QoS-aware Optimal Deployment of LoRa Gateways in UAV-enabled LoRaWANs

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Abstract. *Employing flying gateways such as Unmanned Aerial Vehicles (UAVs) is an attractive approach to providing fast and effective densification for wireless access networks. Flying gateways as UAVs can solve performance issues of different applications, including those involving Internet of Things (IoT) devices. On the other hand, traditional mobile network operators need solutions for integrating IoT technologies such as Long Range Wide Area Network (LoRaWAN) with their 3rd Generation Partnership Project (3GPP) infrastructure. In this paper, we have associated Quality of Service (QoS) parameters from the non-3GPP Long Range (LoRa) technology to the 3GPP-defined network slicing. To ensure the QoS of the IoT devices, i.e., the slices QoS requirements, we have formulated an optimization problem to obtain the minimum number of UAVs and their positions and consider the interference reduction. We also have introduced three optimization strategies for the problem: (i) bi-objective focusing on minimizing the number of UAVs, (ii) bi-objective focusing on the distribution of devices between Spreading Factor (SF) configurations, and (iii) mono-objective to minimize the number of UAVs, used as a baseline. We have evaluated our proposal through analytical modeling and simulations using Network Simulator 3 (ns-3), in which we confirm the QoS assurance and interference reduction.*

1. Introduction

The Internet of Things (IoT) is at the forefront of a new era of wireless communications and mobile networking technologies. The number of IoT devices, such as cars, machines, sensors, and wearables, is estimated to reach tens of billions in the coming years. The accelerated growth of these "connected things" will impact multiple verticals, significantly affecting terrestrial communications networks that are unlikely to provide high-quality services to all devices. Meanwhile, several solutions are being developed to cope with this growth. Low Power Wide Area Network (LPWAN) has been an interesting alternative to satisfy the IoT demands with long range, low power consumption, and Unmanned Aerial Vehicles (UAVs) are being adopted as an option to provide wireless communication solutions with flexibility, dynamicity, and low cost [Lodhi et al. 2022].

LPWAN has gained significant attention due to its ability to meet the diverse demands of IoT applications. Key LPWAN technologies such as Long Range Wide Area Network (LoRaWAN), Sigfox, NB-IoT, and LTE-M have emerged as prominent choices in this category. LoRaWAN stands out because it is an open standard-based networking technology that provides long-range radio communications with high data rates, security, and low power consumption.

The LoRaWAN protocol is deployed at the Media Access Control (MAC) layer and built on top of the LoRa physical layer stack, allowing End Devices (EDs) to establish efficient radio communication through the Adaptive Data Rate (ADR) mechanism. ADR allows ED parameters such as Spreading Factor (SF) and Transmission Power (TP) to be dynamically configured based on network conditions to optimize throughput and power consumption and maximize the number of devices that can be managed by a single gateway [Finnegan et al. 2020]. In this way, the characteristics of LoRaWAN favor its application in dense scenarios with less interference between devices.

Network Slicing (NS) is a 5^{th} Generation Networks (5G)/Beyond 5^{th} Generation Networks (B5G) key enabling technology in recent years. The main objective of NS is to provide multiple virtual networks, enabling different needs to be met in isolation and the most urgent communications to be attended with more reliability and security. In dense IoT deployments, the limited number of channels in a gateway impacts performance degradations. The adoption of an architecture based on Software Defined Network (SDN) with an algorithm for slicing LoRaWAN makes it possible to optimize the performance of the IoT networks [Dawaliby et al. 2021].

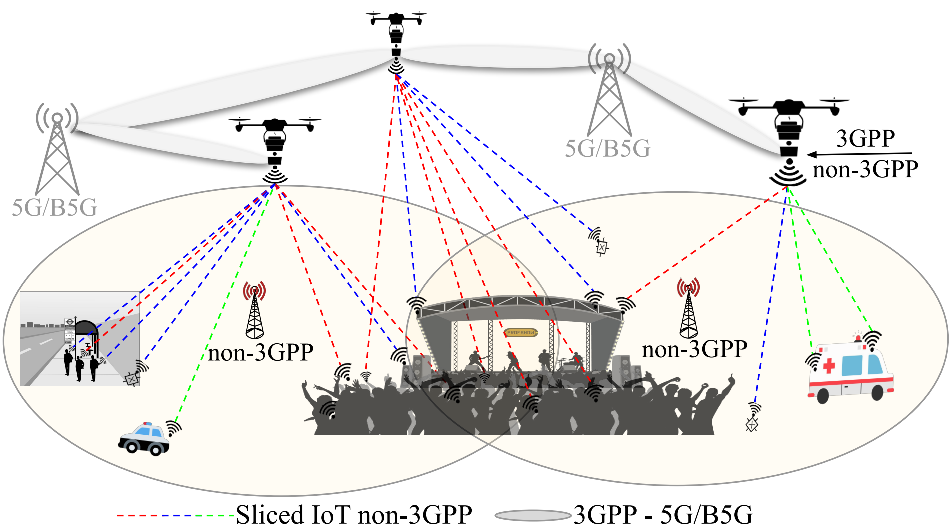

Figure 1. Scenario for LoRaWAN-UAV deployment.

