transmission Rate

FIGURE 7. Performance investigation of the designed resource allocation-based data transmission in LoRa among several conventional methods for (a) Delay, (b) Energy Consumption, (c) Energy Efficiency, (d) Execution Time, (e) Remaining Resource, (f) *SINR*, (g) Throughput, (h) Transmission Rate.

5) Apply the stochastic gradient descent Eq.42. to update the weights of neural networks.
6) Distribute resources to LoRa networks directly based on the DARL model.
7) To optimize the channel, spreading factor, transmission rate, and number of iterations, evaluate the objective functions (Eq. 43).
8) Determine the throughput (Eq. 44), energy efficiency (Eq. 45), transmission rate, and latency (Eq. 47).

V. RESULTS

A. EXPERIMENTAL SETUP

The proposed resource allocation-based LoRa data transmission protocol was implemented using the Python platform. The node attributes were initialized between 20, 40, 60, 80, and 100. Chromosome length, number of population, and maximum number of iterations were fixed at 4, 10, and 50 during the experimental analysis. For the performance comparison, several heuristic algorithms such as Rain Optimization (RO) [32], Energy Valley optimizer (EVO) [33], Remora Optimization Algorithm (ROA) [29]. And Lotus Effect Optimization Algorithm (LEA) [30]. And various methods like Reinforcement Learning (RL) [19], MST [21], Game Theory [26]. and MIX-MAB [28]. were used in the offered resource allocation-based data transmission in LoRa.

B. EVALUATION MEASURES

The performance measure of the explored resource allocation system for data transmission is given below.

(a) Throughput: It is calculated using Eq. 44.
(b) Energy efficiency: It is calculated by Eq. 45.
(c) Transmission rate: It is calculated by Eq. 46.
(d) Delay: The delay parameter is calculated using Eq. 48.

TABLE 2. Statistical analysis of the offered resource allocation-based data transmission in LORA with various algorithms.

Terms	RO [32]	EVO [33]	ROA [29]	LEA [30]	IRLEOA
Node 20					
BEST	1.42105	1.25743	1.49574	1.26803	1.19238
WORST	1.94495	2.48403	3.67674	1.94886	2.34107
MEAN	1.69023	1.45539	1.54755	1.40716	1.27864
MEDIAN	1.8000	1.26714	1.49574	1.26803	1.19238
SD	0.21028	0.34880	0.30951	0.24051	0.28602
Node 40					
BEST	1.31184	1.38123	1.26011	1.36791	1.15710
WORST	3.45336	2.95740	3.94347	3.76183	1.30749
MEAN	1.54647	1.61963	1.40501	1.45527	1.20777
MEDIAN	1.34180	1.38123	1.32256	1.43753	1.15710
SD	0.42962	0.40516	0.40414	0.33150	0.06079
Node 60					
BEST	1.30152	1.35772	1.26714	1.33793	1.19179
WORST	2.48054	2.254464	3.96790	3.726652	2.43809
MEAN	1.56012	1.43091	1.39559	1.38570	1.32557
MEDIAN	1.53704	1.35772	1.2671	1.33793	1.1917
SD	0.26415	0.21208	0.43245	0.33442	0.33183
Node 80					
BEST	1.28218	1.29022	1.29947	1.29890	1.16065
WORST	2.31258	3.50123	3.07781	3.26283	2.23431
MEAN	1.46671	1.40155	1.44560	1.36805	1.25567
MEDIAN	1.28218	1.29022	1.29947	1.29890	1.18519
SD	0.30710	0.30921	0.40401	0.28898	0.23698
Node 100					
BEST	1.30562	1.40418	1.38626	1.26808	1.16223
WORST	3.65044	2.09907	2.91529	3.56086	1.94018
MEAN	1.60585	1.72873	1.60275	1.53429	1.27279
MEDIAN	1.50867	1.75312	1.44557	1.26808	1.18706
SD	0.39331	0.15595	0.35292	0.59301	0.20599

