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***Abstract*—Localization has gained great attention in recent years, where different technologies have been utilized to achieve high positioning accuracy. Fingerprinting is a common technique for indoor positioning using short-range radio frequency (RF) technologies such as Bluetooth Low Energy (BLE). In this paper, we investigate the suitability of LoRa (Long Range) technology to implement a positioning system using received signal strength indicator (RSSI) fingerprinting. We test in real line-of-sight (LOS) and non-LOS (NLOS) environments to determine appropriate LoRa packet specifications for an accurate RSSI-to-distance mapping function. To further improve the positioning accuracy, we consider the environmental context. Extensive experiments are conducted to examine the performance of LoRa at different spreading factors. We analyze the path loss exponent and the standard deviation of shadowing in each environment.**

***Index Terms*—Curve fitting, LoRa, path loss, positioning, RSSI fingerprinting, spreading factor**

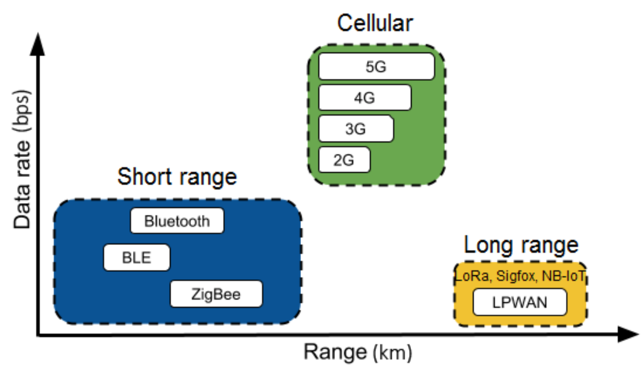

Fig. 1. Range and data rate of different communication technologies

I. Introduction

The fourth industrial revolution is anticipated to depend heavily on the Internet-of-Things (IoT) networks with billions of interconnected devices, where the number is expected to increase exponentially with time. With the era of smart devices comes the need of power efficient, low-cost, long-range and reliable communication technologies. IoT is being explored for scalability and versatility using multi hop networks in industrial processes control [1] [2]. Low power wide area networks (LPWANs) provide the power efficient and long-range solution to the question of IoT scalability. Recent applications in location based services (LBS) have stimulated extensive research on wireless localization [3] and have also accelerated research in the area of activity detection [4]. LBS is now becoming one of the standard features in mobile devices. Among all the localization technologies, wireless received signal strength indicator (RSSI) fingerprinting has proven as an effective ranging technique due to its simplicity and deployment practicability [5]. Fingerprinting based localization avoids hardware deployment cost and effort by relying on existing network infrastructure [6]. RSSI fingerprinting uses the received signal strength to estimate the Euclidean distance between the transmitter and itself; the receiver. This distance can then be used in trilateration algorithms to position the transmitter. Since global navigation satellite system (GNSS) relies on an unobstructed connection between the receiver and the satellite, it has proved unsuitable for indoor navigation. GNSS and allied technologies are power inefficient and weather sensitive; hence, LPWANs present an interesting opportunity in the field of GPS-free positioning systems featuring low power and robust communication channels. LPWAN is a type of wireless communication, which sends small data packets over long distances operating on a battery. They have been specifically designed for the IoT industry. The term LPWAN signifies three characteristics:

1) Low power consumption
2) Wide area coverage
3) Cellular-like infrastructure for Internet connectivity

Fig. 1 briefs on the range versus data rate of different communication technologies. The bandwidth of LoRa is extremely small, but provides an extremely long range, sometimes crossing the traditional 3G/4G cellular networks. Moreover, LPWANs have lower data rates than Bluetooth and ZigBee, and outperform both of them in range.

GPS independent positioning systems are an exciting field of work. Location techniques commonly use GPS, Bluetooth, or radio frequency identication (RFID) technologies [7]. A disadvantage of GPS is that the satellite signals are blocked by obstacles, in addition, variations in weather results in approximations with errors of meters, so it is not possible to use this system as a method for indoor location [8]. RSSI fingerprinting has been implemented using Bluetooth low energy (BLE) systems on a large scale. However, Bluetooth technology has limited coverage and this communication is focused on very short distances to achieve the location.