UAVs have received significant attention in wireless networking applications due to their high maneuverability, flexible deployment, and low-cost deployment. They have been used in several applications, from the military, as border surveillance, to several aspects of our daily lives, e.g., commercial applications such as packet delivery and photography [Marchese et al. 2019]. The potential advantages of using UAV have motivated research into various aspects of UAVs-enabled networks, such as Air-To-Ground (A2G) channel characteristics, optimal UAV placement, and trajectory optimization, among others [Kishk et al. 2020]. For the IoT, UAVs can be used as a flying IoT gateway, e.g., localization applications, environmental monitoring, smart agriculture, etc. [Delafontaine et al. 2020].

Solutions utilizing UAVs as aerial gateways offer distinct advantages over fixed structures. These include the ability for dynamic deployment on demand and serving as complementary infrastructure during peak access demands, particularly in scenarios involving sporadic events or large crowds. In our previous work [Silva et al. 2023], we have proposed to solve the problem of minimizing the number of UAVs and positioning them to achieve the expected levels of QoS with a Mixed Integer Linear Programming (MILP) model.

Table 1. Notation

	Notation	Description
Sets	$\mathcal{P}$	Set of discrete positions
	$\mathcal{K}$	Set of LoRa End Devices
	$\mathcal{L}$	Set of network slices
	$\mathcal{F}$	Set of spreading factor options
	$\mathcal{T}$	Set of transmission power options
	C	Set of configurations where $C \subseteq \mathcal{F} \times \mathcal{T}$
	C_{SF}	Subset of C with every configuration that uses the same spreading factor SF $\in \mathcal{F}$
Data	$S(k,l)$	Association of device k with slice l
	R_k	Uplink traffic of device k
	R_l^{max}	Maximum traffic capacity allocated to slice l
	ρ_l^{QoS}	The QoS threshold for slice l
	$SF(c)$	The spreading factor of configuration c
	$P_{tx}(c)$	The transmission power of configuration c
	$S_{rx}(c)$	The sensibility of the receptor for configuration c
	n	The path loss slope
	$d(p,k)$	The distance between device k and UAV position p
	d_0	The path loss reference distance
	P_{r0}	The path loss reference reception power
	b_l	The LoRa Gateway bandwidth assigned to slice l
	L	The size of the packet sent by the devices in bits
Dec. vars.	$x_{k,c}^{p}$	Binary decision variable representing the association of a device k to a LoRa Gateway positioned at p using configuration c
	y	Continuous decision variable representing the maximum number of devices k using a configuration c with the same spreading factor

The application scenario depicted in Figure 1 illustrates the dynamic deployment of UAVs to address peak demand during a music concert. Each IoT device is associated with a non-3GPP IoT network slice. We also assume that each UAV gateway communicates with a 5G Base Station (BS). Hence, several challenges are emerging, such as (1) Determining the optimal number of UAVs to meet the access overhead, (2) Ensuring resource allocation for varying device demands, given the diversity in their requirements, and (3) Establishing mechanisms to guarantee satisfactory levels of Quality of Service (QoS) while minimizing interference.

Thus, to deal with these challenges, our work proposes (1) minimizing the number of gateways deployed as UAVs, choosing optimal positions, and considering the flexibility of UAVs deployment, (2) providing service in network slices to meet EDs grouped by type of demand, highlighted in the figure in colored dashed lines, and (3), search for ideal parameters SF and TP that achieve the satisfactory levels of QoS and delay. To achieve this, we proposed three strategies: (i) bi-objective with a focus on minimizing the number of UAVs, (ii) bi-objective with a focus on distributing devices between SF configurations, and (iii) mono-objective to minimize the number of UAV. To our knowledge, this is the first work addressing all these challenges.

This work is organized as follows. The literature review is provided in Section 2. Section 3 presents our system model. Our problem is formulated as an MILP in Section 4. Section 5 presents the evaluation and results based on simulations and analytical modeling. Finally, Section 6 closes with conclusions and future works. The main notations used in this paper are summarized in Table 1.

2. Related Work

Our work considers the integration of LPWAN (specifically LoRaWAN), network slicing, and UAV gateways. As there is a lack of prior research considering this integration, we discuss the literature closest to our work. Table 2 presents a synthesis of related works in the literature.

Table 2. Main characteristics of related works.

