

# CS526 - LoRa/LoRaWAN Performance Evaluation

Annie Wu, Callisto Hess, Gregory Maldonado

January 26, 2025

## 1 Background

We evaluated LoRa/LoRaWAN performance around the Binghamton University campus to measure parameters that could potentially affect signal quality, like distance (from the receiver gateway), elevation, motion, and obstruction. We were motivated largely by recent natural disasters like the floods in Spain and aftermath of hurricane Helene in Asheville, which left hundreds of thousands without access to communications infrastructure. A LoRa network could serve as a cheap, resilient, emergency communication network for disaster recovery efforts. Several projects are being developed atop the LoRa network protocol, such as [Meshtastic](#)[1] and [The Clusterduck Protocol](#)[2]. The former supports a decentralized mesh network, and the latter a more traditional architecture with a primary gateway which the nodes communicate with. Of important note is that the system will always be limited by the underlying LoRa protocol, hence our investigation.

## 2 Data Collection

We used the Heltec LoRa 32 V3 board with a Nuand Tri-Band antenna and tried to connect to the Engineering Building LoRaWAN gateway around campus under various conditions. To manage our sessions with The Things Network, we deployed automation with Python which connected to the The Things Network (TTN) MQTT broker and subscribed to all messages from the class TTN app. See [Figure 1](#) for the callback function which handled the parsing and decoding of all incoming messages. This system automated the connection attempt process and allowed us to retrieve signal quality data from TTN after a field session. We attempted to connect to the gateway at 26 different static locations around Binghamton University's campus, and also while driving at different speeds. See [Figure 2](#) for locations and approximate connection strengths. When making a connection attempt, we recorded information like GPS coordinates, elevation (in feet), and other data which ended up not being explored in our investigation like temperature or whether we were in/out doors. All sessions were managed by our platform connection automation, and our full session management implementation can be found in our [GitHub repository](#)[3].

## 3 Data Processing

### 3.1 Data Retrieval

After making connections around campus under different conditions, we processed the results to determine if factors such as distance, elevation, or motion had an effect on the quality or strength of the signal received by the Engineering Building gateway. Thus, we divided our results into static (measurement of the effect of distance and elevation on RSSI and SNR) and mobile (measurement of the effect of speed on RSSI and SNR) sections. We retrieved our connection data from TTN with our automation and matched it with our recorded data such as distance and speed. For many of the locations where we successfully connected to the gateway, we averaged the results of several successful packet exchanges to reduce the effects of outliers. See [Table 1](#) for an example of averaged data.

```

40     # Callback function to handle incoming MQTT messages
41     def on_message(client: mqtt.Client, userdata, message):
42         global decoder
43
44         # Timestamp on reception.
45         current_date = datetime.now()
46
47         # Handle TTN packet format.
48         message_str = message.payload.decode("utf-8")
49         message_json = json.loads(message_str)
50         encoded_payload = message_json["uplink_message"]["frm_payload"]
51         raw_payload = base64.b64decode(encoded_payload)
52
53         if len(raw_payload) == 0:
54             # Nothing we can do with an empty payload.
55             return
56
57         preamble = raw_payload[:4]
58         remaining_payload = raw_payload[4:]
59
60         if str(preamble.decode()) == 'ACG1':
61             try:
62                 message = decoder(remaining_payload)
63             except Exception as e:
64                 print(e)
65                 print("payload: {}".format(remaining_payload))
66                 return
67
68             if message:
69                 print(f'[{current_date}] payload="{message}"')
70
71                 with open(f'logs/{datetime.now().strftime("%Y-%m-%d")}.log', 'a') as fp:
72                     fp.write(f'[{datetime.now()}] payload="{message}"\n')
73

```

Figure 1: Function handling data transmission from TTN.