$$D = \left(\frac{1}{J}\right) \sum_{n=1}^{N} \frac{L_n}{Y_n - L_n} \tag{48}$$

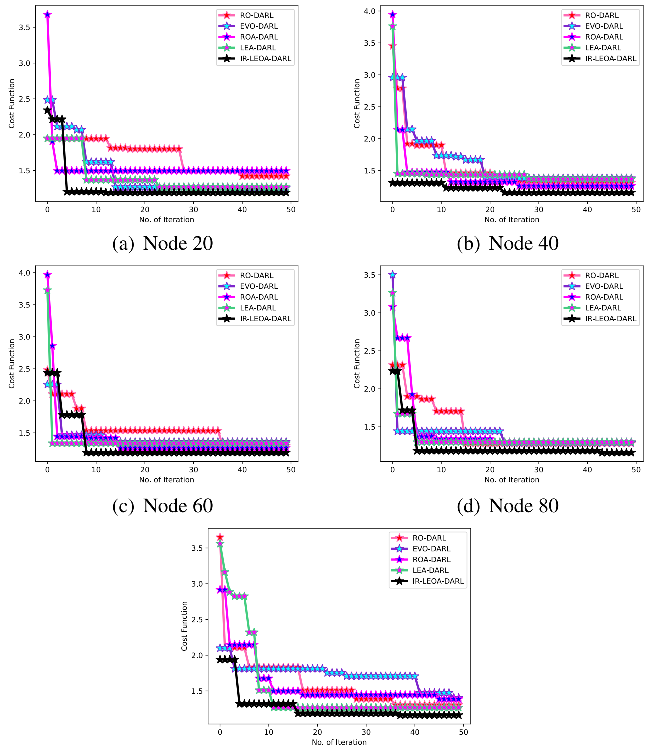
Here, the distance is noted by L_n, and the velocity is indicated by Y_n. J. indicates the data transmission time. (e) Energy consumption is calculated using Eq. 49.

$$E = \sum_{j=1}^{O} U_{t,j} \times Q_{uy,j} \tag{49}$$

Here, the term $U_{t,j}$ denotes the transmission time of packets. The two terminals received power as indicated by $Q_{uy,j}$.

(f) SINR: It is calculated using Eq. 50.

$$S = \frac{|J_k Y_k|^2}{\sum_{j=1}^{o} |J_k Y_k|^2 + L^2} \tag{50}$$



(a) Node 20 (b) Node 40 (c) Node 60 (d) Node 80 (e) Node 100

FIGURE 8. Cost function evaluation of the designed resource allocation-based data transmission in LoRa among several algorithms for (a) Nodes 20, (b) Nodes 40, (c) Nodes 60, (d) Nodes 80, (e) Nodes 100.

Here, J_k indicates the channel vector and Y_k indicates the beam vector for data transmission.

C. PERFORMANCE ANALYSIS OF THE DESIGNED MODEL BY VARYING THE NUMBER OF NODES

The performance estimation of the suggested IR-LEOA-DARL-based resource allocation system for data transmission in LoRa over several heuristic strategies and methods by varying the number of nodes is displayed in Fig. 6. and 7. respectively. Node variations like 20, 40, 60, 80 and 100 were taken in the x-axis for the experimental analysis. The suggested IR-LEOA-DARL-based resource allocation for data transmission over LoRa achieved high transmission rate of 75.12% than RO, 83.17% than EVO, 66.12% than ROA, and 33.20% than LEA at the node variation of 40. The proposed model proved high throughput of 32.69% than RL, 15.01% than MST, 38.02% than Game Theory, and 40.81% than MIX-MAB at the node variation of 60 from Fig. 7. For the performance comparison, the investigated system showed high performance when compared to other conventional resource allocation models for data transmission over LoRas.

D. COST FUNCTION EVALUATION OF THE PROPOSED SYSTEM

The cost function of the suggested IR-LEOA-DARL-based resource allocation for data transmission in LoRa was compared with several heuristic strategies, and it is shown

TABLE 3. Numerical analysis of the offered resource allocation-based data transmission in LoRa with various algorithms.

