On the Performance of Non-Terrestrial Networks to Support the Internet of Things

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Abstract—The advent of the Internet of Things (IoT) era, where billions of devices and sensors are becoming more and more connected and ubiquitous, is putting a strain on traditional terrestrial networks, that may no longer be able to fulfill service requirements efficiently. This issue is further complicated in rural and remote areas with scarce and low-quality cellular coverage. To fill this gap, the research community is focusing on non-terrestrial networks (NTNs), where Unmanned Aerial Vehicles (UAVs), High Altitude Platforms (HAPs) and satellites can serve as aerial/space gateways to aggregate, process, and relay the IoT traffic. In this paper we demonstrate this paradigm, and evaluate how common Low-Power Wide Area Network (LPWAN) technologies, designed and developed to operate for IoT systems, work in NTNs. We then formalize an optimization problem to decide whether and how IoT traffic can be offloaded to LEOS satellites to reduce the burden on terrestrial gateways.

Index Terms—Internet of Things (IoT), non-terrestrial network (NTN), Low-Power Wide Area Networks (LPWANs), SigFox, LoRa, NB-IoT, offloading.

I. INTRODUCTION

By the end of 2025, the number of Internet of Things (IoT) devices will rise to 75 billions worldwide, creating a global market of around 11.1 trillions USD according to some estimates [1]. Functional and robust IoT applications improve our life quality, and provide convenience in many fields, including transportation and logistics (e.g., to support assisted driving or help in the management of goods), healthcare (e.g., to improve workflow in hospitals or facilitate automatic data collection and sensing), agriculture (e.g., to monitor soil and crop parameters), and smart cities [2], [3].

In the 5G era, massive Internet of Things (mIoT), also known as massive Machine Type Communication (mMTC), promotes the support for extremely low-cost low-energy-consumption sensors (e.g., temperature, pressure, humidity, etc.) that transmit small volumes of data but, cumulatively, generate large data rates. To satisfy connectivity requests, standardization bodies and industry players have developed Low-Power Wide Area Network (LPWAN) technologies, such as Long Range (LoRa), Narrowband-IoT (NB-IoT), and SigFox, which define different Physical (PHY) and Medium Access Control (MAC) layers, and operate in the sub-6 GHz bands to provide good balance between range and performance [4].

Nevertheless, inter-connecting billions of smart devices may eventually congest traditional terrestrial networks which, at the same time, may be unable to serve end devices in rural/remote regions or in case of emergency where infrastructures are unavailable or out of order, respectively [5]. To address these issues, the research community is exploring the concept of non-terrestrial networks (NTNs) [6], where Unmanned Aerial Vehicles (UAVs), High Altitude Platforms (HAPs) and satellites expand traditional two-dimensional networks by acting as aerial/space gateways operating from the sky, as illustrated in Fig. 1. Notably, these elements can provide very large continuous and autonomous geographical coverage, even in the absence of pre-existing terrestrial infrastructures, thus offering global connectivity for IoT applications that rely on sensors [7]. Potential beneficiaries of this paradigm, referred to as NTN-IoT, include inter-regional transport, unserved farmlands, ships, mountainous areas, and remote maintenance facilities.

In this context, while the literature generally focuses on IoT for smart cities (e.g., [8], [9]), some recent works have started to explore the applicability of LPWAN technologies to NTN-IoT scenarios. However, most of the prior art considers standalone UAV [10], HAP [11], or satellite [12] systems as a solution to gather and process IoT traffic from terrestrial networks, even though integrated/multilayered aerial/space architectures, as proposed in [13], may further improve quality of service. Moreover, motivated by recent trends in the 3rd Generation Partnership Project (3GPP), NTN-IoT deployments have been studied using NB-IoT [14] and for satellite-only scenarios, with preliminary results published in [15]. However, it is not clear whether some other LPWAN technologies, such as LoRa or SigFox, would provide superior performance for the same NTN-IoT applications. At the same time, the literature often neglects needs and requirements of the rural environment, since most of the analysis is based on urban scenarios.