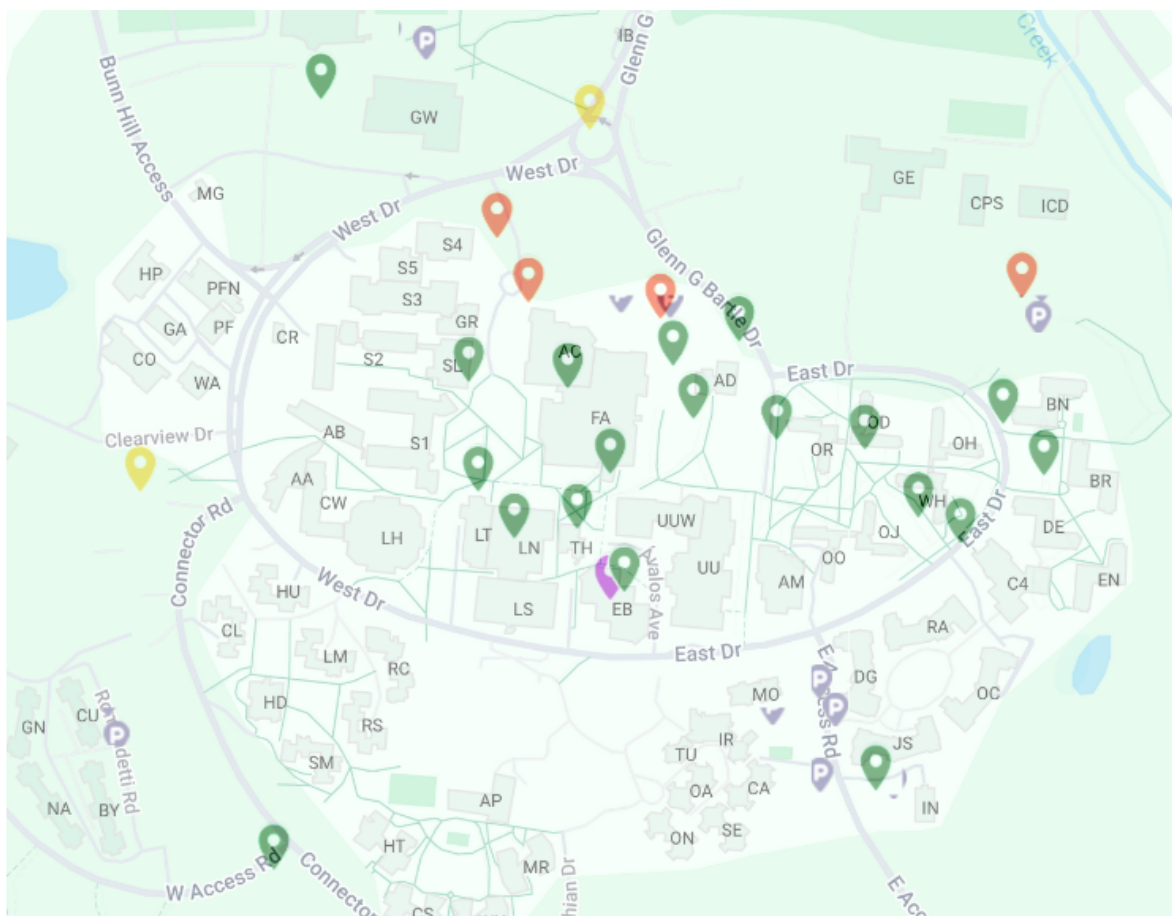


Figure 2: Transmission locations. Green=Reliable, Yellow=Unreliable, Red=None.

Latitude	Longitude	Building	Avg RSSI	Avg SNR	Elevation (ft)
42.087478	-75.967872	EB	-77.75	9.25	961.3
42.088092	-75.968496	Tech Hub	-82	9.5	961.3
42.087995	-75.969369	Bartle Library	-99.17	0.33	988.5
42.088456	-75.96985	Library Tower	-72.93	7.64	988.5
42.089551	-75.969992	Science Library	-85.25	0.5	933
42.090961	-75.969599	Lot C			904
42.090329	-75.96917	Anderson (SL)			912
42.089485	-75.968638	Anderson (FA)	-99	-10.75	927
42.088631	-75.968052	Fine Art	-87.71	6.29	951
42.089179	-75.966916	Lot AD	-64	9.33	929.9
42.089708	-75.967197	Lot A	-63	9.67	930.8
42.090172	-75.967363	Parking Garage			913
42.089935	-75.966303	University Police	-78.33	4.33	915.6
42.088964	-75.965789	Lot B	-80.5	5	926
42.088877	-75.964581	Old Digman Hall	-78.33	9	950
42.088212	-75.963845	Whitney Hall	-73.67	9	943
42.088616	-75.962138	Broome Hall	-91.4	5	943
42.089132	-75.962696	Bingham Hall	-89.25	7.5	935
42.087954	-75.96327	C4	-66	10	956
42.08846	-75.974472	Lot M5	-86.33	4.67	981
42.092326	-75.972001	Event Center	-80.67	7	925
42.092022	-75.968328	Traffic Circle	-84	4	887.2
42.090373	-75.96244	Lot S2			808.5
42.085517	-75.964436	Harpur's Ferry	-91.33	2.33	956.6
42.084733	-75.972638	Nature Preserve	-94	-4.89	1038

