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RSSI-Based Indoor Localization With the Internet of Things

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ABSTRACT In the era of smart cities, there are a plethora of applications where the localization of indoor environments is important, from monitoring and tracking in smart buildings to proximity marketing and advertising in shopping malls. The success of these applications is based on the development of a cost-efficient and robust real-time system capable of accurately localizing objects. In most outdoor localization systems, global positioning system (GPS) is used due to its ease of implementation and accuracy up to five meters. However, due to the limited space that comes with performing localization of indoor environments and the large number of obstacles found indoors, GPS is not a suitable option. Hence, accurately and efficiently locating objects is a major challenge in indoor environments. Recent advancements in the Internet of Things (IoT) along with novel wireless technologies can alleviate the problem. Small-size and cost-efficient IoT devices which use wireless protocols can provide an attractive solution. In this paper, we compare four wireless technologies for indoor localization: Wi-Fi (IEEE 802.11n-2009 at the 2.4 GHz band), Bluetooth low energy, Zigbee, and long-range wide-area network. These technologies are compared in terms of localization accuracy and power consumption when IoT devices are used. The received signal strength indicator (RSSI) values from each modality were used and trilateration was performed for localization. The RSSI data set is available online. The experimental results can be used as an indicator in the selection of a wireless technology for an indoor localization system following application requirements.

INDEX TERMS Indoor localization accuracy, power consumption, Internet of Things, RSSI, WiFi, Bluetooth low energy, Zigbee, LoRaWAN.

I. INTRODUCTION

By integrating technological advancements into buildings, a significant amount of information can be delivered to those who inhabit them in order to improve their experience. Through the development of the Internet of Things (IoT), new low cost and energy efficient devices such as wearables and Bluetooth Low Energy (BLE) beacons have been developed. These devices are capable of communicating with the IoT to allow for smart buildings to poses a greater amount of control that could never have been achieved before [1], [2]. In IoT applications, it is imperative that sensor data should not only be obtained, the location of the sensor node inside of the building also needs to be known in order for the information produced to be useful [3]–[5]. If a centralized server is unaware of the device's positions, the information produced by those device becomes irrelevant and their limited resources are wasted. In order to increase efficiency and improve the experience of those who reside in smart buildings, it is imperative that all devices are able to efficiently determine their location in real-time with minimal knowledge of their surroundings. To determine a position, indoor localization is often performed.

Indoor localization is a system that is used to locate objects or devices inside an environment where Global Positioning System (GPS) cannot be used. GPS is often used in outdoor localization systems as it is the simplest method. However, it consumes a large amount of energy and can be expensive to implement for every node in a large network [6]. Due to a dependency on Line-of-Sight (LoS) between GPS satellites and receivers, GPS cannot be used indoors. Additionally, GPS only provides a maximum accuracy up to five meters [7]. This may be suitable outdoors, where there is plenty of space, but indoors this is not feasible due to limitations in the size of the environment. Therefore, when performing localization indoors, an accuracy of less than one meter is required for a proper localization system. Hence, other methods need to be used in order to determine a device's location [8]–[10].

Designing an indoor localization system has many uses in a variety of areas [11], [12]. Using indoor localization not only provides the added benefit of safety and security, but is also able to improve efficiency in the working environment. One example is in hospitals, where indoor localization can be used for tracking patients [13]. Doctors would be able to know exactly where a patient is located inside the building without needing to provide constant supervision. Another example is in emergency situations, where first responders could use indoor localization to help quickly guide them to anyone who is in distress without needing to know the exact layout of the building [14].

Due to the small size of a majority of IoT devices, their hardware is often quite limited. They contain low storage, minimal processing power, and very basic communication capabilities. Therefore, any localization algorithms that are used need to accommodate to the capabilities of these devices. In order for an indoor localization system to be successful, multiple targets will need to be tracked at once, while continuously updating when any targets are added, moved, or removed from the system.

Unfortunately, indoor localization suffers from a larger number of complications that are not present when performing localization outdoors. For instance, there are many more obstacles indoors, including furniture, walls, and people, which can reflect the signals produced, increasing multipath effects [7], [8], [15]. There are also a large number of wireless electronic devices utilizing WiFi and BLE that are accessing the medium and transmitting information, which could produce noise that would affect the performance of the system.

