

Performance Analysis of Aerial Data Collection from Outdoor IoT Sensor Networks using 2.4GHz 802.15.4

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ABSTRACT

Unmanned Aircraft Systems (UAS), i.e. drones, have been commercially successful in both the consumer and industrial sectors in part due to the wide variety of applications they benefit. In environmental monitoring and precision agriculture, UASs can be utilized for data collection from rural IoT sensor networks. These networks frequently operate over some variant of the IEEE 802.15.4 standard, taking advantage of the standard's low power usage. Consumer 802.15.4 radios are widely available in compact form factors, making them ideal for application in environmental and agricultural sensor networks. Unlike other wireless standards, 802.15.4 is well studied on the ground but has not received rigorous evaluation in three dimensional aerial communication, which introduces new challenges, such as antenna radiation patterns and extreme ranges. This paper provides an initial look at the performance of 2.4GHz 802.15.4 for data collection from a UAS. We provide experimental performance measurements using an outdoor aerial testbed, examining how factors, such as antenna orientation, altitude, antenna placement, and obstruction affect signal strength and reception rate of packets. We find that these parameters play a significant role in reception rate, but have a much weaker impact on received signal strength. We conclude by discussing some takeaways on sensor network configuration for aerial data collection.

CCS CONCEPTS

• **Networks** → **Network measurement**; *Network experimentation*; *Local area networks*; • **Computer systems organization** → **Sensor networks**; • **Applied computing** → *Environmental sciences*; *Agriculture*.

KEYWORDS

Internet of Things, 802.15.4, UAS, UAV, Drone, Sensor Network, Wireless Networks, Precision Agriculture, Aerial networks

ACM Reference Format:

Michael Nekrasov, Ryan Allen, and Elizabeth Belding. 2019. Performance Analysis of Aerial Data Collection from Outdoor IoT Sensor Networks using 2.4GHz 802.15.4. In *The 5th Workshop on Micro Aerial Vehicle Networks, Systems, and Applications (DroNet'19)*, June 21, 2019, Seoul, Republic of Korea. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3325421.3329769>

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DroNet'19, June 21, 2019, Seoul, Republic of Korea

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ACM ISBN 978-1-4503-6772-1/19/06...\$15.00

<https://doi.org/10.1145/3325421.3329769>

1 INTRODUCTION

Unmanned Aircraft Systems (UAS) are a promising technology for data collection from outdoor sensor networks. Environmental and agricultural networks may not have existing internet backhauls for data delivery due to low population densities in rural areas, making UASs a potential data delivery alternative. Further, networks with backhaul connectivity can become damaged by extreme weather, causing network fragmentation and leading to unreachable sensors. To provide connectivity, UASs can be deployed as aerial network relay nodes [5, 16, 18, 23] or as data mules [13, 19]. In addition to mending network fragmentation, UAS applications include post-disaster data collection involving inoperative communication infrastructure [1, 7, 8], supplementing existing communication infrastructure for vehicular networks [9], and rural applications in environmental monitoring [12, 22] and precision agriculture [10, 21].

Many ground-based sensors in these types of networks employ the IEEE 802.15.4 Low-Rate Wireless Personal Area Networks (LR-WPANs) radio standards as well as derivative standards, such as Zigbee [3] for low-rate, low-power connection to Internet of Things (IoT) sensors. Unlike the 802.11 specification, these standards focus on energy performance rather than data rates by sending infrequent transmissions over long distances. Examination of the interaction between these transmission standards and aerial systems is essential to understand the feasibility of aerial data collection.

We identify elements critical to successful data collection from an 802.15.4 2.4GHz network using a moving UAV. We conduct performance measurements on RSSI and packet loss by evaluating the impact of parameters, such as altitude, displacement, antenna orientation, obstruction, transmission rate, and transmitter elevation. We find that altitudes of 150-250ft with a receiver that is mounted to the UAS parallel to the ground are optimal, while the orientation of the transmitter does not have a significant impact on reception.

2 RELATED WORK

Numerous studies have examined 802.15.4 performance in two dimensional space. In [20], the authors offer insight on performance and coexistence with 802.11. [11] discusses 802.15.4 propagation characteristics, while [17] examines person-to-person communication over 802.15.4. However, these two dimensional studies focus heavily on characteristics such as throughput and RSSI and do not address reception rates or the additional challenges of communicating in three dimensions.