Table 1: Consolidated static transmission data from connection attempts.

## 4 Data Analysis

After collecting our data in easy-to-parse formats, we calculated the Pearson correlation coefficients using [Scipy](#)[4] for different independent variables to determine what did or did not affect signal strength and quality received by the Engineering building gateway. An example of our calculation code can be found in [/lora-binghamton/main/python/plot\\_distance\\_elevation.py](#)[5]. We then processed our data with python and plotted our results using a combination of Matplotlib and Google Sheets graphing functionality to display our data in meaningful ways.

### 4.1 Elevation and Distance

Figure 3 shows our findings in evaluating how Elevation and Distance affect signal quality, measured by RSSI and SNR. First, we calculated absolute distance from the gateway's latitude and longitude coordinates using a haversine distance [function](#)[6]. We then calculated Pearson correlation coefficients of -0.117 for Distance vs RSSI, -0.089 for Distance vs SNR, -0.251 for Elevation vs RSSI, and -0.184 for Elevation vs SNR. These values are not statistically significant but we can observe a negative trend among them, which aligns with intuition regarding how radio signals decrease in quality and strength over distance. This lack of statistically significant findings could simply indicate that we need to collect data with larger distance and elevation differences. We were, however, impressed by the quality of signal from the Nature Preserve (this data point appears as the furthest right dot on all four graphs of Figure 3). We hypothesize that this may have been due in part to a clear line of sight from transmitter to receiver.

### 4.2 Number of buildings

Figure 4 shows our findings for how physically obstacles affect signal quality, measured by RSSI and SNR. In our testing, we used the approximate "number of buildings" in the path of the signal. While this measurement is an over-simplification - assuming all buildings have the same dimensions and