Paper	3GPP	non-3GPP	Network Slicing	Wireless Tunning	UAV Deployment	System Modeling	
						LP 1-obj	LP n-obj
[Dawaliby et al. 2019]		✓	✓	✓		✓	
[Dawaliby et al. 2021]		✓	✓	✓			✓
[Tellache et al. 2022]			✓	✓			
[Mardi et al. 2022]		✓	✓	✓		✓	
[Almeida et al. 2022]				✓	✓		
[Shen et al. 2023]	✓		✓	✓			
[Marchese et al. 2019]		✓		✓	✓		
[Mahmood et al. 2022]	✓			✓	✓		
[Silva et al. 2023]	✓	✓	✓	✓	✓	✓	
Our proposal	✓	✓	✓	✓	✓		✓

Recent work has proposed methods for slicing LoRaWAN networks through algorithms that adjust parameters through the ADR mechanism. Dawalibi [Dawaliby et al. 2019, Dawaliby et al. 2021] proposed a dynamic inter-slicing algorithm based on a maximum likelihood estimation that avoids resource starvation and prioritizes one slice over another depending on its QoS requirements. Tellache et al. [Tellache et al. 2022] proposes a Deep Reinforcement Learning (DRL)-based approach for intra-slicing resource allocation in dense LoRaWAN networks. They replaced the standard ADR mechanism with a multi-agent DQN-based algorithm to allocate the SF and TP to the IoT devices in each slice. Mardi et al. [Mardi et al. 2022] use a centralized coalition game-based network slicing strategy to efficiently manage LoRa nodes. They propose a Machine Learning (ML) technique to cluster devices according to their bandwidth and maximum likelihood estimation needs, allocate resources for the slices, associate those devices into slices, and optimize the device's parameters. They present results that improve the traditional LoRaWAN by avoiding resource starvation and prioritizing slices based on their QoS.

All these works consider strategies with static gateways to serve LoRa devices and do not consider any gateway position adjustment strategy. Unlike this, we consider the positioning of the gateways, based on the network parameters, the characteristics of the devices for association with the slices, and the expected limits of QoS and interference, as input for an optimization model in search of better results.

From the point of view of UAVs works, several have been proposed to optimize and expand network infrastructure using UAVs as mobile base stations. Almeida et al. [Almeida et al. 2022] presents to use DRL to position UAVs as access points according to users' traffic demands to maximize network utility. They present a DRL approach technique search to learn and adapt autonomously to different scenarios' dynamic conditions and requirements. However, this work uses the network parameters statically to define the UAVs placement without any network parameter tuning. Shen et al. [Shen et al. 2023] present an optimization framework for resource slicing in drone-assisted 3GPP Cellular Vehicle-to-everything (CV2X) vehicular networks, and their objective is to maximize the utility network subject to QoS restrictions. Marchese et al. [Marchese et al. 2019] propose a use case that employs an UAV acting as a LoRaWAN gateway and integrated with a simulated satellite to extend the coverage of the LoRa network in scenarios with a lack of communication infrastructure. A strategy that uses UAVs as edge nodes to serve Wi-Fi-interfaced IoT devices and 5G UEs via mm-wave is presented by [Van and Trung 2021]. This work introduces a task admission policy with a flow control scheme that does not consider the interference between devices. Mahmood et. al. [Mahmood et al. 2022] presents a particle swarm optimization-based location algorithm (PSO-L) to maximize the achievable sum rate (ASR) for the optimal UAV placement.

Nonetheless, our work considers deploying LoRaWAN gateways in UAVs, taking advantage of their deployment flexibility and positioning adjustment. Furthermore, the main focus is on MILP strategies to reduce costs by minimizing the number of UAVs and to improve QoSs by associating LoRa End Devices (LoRa-EDs) with slices and configuring their communication parameters, for example, SF and TP to achieve expected objectives while reducing interference.

In our previous work [Silva et al. 2023], we have proposed to solve the problem of minimizing the number of UAVs and positioning them to achieve the expected levels of QoS with a MILP model. In this work, we are expanding the search space and incorporating new constraints. Additionally, we employ a bi-objective approach to minimize interference simultaneously to enhance the robustness of the proposed model.

3. System Model and Problem Statement

In this section, we present the system model for positioning LoRa gateways deployed in UAVs that provide access to LoRa-ED associated with slices and define the problem to reduce interference and fulfill the QoS requirements.

3.1. System Model

We assume a network defined by a set of LoRa-ED with static positions randomly distributed in space and a set of LoRa Gateway (LoRa-GW) deployed in UAV. Each device is associated with a non-3GPP Internet of Things (IoT) network slice. Additionally, we assume that each UAV-mounted gateway communicates with a 5G BS operating in a sub-6GHz frequency band, configured with parameters that fulfill the gateway's requirements, not imposing any restriction on them. Our primary objective is to minimize the quantity of LoRa-GWs required to satisfy each network slice's Quality of Service (QoS) criteria. To do so, we minimize the number of positions in a discrete space assigned to LoRa-GW

UAVs, by doing so, we intend to find the best locations to position these UAVs, where the UAV routing problem is not a concern of this work.