When performing indoor localization, a number of different wireless technologies have been proposed and tested in literature. The most common technologies are: WiFi, Bluetooth, Radio Frequency Identification (RFID), Ultra-Wide Band (UWB) and cellular [8]. However, each of them have their own advantages and disadvantages when used for localization. Due to the high availability of access points that are now found in buildings, WiFi has become the simplest option, as any additional hardware that is needed is minimal. Unfortunately, WiFi access points are often placed to maximize signal coverage, not for localization. WiFi also consumes a large amount of power, which if used for tracking would quickly deplete a device's battery, which is not ideal for most localization systems [16]. With the recent emergence of BLE and beacons, it has become more feasible to place inexpensive beacons around an environment than it is to rearrange existing hardware and use that for localization [17], [18]. On the other hand, the main disadvantage of using beacons is that most require batteries to function. Once the battery is depleted, the beacon will no longer function and either the beacon or the battery it contains will need to be replaced. As different as all the wireless technologies seem to be, they also contain a commonality in that they all are able to follow the same positioning algorithms if required.

So far, a standard model for indoor localization has not been developed due to obstacles, floor layouts, and reflections of signals that can occur [8]. Some of the most common models that are used in localization systems are: Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Received Signal Strength Indicator (RSSI). AoA systems use an array of antennae to determine the angle, from which the signal propagated [8], [19], [20]. Triangulation is then used along with the geometric principle of angles of triangles to determine the position of the receiver. AoA techniques often require complex hardware and must be calibrated in order for an accurate position to be obtained. ToA is one of the most accurate techniques available. Through the use of synchronized clocks, the signal propagation time between the transmitter and receiver can be determined [19], [20]. ToA uses time stamps embedded in transmitted packets along with the received time to determine how far the packet had to travel to reach the destination. However, when using a ToA set up, devices in the network need synchronized clocks, which requires additional hardware, thus increasing the cost of the system. TDoA is similar to ToA in that it requires devices to have synchronized clocks, but it uses the signal propagation time to multiple receivers to find the absolute signal propagation time [20]. The distance can then be calculated by the differences in arrival time of the packet to the different receivers. RSSI is one of the most popular and simplest methods for localization [21]–[23]. The main reason for its popularity is that finding the RSSI requires no additional hardware and can be found on any device utilizing almost any type of wireless communication technology. RSSI works by measuring the signal strength of packets on the receiver. It is often used for finding the distance between the transmitter and the receiver, since the signal strength decreases as the signal propagates outward from the transmitter. Since propagating signals are greatly susceptible to noise in the environment, RSSI often leads to inaccurate values that can cause errors in the positioning system.

In this paper, through extensive experimentation, a comparison between the accuracy and power consumption of WiFi, BLE, Zigbee, and LoRaWAN is performed. The wireless technologies were chosen based on factors such as popularity, public availability, and use in the IoT. Zigbee is a popular low-power technology, often used in IoT applications. BLE and WiFi are both heavily present in society. Most devices are able to connect with at least one or both of these, allowing a network of devices to be created. LoRaWAN is a novel technology that is not as prevalent as the previous technologies mentioned. Transmitting at 915MHz and sacrificing high data rates, LoRaWAN nodes can reach distances of 15000 meters, which can greatly limit the number of nodes required in order to cover an environment. All tests were performed using a trilateration technique where the RSSI values were utilized in determining the approximate distances between the transmitting nodes and the receiver. Two different environments were used for experimentation in order to compare results accross multiple scenarios.

According to experimental results:

- RSSI-based indoor localization techniques are affected by the environment. However, some wireless technologies are more prone to environmental changes than others.
- BLE is a promising, low power, and cost efficient solution for IoT localization in small crowded areas, due to its high localization accuracy in the two examined environments.
- WiFi is a reliable technology that can also be used for localization due to its high availability. However, WiFi consumes the most power out of all the examined technologies.
- LoRaWAN has a great transmission range and low energy requirements that are useful for IoT localization in large areas, but it was the worst in terms of performance for indoor localization.
- Zigbee has a similar low energy requirement to LoRaWAN, while its performance is much higher in the two examined environments.