Alternatively, there have been previous works that study 802.11 performance in three dimensional space. Both [2] and [14] reveal that the high mobility of UAVs can result in poor performance in 802.11. Additionally, [4] and [24] show that due to the toroidal radiation patterns in consumer omni-directional antennas, signal

quality can be strongly affected by antenna orientation for 802.11 devices in three dimensional space. Given that 802.11 performance changes in three dimensions, there is reason to believe that 802.15.4 will also change and, henceforth, should be studied.

Most closely related to our work, [15] reveals that 802.15.4 devices are sensitive to antenna orientation in three dimensional space. However, the statistics in this paper are from stationary sensors no further than three meters from each other, whereas our measurements are taken from a mobile drone as far as 300m away. Thus our work is, to our knowledge, the first performance measurement study of 802.15.4 ground-air data collection performance from a UAS.

3 METHODS

In March 2019, we performed experimental measurements in an outdoor aerial testbed near our university. In our experiments, IoT nodes running the 802.15.4 protocol were placed on the ground, broadcasting messages at 500ms intervals. The UAS was flown over the network to collect data. We conducted nine total experimental runs divided evenly across three locations. Each run comprised thirteen altitudes, spanning roughly one hour of flight time, for a total of nine hours of flights.

3.1 Equipment

We used six Digi WRL-15126 XBee3 RF 2.4GHz transceivers utilizing 802.15.4. The advertised outdoor range for each node is 1200m at a power of 8dBm and a receiver sensitivity of -103dBm. We selected the XBee3 2.4GHz (as opposed to 900MHz or 868MHz) radio, a common off-the-shelf IoT radio, to make our work comparable to previous research [11, 15, 17, 20].

IoT Transmitters: Four XBee radios served as IoT transmitters, mounted on a SparkFun XBee Explorer with a USB-to-Serial converter, and controlled by a SparkFun Teensy LC. An external battery supplied power to the Teensy LCs through its own USB-to-Serial converter and forwarded power to the XBee. The nodes were configured to broadcast packets, 23 bytes each, every 500ms. The packet contained unique device and sequence identifiers and a randomly generated floating point number to simulate sensor data.

Figure 1 shows each transmitter configured for slightly different experimental conditions:

- **Horizontal:** Laid flat on ground.
- **Vertical:** Placed on edge on ground.
- **Elevated:** Mounted to pole 0.5 meters above ground.
- **Obstructed:** Laid flat under 1 quart of debris.

For each trial, transmitters were placed in a line approximately 11m apart with no obstruction within the 15cm vicinity. XBee placement was randomized for each trial, and GPS coordinates were recorded manually from repeated readings using a smartphone GPS.

Unmanned Aircraft System: Figure 1e shows the UAS, a DJI Matrice 100, which communicates with a remote control at 5.725 - 5.825 GHz (outside our monitoring frequency of 2.4GHz). We equipped the UAS with two XBees set to receive only. They were mounted to the bottom of the UAS with the *horizontal receiver* parallel to the ground and the *vertical receiver* perpendicular to the ground.

Packets and their associated received signal strength indicator (RSSI) reported by the XBee radios were stored via a USB-attached on-board Raspberry Pi2 Model B. The location of the UAS for the duration of each trial was recorded from the Matrice 100 GPS connected via UART to the Pi, sampling at a rate of 50Hz.

The UAS was flown in a straight line approximately over the transmitters at an average speed of about 2.2m/s (5mph). The flight path of each trial and altitude varied, as the flights were manually executed under varying wind conditions. Each flight reached a total horizontal distance of 250-300m in both directions from the nearest transmitter (depending on local topography). For each trial, we flew at 13 altitudes (in relation to the lowest transmitter): 30ft, 40ft, 50ft, 60ft, 70ft, 80ft, 90ft, 100ft, 150ft, 200ft, 250ft, 300ft, and 400ft.