To fill these gaps, in this paper we evaluate via simulation the performance of several NTN-IoT configurations, considering different LPWAN technologies (i.e., LoRa, NB-IoT, SigFox) and non-terrestrial architectures (i.e., UAVs, HAPs, LEO satellites, and their combinations). Then, we provide guidelines on how to dimension these systems as a function of several parameters including the radius of the service area and the density of IoT sensors and gateways. We demonstrate that, while LoRa is the best option for LEO satellites in terms of both coverage and goodput, NB-IoT is more desirable to connect UAVs and HAPs. Moreover, we raise the question of where to process IoT data, and develop an optimization problem to decide whether IoT sensors should offload (part of) their traffic to NTNs to reduce the congestion of terrestrial networks.
gateways. We see that the probability of successful transmission improves by up to 30% when some processing tasks are delegated to LEO satellites.

II. ENABLING TECHNOLOGIES FOR LOW-POWER WIDE AREA NETWORK

Vaezi et al. introduce two main categories of use cases [7], namely massive Internet of Things (mIoT) and Critical Internet of Things (CIoT), where mMTC is designed to support many low-cost sensors that continuously transmit small streams of data, and CIoT involves fewer devices handling larger volumes of data. Industrial control, robotic machines, and autonomous vehicles are examples of CIoT, whereas mMTC describes applications for data collection through sensors, for example in smart agriculture and/or smart city scenarios [16]. As such, the IoT market is fragmented, with many organizations promoting different (and somehow conflicting) access technologies and vertical solutions. In this work, we focus on mIoT, and compare three main LPWAN technologies, as described below and summarized in Table I.

A. SigFox

SigFox [17] devices operate in the 863/870-MHz ISM spectrum with a transmit power of 14 dBm in Europe. They use a bandwidth of 100 Hz (1.5 kHz) in uplink (downlink), offering a data rate of 100 (600) bps with 12 (8) bytes of maximum payload. Given the small packet size, this solution promotes low energy consumption and prolonged battery life of the devices. Using Ultra-NarrowBand (UNB) modulation, combined with Differential Binary Phase Shift Keying (DBPSK) and Gaussian Frequency-Shift Keying (GFSK), SigFox achieves wide-range communications between 10 and 50 km, and robustness against noise. It exploits frequency-hopping spread-spectrum (FH-SS) and repetition code, where the transmitter copies the message into three slices and successively transmits them through three randomly selected sub-frequency bands, both of which provide immunity to interference.

B. LoRa

LoRa, including LoRaWAN, is a proprietary LPWAN technology designed and patented by Semtech [8]. In this paper we consider LoRa Class A networks [18], where transmissions are always initiated by the end devices. Specifically, LoRa devices operate in the 868-MHz ISM spectrum, with a bandwidth of 125 kHz and a maximum transmit power of 14 dBm, which is the same as SigFox.

At the PHY layer, it implements Chirp Spread Spectrum (CSS) modulation which guarantees robustness to interference. LoRa devices can choose different Spreading Factors (SFs), with $\text{SF} \in \{7, \ldots, 12\}$, which is a function of the number of bits sent per symbol. Notably, the SF is inversely proportional to the raw data rate $R_s$ (up to around 6.5 kbps with SF7), i.e.,

$$R_s = \text{SF} \cdot \frac{B}{2^{\text{SF}}},$$

where $B$ is the bandwidth. The SF also determines the transmission duration, i.e., the time on air (ToA), computed as

$$T = \frac{2^{\text{SF}}}{B} \left(8 + \max \left(5 \left[\frac{8L - 4 \text{SF} + 24}{4 \text{SF}}\right], 0\right)\right),$$

where $L$ is the size of the message in bytes [19]. Transmissions with a higher SF require more time, which allows a reduced sensitivity at the receiver (from $-132$ dBm with SF7 to $-143$ dBm with SF12, as reported in Table I) and wider coverage (up to 14 km with SF12). Generally, the SF is assigned based on the power level, where each device uses the lowest possible SF such that the received power is still above the gateway sensitivity. However, if multiple devices operate in similar conditions, they will select the same SF, which increases the collision probability. This is especially true in the NTN-IoT scenario, where devices tend to choose the highest possible SF to maximize the communication range, which
TABLE I: Summary of the LPWAN technologies. SF, \( k \in \{7, \ldots, 12\} \), is the SF in LoRa, while \( R \) is the number of repetitions in NB-IoT.