LPWANs provide a middle ground between GNSS and BLE positioning systems. Unlike BLE systems, they have a range of kilometers and enable outdoor localization. On the other hand, unlike GPS, LPWANs work indoors without a direct line-of-sight with the transmission satellites. LPWANs not only increase the range but also allow for reliable positioning both in indoor and outdoor environments due to their low frequency band and consequently less signal attenuation. The RSSI-to-distance mapping is a suitable alternative to construct a robust, deployment based positioning system due to its dependence on the environment of operation. Since LoRa networks are expensive to set up, extensive planning is necessary before their deployment. Therefore, in this paper we present a comprehensive analysis of RSSI fingerprinting using LoRa networks for both indoor and outdoor locations. More specifically, we obtain the patterns of received power on a LoRa gateway at various distances from its transmitting end-device and model the large-scale path loss characteristics from the readings. Using a log-distance path loss model, we evaluate the path loss exponent (PLE) of various environments. Furthermore, we also characterize the standard deviation of shadowing for different environments. The study is, therefore, a pre-cursor to make positioning/localization systems using the LoRaWAN technology.

The rest of the paper is organized as follows. In Section II, we briefly describe characteristics of LoRa technology. Section III provides the details of data collection. Section IV presents the analytical details followed by the outdoor and indoor analysis. We conclude the paper by profiling our environment using path loss exponent and standard deviation of shadowing.

II. LoRa Technology

A. Characteristics of LoRa Technology

The LoRa protocol works on three completely different frequency bands: 867–869MHz, 902–928 MHz and 430–510 MHz. The bandwidth of LoRa in all scenarios can either be 125 kHz, 250 kHz or 500 kHz [9]. LoRa uses chirp signals to modulate information. A chirp is a tone in which frequency changes with time. Fig. 2 shows chirps; the solid lines represent an up-chirp whereas the dotted lines represent a down-chirp.

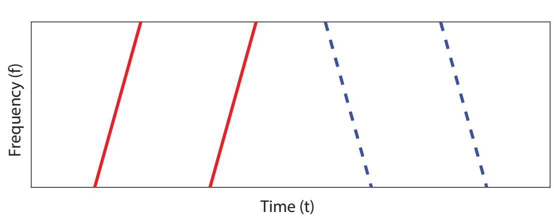

Fig. 2. Chirp spread spectrum of LoRa technology.

The chirps in LoRa modulation are cyclic and the frequency jumps determine how data is encoded. A symbol represents one or more bits of data. If the symbol has a spreading factor of 7, it carries 7 bits and the values can range from 0-127. These divisions of frequency are called chips. The chips/s are defined by the bandwidth. For a bandwidth of 125 kHz, we can transfer 125000 chips/s. The symbol rate can be calculated as

$$Rs = \frac{BW}{2^{SF}} = \frac{Rc}{2^{SF}} \quad [\text{symbols}/s], \tag{1}$$

where BW is the bandwidth, R_c is the chip rate and SF is the spreading factor, as shown in [10]. The time-on-air is directly affected by the spreading factor. A larger spreading factor signifies a higher symbol duration (or in other words, more raw bits) and more time-on-air [11], hence mapping a larger physical range. This relation of SF and signal range has direct implications on the RSSI to distance mapping.

B. Limitations of LoRa Technology

The LoRa technology has limited support for real-time applications. The long range of LoRa comes at the price of a low data rate of 27 kbps [12]. LoRa imposes a 1% duty cycle, which causes long intervals between consecutive packet transmissions. This is a problem inherent to most of the sub-bands used by LoRa, hence, it will not likely be suitable for applications that require frequent, real-time, location information [13].

III. Data Collection Setup

Our data collection setup consists of a gateway and an end device (ED) as shown in Fig. 3. We use Dragino LG01 LoRa Gateway [14] while the ED is a LoRa wireless transceiver shield attached to an Arduino Uno development board. The gateway receives LoRa modulated packets from the ED on 433 MHz frequency band. We use 2.5 dBi antennas for signal transmission and reception.

The ED is programmed to send one LoRa modulated packet periodically. The LG01 Gateway is connected through a LAN (local area network) cable to a processing unit. This creates a network port between our processing machine (i.e., a personal computer, PC) and the gateway. The PC uses Python with the `paramiko` library to open a Secure Shell (SSH) tunnel with the gateway, which is used to telnet the gateway at its local IP address. The PC then uses `openpyxl` to log the collected RSSI readings in a file.

For RSSI fingerprinting in LOS conditions, we selected an open real-life environment in order to avoid reflections from any surrounding structures. A 3D view of the environment chosen for the collection of outdoor LOS data can be seen in Fig. 4. We collected RSSI data up to a distance of 25 m in an open-air LOS setting. Data is collected in 21 constant incremental steps from 1 m to 25 m. These readings are then concatenated to form a large dataset of 35,280 readings of 126 (21 increments x 6 SFs) different combinations.

