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Comparative Analysis of Resource Allocation Strategies in LoRa Networks: Optimizing Performance and Power Efficiency

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Abstract: Internet-of-things (IoT) systems are expected to be integral to every aspect of human life. The number of IoT applications is exponentially growing, especially the low-power wide-area network (LPWAN). LPWAN is an emerging IoT networking paradigm with three main characteristics: low-cost, large-scale deployment, and high energy efficiency. IoT systems are becoming more and more important in a variety of areas, and LPWAN are essential because of their affordability, scalability, and energy efficiency (EE). One of the most popular LPWAN technologies, LoRaWAN, has performance issues with resource allocation (RA). This article investigates the architecture of the LoRaWAN network, emphasizing its primary resources and their characteristics. We classify current RA approaches, talk about important obstacles, and investigate future perspectives for LoRaWAN RA research. We also report a case study that improves resource distribution in LoRa networks by applying Spreading Factor Optimization (SFO) and the Hungarian algorithm. Our results demonstrate that, in comparison to conventional methods, the suggested SFO and Hungarian-based RA algorithms efficiently lower power consumption and enhance EE.

Keywords: LoRa, LoRaWAN, Resource allocation, Hungarian Algorithm, Spreading Factor Optimization algorithm.

1. Introduction

IoT networks are growing quickly, with the goal of connecting half a billion devices for use in smart cities, industry, and sensing to improve sustainability and efficiency. A crucial IoT solution, LPWAN technologies allow for long-range, low-power communication that is perfect for energy-constrained sensors [1]. With an emphasis on cost-effectiveness, coverage, data rate, and power efficiency, LPWANs offer a different approach to wireless WANs than traditional ones, which prioritize high data rates and low power consumption. Cellular (such LTE-M and NB-IoT) and non-cellular (like LoRa, ZigBee, Sigfox, and Ingenu) LPWAN technologies are separated out. LoRa and other non-cellular LPWANs use unlicensed frequency spectrum to function. LoRa Alliance supports LoRa, a well-known non-cellular technology utilized in smart cities, agriculture, environmental monitoring, and industrial. Because LoRa operates in the congested ISM frequency region, efficient RA and interference management are necessary to guarantee peak performance [2].The purpose of this study is to investigate different RA mechanisms used by LoRaWAN, a major player in the LPWAN industry. Furthermore, we present an approach that is both straightforward and efficient for optimizing power consumption in LoRa networks by the strategic assignment of subcarriers and spreading factors to various LoRa nodes.

The main contributions of this work can be summarized as follows:

- Compare with different methods of resource allocation in the LoRa network with a specific focus on Spreading Factor as well as Transmit Power.
- Come up with ideas that can be used to decrease the amount of energy that is used by LoRa networks but still maintain its performance which is an aspect rarely addressed in other studies.
- Analyze actual situations showing how network performance and power consumption are impacted by various combinations of Spreading Code, Transmit Power, and Spreading Factor.
- Present concrete steps that will help improve existing design concepts of LoRa networks for the operators to be able to make decisions based on our results.

The rest of the paper is organized as follows: Section 2 provides an overview on LoRa and LoRaWAN. Then, Section 3 surveys resources allocation methodologies in LoRaWAN and sheds the light on some interesting RA challenges and future research directions in LoRaWAN. Section 4 provides our System Model. Section 5 discusses our results. Finally, the paper is concluded in Section 6.

2. OVERVIEW ON LORA AND LORAWAN

This section provides an overview on the main components and principles of operation of LoRa and LoRaWAN.

2.1 LoRa Technology

LoRa, which was created by Cycleo in 2009 and later acquired by Semtech, is a widely used LPWAN technology because of its inexpensive, self-contained network architecture in unlicensed ISM bands. The chirp signals of LoRa are modulated using Chirp Spread Spectrum (CSS) to enhance robustness against noise and interference while requiring less power. Its coverage range is usually between 5 and 15 km. Ten chirps are used as a preamble in every LoRa packet, and then the data payload and six synchronization chirps follow. Depending on the Spreading Factor, chirps can encode several bits. For instance, SF9 encodes nine bits. Although they reduce data rate, higher SF values increase noise resilience [2]. The SF is not the sole parameter or resource in LoRa networks. Below, we outline various resources, their permissible ranges, and their interrelations as documented in [3]:

- **Code Rate (CR):** Within the fields of information theory and telecommunications, CR denotes the percentage of the data stream that comprises valuable, original information. CR values 4/5, 4/6, 4/7, and 4/8 are available for LoRaWAN.
- **Carrier Frequency (CF):** LoRa works on license-free sub-GHz ISM bands, which vary by region and include 433 MHz, 868 MHz, and 915 MHz. LoRa operates in the 868–870 MHz range with nine channels throughout Europe. The first three channels, each with a bandwidth of 125 kHz, are required. FSK modulation is used on the ninth and tenth channels, which are both at 868.3 MHz and have a bandwidth of 250 kHz.
- **Bandwidth (BW):** The band of frequencies used to send signals is referred to as BW. Different BW in LoRaWAN are available: 7.8, 10.4, 15.6, 20.8, 31.2, 41.7, 62.7, 125, 250, and 500 kHz. But only 125 kHz and 250 kHz BWs are used in Europe.
- **Transmission Power (P_{tx}):** LoRa nodes are allowed to send signals between 2 and 14 dBm in range.
- **Spreading Factor (SF):** in LoRa is represented by a number between 7 and 12. While higher SF values decrease data throughput and increase airtime, they also boost signal quality and communication range [3]. Although perfect orthogonality isn't realistically feasible, SFs are ideally thought of as orthogonal in LoRaWAN to avoid interference [4].

2.2 LoRaWAN Architecture

LoRaWAN is a MAC layer protocol developed by the LoRa Alliance that makes use of Semtech's LoRa technology [5]. With end devices, gateways, and network/application servers arranged in star network architecture, they are compatible with device classes A, B, and C. Data is sent by end nodes (ENs) to gateways, which then route it to network servers as shown in Fig.1. LoRaWAN manages data rates and minimizes collisions, making it ideal for the Internet of Things due to its great range, low cost, low power consumption, and resilience in unlicensed spectrum [6].

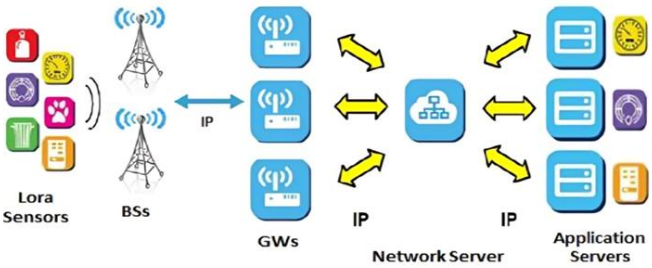

FIGURE 1. LoRaWAN Architecture.

3. RESOURCES ALLOCATION METHODOLOGIES AND METHODOLOGIES IN LORAWAN

This section outlines RA methods in LoRaWAN, emphasizing their impact on system performance, including throughput, energy use, data rates, and range. Resource Allocation Methodologies

- **Distance-Based SFs Allocation**

LoRa end devices that participate in distance-based SF assignment get SFs determined by how close they are to the gateway. For shorter Time on Air (ToA), lower sensitivity, lower energy consumption, and faster data speeds, devices close to the gateway receive smaller SFs. Larger SFs improve communication range with increasing distance, but the advantages of smaller SFs are diminished. SFs Allocation Based on Channel State Information (CSI) [4]. Shadowing and channel fluctuation are not taken into account in distance-based SF allocation. In order to solve this, a plan that was put up in [7] assigns SFs in accordance with real-time CSI, outperforming more established distance-based techniques in terms of performance.

- **Adaptive Data Rate (ADR)**

For LoRaWAN to maximize spectrum efficiency, network servers can dynamically modify parameters like SF, BW, and P_{tx} thanks to ADR. The server determines the optimal configuration for dependable message receipt at gateways by evaluating signal strength; these changes are then communicated to ENs. While [9] established the Enhanced ADR (EADR) method, which balances energy consumption and delivery ratio by using capture effect and other parameters to optimize end-node performance, [8] employed ADR to increase EE and packet delivery ratio in noisy suburban regions.