Let $\mathcal{K} = \{k_1, ..k_k, .., k_{|\mathcal{K}|}\}$ the set of LoRa-EDs connected to LoRa-GWs. Each LoRa-ED $k \in \mathcal{K}$ is associated with a specific slice from the set $\mathcal{L} = \{l_1, ..l_l.., l_{|\mathcal{L}|}\}$. Every slice is created on physical network hardware, specifically on LoRa-GWs, where the bandwidth is divided between the slices that are defined by QoS requirements of IoT applications. The configuration set $C = \{c_1, ..c_c.., c_{|C|}\} \subseteq (\mathcal{F} \times \mathcal{T})$ contains possible combinations between $\mathcal{F}$, the set of SFs, and $\mathcal{T}$, the set of TPs. The space is discretized into a set of candidate positions $\mathcal{P} = \{p_1 = (x_1, y_1, z_1),\ p_2 = (x_2, y_2, z_2),\ \ldots,\ p_{|\mathcal{P}|} = (x_{|\mathcal{P}|}, y_{|\mathcal{P}|}, z_{|\mathcal{P}|})\}$ of points uniformly distributed along three orthogonal axes and equally spaced by a distance d, at which LoRa-GWs deployed in UAVs can be placed. We characterize the QoS as

$$QoS_{c,l} = \overline{r_{c,l}} + (1 - \overline{d_{c,l}}) \tag{1}$$

, where $r_{c,l} = SF(c) \cdot b_l \,/\, 2^{SF(c)}$ (bits/s) is the data rate achieved by configuration $c \in C$ for slice $l \in \mathcal{L}$, $d_{c,l} = s \,/\, r_{c,l}$ is the transmission delay for configuration $c \in C$ and slice $l \in \mathcal{L}$, $SF(c)$ represents the bit rate per symbol of the SF option associated with the configuration $c \in C$, b_l is the bandwidth allocated in the LoRa-GW to the channel associated with the slice $l \in \mathcal{L}$, and s is the size, in bits, of the packet sent from a device $k \in \mathcal{K}$ through a LoRa-GW. $\overline{r_{c,l}}$ and $\overline{d_{c,l}}$ are the normalized values for data rate and delay, respectively, obtained through the division of the original values by the highest possible values for a LoRa link.

In the uplink direction, the signal transmitted from a LoRa-ED must be received by the LoRa-GW with power higher than the sensibility of its receiver for the used SF, otherwise, it cannot be decoded. This signal, however, is subject to degradation due to a series of factors, such as surface reflection, absorption, or refraction. Aiming to represent the signal attenuation over the distance traveled, we consider a Log-Distance Path Loss (LDPL) model where $P_L(p, k)$, representing the power lost by the signal transmitted from device $k \in \mathcal{K}$ to LoRa-GW placed at candidate position $p \in \mathcal{P}$, is defined as

$$P_L(p, k) = 10 \cdot n \cdot \log_{10}\left(\frac{d(p, k)}{d_0}\right) + P_{r0}, \tag{2}$$

where $d(p, k)$ is the distance between the candidate position $p \in \mathcal{P}$ and the device $k \in \mathcal{K}$, while the parameters n, d_0 and P_{r0} are obtained experimentally, and represents the function slope, the reference distance, and the reference reception power respectively.

3.2. Problem Statement

Given the set of candidate positions for LoRa-GW UAVs $\mathcal{P}$ and a static distribution of LoRa-EDs $\mathcal{K}$, our objective is to: (i) determine the minimum number of UAVs able to fulfill the QoS requirements of all devices according to the associated slice $l \in \mathcal{L}$, while also (ii) finding the best position for UAVs and the best configuration $c \in C$ for each LoRa-ED, to reduce the interference in the system.

4. Problem Formulation

In this section, we formulate the problem of jointly optimizing the placement of UAVs, their assignment and configuration for each LoRa-ED.

4.1. Objective Function

Let $x_{k,c}^{p} \in \{0, 1\}$ be a binary decision variable, indicating whether a LoRa-GW placed in an UAV was deployed at the candidate position $p \in \mathcal{P}$ to serve a device $k \in \mathcal{K}$. We consider a UAV as deployed if some candidate position $p \in \mathcal{P}$ is assigned to at least one device with any configuration

$$N_{\text{UAVs}} = \sum_{p \in \mathcal{P}} \left\lceil \sum_{k \in \mathcal{K}} \sum_{c \in C} \frac{x_{k,c}^{p}}{|\mathcal{K}|} \right\rceil. \tag{3}$$

In an isolated LoRaWAN network, LoRa-EDs may interfere with each other's signals when received simultaneously and with enough potency by the LoRa-GW. This interference is more meaningful when both devices use the same SF [Magrin et al. 2017]. Therefore, the fewer devices transmitting with a given SF, the lower the signal overlap probability at the LoRa-GW. In this way, we define the best positioning of LoRa-GWs as the one that allows the minimum concentration of LoRa-EDs in a single SF, to achieve it, we define the continuous decision variable y as the maximum number of LoRa-EDs using the same SF,

$$y \geq \sum_{c \in C_{\text{SF}}} \sum_{p \in \mathcal{P}} \sum_{k \in \mathcal{K}} x_{k,c}^{p}, \quad \forall SF \in \mathcal{F}. \tag{4}$$

We introduce the objective function, defined as the joint minimization of the number of deployed UAVs and the maximum number of devices assigned to a single SF

$$\text{minimize} \quad \alpha \cdot N_{\text{UAVs}} + \beta \cdot y, \tag{5}$$

where the importance of each objective can be fine-tuned through the weights α and β. Specifically, α is the weight associated with prioritizing the reduction of the number of UAVs, while β is the weight associated with minimizing the number of devices associated with each SF. Adjusting these weights allows for the customization of the optimization process based on the relative importance assigned to each objective.