We employed a similar setup and procedure to collect NLOS indoor data for 18 instances of distance in four different environments at SF7. The four considered environments are the ground floor (floor 0), floor 1, floor 2 and floor 3 of the building with varying propagation conditions. The data collected from each environment is then concatenated to form a dataset of 16,811 readings of 72 different combinations. A 3D model of the NLOS data collection site is shown in Fig. 5.

IV. Data Analysis

Mostly the radio propagation models are developed using a combination of analytical and empirical techniques. In this study, we employ curve fitting to estimate a model for RSSI to distance mapping. This approach offers the advantage of accounting various factors implicitly that may be known or unknown, and can be tested by collecting new data in different environments.

The received power P_r in dBm over a wireless link between a transmitter and a receiver is generally given by

$$P_r = P_t - L, \tag{2}$$

where P_t is the transmission power (dBm) and L is the path loss described as

$$L = 10n \log_{10} d + \beta, \tag{3}$$

where d is the distance between the transmitter and the receiver, and n is the path loss exponent (PLE). The parameter β is the fixed path loss. A correct choice of the free space reference distance is necessary for the propagation environment. We selected a reference distance (d_0) of 10 m, which is appropriate for micro-cellular systems [15]. The path loss can be represented as

$$\mathrm{PL(dB)} = \mathrm{PL}(d_0) + 10n \log_{10}\left(\frac{d}{d_0}\right), \tag{4}$$

where PL represents the path loss (dB), PL(d_0) represents the path loss at 10 m. The reference path loss calculated through d_0, combined with n provides the path loss for the distance d.

After finding path loss from (4), we use equation (2) to calculate the received power P_r. The transmission power is -19 dBm at the ED during data collection. RSSI fingerprinting requires a probabilistic map of received power to the transmitter-receiver (T-R) distance. To calculate the probability

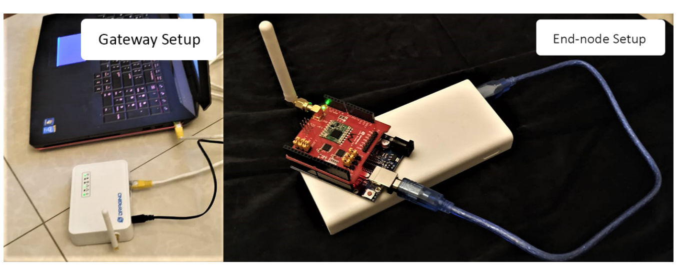

Fig. 3. Data collection setup using Dragino LG01 LoRa Gateway and LoRa ED transceiver.

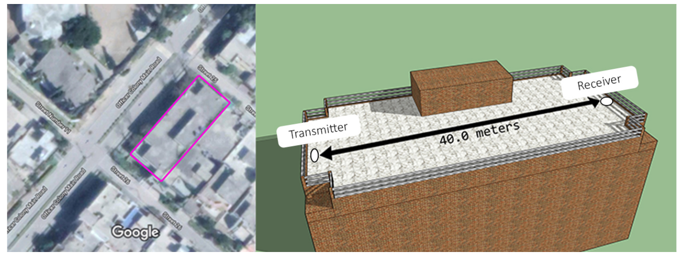

Fig. 4. Outdoor LOS data collection site

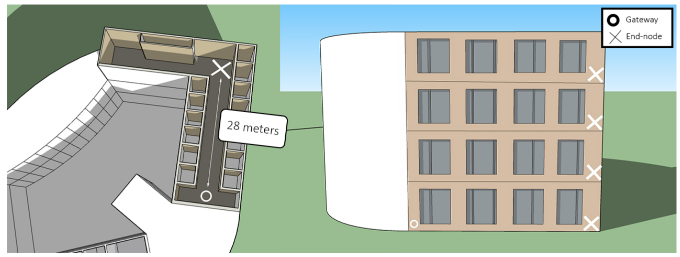

Fig. 5. A 3D view of NLOS indoor data collection site.

of obtaining a particular RSSI (dBm) at a fixed T-R distance, we use

$$Pr\left[P_r(d) < \gamma\right] = Q\left(\frac{\overline{P_r(d)} - \gamma}{\sigma}\right) \tag{5}$$

where $Q(\cdot)$ is the Gaussian Q-function defined as

$$Q(z) = \frac{1}{2}\left[1 - \mathrm{erf}\left(\frac{z}{\sqrt{2}}\right)\right] \tag{6}$$

As shown in [15]. Eq. (5) determines the probability that the received signal power remains below a certain threshold γ (dBm). This probability is used to estimate the RSSI that will be achievable in a given setup. As the path loss varies with environment, hence this probability also varies across different channel propagation conditions. We use equations (5) and (6) to analyze the path loss exponent and standard deviation of shadowing at the outdoor LOS and indoor NLOS environments.