- **Heuristic Algorithms (HA)**

In LoRaWAN, HA gives approximate answers by prioritizing speed over precision. A heuristic approach for optimizing LoRaWAN parameters, such as CF and SF, was created in [10]. Its goal is to increase packet delivery by decreasing channel use and packet collisions. In a similar idea, it is suggested a heuristic technique to increase network throughput, communication range, and connection dependability while reducing power consumption and collisions [3].

- **Genetic Algorithm (GA)**

By modeling natural selection, GA solves both bounded and unbounded problems optimally. Through the optimization of SFs and P_{tx} for ENs and the strategic distribution of channels to address near-far concerns. To choose the best transmission configurations based on different quality of service (QoS) needs, [11] authors presented a hybrid genetic-fuzzy logic technique. To improve system performance overall, this approach—which was tested for voice, text, and image transmission—included a unique ADR model.

- **Traditional Machine-Learning (ML) Methods**

Research on machine learning methods for SF assignment in LoRa networks has been spurred by recent developments in the field. SF assignment, for example, is a classification problem that [14] suggests addressing with support vector machine (SVM), Naive Bayes, and K-nearest neighbor (KNN) approaches given the normal SF range of 7 to 12.

- **Reinforcement-Learning (RL) Methods**

Along with supervised and unsupervised learning, RL is a fundamental machine learning technique that teaches an agent how to map circumstances to behaviors in order to maximize rewards in the future. Channel selection, SF, and other network resources can all be optimized with the help of RL. In [12], the best transmission parameters were chosen using centralized multi-agent reinforcement learning algorithms, where agents represented LoRa nodes and made use of Deep Q-Networks (DQN). In a similar idea, it is suggested resource management plans for SFs with a restricted number of channels in order to save energy expenses in LoRa networks by approximating the action-value function with deep neural networks (DNNs) [13]. Also, in [1] the authors use the reinforcement learning method is used to determine the parameters involved for minimizing the transmission power.

- **Integer Linear Programming (ILP)**

Taking into consideration network characteristics, application requirements, and trade-offs between data rate, range, and power consumption, ILP is used for SFO in LoRa networks to choose the best SF for data transmission. ILP seeks to balance these aspects in order to improve network performance. Larger SFs take longer to transmit data, but use less power overall. Lower SFs require more power. Selecting the right SF helps save power usage without sacrificing reliability of performance [15]. Section 4 will explore ILP using the SFO to significantly improve performance.

3.1 Resource Allocation Challenges

Multi-Armed Bandits (MAB) For LoRaWAN Resources Allocation

MAB is a reinforcement learning method where an agent chooses from a variety of possibilities (or "arms") in order to maximize rewards. It was inspired by bandit machine games. Identifying the most rewarding behaviors requires striking a balance between taking use of known ones and investigating unknown ones. When creating communication algorithms and allocating resources in LoRa networks, MAB is especially helpful. Different combinations of parameters (SF/BW/CF/CR) are regarded as bandits in this context, and performance measures like data rate, EE, and latency are reflected in the rewards.

- **Deep-Learning (DL) Based Collision Detection and SF Assignment**

DL is a branch of machine learning that uses multiple layers of artificial neural networks (ANNs) to automate feature extraction while simulating the human brain. In contrast to conventional techniques that depend on characteristics that be manually retrieved, DL modifies weights and biases while training on sample data. DL has been utilized to optimize P_{tx} for EE in LoRa networks. This uses real-world data to train ANNs directly, which has been shown to be over ten times more successful than conventional model-based methods.

- **Joint SubCarrier, SF, and Time-Slots Allocation**

Research on SF assignment in LoRa networks demonstrates how it affects performance, although other factors also have an impact. Consequently, a combined method that takes into account other variables like time slots and subcarriers is required. It is predicted that a combined SF-time slot-subcarrier approach will greatly enhance performance.

* The Resources Allocation Methodologies are summarized in Table 1.