3.2 Location

The experiments were conducted at three locations, with varying topography, in a coastal grassland reserve near the university. The area is relatively flat with minor obstruction due to tall grass and bushes. The three locations are as follows

Road: Transmitters were deployed along a 200m section of a flat dirt road. The area had the lowest level of natural obstruction among the three experimental sites.

Grassy: Transmitters were deployed in a field with tall grass and nearby bushes, ≈ 1 m tall, but with the immediate 15cm around each transmitter unobstructed.

Hills: Transmitters were deployed on the uneven terrain of hills with a shallow trench, (≈ 0.5 m deep), cut out by erosion. Tall grass and a denser concentration of bushes were prevalent, but the immediate 15cm surrounding the transmitter was unobstructed.



Figure 1: Experiment Equipment.

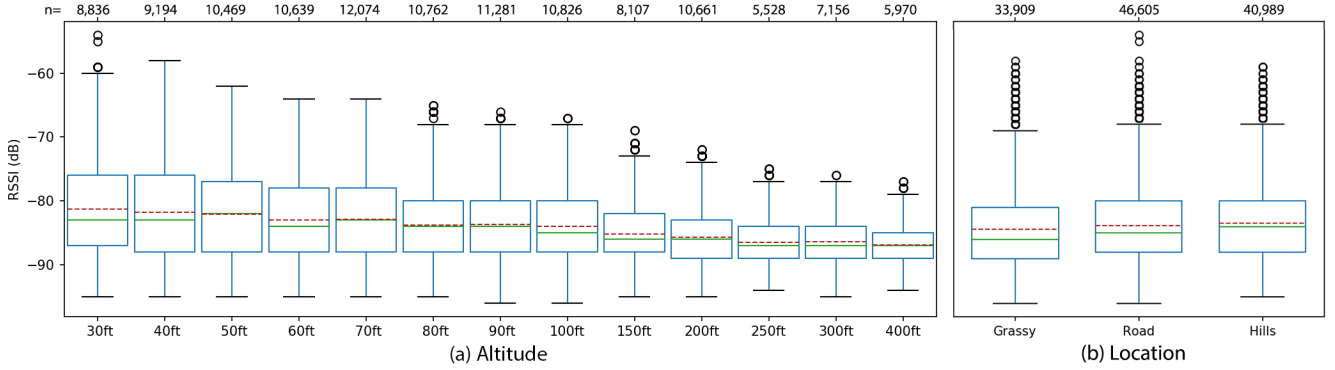


Figure 2: RSSI by Altitude and Location.

4 RESULTS

Our results comprise nine hours of collected data, totaling 121,503 received packets, including only the experimental portion of each flight; landing, takeoffs, and transitions between experiments are omitted.

4.1 RSSI Analysis

Past measurement studies of UAV-ground communication have focused on RSSI as a key indicator of performance [2, 4, 24]. RSSI is often the only signal metric reported by radio modules. We examine how RSSI is affected by varying experimental parameters. We present the results without filtering for outliers. Given the literature, we expected:

- **Altitude & Displacement:** Receivers should have the best reception in proximity to a transmitter.
- **Location:** Obstacles introduce interference, so the unobscured *road* should have the best signal.
- **Transmitter/Receiver Configurations:** *Horizontal* transmitters and receivers should have the best reception overall. Obstructions should decrease reception, while higher elevations should increase reception.

Altitude: In practice, we found that higher altitudes have fewer high RSSI values, shown in Figure 2a. However, the mean (dashed-red) and median (solid green) RSSI values remain nearly constant as altitude increases.

Location: Figure 2b shows that the mean and median RSSI values remain nearly the same as location changes. However, the most obstructed site (*Hills*) displays the highest median RSSI, and the area of least obstruction (*Road*) yields the greatest variance in RSSI values.

Transmitter/Receiver Configurations: Figure 3 shows that *transmitter* orientation minimally affects mean RSSI, while *receiver* orientation has a more pronounced impact. All four transmitters had lower mean RSSI for the *vertical receiver* than the *horizontal receiver*.

While all transmitters broadcast at the same rate, the *elevated* transmitter receives a greater number of packets than the *obstructed* one (10k or more). However, the *obstructed* transmitter shows the highest mean RSSI.