| Characteristic                  | Sigfox | LoRa          | NB-IoT          |
|--------------------------------|--------|---------------|-----------------|
| Modulation                     | UNB    | CSS           | QPSK            |
| Bandwidth (Uplink) [kbps]       | 100 Hz | 125 kHz (Class A) | 180 kHz        |
| Max. data rate (Uplink) [kbps]  | 0.1    | 6 (SF7)       | 90 (QPSK)       |
| Max. range [km]                | 50     | 14 (SF12)     | 10              |
| Energy consumption             | Very low| Low          | Low             |
| Tx. power [dBm]                | 14     | 14            | 23              |
| Interference immunity          | FH-SS and repetition coding | SF orthogonality | Repetition coding |
| Sensitivity threshold [dBm]     | -140 dBm | -127 - 2.5(SFk - 7) | -102.2 - 2.8\log_2(R) |
| Device cost [USD]              | 5      | 10            | 12              |

may create interference. Based on the assumption of quasi-orthogonality among different SFs [20], we propose a new method (referred to as LoRa+ in the rest of the paper) where end devices scramble across different SFs to reduce the impact of interference, regardless of the value of the sensitivity.

C. NB-IoT

NB-IoT is an LPWAN technology designed, developed and standardized by the 3GPP. NB-IoT devices use Orthogonal Frequency Division Multiple Access (OFDMA) with 180 kHz of bandwidth, and a transmit power of 23 dBm. The subcarrier spacing is 15 kHz in downlink, and 15 or 3.75 kHz (15 kHz) for single-tone (multi-tone) transmissions in uplink.

NB-IoT supports repetition coding, with up to 2048 (128) repetitions in downlink (uplink), which achieves coverage extension up to 10 km. Also, it improves the receiver sensitivity via coherent addition of the symbols and incoherent addition of thermal noise, but simultaneously increases the system latency. Notably, the sensitivity decreases by 2.8 dB whenever the number of repetitions is doubled [21], as reported in Table I. Unlike LoRa, NB-IoT is not immune to interference since repetition codes are not orthogonal, but allows for synchronization despite some additional cost and complexity in the device.

The channel access is based on Slotted ALOHA, which guarantees faster response time than other LPWAN technologies. In this paper, with the assumptions of Quadrature Phase Shift Keying (QPSK) modulation, code rate of 1/3, and around 30% of the uplink resources reserved, NB-IoT supports a data rate up to 90 kbps as considered in [22].

III. SYSTEM MODEL

In this section we introduce our scenario (Sec. III-A), and the link-level model including channel model, the signal detection policy and the traffic model (Sec. III-B).

A. Scenario

Our scenario consists of a ground-to-air/space uplink system in which Low Earth Orbit (LEO) satellites (L), HAPs (H), UAVs (U), terrestrial gateways (TG), and IoT devices (ID) form a 3D network. Specifically:

- LEO satellites are deployed at \( h = 600 \) km, and offer several advantages like huge coverage and good Line of Sight (LOS) connectivity, at the expense of some delays due to the very long distance.
- HAPs are deployed in the stratosphere at \( h = 20 \) km, and implement solar charging technology to provide long-life and stable wireless connectivity.
- UAVs fly at \( h = 0.6 \) km, and guarantee lower delay and installation/management costs than HAPs. However, they provide limited coverage, and incur significant energy consumption for propulsion and hovering.