The RSSI dataset that was built from the experiments is available online [24].

The rest of this paper is organized as follows: the related work is reviewed in Section II, followed by a brief description of the wireless technologies in Section III. The localization system is presented in Section IV. The experimental methodology and setup are discussed in Section V along with the results in Section VI. Section VII concludes this work.

II. RELATED WORK

In recent years, many approaches have been developed in an attempt to create an efficient indoor localization systems. An ideal system would be functional in numerous environments and be able to track a large number of targets with minimal error. To determine the optimal wireless technology for indoor localization, a number of comparisons between existing technologies have been performed in literature.

In [25], a comparison between BLE and WiFi is demonstrated while running on an Android smartphone. Experiments were performed utilizing trilateration in both outdoor and indoor environments. Testing also included using LoS and non-LoS conditions and were compared with propagation characteristics to determine which technology would be preferred in a localization system. To find the distance between nodes, RSSI measurements were used along with a lognormal attenuation model. The results demonstrated that BLE is more accurate than WiFi when used for localization. It was found that the BLE propagation model was able to better relate RSSI values to distances compared to WiFi, thus creating a system with better accuracy. While the power consumption of the different technologies was noted, no actual power data was found on the devices utilized.

The work introduced in [26] also uses an RSSI based trilateration approach to compare the wireless technologies ISM868 and Zigbee. Similar to the experiments performed in [25], tests were done in both outdoor and indoor environments using the path loss model to convert measured RSSI values to a distance. Results concluded that while both technologies produced poor results when used for localization, Zigbee did perform the best of the two. However, a portion of the error could be attributed to the hardware components that were selected in the comparison. To test using ISM868, a fall detector was used as the transmitting device. Since the fall detector is a hardware device that would never be used for localization purposes, it is reasonable that it would have a poor performance.

RFID is also a wireless technology that has been experimented with to determine its accuracy for localization purposes. In [27], a comparison is performed between passive RFID and BLE for locating objects in outdoor environments. Common to the other papers, RSSI is used along with the path loss model to perform trilateration in locating an object. Experimental results demonstrated that BLE has a much greater accuracy than RFID, as it can better identify the object that is being located with a higher accuracy. While having a high accuracy, the proposed system only used two devices instead of the usual three that are normally required for properly determining a position in a 2D space.

In this paper, we expand on these works and additionally compare the wireless communication technologies WiFi (2.4GHz band), BLE, Zigbee, and LoRaWAN. In addition, prototypes are used that are capable of testing each of the different technologies. Comparisons between the different technologies include the accuracy and the power consumption of the devices used.

III. WIRELESS TECHNOLOGIES

When selecting a wireless technology, factors such as the transmission range, radio coverage, bitrate, as well as the battery life, and the power requirements should always be considered for a given application. In this section, the four previously mentioned IoT wireless communication technologies that can be used for indoor localization are discussed.

A. IEEE 802.11N - WIFI

First released in 1997 using the IEEE 802.11 standard, WiFi has become one of the most commonly used wireless technologies [28]. WiFi is mainly used in Wireless Local Area Networks (WLAN) through the use of the 2.4GHz or 5GHz frequency bands. In order to connect to a WLAN, a wireless access point is required.

IoT devices make use of WiFi due to its wide availability in many areas. WiFi also has high security and privacy standards. However, WiFi networks are deployed for communication, so while connectivity and data rate are a high priority, localization is not their main concern. At the same time, the wide availability of WiFi can pose some challenges in the near future. As the number of the devices that have access to the medium increases, it becomes overcrowded and interference problems may arise.

B. BLUETOOTH LOW ENERGY - BLE

Introduced by Bluetooth Special Interest Group in 2010, Bluetooth Low Energy (BLE) was designed for applications that do not require large amounts of data transfer while reducing the power consumption and cost of the devices [29]. In comparison with traditional WiFi, BLE has much lower energy requirements, hence, its bitrate is also lower.