TABLE 1. Summary of Resources Allocation Methodologies in LoRa Networks

	Used Methods	Ref.	Simulation Tool	Contribution
1	Distance-Based SFs Allocation method	[4]	Numerical Simulation Matlab	Enhance throughput at imperfect Sfs
2	CSI-Based SFs Allocation	[7]	Matlab	Using Dynamic SF to improve the performance
3	Adaptive Data Rate (ADR)	[8]	OMNET ++ With FloRa	Reduce EC and enhancing the PDR
		[9]	Python	Optimize EC and delivery ratio by CR

4	Heuristics Algorithm Method (HA)	[3]	Matlab	Decrease PC and increase network throughput
		[10]	LoRaSim	Decrease PC and Increase PD
5	Genetic Algorithm Method (GA)	[11]	FUZZY logic	Select optimal Tx configuration with required QOS
6	Reinforcement Learning Method (RL)	[12]	PyLTEs optimization	Presenting a novel heuristic algorithm for LoRa
		[13]	OPNET with Python	Showing a good performance in terms of EC
		[1]	Python	Use RL to enhance resource allocation efficiency in LPWANs
7	Traditional Machine Learning (ML)	[14]	Numerical Simulations	Proposed a SF assignment using traditional ML
8	Integer Linear Programming (ILP)	[15]	LoRaSim	Present an energy-efficient ILP to optimize SF allocation

4. SYSTEM MODEL

The focus of this work is on a LoRaWAN network consisting of a single GW and ENs. Around the GW, the ENs are evenly dispersed over a circle with a radius of R = 20 km. Both small-scale and large-scale fading are expected to occur in the channels connecting the GW to ENs. It is anticipated that the channel h_n of the n^{th} end node will fade on a small scale according to an independent identically quasi-static Rayleigh distribution. The Log distance path loss model with shadowing is used to express the large-scale path loss between the GW and the n^{th} end node, as follows [18]:

$$PL_n = -20\log\left(\frac{\lambda}{4\pi d_0}\right) + 10\,\alpha\log\left(\frac{d_n}{d_0}\right) \qquad (1)$$

Where d_o is the reference distance, λ is the wavelength, and α is the path loss exponent for an end node at distance d_n from the GW, and PL_n is the path loss in dB. Every end node uses a Chip Spread Spectrum modulated signal on a particular sub-carrier and SF to send its messages to GW. The GW receiver's sensitivity level and data transmission rate are both managed by the SF. Larger SFs boost sensitivity, which increases LoRa signal communication range. The following equation can be used to determine the sensitivity of the GW [18]:

$$S_{SF} = -174 + 10\,log(BW) + NF + SNR_{SF} \qquad (2)$$

The thermal noise power at a BW of 1 Hz is represented by the constant value of -174. The temperature of the receiver, however, may cause variations. The receiver's noise floor, indicated by NF, is determined by the hardware architecture of the receiver. The threshold SNR for identifying the received signal for a given SF is denoted by SNR_{SF}. Furthermore, the smallest P(n, SF) value needed for the n^{th} end node to be successfully received at the GW on a particular SF can be stated as follows if S and PL are identified [18]:

$$P_{n,SF} = S_{SF} + PL_n \qquad (3)$$

It's important to note that LoRa ENs can range from 2 dBm to 20 dBm in power. However, because of hardware limitations, the maximum power is usually limited to 17 dBm.

Proposed Algorithm (Alg1): In order to reduce the overall network P_{tx}, we provide a RA mechanism that allocates the best SFs and frequency channels. There are 48 SF-SC combinations (6 SFs and 8 SCs) that each EN can utilize. LoRa channels have center frequencies separated by 0.3 MHz and operate in the unlicensed EU863-870 MHz range. In order to improve noise and interference robustness, the upper layers of LoRaWAN, which are based on Semtech's CSS modulation, employ chirp signals that exhibit linear frequency change over time. The SF, which varies from 7 to 12, determines how many data bits are sent every chirp. For example, modulating seven data bits per signal when using SF7. As a result, increasing the SF lengthens a packet's transmission time, or ToA, which is defined as [17]:

$$ToA = n_s\ \frac{2^{SF}}{BW} \qquad (4)$$

Where $n_s$the number of symbols per packet, and BW is the signal BW. This means that the SF is inversely proportional to the achievable data rate, which is given as follows [3]:

$$R_b = CR \times BW\ \frac{SF}{2^{SF}} \qquad (\mathbf{5})$$

When several ENs utilize different SFs, they can transmit on the same sub-carrier without interfering with each other since LoRa signals with different SFs are, in theory, orthogonal. Concurrent transmissions and IoT connectivity are improved by this orthogonality. It is not possible to achieve full orthogonality, and the capture effect may result in interference if different nodes utilize the same sub-carrier and SF at the same time. According to Table I of [19], if a signal's signal-to-interference-plus-noise ratio (SINR) is higher than its co-SF interference threshold, the signal will survive. Therefore, preventing collisions, reducing power consumption, and enhancing bit error rate (BER) performance all depend on an efficient SF and sub-carrier assignment mechanism. When determining the P_{tx} needed to satisfy the SF's target SNR and sensitivity thresholds, each end node should take into account the SF, SC, gateway distance, and channel condition data. With an O(|V|^3) complexity, the Hungarian method (Kuhn-Munkres) is ideally suited for effectively matching ENs with SF-SC combinations in order to maximize performance. Figure 2 shows that the P_{tx} needed for an end node to employ a certain SF-SC combination is represented by the weight of each edge. The input for the Hungarian method is a square ($M \times N$) cost matrix formed by these weights, as indicated in Table 2. The larger set's size, M, is indicated here (M = max (N, C)). Dummy combinations with no cost are added to the rows if (N > C). This configuration leaves certain nodes unserved for the following time slot while serving the ENs with the least amount of total power consumption1. On the other hand, if (N < C), some SF-SC combinations are left unutilized when dummy ENs with no cost is added to the columns.

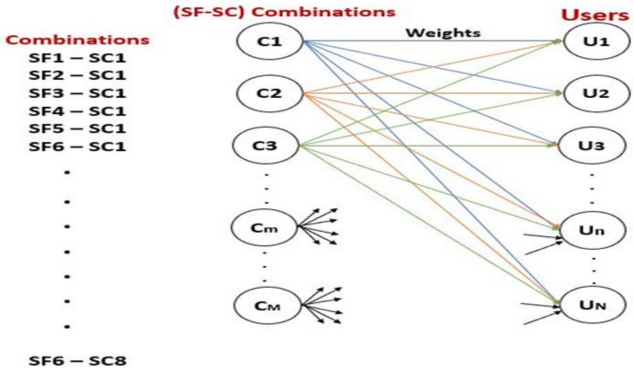

FIGURE 2. Hungarian Matching. [17]

TABLE 2. Hungarian Cost Matrix.

EN_N \ C_M	C_1	C_2	…	C_m	…	C_M
EN_1	$P_{1,1}$	$P_{1,2}$	…	$P_{1,m}$	…	$P_{1,M}$
EN_2	$P_{2,1}$	$P_{2,2}$	…	$P_{2,m}$	…	$P_{2,M}$
…	…	…	…	…	…	…
EN_n	$P_{n,1}$	$P_{n,2}$	…	$P_{n,m}$	…	$P_{n,M}$
…	…	…	…	…	…	…
EN_N	$P_{N,1}$	$P_{N,2}$	…	$P_{N,m}$	…	$P_{N,M}$

[a] Where $P_{n,m}$ is the transmit power at n end node and m combination of SF-SC

Each EN can be assigned one of 48 SF-SC combinations given LoRa's six SF values (SF_i) for (i ∈ {7, 8, 9, 10, 11, 12}) and eight subcarriers (SC_j) for (j ∈ [1, 8]). Certain formulas can be used to calculate the transmit power ($P_{n,m}$) required for the nth end node using the (m^{th}) combination. The work is formulated as an optimization problem with the goal of minimizing overall power consumption and preventing collisions, which will enhance BER and decrease retransmissions. This problem falls under the category of a Linear Sum Assignment Problem (LSAP), which is a fundamental combinatorial optimization problem with wide applicability that includes matching two sets (ENs and SF-SC combinations) [16], [20].