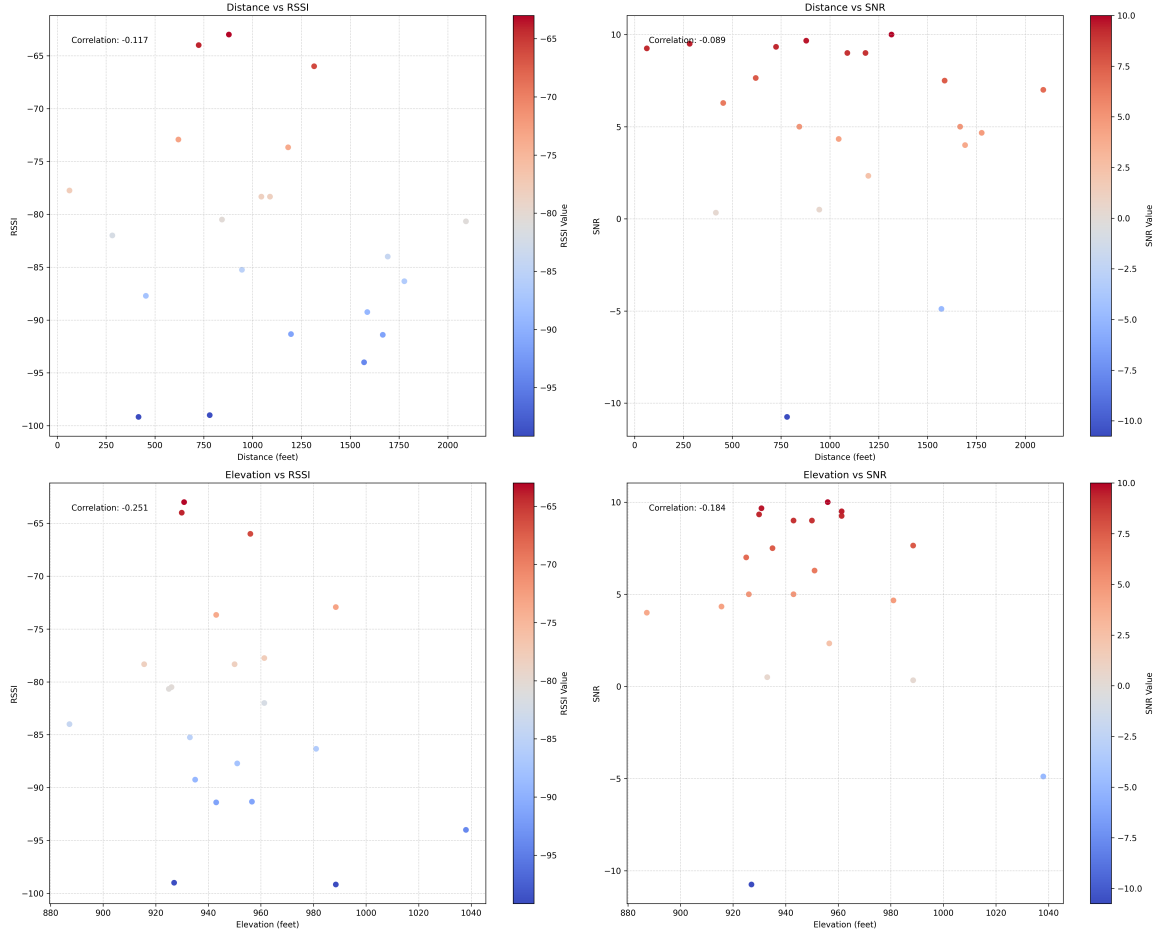


Figure 3: Elevation and Distance effects on RSSI and SNR.

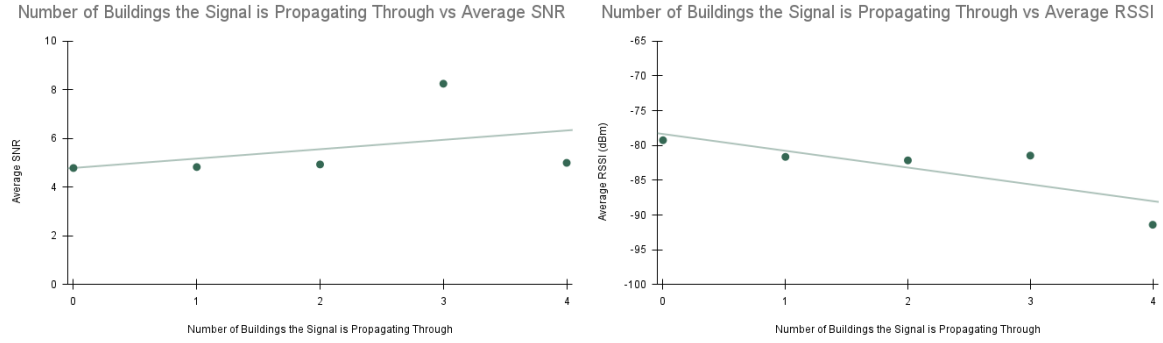


Figure 4: Effect of obstructing buildings on signal quality.

composed of the same material - it allows us to have a general idea of path loss for a LoRa signal. We can observe a positive trend among the "number of buildings" and the signal's RSSI value. This is expected behavior, as the "number of buildings" the signal has to propagate through, the weaker the signal will be once it has been received by the gateway. In addition, we observed a positive trend among the "number of buildings" and signal-to-noise ratio received by the gateway. While there could be many factors to attribute to this positive trend, we believe its a combination of the small sample size, ranging values of external noise across the campus, and path loss assumptions. However, we can conclude with our findings, that LoRa can still perform reliably even with noisy infrastructure in the signal's path.