BLE is ideal for short range periodic transmission of small amounts of data. The low power consumption of BLE has led to a number of new devices in the IoT. The number of applications utilizing BLE has also greatly increased over the past several years. New devices have been developed, with applications in fields such as healthcare, sports, fitness, and security, to home entertainment. One type of device that has been created is known as a beacon [30]. Beacons are small, inexpensive devices which periodically transmit packets of information to all nearby BLE enabled devices.

C. ZIGBEE - IEEE 802.15.4

Zigbee is a communication protocol known for its simplicity, low-power usage, and secure networking capabilities [31]. Zigbee is based on the IEEE 802.15.4 standard, which defines the operating point for wireless personal area networks (WPANs) with low-data rate antennas. Devices using IEEE 802.15.4 are able to control the flow of information and prevent any loss of data by using carrier-sense multiple access with collision avoidance (CSMA/CA). Devices using Zigbee are designed with features such as link quality and energy detection, which allow for measurements such as the RSSI to be easily determined.

Zigbee has a greater range than BLE as it can transmit farther by using a mesh network of relay nodes to reach a destination. Zigbee is commonly used for WSN localization due to its low power requirements. However, extra hardware is required which makes it less popular among current IoT users.

D. LORAWAN

Originally developed by the LoRa Alliance, the Long Range Area-Wide Network (LoRaWAN) protocol transmits at a low frequency of 915MHz [32]. The benefits of using a frequency lower than 2.4GHz is that the larger wavelength allows for signals to pass through walls and obstacles without any issues. This in-turn also allows for signals to reach much further distances. Since the 915MHz frequency utilized by LoRaWAN is relatively vacant, it does not interfere with any other transmitting devices therefore, nodes communicating using it are not as susceptible to noise.

LoRaWAN is more secure than other wireless technologies for IoT since it can transmit encrypted data at a different frequency. Its wide transmission range makes it ideal for a variety of smart city programs. The disadvantage of using such a low frequency is a reduction in the data rate that can be transmitted between devices. However, for indoor localization the data rate is not an issue as the nodes are not transmitting large amounts of information. Due to the 915MHz band being unlicensed, it is free for anyone to use for their personal networking needs. Cost is often an issue when using LoRaWAN as large antennas and extra hardware are required to access the medium. With LoS, LoRaWAN is effective for long range outdoor localization, but in short range indoor localization can pose some challenges.

TABLE 1. Wireless technologies characteristics.

Technology	Transmission Range (m)	Bitrate (Mbit/s)	Power Requirements
IEEE 802.11n	70	288.8	Moderate
BLE 4.0	60	25	Low
Zigbee	75	0.25	Low
LoRaWAN	15000	0.05	Extremely Low

E. COMPARISON OF WIRELESS TECHNOLOGIES

The characteristics of the four technologies related to indoor localization are shown in Table 1. When it comes to selecting a wireless communication technology, the transmission range is an important factor that needs to be taken into account. By selecting devices that provide a higher transmission range, a fewer number of devices would be required to cover an area. The ranges listed in Table 1 are those given on the data sheets for each of the modules when LoS is available between devices and they are set to maximum transmit power. If obstructions are placed between the devices, the range would decrease. In terms of transmission range, LoRaWAN has the greatest potential, while the other three technologies have similar capabilities.

The bitrate is another factor that can also affect localization. The higher the amount of data that can be exchanged between devices, a more accurate localization can take place. Although WiFi has the largest bitrate, the other three technologies provide a rate sufficient enough for basic data exchange to occur and for localization to take place.

The power requirement is among one of the most important factors when selecting a wireless technology, especially for IoT devices. The power consumed by a device is affected by the transmission power and interval which in-turn affect the lifespan of the device. Based on the maximum transmission range, it is clear that LoRaWAN has the lowest power requirements overall. This is followed by BLE, which was designed for low power usage in IoT devices. Zigbee, which was initially designed for WSN, also has low power requirements, while WiFi has the worst performance consuming a large amount of power.