A. Outdoor Data Analysis

We performed logarithmic curve fitting on the RSSI data to determine RSSI to distance mapping for different SFs. Fig. 6 shows distance vs RSSI curves, which are obtained using numerical curve fitting. It is observed that, at a given distance, the RSSI obtained at SF7 is more than that of SF12. This shows that, for the same distance, SF7 can map more RSSI values as compared to the other SFs.

In the outdoor LOS environment, the values of the slope (i.e., PLE) and the root mean square error (RMSE) at different spreading factors are given in Table I. It can be seen that the PLE for SF7 is approximately 2.4 while it is higher for other SFs. The RMSE provides the standard deviation of shadowing, which is the lowest for SF7. It implies that SF7 is less likely to be affected by the environmental shadowing

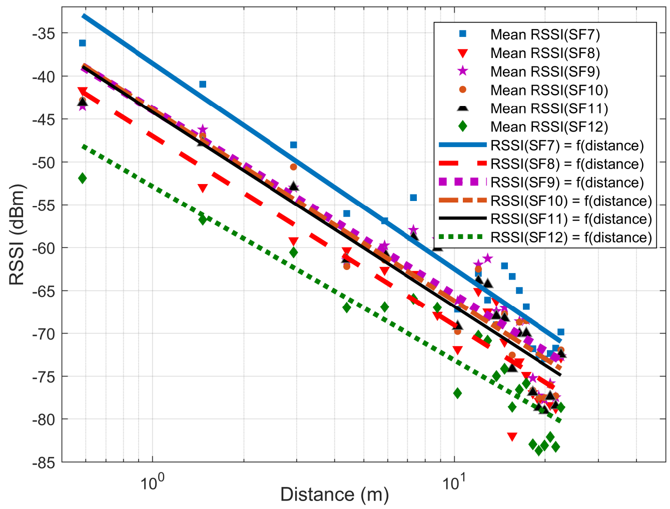

Fig. 6. The variation of mean RSSI with distance at different SFs for outdoor LOS environment.

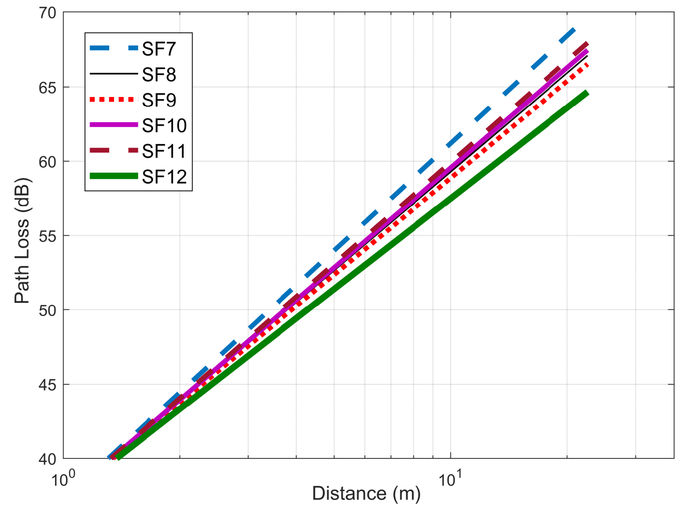

Fig. 7. The variation of path loss with distance for different SFs for outdoor LOS environment.

TABLE I
OUTDOOR PATH LOSS AND STANDARD DEVIATION OF SHADOWING FOR DIFFERENT SFS

SF	Path loss exponent	RMSE (dB)
7	2.397	3.055
8	2.206	3.490
9	2.164	3.888
10	2.233	3.805
11	2.269	3.881
12	2.027	3.344

than the other SFs. Therefore, we will use SF7 to profile the indoor environments in the next subsection.