In this context, the availability of multi-layered networks can provide better coverage and flexibility compared to standalone deployments. Based on our initial results in [13], in Sec. V we will study the case of HAP relays for an upstream LEO satellite connected to the core network. We assume that each NTN platform is equipped with multiple receivers working in parallel, where the center frequency of each receive path is individually configured. Also, the mobility of NTN platforms is neglected.

IDs and TGs are uniformly distributed with a density \( \rho_{1D} \) and \( \rho_{TG} \), respectively, over an area of interest (AoI) \( A \), which is a circular area of radius \( r \) split in cells of equal size.

B. Link-Level Model

a) Channel model: The received power \( P_{ij} \) from transmitter \( i \) to receiver \( j \), \( (i,j) \in \{TG,U,H,L\} \), is expressed as

\[
P_{ij} = P_t \cdot P_{L_i} \cdot G_{ij} \cdot \| h_{ij} \|^2 ,
\]

where \( P_t \) is the transmit power (which depends on the adopted LPWAN technology), \( G_{ij} \) is the cumulative antenna gain, and \( \| h_{ij} \|^2 \) is the fading. The path loss \( P_{L_i} \) depends on the type of link and, besides free-space path loss, accounts for atmospheric attenuation as described in [23]. In this work different channel models are used based on the link: (i) for the ground-to-ground (ID-TG) link we use the link performance model described in [8], which computes the interference at reduced complexity via pairs of look-up tables; (ii) the ground-to-air (ID-{U,H}) link is modeled using a Nakagami-m0 fading model, as done in [24]; (iii) for the ground-to-
TABLE II: System parameters.

| LPWAN technology | LoRa | NB-IoT | Sigfox | Relay | Altitude of UAV/HAP/LEO (h) [km] | Additional pathloss for (LOS, NLOS) [dB] | Other Parameters |
|------------------|------|--------|--------|-------|---------------------------------|--------------------------------------|------------------|
| Tx power (\(P_t\)) [dBm] | 14   | 23     | 14     | 52    | 0.6/20/600                      | (0.0154, 18.4615)                   |                  |
| Carrier frequency [GHz]  | 0.868| 0.900  | 0.868  | 38    | Shadowed-Rician fading factor (\(\omega, b_0, m\)) | (1.29, 0.158, 19.4) |                  |
| Bandwidth (\(B\)) [MHz] | 0.125| 0.18   | 0.2    | 400   | Nakagami fading factor (\(m_0\)) | 15                                  |                  |
| Tx. antenna gain [dB] | 2.15 | 0      | 2.15   | 37.9  | ID transmission rate \(\lambda\) [tx/s] | 1/1800                             |                  |
| Rx. antenna gain [dB] | 8    | 8      | 8      | 0     | Max. payload size [byte] | 12                                  |                  |
| Receiver noise figure (NF) [dB] | 3    | 3      | 3      | 0     |                                  |                                     |                  |

space (ID-L) link the fading is based on a Shadowed-Rician model [25]. Channel parameters are listed in Table II. Then, the Signal to Noise Ratio (SNR) \(\gamma_{ij}\) is:

\[
\gamma_{ij} = P_{ij} / (B N_0 + NF),
\]

where \(B\) is the bandwidth, \(N_0\) is the thermal noise power spectral density, and \(NF\) is the noise figure. In case the HAP acts as a relay of an upstream LEO satellite in a multi-layered system [13], we implement a decode-and-forward (DF) protocol where the SNR is constrained by the weakest link, i.e.,

\[
\gamma_{DF} = \min(\gamma_{ij}), \ (i, j) \in \{ID, TG, U, H, L\}.
\]

b) Signal detection policy: Let \(S\) be the receiver sensitivity as reported in Table I for the different LPWAN technologies. Successful packet transmission is subject to the following condition:

\[
P_{ij} \geq S.
\]

While SigFox and NB-IoT are in a noise-limited regime, for LoRa the sensitivity depends on the SF. Therefore, a packet with \(SF_k\), \(k \in \{7, \ldots, 12\}\), is correctly decoded if, for every set of interfering packets with the same SF, the received power is above the sensitivity threshold \(S_k\) [8].

c) Traffic model: We refer to the Mobile Autonomous Reporting (MAR) model, introduced in [26]. Hence, the payload size at the application is stochastic, and follows a Pareto distribution with 12 bytes of maximum size as per SigFox capacity limitations. In addition, IDs transmit IoT data at constant periodicity, modeled as a Poisson distribution of rate \(\lambda = 1/1800\) transmissions/s.