Another factor that should be considered when it comes to IoT is the device size and the cost of the necessary hardware. WiFi and BLE tend to have small sizes and a lower cost [33], [34]. While devices using Zigbee are usually larger and require special antennas [35], [36]. LoRaWAN also requires specific hardware to access the frequency band hence, it tends to be more expensive. However, the final cost can vary based on application requirements and specifications.

IV. LOCALIZATION SYSTEM

A wireless indoor localization system should take advantage of signal characteristics and use techniques to provide accurate location information. In this section, the signal features, the indoor positioning technique and the performance metrics used to evaluate the system are discussed.

A. RECEIVED SIGNAL STRENGTH INDICATOR

Received Signal Strength Indication (RSSI) is one of the most commonly used characteristics for indoor localization. It is based on measuring the power present in a signal sent from an access point to a client device or vice-versa. As radio waves attenuate according to the inverse-square law, the distance can be approximated based on the relationship between the transmitted and received signal strengths, as long as no other errors contribute to incorrect measurements. The combination of this information with a propagation model can help to determine the distance between the two devices.

It can be assumed that as the number of available access points increases, a greater amount of information can be collected. Hence, the accuracy could be increased if relevant information is obtained. This, however, also works as a trade-off. An increase in the number of access points would increase the interference between different signals. A key challenge in wireless localization systems is that the range measurements are often associated with errors. RSSI techniques are among the cheapest and easiest methods to implement, but they do not provide the best accuracy. Filtering is necessary to improve system accuracy using RSSI-based localization.

B. TRILATERATION

Trilateration is a model-based technique that is able to determine the 2D position of an object on the basis of the distance from three reference points along with the location of those points. To calculate using trilateration, three transmitting nodes placed in known locations along with a receiver are required. The transmitting nodes are set to continuously broadcast packets. Doing this allows the receiver to obtain any transmissions that take place over the medium and record the RSSI values of the packets. The RSSI values can then be converted to a length, which can provide the estimated distance between the nodes. To relate the determined RSSI values to a distance, the path loss model [37] was used, which can be seen here:

$$RSSI = -10nlog_{10}(d) + C \tag{1}$$

In this equation, n is the path loss exponent that varies depending on the environment, d is the distance between the transmitting and receiving devices, and C is a fixed constant that accounts for system losses. The path loss model was selected due to its ability to quickly determine a distance based on the RSSI values. Using the path loss model also allowed for environmental factors to be taken into account. Since RSSI values can fluctuate based on interference in the surrounding area, the path loss model can try to reduce some of the error that occurs, as the path loss exponent needs to be calculated for every environment before it can be used. However, due to the power level of the signal emitted from the transmitter not being precisely known, in many cases the path loss equation cannot be inverted and other methods are required to determine a distance [38], [39].

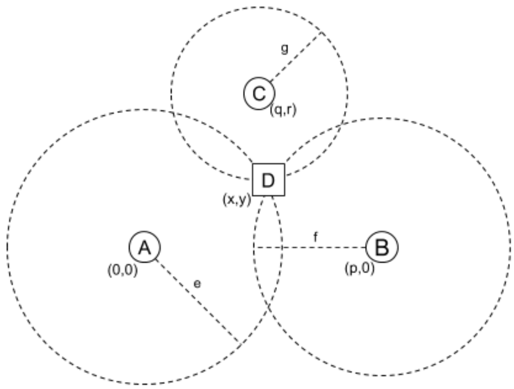

FIGURE 1. General setup for trilateration.

To determine a node's position using trilateration, a number of assumptions need to be made, one of which is that the location of all the transmitting nodes is known. To make calculations easier, the coordinate frame of the nodes was configured around a single node. This node was set up to be stationary at the origin and the other nodes were normalized with reference to that node.