### 4.3 Motion

To evaluate the performance of LoRa communication under motion, data was collected using a GPS tracking application [7] during a hiking activity, with the LoRa device connected to TTN. The GPS application logged positional data, while LoRa telemetry data, including RSSI, SNR, and Received Time, was retrieved through the TTN API. Custom Python scripts (`ttAPI.py` and `parsingJSON.py`) were developed to parse JSON data from TTN, allowing extraction of additional parameters such as Frequency and Airtime. Data synchronization was performed by mapping GPS timestamps with LoRa telemetry data, accounting for a time bias of approximately 0.003 seconds to minimize mismatches caused by asynchronous data collection. Missing or unsynchronized data points were supplemented from the JSON files to ensure comprehensive analysis. The final processed dataset enabled the calculation and visualization of key performance metrics, as shown in Figures 5 and 6.

To address the occurrences of longer airtime, the relationship between airtime and spreading factor (SF) was analyzed. Out of 215 data points, 203 points used SF=7, while only 12 points used SF=9, indicating that higher spreading factors are rarely utilized. This suggests that only difficult environmental conditions, such as weak signals or high interference, necessitate the use of higher SF. As expected, higher SF values lead to longer airtime, as the increased spreading factor spreads the data across more chirps, improving the chances of successful transmission under challenging conditions.

## 5 Conclusion & Findings

We cannot say definitively that Elevation, Distance, or Speed independently affect LoRa signal quality through degrading RSSI or SNR values. Despite this, we did observe negative trends in considering the effects of Elevation and Distance on signal, which we would expect to hold with the inclusion of more data. Simply expanding the locations to further around campus and the greater Binghamton/Vestal area could be enough to draw more statistically significant conclusions. As far as Speed is concerned, our results were also inconclusive. Puzzlingly, the correlation coefficients of RSSI vs Speed and SNR vs Speed are positive and negative, respectively. This also indicates that we simply do not have enough data to locate strong trends. A confounding factor here may be found in interference around campus through buildings or other wireless signals. An interesting way to remove these factors would be to

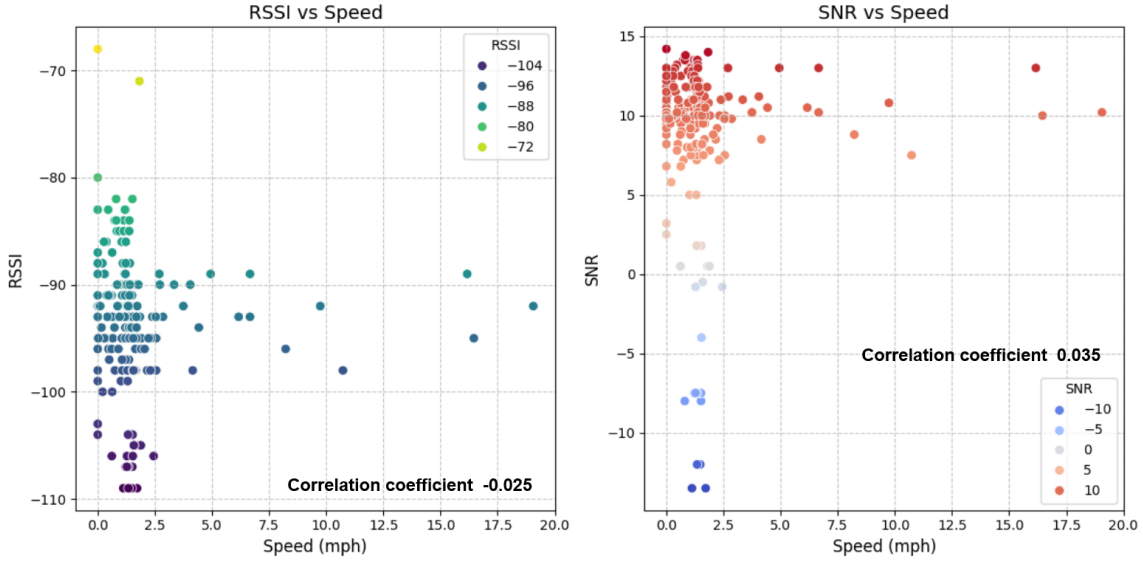


Figure 5: Effect of speeds on signal quality. The analysis shows that speed has minimal correlation with signal strength (RSSI) and signal quality (SNR), with correlation coefficients of  $-0.025$  for RSSI vs Speed and  $0.035$  for SNR vs Speed. This indicates that motion has little impact on LoRa performance in the tested conditions.

attach a transmitter to a drone and fly it in straight lines towards the gateway at different speeds. This would isolate speed as the only independent variable being measured. We did find an approximately linear relationship in evaluating the quantity of buildings between transmitter and receiver, and signal degradation. This follows intuition, and bodes poorly for deploying LoRa disaster recovery systems in urban environments, but does not rule out rural environments where it may be arguably more helpful in saving lives.