4.2. Constraints

Single Assignment per Device – for each device $k \in \mathcal{K}$, exactly one combination of configuration $c \in C$ and UAV position $p \in \mathcal{P}$ must be assigned

$$\sum_{p \in \mathcal{P}} \sum_{c \in C} x_{k,c}^{p} = 1, \quad \forall k \in \mathcal{K}. \tag{6}$$

LoRa-GW Capacity – the sum of uplink traffic $\mathcal{R}_k$ from all devices $k \in \mathcal{K}$, must not exceed the maximum traffic capacity $\mathcal{R}_l^{max}$ reserved for a slice $l \in \mathcal{L}$ in each LoRa-GW placed in a UAV deployed at position $p \in \mathcal{P}$. To ensure this, we define the constraint

$$\sum_{k \in \mathcal{K}} \sum_{c \in C} S(k, l) \cdot x_{k,c}^{p} \cdot R_k \leq R_l^{max}, \quad \forall l \in \mathcal{L}, \forall p \in \mathcal{P}, \tag{7}$$

where $\mathcal{S}(k, l) \in \{0, 1\}$ is a mapping function over the input data, returning 1 when device $k \in \mathcal{K}$ is associated with slice $l \in \mathcal{L}$, and 0 otherwise.

QoS Bound – a minimum QoS ρ_l^{QoS} must be granted to every device assigned to slice $l \in \mathcal{L}$

$$\sum_{p \in \mathcal{P}} \sum_{c \in C} x_{k,c}^{p} \cdot S(k,l) \cdot QoS_{c,l} \geq \rho_l^{QoS}\ ,\ \forall l \in \mathcal{L}, \forall k \in \mathcal{K}. \tag{8}$$

Signal Attenuation – the association between a LoRa-ED and a LoRa-GW can be made only when the distance between them allows communication, as defined by

$$\sum_{p \in \mathcal{P}} \sum_{k \in \mathcal{K}} \sum_{c \in C} x_{k,c}^{p} \Big[P_{tx}(c) - P_L(p,k) \Big] \geq S_{rx}(c), \tag{9}$$

where $P_{tx}(c)$ is the transmission power associated with the configuration $c \in C$, and $S_{rx}(c)$ is the sensibility of the LoRa-GW for the configuration $c \in C$. Finally, we define the UAV deployment optimization problem as (5) subject to (6) – (9).

5. Performance Evaluation

In this section, we evaluate the Mixed Integer Linear Programming model proposed to solve the problem of finding the best positions among a set of candidate positions $\mathcal{P}$ to deploy the minimum number of UAVs that satisfy the requirements of the LoRa-EDs while granting a minimum QoS.

5.1. Evaluation Setup

We consider distributing a set of LoRa-EDs randomly in an urban outdoor environment with dimension 10 Km^2. The LoRa-EDs are distributed using different sets of coordinates for each running instance through a log-normal mixing distribution capable of generating realistic spatial traffic patterns for network simulations in urban environments adapted from [Lee et al. 2014].

We also defined $\mathcal{P}$ as the distribution of points in the positioning space available for UAVs deployment. The number of candidate positions is obtained of $|\mathcal{P}| = n^2$ for $n \in \mathbb{N}$ and $2 \leq n \leq 8$, all evenly spaced and at the same altitude of 45m in accordance with National Civil Aviation Agency (ANAC) [Brazil 2017] and European Union Aviation Safety Agency (EASA) [Europe 2019] regulations. For every slice $l \in \mathcal{L}$, we define the same QoS lower bound of 0.9. We conducted ten simulations with random seeds to the simulator's pseudo-random number generator (MRG32k3a). Results present the values with a confidence interval of 95%.

We have evaluated three distinct strategies based on the weight parameters for (i) bi-objective optimization, with a primary emphasis on minimizing the number of UAVs (BMinUAV). By setting the weight $\alpha > \beta \cdot |\mathcal{K}|$, we ensure that the secondary objective does not influence the primary one. Similarly, we define (ii) bi-objective, focusing primarily on minimizing the maximum number of LoRa-EDs assigned to the same SF (BMinSF) with $\beta > \alpha \cdot |\mathcal{P}|$. Finally, (iii) mono-objectively minimize the number of deployed UAVs (MMinUAV), which is achieved by setting $\beta = 0$. The problem is solved using SCIP Optimization Suite 8.0 [Bestuzheva et al. 2021] with a time limit of 30 minutes, and the solutions are simulated using ns-3 with an adaptation of LoRaWAN module allowing slicing.