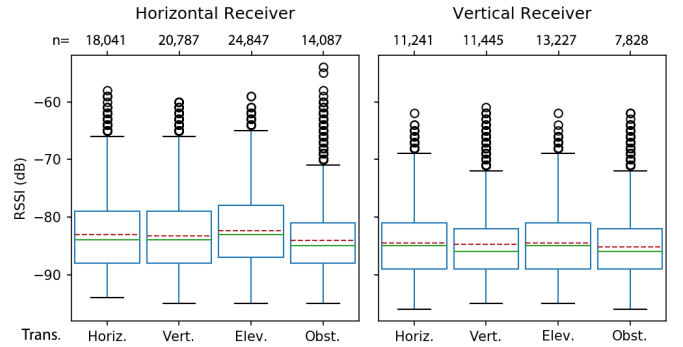


Figure 3: RSSI distributions by antenna configuration.

Horizontal Displacement: Figure 4 shows that horizontal displacement is the strongest factor influencing mean RSSI when compared to relatively minor mean RSSI fluctuations found with other experimental parameters. Transmitter/receiver pairs show increased deviation in mean RSSI as displacement increases.

The impact of horizontal displacement and receiver orientation on RSSI is strongest for the *horizontal receiver* across all transmitter

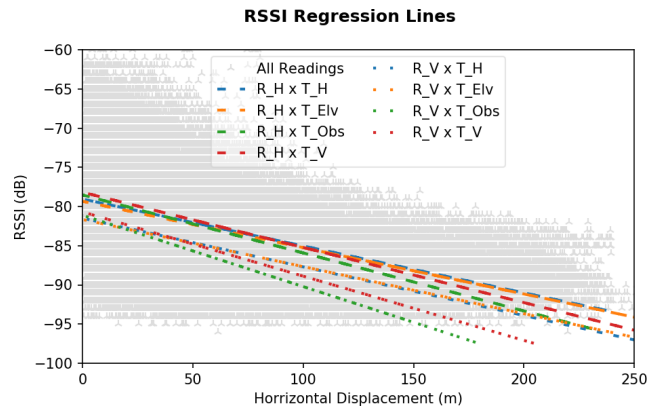


Figure 4: Relationship between RSSI and horizontal displacement. Linear regression plotted for each transmitter/receiver pair.

configurations with the *elevated transmitter* and *horizontal transmitter* performing best across all configurations. Unlike the results from the analysis of distribution, the *obstructed transmitter* showed lower RSSI at greater distances than other transmitters.

Statistical Comparison of Distributions: To verify whether the observed differences between mean RSSIs across all experimental parameters are meaningful, we performed non-parametric Kruskal-Wallis and Kolmogorov-Smirnov tests to compare the empirical cumulative RSSI distributions. The tests reveal differences in the distributions between the groups even as the observed mean RSSIs are not meaningfully different. Consequently, the mean RSSI estimation is a poor metric for comparison of experimental parameters in our data.

4.2 Packet Reception Rate Analysis

We concluded the previous section with the result that analysis of RSSI alone does not provide a complete picture of signal quality for our data. Successful reception is most likely in a favorable RSSI, while lost packets are unaccounted for (as their RSSI is never reported to the receiver). While our analysis of RSSI showed little mean fluctuation between experimental configurations, our total number of received packets indicates significant differences in signal quality. These differences are not accounted for by RSSI; we therefore consider alternate metrics.

While *throughput* is a common performance metric for 802.11 networks, it may be inappropriate for 802.15.4, since typical IoT applications do not saturate the bandwidth. Instead, real applications, such as outdoor sensor networks that may lack access to the power grid, optimize for low-power consumption. We propose analyzing Packet Reception Rate (PRR), which is the number of packets received divided by the calculated number sent, instead. Because each packet loss is wasted energy, PRR is a more appropriate performance metric.