## References

- [1] Meshtastic. (2024) Meshtastic: Open-source mesh network for long-range communication. Accessed: 2024-12-05. [Online]. Available: <https://meshtastic.org/>
- [2] C. Protocol. (2024) Clusterduck protocol: A decentralized communication protocol. Accessed: 2024-12-05. [Online]. Available: <https://clusterduckprotocol.org/>
- [3] GMaldona, “Lora binghamton - ttn mqtt,” 2024, accessed: 2024-12-05. [Online]. Available: <https://github.com/gmaldona/lora-binghamton/tree/main/python/ttn-mqtt>
- [4] Scipy Documentation, “Scipy - Pearson Correlation Computation,” <https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pearsonr.html>, accessed: 2024-12-05.
- [5] callistoh, “Lora binghamton - plot distance elevation script,” 2024, accessed: 2024-12-05. [Online]. Available: [https://github.com/gmaldona/lora-binghamton/blob/main/python/plot\\_distance\\_elevation.py](https://github.com/gmaldona/lora-binghamton/blob/main/python/plot_distance_elevation.py)
- [6] StackOverflow Community, “Haversine Distance Function - Python Code,” <https://stackoverflow.com/a/4913653>, accessed: 2024-12-05.
- [7] GPS Tracks App, “GPS Tracks,” accessed: 2024-12-05. [Online]. Available: <https://apps.apple.com/app/id425589565>