IV. Optimized Offloading

Besides (inter)connecting IDs, NTNs can act as complementary computing servers for processing IoT data, in addition to (or in place of) TGs in hot-spot (or rural) areas, respectively [27]. As a case study we focus on LoRa, and consider the scenario in which IDs offload data to a LEO satellite with probability \(\eta\), while with probability \((1-\eta)\) the data is processed onboard the TG they are connected to [28]. We introduce the following assumptions:

1) For ground-to-ground (ID-TG) communication, IDs use SF\(k\), \(k \in \{7, \ldots, 12\}\), based on the model in Sec. II-B.

2) For ground-to-space (ID-L) communication, IDs use SF\(v\), \(v \in \{SF_{\min}, \ldots, 12\}\), where \(SF_{\min} = \{7, 9, 11\}\) is proportional to the quality of the ID-L link. This approach prevents IDs from choosing the same SF in the attempt to maximize the coverage range towards the LEO satellite. For a given SF\(k\) in the ID-TG link, the optimal offloading factor \(\eta_k^*\) must be dimensioned to maximize the success probability \(P_{S_k}\), i.e., the probability that there are no collisions (or there are no IDs using the same SF) in the ToA. We have that

\[
P_{S_k}(\eta_k) = \left[1 - \eta_k\right] P_{S_k}^{TG} + \eta_k P_{S_k}^L.
\]

In Eq. (7), \(P_{S_k}^{L}\) is the success probability in the ID-L link, and \(P_{S_k}^{TG}\) is the success probability in the ID-TG link, i.e.,

\[
P_{S_k}^{TG}(\eta_k) = e^{-(1-\eta_k) \lambda T_k |\mathcal{D}_k|},
\]

where \(|\mathcal{D}_k|\) is the number of devices that use SF\(k\) towards the TG, \(T_k\) is the ToA using SF\(k\) (see Eq. (2)), and \(\lambda\) is the rate at which IDs generate data. Then, the optimization problem is:

\[
\begin{align}
\arg\max_{\eta_k} \quad & P_{S_k}(\eta_k) \quad \text{(9a)} \\
\text{subject to} \quad & \eta_k \in [0, 1] \quad \text{(9b)}
\end{align}
\]

The problem in (9) is subject to the optimization of \(P_{S_k}^{L}\), which requires that the IDs offloading data to the LEO satellite (with probability \(\eta^*\)) choose their SF\(v\) so as to maximize the success probability in the ID-L link. This is formalized as:

\[
P_{S_k}^{L}(\eta_k) = \arg\max_{\alpha_v} \quad \sum_{v=SF_{\min}}^{12} \alpha_v e^{-\alpha_v \lambda |\Delta(\eta_k)|},
\]

subject to

\[
\begin{align}
\sum_{v=SF_{\min}}^{12} \alpha_v = 1, & \quad (10b) \\
|\Delta(\eta_k)| = \sum_{j=7}^{12} \eta^*_j |\mathcal{D}_j| + \eta_k |\mathcal{D}_k|, & \quad (10c) \\
\alpha_v \in [0, 1], & \quad (10d)
\end{align}
\]

where \(\alpha_v\) is the probability that an ID chooses SF\(v\) in the ID-L link, and |\(\Delta(\eta_k)\)| denotes the total number of IDs that offload data to the LEO satellite. The results of the optimization problem in (9) will be presented in Sec. V-D.