The variation in path loss at different spreading factors with respect to distance is shown in Fig. 7. The results prove that the SF7 experiences more path loss than other SFs, and consequently, has a shorter range than SF8 to SF12. The RSSI-to-distance function maps a particular RSSI value (dBm) to a range of distances. Since SF7 provides a lower range than other SFs, it maps more RSSI values to a smaller range of distances, hence creating a one-to-some mapping as compared to SF12's one-to-many RSSI-to-distance mapping. This sensitivity provides the most precise RSSI-to-distance maps. Because of its higher range, SF12 experiences the least path loss during propagation.

The probability that the RSSI falls below a certain threshold is shown in the cumulative distribution function (CDF) of Fig. 8. It shows that the probability of an SF7 signal to go below -85 dBm is negligible. Hence, at a distance of 12.8 m, SF7 will always provide a signal strength above -83 dBm. This shows that SF7 maps more RSSI values to the same range of distances than SF8 to SF12. This accurate mapping is achieved at the cost of a smaller range of distances as SF7 pans less area than SF12.

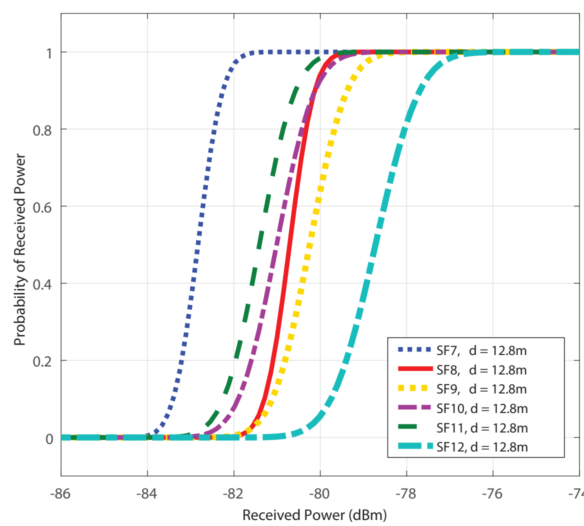

Fig. 8. The cumulative distribution function (CDF) showing the probability of outdoor LOS RSSI at different SFs.

It can be seen in Table II that the spreading factor of 7 provides the best resolution on the training set, equal to 3.928 meters.

TABLE II
ACCURACY OF RSSI TO DISTANCE MAPPING FOR DIFFERENT SFS IN OUTDOOR LOS ENVIRONMENTS

SF	Resolution (m)
7	3.928
8	6.332
9	6.950
10	5.920
11	6.356
12	6.087

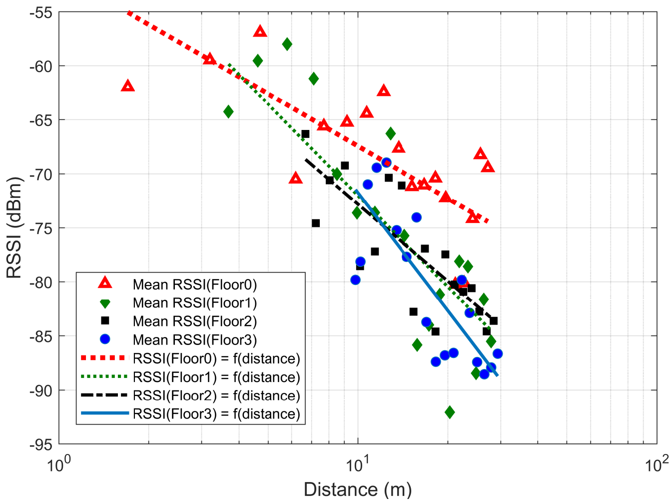

Fig. 9. The variation of mean NLOS RSSI between floors of a building.

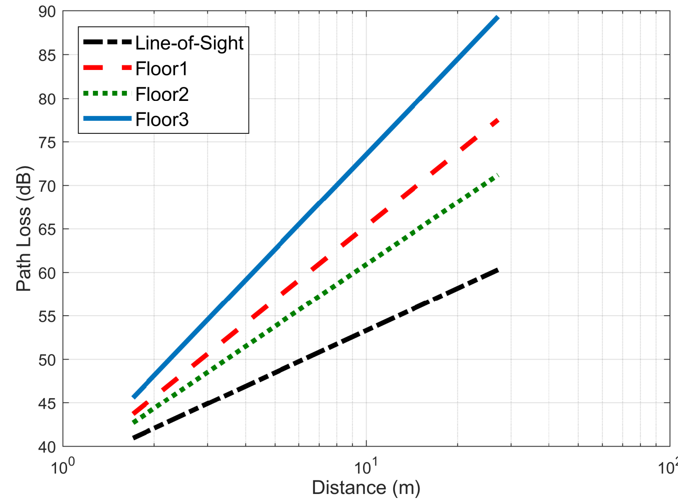

Fig. 10. The variation of indoor NLOS path loss between floors of a building.