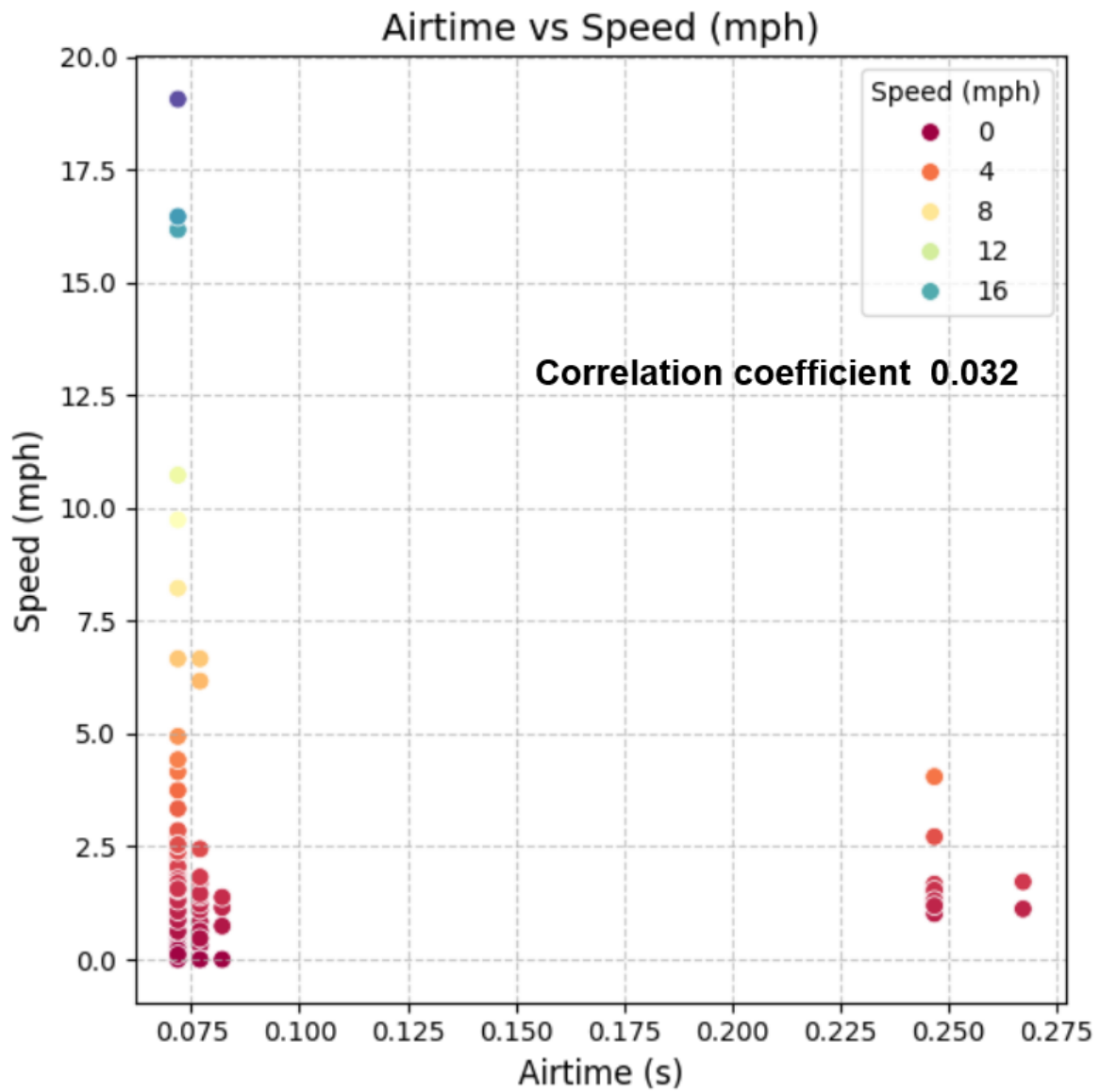


Figure 6: Effect of speeds on airtime. Correlation coefficient: Airtime vs Speed = 0.032, showing minimal impact of speed on airtime.



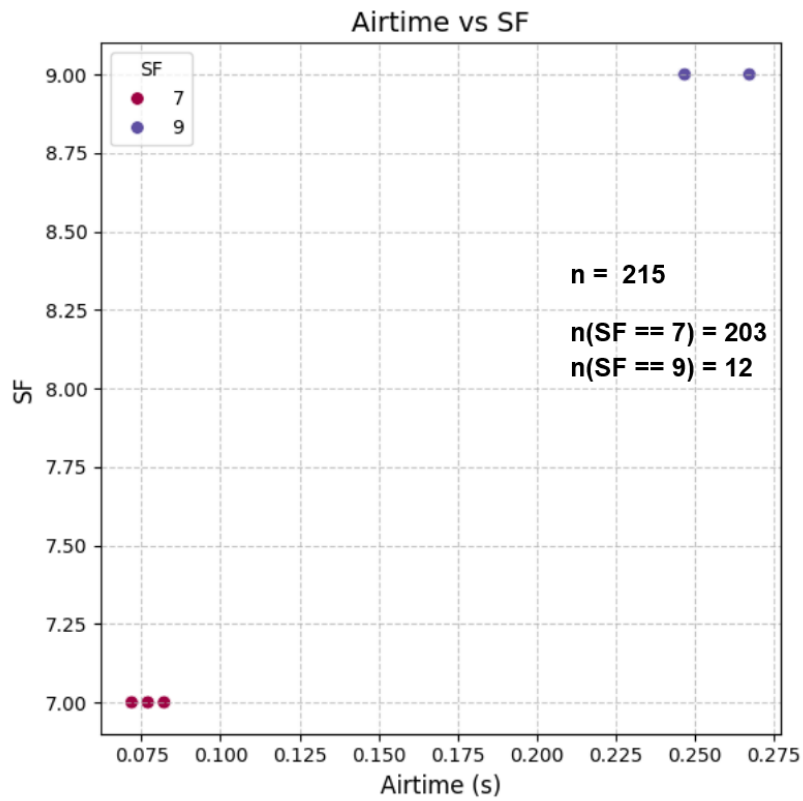


Figure 7: Relationship between airtime and spreading factor. SF=7 accounts for the majority of transmissions (203 points), while SF=9 appears in challenging conditions, leading to significantly longer airtime.