The general layout of a trilateration experiment can be seen in Fig. 1. In the setup, node A was set to be stationary at the origin *(0,0)*. Node B was placed along the positive horizontal axis with respect to node A, giving a coordinate of *(p,0)*. Node C can then be placed with respect to nodes A and B in the positive horizontal and vertical axis, producing a coordinate of *(q,r)*. Node D is the receiver, placed at the known coordinates *(x,y)*. The calculated distances to the receiver from nodes A, B, and C are referred to as e, f, and g respectively, which can be determined using the path loss model in Eq. (1). Once the positions of the transmitters and the distances to the receiver are determined, a new set of equations can be created. Using the general formula of a circle, three equations (2), (3), and (4), were determined corresponding to nodes A, B and C respectively. By solving this set of equations and finding the overlapping point, the position of the receiver can be found.

$$e^2 = x^2 + y^2 \tag{2}$$
$$f^2 = (x-p)^2 + y^2 \tag{3}$$
$$g^2 = (x-q)^2 + (y-r)^2 \tag{4}$$

In these three equations, there are two unknowns that can be determined-x and y-which correspond to the estimated location of the receiver, and which should satisfy all three equations. By using simple reduction techniques, a solution can be determined. By subtracting Eq. (2) from (3), the variable y can be eliminated. The remaining parameters are those of the single unknown variable x, the distance between nodes

A and B, and the distances between the transmitting nodes A and B with the receiver node D. After some rearranging, the final result can be seen here:

$$x = \frac{e^2 - f^2 + p^2}{2p} \tag{5}$$

In order to produce a single solution for the y position of the receiver node, another subtraction can be performed, this time using Eqs. (2) and (4). After solving and rearranging, the solution for y can be seen in Eq. (6). This equation is entirely in terms of known parameters which can be substituted in to solve for a value.

$$y = \frac{e^2 - g^2 + q^2 + r^2}{2r} - \frac{q}{r}x \tag{6}$$

C. ACCURACY AND POWER CONSUMPTION

To determine which wireless communication technology produces the most accurate results, the error between the actual and the estimated position can be found using the Mean Squared Error (MSE). The MSE is a calculation of the difference between two points to find the error. The formula used can be seen here:

$$Error = \sqrt{(x_{calc} - x_{real})^2 + (y_{calc} - y_{real})^2} \tag{7}$$

In this equation, x_{calc} and y_{calc} is the calculated position, and x_{real} and y_{real} is the actual position of the receiver. Once the errors for all the tests performed are determined, an average can be taken that can then be compared to the other wireless communication technologies to determine which produced the most accurate results.

In addition to accuracy, the power consumption of the wireless technologies was also determined. To measure the power consumption of the different wireless communication technologies, one of the transmitting nodes was connected to a Monsoon Power Monitor. The Monsoon is capable of taking 5000 samples per second which provides a large set of data defining the power usage of the device at all times. To do this, the Monsoon could supply a voltage, measure the current draw, and display the average power consumed. To measure the power consumed only by the wireless technologies, two power measurements were taken. The first when the node was transmitting, the second when the node was idle. By subtracting the two, the power consumed only by the transmitting operation of the device could be found.

V. EXPERIMENTAL TESTBED

This section describes the experimental environment along with the hardware components that were used and the path loss model. To evaluate the different wireless technologies, four indoor localization systems were built, one for each wireless technology.

A. ENVIRONMENT

Each indoor localization system was tested in two rooms with varying conditions to determine how different real-world environments would affect the results.

FIGURE 2. Experimental environment 1.

FIGURE 3. Experimental environment 2.

The first environment used for experimentation was an 10.8m x 7.3m research lab, shown in Fig. 2. This lab was selected due to the large size, the number of computers, and the large quantity of WiFi and BLE devices that could possibly cause any interference, making it a very noisy environment for experimenting.

The second environment used was a 5.6m x 5.9m meeting room, shown in Fig. 3. The meeting room was an ideal testing area as it demonstrated conditions contrasting those in the research lab. The meeting room was a much smaller space that contained only tables and chairs. No devices were present in the environment that could cause significant interference in the area, creating a low-noise environment for testing.

B. EXPERIMENTAL METHODOLOGY

A set of tests was conducted to determine how accurate the localization would be when performed over a range of distances between the receiver and transmitters for all the indoor systems.