We group the experimental data by displacement into ten meter concentric circular sectors radiating out from each transmitter. To determine the sector into which a packet from a particular transmitter falls, we compare the UASs high frequency (50Hz) on-board GPS with the manually recorded transmitter location. To estimate the number of packets sent by a transmitter, we calculated the product of the pre-programmed transmission rate and the time-in-sector by the UAS.

$$PRR = \frac{\text{\# of packets received}}{\text{time in sector} * \text{transmission rate}}$$

Figure 5 represents the observed mean PRRs. To evaluate our findings, we used Poisson regression with the number of received packets as the outcome and the number of sent packets as the offset variable, which gave us a model that estimates PRR for comparing across experimental parameters. We used robust variance estimation via GEE (General Estimating Equations) to compensate for slight deviations from model assumptions. We used the experimental parameters as covariates: transmitter/receiver configuration, location, altitude, and displacement sectors. As the PRR metric is calculated in part by displacement sectors, the reported results

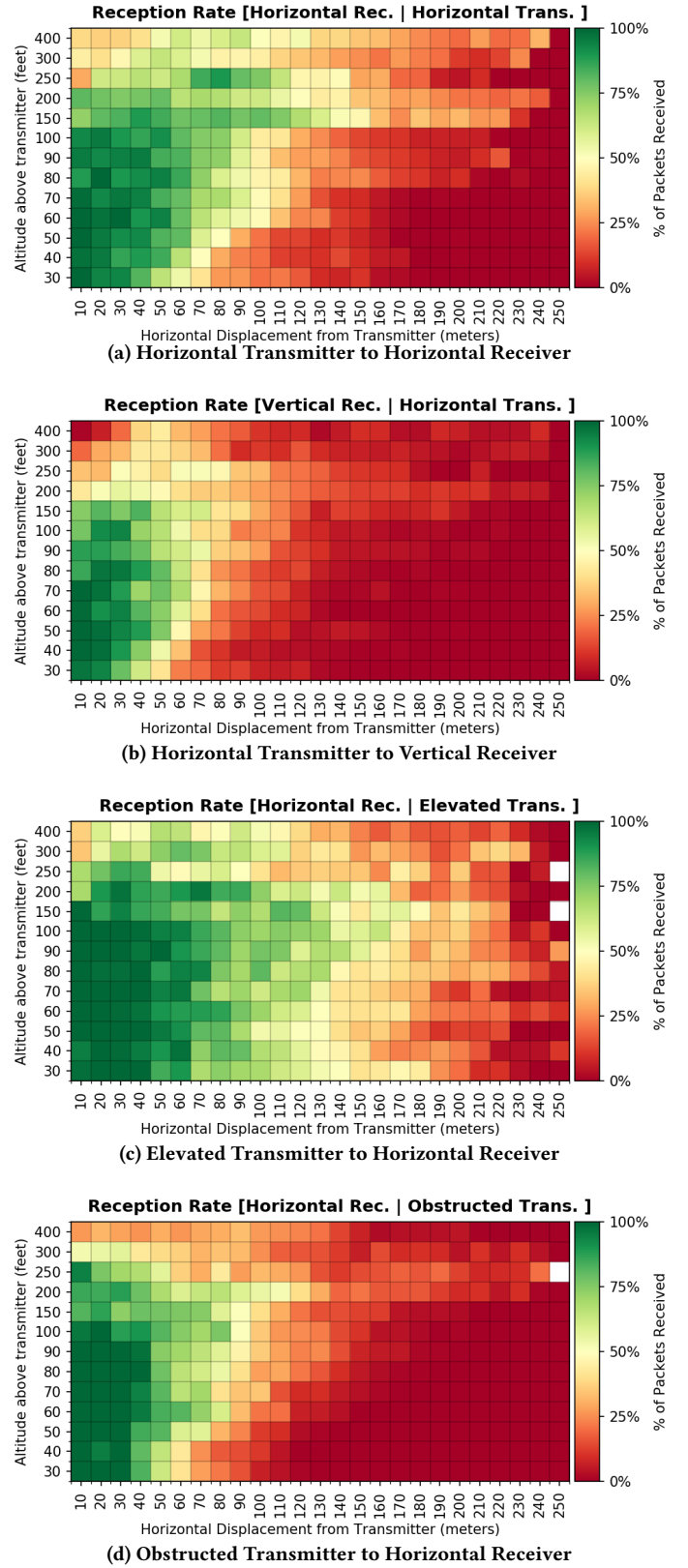


Figure 5: Reception rates grouped by altitude and 10m displacements from transmitter. Cells with fewer than 5 sent packets are left blank. Note that altitude is reported in feet, and displacement is in meters.

account for displacement while controlling for other experimental parameters, including location, which did not impact PRR. For reported confidence intervals (CI), we have $p\text{-value} < 0.0001$.