B. Indoor Data Analysis

Fig. 9 shows the variation of RSSI at different floors of a building. The RSSI values are higher at the ground floor than that of floors 1, 2 and 3. Floor 1 and 2 show anomalous behaviour due to diffraction and superposition of waves.The standard deviation of shadowing at each floor is provided by the RMSE, which is given in the Table III.

TABLE III
STANDARD DEVIATION OF SHADOWING FOR DIFFERENT FLOORS IN INDOOR NLOS ENVIRONMENTS

Floor	Path loss Exponent	RMSE (dB)
Ground	1.609	4.624
1^{st}	2.809	5.409
2^{nd}	2.369	3.563
3^{rd}	3.632	4.416

How path loss varies in NLOS conditions with distance at each floor can be seen in Fig. 10. LOS path loss is also shown to highlight that LOS has the least slope or the lowest PLE.The path loss exponent of ground floor can be explained by the tunnel effect of indoor LOS environments. Tunnels act as waveguides and provide a path loss exponent between 1.6 to 1.8 [15] .The path loss experienced by floor 2 is less than that of floor 1 due to the effects of superposition. Diffraction of waves from two walls (floor 1 and floor 2) cause them to superimpose at the receiver and provide a higher RSSI.

It can be seen in Table IV that the best resolution has been achieved on floor 3 as compared to the other floors. It evidences that the distance measurement is accurate up to 4.550 meters.

The probability that the received signal level will be below γ at different floors is shown in Fig. 11. It shows that the probability of an SF7 signal at floor 3 to go below -180 dBm is zero. Hence, at a distance of 20m, floor 0 would give an

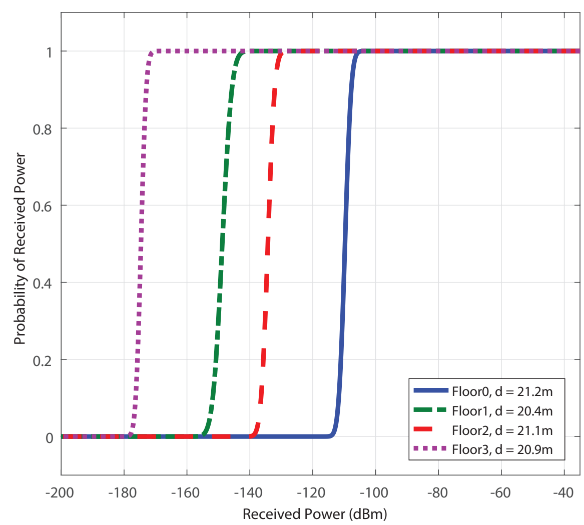

Fig. 11. The cumulative distribution function (CDF) showing the probability of indoor NLOS RSSI at different floors

TABLE IV
ACCURACY OF NLOS RSSI TO DISTANCE MAPPING AT DIFFERENT FLOORS

SF	Resolution (m)
Ground	22.969
1^{st}	6.837
2^{nd}	5.189
3^{rd}	4.550

RSSI of -108 dBm whereas floor 3 would will always provide a signal strength above -175 dBm.

The non-overlapping slopes of the CDF suggest that LoRa could be used in indoor NLOS localization, by using machine learning to predict the number of obstacles between the user and the receiver. By training the machine learning models to predict the number of obstacles between the transmitter and the receiver, and the T-R distance, we can create a robust localization system unique to the environment it is operating in. The positioning system deployed using LoRa technology would require a calibration-based deployment approach as the path loss varies with environments.

V. Conclusion

This paper aimed to analyze RSSI fingerprinting in LoRa networks. The method employed path loss for the estimation of the probability of RSSI to go below a certain value. This method provides a quantitative measure of estimating the probability of obtaining a range of RSSI at the receiver. We have extensively tested LoRa for NLOS localization and concluded that machine learning algorithms could use RSSI to predict the number of obstacles. Future work includes a thorough testing of LoRa communication using machine learning algorithms at different environments for the purpose of obstacle/ environmental profiling. The conclusions of this paper can be used alongside time difference of arrival (TDoA) localization to create a robust positioning system.

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