TERMS	RO [32]	EVO [33]	ROA [29]	LEA [30]	IR-LEOA	TERMS	RO [32]	EVO [33]	ROA [29]	LEA [30]	IR-LEOA
Throughput						Transmission rate					
20	63.71321	73.74989	66.74211	71.87788	77.09915	20	0.065034	0.01749	0.220758	0.102026	0.307028
40	50.01754	64.50562	56.69377	65.47783	71.45211	40	0.365569	0.146493	0.519466	0.182894	0.666593
60	48.29954	59.18683	48.04935	53.73787	68.64573	60	0.683979	0.172371	0.571812	0.219242	0.757752
80	47.62645	52.31128	42.5267	46.68946	63.01844	80	0.686527	0.392656	0.742538	0.72745	0.9657
100	44.46568	47.82249	41.2885	41.00332	57.8528	100	0.752302	0.640598	0.804194	0.904882	0.994097
Delay						Execution time					
20	0.639573	0.656577	0.617048	0.608314	0.60458	20	54.53159	29.67963	27.76247	23.6463	19.01
40	0.696145	0.669682	0.755838	0.629628	0.627389	40	61.90652	37.22279	61.71676	55.15645	36.45074
60	0.784864	0.790502	0.724848	0.758141	0.71545	60	66.70187	54.38201	78.52085	58.9637	44.31753
80	0.821858	0.827274	0.825838	0.82747	0.719988	80	86.00105	81.09755	91.70418	67.26606	49.70728
100	0.842736	0.860821	0.880763	0.835285	0.736651	100	91.80877	89.54866	97.12958	71.18153	50.53975
Energy consumption						SINR					
20	0.12257	0.105632	0.079183	0.052733	0.044878	20	2.479307	0.91103	8.594868	0.327632	12.22789
40	0.180555	0.171015	0.114972	0.144493	0.045321	40	3.717039	3.743654	11.23177	5.485692	12.65619
60	0.198124	0.243654	0.162942	0.154841	0.061575	60	5.64985	7.055072	13.54985	6.596905	16.8509
80	0.408845	0.27431	0.46842	0.281064	0.269526	80	9.296912	10.36657	17.0515	6.85454	17.61501
100	0.45544	0.415006	0.483875	0.399411	0.330788	100	17.90984	12.73766	19.93991	19.65154	19.98287
Remaining resources						Energy efficiency					
20	1.880956	0.987991	1.19087	1.525559	1.997246	20	20.56483	27.84397	28.87045	29.66613	29.70447
40	1.940438	1.575742	1.670066	1.592469	2.438585	40	19.05063	26.86603	21.12278	25.65585	28.25514
60	3.276667	3.066888	3.246375	1.959542	3.939311	60	17.63322	23.87098	17.85359	17.4389	26.48912
80	4.268012	4.61647	5.099839	3.737963	5.148865	80	11.6762	7.936355	17.14026	14.81231	23.71643
100	5.466759	5.423166	5.457842	4.754091	5.53256	100	5.142582	5.349534	7.745434	9.678026	15.65184

in Fig. 8. At the iteration of 30, the developed IR-LEOA-DARL-based resource allocation system over LoRa had given low convergence of 67.93% than RO, 73.22% than EVO, 40.55% than ROA, and 80.72% than LEA. Hence, the implemented model's convergence rate is low compared to existing resource allocation models over LoRas.

E. NUMERICAL ANALYSIS BY VARYING NUMBER OF NODES

Table 3. shows the numerical analysis of the proposed resource allocation scheme in LoRa by varying the number of nodes as 20, 40, 60, 80, and 100. Metrics such as delay, transmission rate, throughput, energy consumption, execution time, SINR, remaining resources, and energy efficiency were used for the experimentation. When compared to the conventional models, the throughput of our model is improved by 21% to RO, 4.54% to EVO, 15.5% to ROA and 7.26% to LEA, for considering the total number of nodes as 20. The transmission rate of proposed IR-LEOA is enhanced with 40.66% better than RO, 14.59% better than EVO, 30.05% better than ROA and 32.75% better than LEA for taking the number of nodes as 80. The delay of our model is obtained with 8.84%, 9.49%, 1.29%, and 5.63% than RO, EVO, ROA, and LEA for the number of nodes as 60. For taking the number of nodes as 20, the total execution time of our model is better than 65.13%, 35.94%, 31.52%, and 19.6% when compared to RO, EVO, ROA, and LEA. The energy utilization of our developed method is improved with 74.89%, 73.49%, 60.58%, and 68.63% than RO, EVO, ROA, and LEA. The SINR of developed IR-LEOA is enhanced with 11.57% better than RO, 56.88% better than EVO, 0.21% better than ROA and 1.68% better than LEA for taking the number of nodes as 100. For the number of nodes as 40, the remaining resources of our model are progressed with 25.67%, 54.75%, 46.01%, and 53.13% when compared to RO, EVO, ROA, and LEA. The energy efficiency of the proposed IR-LEOA is improved with 48.31% better than RO, 5.17% better than EVO, 33.76% better than ROA and 10.13% better than LEA for taking the number of nodes as 40. This calculation concludes that the offered resource allocation-based data transmission model provides promising performance in LoRa.