The proposed problem can be expressed as follows [17]:

$$Min_{\{x_{n,m}\}} \sum_{n=1}^{N} \sum_{m=1}^{M} \quad x_{n,m} \quad P_{n,m} \qquad (6a)$$

Subject to

$$S_{n,m} \geq \theta_m \quad , \quad \forall n \in \{1, \dots N\},\ m \in \{1, \dots, M\} \quad (6b)$$

$$\sum_n x_{n,m} \leq 1 \ , \qquad \forall m \in \{1, \dots, M\} \quad (6c)$$

$$\sum_m x_{n,m} \leq 1 \ , \qquad \forall n \in \{1, \dots, N\} \quad (6d)$$

$$x_{n,m} \in \{0,1\} \quad , \quad \forall n \in \{1, \dots N\},\ m \in \{1, \dots, M\} \quad (6e)$$

The assignment element is represented as $x_{n,m}$, where m = 1 if the n^{th} ENs are allocated the m^{th} combination (C_m) and zero otherwise. Considering that $C = \{P_{n,m}\}$ is the MXN cost matrix, $P_{n,m}$ is the cost of assigning the n^{th} and the m^{th} entries. The goal is to find an assignment that will cost the least overall. The sensitivity ($S_{n,m}$) of EN_n is greater than the sensitivity threshold of the SF_i of C_m combination, as indicated by constraint (6b) [19]. Each combination can only be allocated to one EN, according to constraint (6c). Constraint (6d), on the other hand, guarantees that every end node is allocated to a maximum of one combination. Between end node n and combination m, constraint (6e) represents a binary selection index. The literature has used a variety of algorithms to solve LSAPs. In 1946, Easterfield presented a non-polynomial method with an O ($2^n\ n^2$) time complexity [21]. Kuhn introduced the Hungarian algorithm in the 1950s, which uses graph theory and the duality of linear programming to solve the problem in O (n^4) time [22]. Further reductions in the complexity of LSAP to O (n^3) were achieved by Munkres [23], Edmonds, and Karp [24] using variations of the Hungarian method.

- If constraint (6b) holds true for the n^{th} EN and C_m, the weight of the edge between them, as depicted in Fig. 2, represents the minimum required power for successful reception ($P_{n,m}$).
- If any constraint is violated, a significantly large power value is assigned to the corresponding edge to discourage its selection during RA.
- The Hungarian algorithm addresses the matching problem using a square matrix. Given that we have $N > M$, we introduce $(N - M)$ dummy combinations starting from row $M + 1$.
- Upon completion of the algorithm, if any end node is matched with a dummy combination, it indicates that this end node is inactive during the current time slot. The Kuhn-Munkres Hungarian algorithm takes the cost matrix as input and produces the optimal assignment matrix. In this matrix, each row and column is represented as a one-hot vector, containing a single logic-one element, with all other elements being logic-zero.

▪ To further clarify the implementation details of the proposed Algorithm, we present the pseudo code for the Hungarian Method applied to resource allocation in LoRa networks:

1: **Input**: Cost matrix C of size n × m where n is the number of End Nodes and m is the number of resources.
2: **Output**: Allocation matrix A and minimum cost.
3: Initialize matrix C′ from matrix C by subtracting row minima.

4: Subtract column minima from matrix C′.
5: Initialize zero matrix A of size n × m.
6: while not all rows and columns are covered **do**
7: Find the optimal assignment in matrix C′ using the Hungarian algorithm.
8: Update allocation matrix A based on the optimal assignment.
9: Cover the rows and columns of the assigned zeros.
10: Update uncovered elements in matrix C′.
11: **end while**
12: Calculate minimum cost based on allocated resources.
13: **return** Allocation matrix A and minimum cost. = 0

- To illustrate the optimization process in resource allocation, we provide the pseudo code for the Spreading Factor Optimization (SFO) method applied to LoRa networks:

1: **Input**: Network parameters, channel conditions, and node requirements.
2: **Output**: Optimal Spreading Factor allocation for each End Node.
3: Initialize array SF to store Spreading Factors for each End Node.
4: **for** each End Node *i* **do**
5: Evaluate channel conditions CC_i for End Node *i*.
6: **if** CC_i is good **then**
7: Set SF [i] ← 7 {Higher data rate}
8: **else if** CCi is moderate then
9: Set SF [i] ← 10 {Balanced approach}
10: **else**
11: Set SF [i] ← 12 {Lower data rate for poor conditions}
12: **end if**
13: **end for**
14: Return array SF containing optimal Spreading Factors for all End Nodes. =0