5.2. Evaluation Results

We organize our results section by first discussing the solution time required by the proposed methods and the baseline. Then we present a study on the number of UAVs required by each technique and the number of devices to be served, then we demonstrate the packet loss rates and the delay and QoS results obtained.

Solving Time

Figure 2 illustrates the average time required to solve instances based on the density of LoRa-EDs. Figure 3 shows the average time required relative to the number of candidate positions. For the former, we maintained a fixed number of candidate positions $|\mathcal{P}|$ at 25,

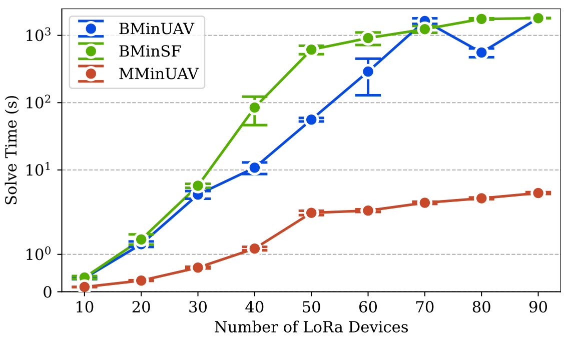

Figure 2. Comparison of solving time per device density for different strategies.

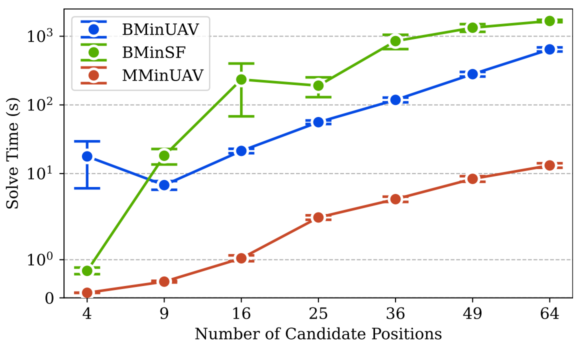

Figure 3. Comparison of solving time per number of candidate positions for different strategies.

whereas for the latter, the number of LoRa-EDs $|\mathcal{K}|$ was set to 50, those same values will be used for the remainder of the evaluation. For instances with more than 70 devices or 49 candidate positions, the time limit starts to be reached, in these cases, the mean optimality gap is below 2%, and does not exceed 15%. It is worth noting that MMinUAV can solve all instances in less than 20 seconds, while bi-objective strategies tend to reach the time limit more quickly.

Number of Deployed UAVs

It can be observed in Figure 4 that, as the number of LoRa-EDs rises, the number of deployed UAVs also increases as expected, e.g., for ten devices, just one UAV is enough to meet them while maintaining acceptable levels of QoS, which can be seen in the graphic by the overlapping of symbols, as the density of devices increases, more UAVs are needed to ensure that the minimum QoS is met, as denoted by the rising curves.

Furthermore, Figure 4 illustrates the consistency in minimizing the amount of UAVs needed to serve LoRa-EDs. This holds whether reducing the count of UAVs in the mono-objective MMinUAV solution or prioritizing UAV minimization as the principal focus in the BMinUAV bi-objective approach. In other words, when aiming to minimize the number of UAVs in BMinUAV, consequently, the bi-objective solution converges towards the mono-objective MMinUAV, which can be seen in the overlap of the red and blue curves in Figure 4.

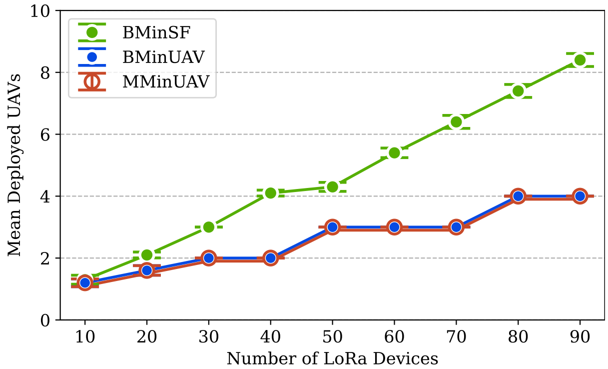

Figure 4. Comparison of mean deployed UAVs per device density for different strategies.

Additionally, it is noteworthy that there is a distinction in the results, e.g., for 40 devices, two UAVs are sufficient in MMinUAV and BMinUAV, whereas for BMinSF, 4 UAVs are needed. This difference arises from BMinSF evenly distributing the LoRa-EDs across the SF configurations. BMinSF requires the deployment of an increasing number of UAVs compared to other strategies because using lower SFs values reduces the signal range for the LoRa-EDs, thereby necessitating a higher number of UAVs to mitigate the interference.