V. Performance Evaluation

In this section, we compare the performance of the LPWAN technologies introduced in Sec. II for different NTN configurations, in terms of network capacity (Sec. V-A), success probability (Sec. V-B), and coverage (Sec. V-C). Then, in Sec. V-D we validate the offloading framework described in Sec. IV based on LoRa.
A. Network Capacity

We consider a scenario with up to $10^6$ IDs uniformly distributed in an AoI of radius $r = 0.35$ km as defined by the coverage range of the UAV, i.e., the most constrained NTN platform. In Fig. 2 we see that, when the number of IDs is lower than $10^3$, the interference is negligible and all LPWAN technologies guarantee similar values of goodput, with high success probability. For SigFox, as the ID density increases, and despite using FH-SS to reduce the interference, the goodput is eventually constrained by the limited capacity available at the PHY layer (below 100 bps on average), and is up to 10 times lower than its competitors. On the other hand, NB-IoT provides the highest goodput for UAV- and HAP-enabled networks (up to $1.5 \cdot 10^6$ bytes/hour) given the higher data rate at the PHY-layer (up to 90 kbps with QPSK modulation). However, the goodput drops below $10^5$ bytes/hour when LEO satellite links are considered, where LoRa shows instead superior performance, with a goodput of $3 \cdot 10^5$ bytes/hour. In fact, the flexibility of LoRa allows IDs to select higher SFs to operate at much lower sensitivity compared to NB-IoT (the gap is up to 20 dB), thus increasing the communication range.

In addition, we evaluate the performance of LoRa+ in which SFs are assigned based on the model described in Sec. II-B to minimize interference. This approach increases the capacity by about 50% compared to the baseline LoRa implementation, and the maximum goodput is close to $10^6$ bytes/hour.

B. Success Probability

Similar trends can be observed in Fig. 2b, which shows the average success probability based on the definition in Eq. (7).

In addition, in Fig. 3 we focus on LoRa, and consider a multi-layered network in which a HAP acts as a relay of an upstream LEO satellite (ID-H-L) vs. two standalone configurations in which IDs communicate with the TG (ID-TG) or the LEO satellite (ID-L). In this scenario $\rho_{TG} = 1$ TG/km$^2$ and $\rho_{ID} = 10$ ID/km$^2$. We see that both TGs and LEO satellites can serve most ID requests with success, even though ID-TG involves more expensive network densification as the radius of the AoI increases. Moreover, ID-H-L outperforms standalone ID-L by around 10% for $r < 15$ km, after which the scenario is constrained by the limited coverage area of the HAP, as explained in the next subsection.

C. Network Coverage

In this third set of results we focus on the coverage performance of LoRa and NB-IoT, since SigFox was observed to provide insufficient capacity to support NTN-IoT.

In Table III we report the maximum achievable range $r$ and the minimum possible elevation angle $\theta$ for which the received power is higher than the lowest sensitivity. We observe that LoRa outperforms NB-IoT under both metrics thanks to the lower sensitivity. Moreover, LEO satellites provide the largest coverage area (up to 1450 km), as they operate in LOS and suffer from less severe visibility constraints than other NTN platforms. Interestingly, UAVs provide limited coverage compared to TGs. In fact, UAVs fly at low altitude, which implies that the elevation angle is very low: this means that the link is longer, which makes the signal experience more attenuation.
Similarly, Fig. 4 represents the minimum number of NTN platforms that need to be deployed to cover an AoI of radius \( r \) while ensuring successful packet transmission as described in Eq. (6). As expected, platforms at higher altitude like LEO satellites provide better coverage despite the resulting lower capacity as shown in Fig. 2, and NB-IoT needs more platforms to connect IDs compared to LoRa.

\[ \text{Min. number of NTN platforms} \]