5. RESULTS AND DISCUSSION

TABLE 3. Simulation parameters

Parameters	Value
Number of End-Nodes (ENs)	Up to 250
SF values	7 , 8 , 9 , 10 , 11 and 12
Reference distance (m) (d0)	40
BW (kHz)	250
Variance (sigma) (dB)	3
Path loss exponent (α)	4
No. of channels used (SC)	8

In this section, we provide representative simulations to evaluate the performance of the proposed algorithm (Alg1). Each time slot is assumed to equal the largest ToA of SF 12 to avoid interference. Table 3 shows the simulation parameters and settings [10]. In the following, we compare the performance of the proposed algorithm with:

- **The random assignment algorithm of both SFs and SCs without repetition (Alg2):** Each EN is randomly assigned both SC and SF. The nodes are assumed to operate with the minimum power required for successful transmission [9].
- **The distance-based SF assignment with maximum power (Alg3):** According to their respective distances from GW, the ENs are assigned SFs [4]. It is assigned that the farthest EN has the highest SF and the nearest EN the lowest SF. The users receive SCs at random. At 14 dBm, the maximum power level, each EN operates.
- **The distance-based assignment with Hungarian channel assignment (Alg4):** The ENs receive SFs according to how far away they are from GW. Concurrently, SCs are distributed utilizing the Hungarian algorithm to guarantee that the system runs with the least amount of overall power consumption.
- **The random assignment algorithm of both SFs and SCs with repetition (Alg5):** Random SF and SC assignments are made to every EN, which uses the least amount of power necessary for successful transmission. To prevent interference, numerous time slots are used, with each time slot equal to the longest ToA for SF 12 for $N > 48$, which exceeds the number of eligible SF-SC combinations (C).

Fig. 3, The power consumption of the five algorithms is plotted against the number of end nodes (where $N \in \{50, 100, 150, 200, 250\}$). Notably, we assume employing numerous time slots to be able to service all users for $N > 48$, which is bigger than the number of possible combinations (C). To prevent interference, each time slot is taken to be equivalent to the longest duration SF 12 is on the air. The findings demonstrate that the suggested Hungarian algorithm with SFs distribution (Alg1) performs better than distance-based assignment with Hungarian and channel distribution (Alg4) by 15.78%, random assignment without repetition (Alg2) by 40.86%, and distance-based assignment with maximum power and random channel distribution (Alg3) by 85.83% in total transmitted power. Finally, random distribution with repetition (Alg5) by 66.53%.

The results indicate that Alg5 uses a random distribution with repetition, and Alg2 uses a random distribution without repetition, producing somewhat comparable results. Also, Alg3 has the largest power consumption because it does not consider power adaptation. Furthermore, because Alg4 uses the Hungarian algorithm to merge power adaption and SC allocation, it comes out as the second most effective algorithm after our proposed approach.

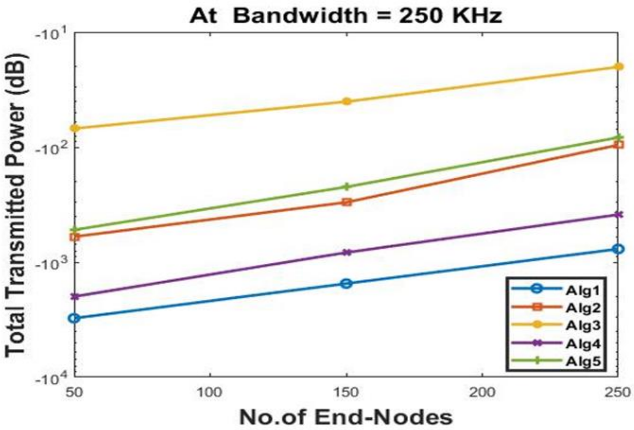

FIGURE 3. Total Transmitted Power at different no. of ENs.

Figure 4 shows the EE of the LoRaWAN system for various numbers of ENs ($N \in \{50, 100, 150, 200, 250\}$) with a bandwidth of 250 kHz. The results show that Alg1, the suggested Hungarian algorithm, outperforms Alg2, Alg3, Alg4, and Alg5 by 73.04%, 96.83%, 56.78%, and 75.65%. Undoubtedly, the algorithm we proposed, Alg1, has the highest energy efficiency. Alg4, the second-ranked algorithm, and Alg3, the least efficient algorithm, are in order of decreasing EE.