F. STATISTICAL ESTIMATION OF THE OFFERED RESOURCE ALLOCATION OVER LPWAN

Table 2. displays the statistical analysis of the suggested IR-LEOA-based resource allocation for data transmission over the LoRa systems. The developed IR-LEOA-based

resource allocation system over LoRa specified a best value of 12.03% than RO, 10.70% than EVO, 44.03% than ROA, and 95.82% than LEA at the number of node 20. The resource allocation system offered in LoRa based on IR-LEOA was more effective than the other traditional models regarding performance efficiency.

VI. DISCUSSIONS

An adaptive reinforcement learning-based resource allocation scheme based on a hybrid optimization strategy has been developed in this research work. Various evaluation measures are considered for analyzing the resource allocation efficiency of our model concerning several previously developed models. By examining the result, the resource allocation performance is greatly improved in our model, and a detailed description is given below. The throughput of the proposed IR-LEOA model is 68.64% for the nodes as 60. The execution time and delay of the proposed resource allocation model are significantly lower than those of the conventional algorithms. However, the energy efficiency of the model is greatly improved in the proposed model. The transmission rate accomplished by our model for considering the number of nodes as 100 is 0.99bps. For node 80, the delay of our model is achieved with 0.71sec, which is lower than conventional techniques. The total execution time of our model is significantly lowered and attained with 19.01sec for the node variation as 20. The energy consumption of our method is highly reduced, which is achieved with 0.26J for the node variation of 80. The SINR of this developed scheme is 12.65dB for the total number of nodes 40, which is highly enhanced than the previous models. Considering the total number of nodes 100, our model's remaining resources and energy consumption are achieved with 5.53 and 15.65J, which is more impressive than the previous models. The results revealed that the resource allocation efficacy of this offered IR-LEOA method is superior to earlier models by analyzing all the metrics used for validation.

VII. CONCLUSION

A newly developed resource allocation-based data transmission in LoRa was used to improve the transmission data rate with minimal transmission power. It helped to enhance wireless communication applications without interference and network congestion. Here, the DARL technique was used to identify the variables to minimize the transmission power. It effectively solved the resource allocation issues using suggested IR-LEOA in large-scale IoT networks. The LEA and ROA strategies were combined to implement an IR-LEOA. It was used to select the parameters in the DARL model optimally. The designed IR-LEOA was developed to tune the network resources or parameters like channel, spreading factor, transmission power, and number of iterations from the DARL model to increase the throughput, energy efficiency, and transmission rate and minimize the latency. The agents produced by the DARL model were used to match the terminal nodes in the LoRa server. When the DARL agent was generated, the optimal transmission variables were sent to the network terminal hub. This optimization strategy was used to analyze the transmission rate, latency, energy efficiency, and throughput. The suggested IR-LEOA-based resource allocation over LoRa achieved higher energy efficiency of 21.03% than RO, 17.70% than EVO, 25.77% than ROA, and 67.24% than LEA. Many experiments were conducted to validate the performance of the suggested system with various performance metrics.

VIII. FUTURE SCOPE

Even though the current research has significantly improved resource allocation-based data transmission in LoRa networks, several areas still need to be explored. In particular, the following topics will be the focus of future work:

- Strengthening security by adding strong security controls to protect data transfer in LoRa networks from possible intrusions and weaknesses.
- Creating effective procedures and frameworks to expedite system maintenance procedures, especially in the case of node malfunctions or network outages.
- Investigating ways to improve resource allocation algorithms to guarantee scalability and flexibility in ever-more complicated Internet of Things contexts.
- Field trials and deployment studies will validate the suggested procedures in real-world circumstances and evaluate their practicability and efficacy.

Future research endeavor will concentrate on these topics.

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