Packet Delivery Rate

The MMinUAV strategy, in contrast, does not distinguish between candidate positions, whereas BMinUAV selects positions and associates LoRa-EDs to configurations that allow a better distribution of devices between SFs, consequently reducing the interference between LoRa-EDs and enhancing the packet delivery rate as depicted in Figure 5. Another noteworthy observation is the spikes amidst the overall declining trend in the datasets of 40 to 50 devices and 70 to 80 devices, attributed to a one-unit increase in the number of deployed UAVs.

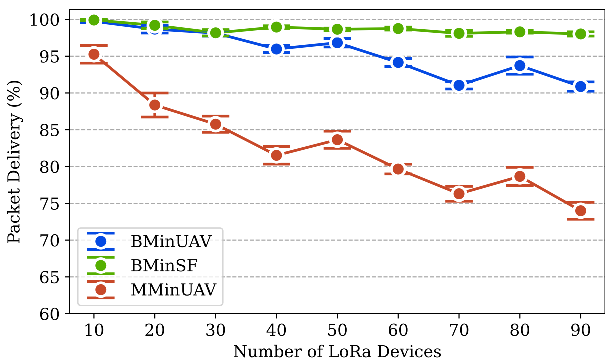

Figure 5. Comparison of packet delivery per device density achieved by the simulation for different strategies.

Regardless of the chosen strategy, the packet delivery rate demonstrates an inverse correlation with the density of LoRa-EDs. Despite that, BMinSF can maintain a higher delivery rate across all scenarios in both Figure 5 and Figure 6, as deploying a higher

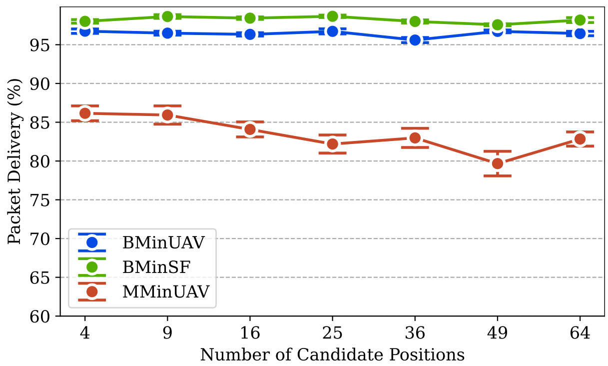

Figure 6. Comparison of packet delivery per number of candidate positions for different strategies.

number of UAVs allows for optimal device distribution among SFs. In Figure 6, it becomes evident that the number of candidate positions seems to have little impact on the packet delivery rate for the evaluated instance sizes. This behavior remains consistent across all other evaluated metrics, and consequently, they are not plotted.

QoS Results

For the MMinUAV strategy, the UAV position selection is arbitrary. However, for the bi-objective strategies, the UAVs deployment positions will be crucial for achieving a better distribution of devices among SFs. Nonetheless, an increase in the number of candidate positions does not guarantee a solution with higher quality once the new set of candidate positions does not encompass the elements of the previous set. Furthermore, even though there is a possibility that the process of discretizing the space may lead to the loss of the best positions for the actual problem, the relaxed model can consistently find solutions that reduce the interference between LoRa-EDs, enabling a high delivery rate.

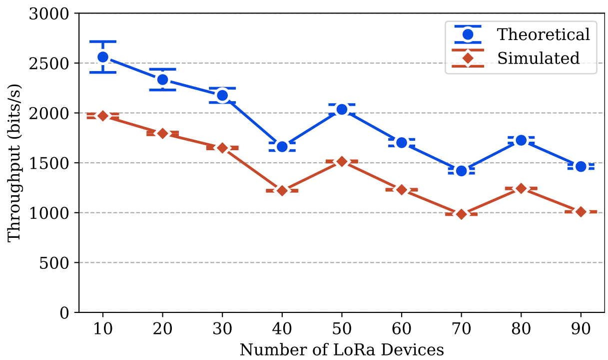

Figure 7. Mean theoretical data rate for the solution and simulated throughput by device density for BMinUAV strategy.

As depicted in Figure 7 and Figure 8, the theoretical values calculated in the model for throughput and delay, respectively, closely align with the actual values observed during the simulation. However, the value observed in the simulation is always below the theoretical one. As a result, some devices may experience a service below the expected minimum, although the mean QoS is above the bound for every instance size in Figure 10

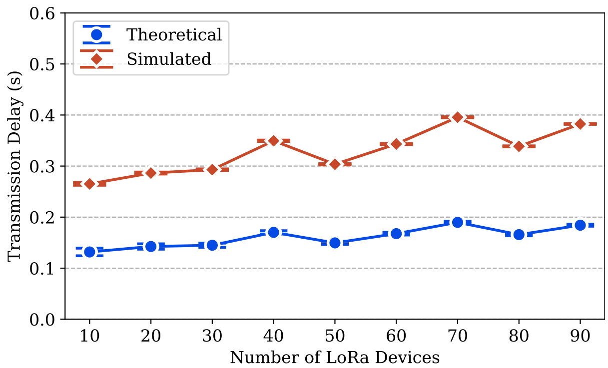

Figure 8. Mean theoretical and simulated transmission delay for the solution by device density for BMinUAV strategy.