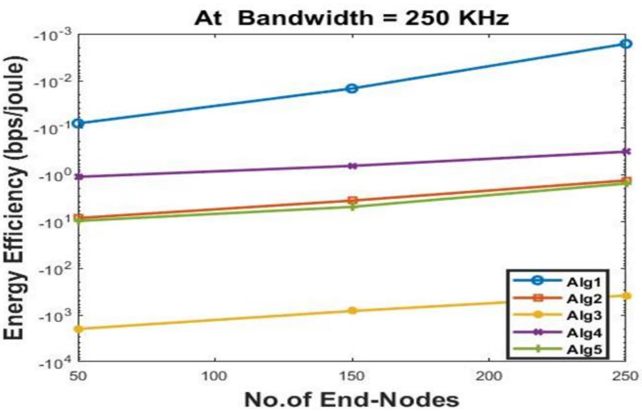

FIGURE 4. Energy Efficiency at different no. of ENs.

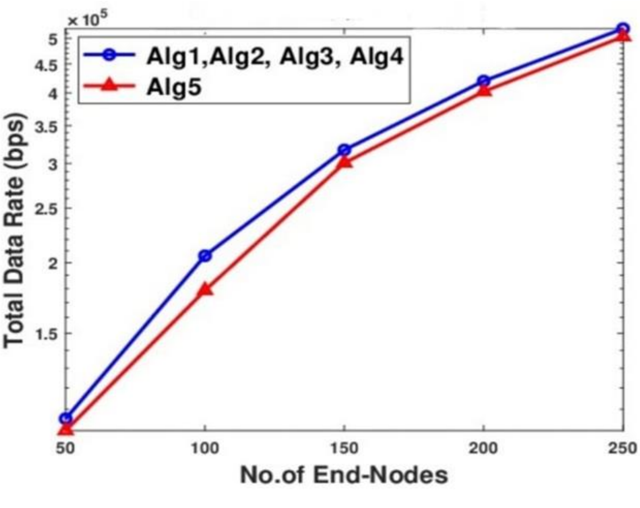

FIGURE 5. Data rate at different no. of ENs

Figure 5 indicates that the data rate is consistent across Alg1, Alg2, Alg3, and Alg4, all outperforming Alg5, which has the lowest data rate at 250 KHz.

The Hungarian method and SFO are compared in Fig. 6 with respect to the minimal overall transmitted power needed for varying numbers of ENs. Because the SFO approach uses less power than the Hungarian algorithm, it is more effective for LoRa applications that are power-sensitive.

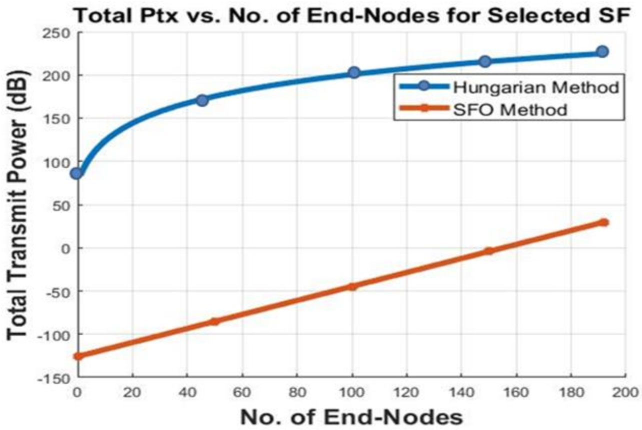

FIGURE 6. Comparison between Hungarian and SFO methods.

6. CONCLUSION

This paper has provided a comprehensive overview of the applicability of resource allocation techniques in the area of LoRa networks. Also, this work shows that the performance of the proposed algorithms Hungarian and SFO algorithms reduces the power consumption and improves the energy efficiency compared with other conventional algorithms especially SFO algorithm. The discussion has identified challenges and hurdles that need to be addressed to establish viable resource allocation protocols for LoRaWAN. Our future plan is to test with more than enough end nodes and also experiment with different network conditions in as many various aspects as possible especially if there are diverse rates of work in the situation so we can identify how reliable our approach will be under such circumstances. Also, our objective is to assess our algorithm we have proposed based on different applications which have QoS requirements among them that one includes UAVs.

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