Transmitter/Receiver Configuration: Receiver orientation noticeably impacts packet loss. The expected *vertical receiver's* PRR is 56.9% of the *horizontal receiver's* (95%CI:55.6-58.3). Comparing Figure 5a to Figure 5b, the *vertical receiver's* PRR is lower at higher altitudes and displacements. In contrast, the *vertical transmitter's* expected PRR is 110.9% of the *horizontal transmitter's* PRR (95%CI:107.4-114.5). Because these graphs are similar to those above, we omit them.

Elevating the transmitter 0.5m off the ground has an expected PRR 125.4% to that of the *horizontal transmitter* (95%CI:121.6-129.3). Figure 5c shows that the PRR was best for lower altitudes, where elevating the transmitter overcomes ground obstacles (such as tall grass) to establish line-of-sight with the UAS.

Obstructing the transmitter in debris produces an expected PRR of 74.5% to that of the *horizontal transmitter* (95%CI:71.7-77.4). Figure 5d shows that, while the *obstructed transmitter* maintains a high PRR when the UAS is in proximity, the maximum displacement at which the UAS has good reception is lower than other configurations, especially at lower altitudes.

Altitude: While proximity to transmitter improves PRR at low altitudes, higher altitudes typically produce a better PRR at greater displacement. For example, the expected PRR at 30ft is 76.0% of the PRR at 150ft (95%CI:71.5-80.8). Altitudes of 150-250ft are optimal overall and the PRR in this range is not statistically different from either bound. Altitudes exceeding 250ft see a decline in PRR; for example 400ft has a PRR 56.5% of the PRR at 150ft (95%CI:52.5-61.1).

5 DISCUSSION

Optimal Altitude: Although low altitudes generally improve PRR and RSSI, higher altitudes provide better connectivity at greater displacements because they provide a steeper angle between UAS and transmitter, which can help reduce signal blockage from obstacles. An altitude between 150ft and 250ft provides the best overall reception in our scenarios.

Characterizing Effective Reception Range: Digi advertises an effective total distance of 1200m for the XBee3, with the caveat that "[a]ctual range will vary based on transmitting power, orientation of transmitter and receiver, height of transmitting antenna, height of receiving antenna, weather conditions, interference sources in the area, and terrain between receiver and transmitter" [6]. However, we were only able to capture a packet at a maximum total distance of 297m in our experiments. When accounting for the UASs altitude, this corresponds to a 278m maximum horizontal displacement from the transmitter, but the UAS was highly unlikely to receive a packet at this displacement.

To best compare deployment configurations, we propose an **effective reception range** (ERR_N) metric. We define this as the horizontal displacement at an altitude of 150ft-250ft, at which we have an average $PRR > N\%$ for all displacement up to and including that range. We list ERR_{25} , ERR_{33} and ERR_{50} values for transmitter/receiver configurations in Table 1.

	Trans.	ERR_{25}	ERR_{33}	ERR_{50}	Max vel. at 1p/s
H Rec.	Horiz.	180m	150m	130m	144 m/s
	Vert.	190m	180m	150m	159 m/s
	Elev.	200m	200m	140m	153 m/s
	Obst	120m	110m	80m	88 m/s
V Rec.	Horiz.	100m	90m	60m	69 m/s
	Vert.	110m	100m	70m	80 m/s
	Elev.	100m	90m	50m	70 m/s
	Obst	60m	40m	20m	80 m/s

Table 1: Effective Reception Range and Velocity.

Transmission Rate Selection: IoT deployments typically minimize the transmission rate to save power. However, we found that this may be difficult when performing aerial data collection with a UAS, since the flight time on consumer multi-copters as of spring 2019 is 1200 seconds per battery. As flight speed is directly related to successful data capture at a particular data transmission rate, multi-copter battery capacity constrains viable rates. Fixed-wing aircraft are also constrained as they have a minimum flight speed $> 10\text{m/s}$.