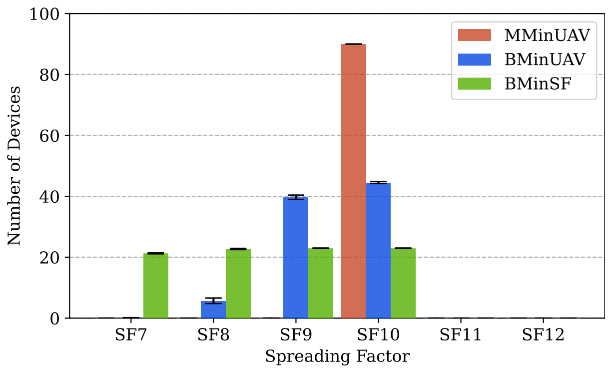

Figure 9. Mean number of LoRa-EDs assigned per SF configuration for 10 instances of 90 devices and 25 candidate positions.

and Figure 11. Nonetheless, applying a constant factor to the QoS bound derived from the experimental evaluation could effectively correct this difference.

The BMinSF strategy can maintain a higher QoS as the density of LoRa-EDs increases. This occurs because the higher number of deployed UAVs enables the homogeneous distribution of devices among the SF7 to SF10, as illustrated in green bars in Figure 9. Consequently, the number of LoRa-EDs assigned to SF7 to SF8 leads to improved QoS. Notably, no LoRa-ED were associated with SF11 or SF12, as they could not reach the QoS theoretical limit. Thus, the number of UAVs deployed in the area can maintain distances to the LoRa-EDs in a range within the SF7–SF10 reachability. The BMinUAV, blue in Figure 9 distributes SFs between SF8 and SF10 but prioritizes SF9 and SF10, showing that this method obtains the better SFs distribution than the MMinUAV (red), which in turn concentrates the distribution on SF10. As well as in the BMinSF, the distribution of SFs in the BMinUAV makes interference reduction possible and improves the delivery rates compared to the MMinUAV.

6. Conclusions

In this paper, we establish a connection between QoS parameters of non-3GPP LoRa technology and 3GPP-defined network slicing. Our primary objective is to jointly determine the minimum number of UAVs and their best position in order to reduce the interference between devices while ensuring a minimum QoS for the IoT devices. A key approach to reduce the interference is the even distribution of LoRa-EDs between SF configurations.

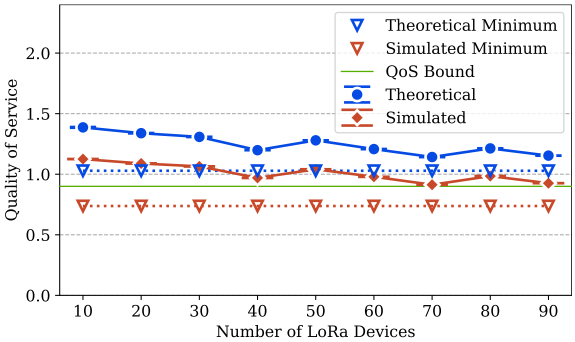

Figure 10. Mean theoretical and simulated QoS for the solution by device density for BMinUAV strategy.

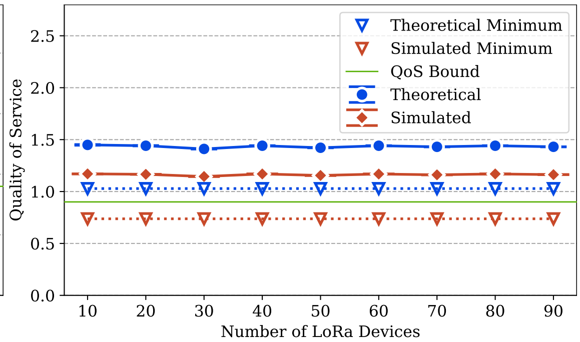

Figure 11. Mean theoretical and simulated QoS for the solution by device density for BMinSF strategy.

Given three distinct strategies, we evaluate our proposal through analytical modeling and simulations using the ns-3 platform. These evaluations validate the effectiveness of our approach in ensuring QoS and reducing interference. More details about the evaluation environment and all source code are publicly available in the GitHub repositories[1,2].

The evolution of this work aims to find ways to improve the performance of the optimization model to achieve better scalability of the algorithms and improve performance. Given the complexity of these solutions, the natural direction of this search is to adopt an integrated approach of deep reinforcement learning that combines Particle Swarm Optimization (PSO) or Genetic Algorithms (GA) for policy optimization in a deep-Q network (DQN) to cumulative rewards maximization.

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