**D. Offloading**

In this section we consider a scenario in which IDs can offload data to a LEO satellite in the attempt to maximize the success probability, based on the optimization framework described in Sec. IV. IDs (TGs) are uniformly distributed with density \( \rho_{\text{ID}} \) over an AoI of radius \( r = 5 \) km. The payload size is fixed to 50 bytes, and the transmission rate is \( \lambda = 1/360 \) transmissions/s [26]. Simulation results are given for \( \text{SF}_{\text{min}} = \{7, 9, 11\} \), i.e., as a function of the quality of the ID-L link as explained in Sec. IV, and benchmarked against a “Standalone TG” scheme in which data are processed onboard the TGs (i.e., \( \eta^* = 0 \)).

\[ \text{Average success probability, with } \rho_{\text{ID}} = 50 \text{ ID/km}^2. \]

\[ \text{Average success probability, with } \rho_{\text{TG}} = 0.1 \text{ TG/km}^2. \]

\[ \text{Fig. 5: Average success probability vs. the TG density (left) and the ID density (right), considering different offloading options. We set } r = 5 \text{ km.} \]

**a) TG density:** In Fig. 5a we evaluate the impact of the TG density in terms of the success probability, when \( \rho_{\text{ID}} = 50 \) ID/km\(^2\). As expected, when the TG density is low, LEO offloading can increase the success probability by up to +30% compared to the “Standalone TG” baseline, especially in good channel conditions, i.e., when the received power in the ID-L is likely above the sensitivity threshold. In particular, the additional computational capacity available at the LEO satellite can serve processing requests relative to cell-edge IDs, i.e., the most resource constrained network entities, which may otherwise not be able to communicate to TGs. Moreover, when TGs are sparse, the ID-TG link is longer, which motivates more IDs to choose a higher SF to increase the coverage range, thus increasing the probability of collisions in the “Standalone TG” scenario. However, as the TG density increases, IDs are progressively closer to the TGs, and the more favorable channel on the ground gradually promotes onboard processing.

**b) ID density:** In Fig. 5b we study the success probability as a function of the ID density, when \( \rho_{\text{TG}} = 0.1 \) TG/km\(^2\). In general, as the ID density increases, the probability of collisions also increases, which may decrease the success probability to less than 50% for \( \rho_{\text{ID}} = 50 \) ID/km\(^2\) if “Standalone TG” is considered. In turn, LEO offloading reduces the computational burden onboard the TGs, which improves the success probability, despite introducing some delays. Still, the benefit of the offloading in terms of success probability ranges from +11% when \( \rho_{\text{ID}} = 10 \) to around +30% when \( \rho_{\text{ID}} = 50 \)

**TABLE III: The maximum distance between devices and platforms**

| Platform | LoRa | NB-IoT |
|---------|------|--------|
|         | \( r \) [km] | \( \theta \) [deg] | \( r \) [km] | \( \theta \) [deg] |
| TG      | 14.3 | N/A    | 8.7 | N/A |
| UAV     | 8.4  | 4      | 6.8 | 5   |
| HAP     | 104.6| 10.3   | 90.4| 12  |
| LEO     | 1463.9| 14.7| 1278.8| 48 |
ID/km² in case of perfect channel conditions.

VI. CONCLUSIONS AND FUTURE WORK
NTN is a promising technology to improve coverage and capacity of rural and remote areas. In particular, UAVs, HAPs, and satellites may serve as aerial SPACE gateways to collect and process IoT data from on-the-ground sensors, a paradigm referred to as NTN-IoT. Along these lines, we evaluated the performance of different LPWAN technologies for IoT (i.e., LoRa, Sigfox, and NB-IoT) to communicate with NTN platforms. From our results, NB-IoT emerged as the most desirable technology to connect HAPs and UAVs, while LoRa turned out as the best approach for LEO satellites. Based on that, we considered a scenario in which IoT sensors use LoRa to offload some data to LEO satellites, as a solution to alleviate the burden of data processing onboard the gateways. We demonstrate that LEO offloading can minimize the risk of collisions especially in sparsely-deployed networks, or when the density of sensors increases.

As part of our future work, we will analyze the performance of the NTN-IoT paradigm considering the mobility of NTN platforms, and as a function of some other metrics such as energy consumption and latency.

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