We flew the quad-copter at an average speed of 2.2m/s (5mph). On a single battery, the UAS could cover 2.6km at this speed. This is already a relatively small coverage area, when accounting for a round trip flight - approaching the lowest feasible flight speed for UAS-based data collection.

At our low flight speed, both 500ms and 1s inter-packet transmission rates produced similar RSSI and PRR values. However at slower rates we received too few packets for a meaningful analysis. At one packet per 15 seconds we received an average of only 258 packets per transmitter-receiver pair across all locations, altitudes, and repeated trials. For one packet per minute the average per transmitter-receiver pair was only 127 packets. Given the experimental results, it is difficult to determine the max flight speed that will guarantee delivery at low transmission rates as the data is sparse and collection is limited by battery capacity.

To estimate a rough upper bound for the max flight speed that guarantees delivery of at least one packet, on a flight path that takes the UAS directly over a transmitter, we propose the formula below. We use our ERR_N metric (that gives a minimum PRR $> N\%$ across the range).

$$\text{Max Flight Speed} = \max_{1 < N \leq 100} \left(\frac{2 * ERR_N * N}{\text{Transmission Rate} * 100} \right)$$

This does not account for signal characteristics that may degrade from increased speed, such as Doppler shift in the signal or increased EM emissions from the motors. Additionally, in practice a UAS is unlikely to fly directly over all transmitters, and would instead graze only a portion of the coverage area.

We provide the upper bound of speeds for one packet per second transmission rate in the last column of Table 1. The reader can estimate other transmission rates by dividing this number by their hypothetical rate. Traditional IoT deployment transmission rates typically exceed one packet per minute and may be unserviceable for aerial collection using current battery technology.

Optimal Antenna Orientation: Previous work is based on the idea that radiation patterns cause antenna orientations to affect signal quality. In our work, the antenna orientation of the *transmitter* did not significantly impact performance, while the orientation of the *receiver* had a far greater impact, with the vertically mounted receiver performing substantially worse than the horizontally mounted one. In our case, this may indicate that signal radiation is a smaller factor than minor fluctuations in line-of-sight. Unlike past experiments that employed a 2.8cm straight wire as an antenna for a 802.15.4 2.4GHz CC2420 transmitter [15], our setup employed a coiled embedded antenna directly on the comparatively smaller XBee.

While [15] studied distances of < 10m, our work includes signals at distances > 250m where the topography and antenna's geometry might reduce impact of orientation. The better performance of the receiver could be due to the superior line of sight to a flat mounted receiver. The *horizontal receiver* was parallel to ground at all times, while the *vertical receiver's* own body may have blocked the signal from unfavorable angles.

A further consideration for transmitter orientation is that aerial networks might serve as auxiliary modes of connection to on-the-ground infrastructure. In this case, ground transmitters would be best tailored to communicate with one another without taking communication with the UAS into account.

Elevating Transmitters: In IoT deployments where elevating the 802.15.4 radio is possible, it is advisable to do so. While the *elevated transmitter* had a very similar RSSI performance to the *horizontal transmitter* on the ground, the PRR of the elevated transmitter was much improved, especially for lower UAS altitudes. The transmitter seems to clear much of the ground-level obstruction and attain better line of sight to the UAS when elevated just half a meter above the ground in our scenario. The optimal height for a transmitter may depend on the network topography.

Obstruction: Sensor nodes are frequently deployed in the field with little protection from extreme weather. Nodes and antennas can be affected by various obstructions, including dirt from rain or wind. While we find that obstruction minimally affects reported RSSI, it has a significant impact on PRR.

Communication with buried sensors is possible at a high loss rate. However, most packets are lost at greater distances, wasting transmission power. If the IoT device relies on solar power, which may likewise become obstructed, this exacerbates the issue.

Future Work: As part of future work we would like to examine performance of aerial collection using 802.15.4 in other environments, such as urban IoT networks, and for other models of sensors, including those with external mono-pole antennas. Additionally, we would like to run more tests with varying types of obstruction, for example metal objects such as those that may cover sensors in a disaster. We hope to apply these efforts to better understand the applicability of UAS networks for post-disaster recovery in a more urban environment.

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