All experiments were conducted in the evening to ensure that a minimal amount of extra transmitting device would be in the area, attempting to communicate using the same medium. Due to the fact that RSSI values are prone to interference, using a controlled environment would allow all the tests performed to produce more consistent readings. To ensure that an appropriate RSSI was used in the calculations rather than one due to a spike in interference, for each of the

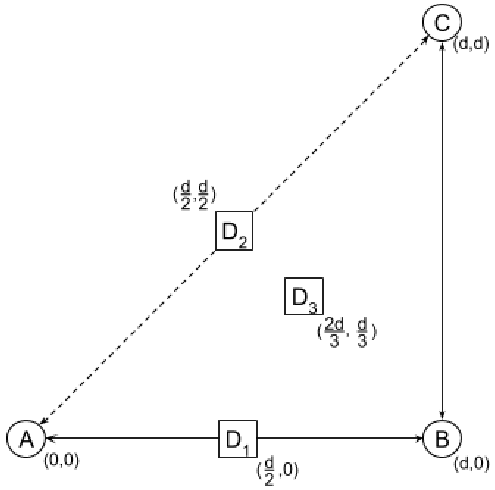

FIGURE 4. Setup used for experiments.

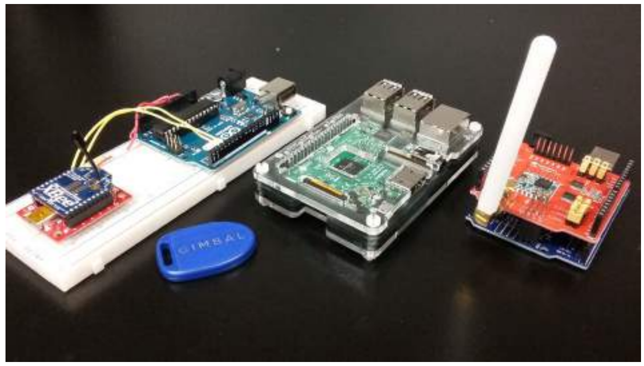

FIGURE 5. Equipment used in setting up the experiments. From left to right: Zigbee (Arduino Uno with Series 2 XBee), BLE (Gimbal Series 10 Beacon), WiFi (Raspberry Pi 3 Model B), LoRaWAN (Arduino Uno with Dragino LoRa Shield).

testing points approximately 100 readings from each of the transmitters were taken and averaged.

Overall, nine tests were performed in each of the environments. A variety of distances were used along with multiple receiver locations to determine the accuracy of the wireless technologies. A general overview of the experimental setup created can be seen in Fig. 4.

To set up the experiments, a right angle triangle was created between the nodes. Where the distance, d, between nodes A and B, and B and C, was set to be equal. For our experiments, the three distances that were selected for testing were at 1, 3, and 5 meters. The receiver was set to one of three positions: in the center between nodes A and B (D_1), in the center between nodes A and C (D_2), and in the centroid of the triangle (D_3).

In both environments, nodes were placed on tables when performing experiments. This was done to limit the number of reflections of transmitted signals off the ground, reducing the multi-path signal effects that occur while transmitting. Placing nodes on tables also allows tests to be performed at a height similar to someone who is carrying a receiving device in their pocket, or wearing one on their wrist.

C. HARDWARE COMPONENTS

The different hardware components used during the experiments are shown in Fig. 5.

For the WiFi experiments, four Raspberry Pi 3 Model Bs [40] were used. The devices contained an onboard 2.4GHz WiFi chip antenna. Hence, a simple WLAN could be created using said antennas by programming them to transmit and receive signals. Three nodes were configured to be the transmitters and one node was set to be the receiver. The receiver node was set up as a router, where it would broadcast a signal that the other nodes could use to connect to the WLAN and provide communication capabilities between the devices. Each of the transmitting nodes continuously polled their WiFi antenna, scanning for any available signals along with their measured RSSI values. The RSSI values would then be transmitted to the receiver along with the identity of the node that was sending the data. All received data would then be displayed on the terminal of the device. To record the measured RSSI values, a computer was connected to the network of the receiving node.

For the BLE experiment, three Gimbal Series 10 Beacons [34], developed by Qualcomm, were used as transmitting devices. For the purposes of this experiment, the Gimbal Beacons were configured using the iBeacon protocol developed by Apple [41]. The iBeacon packet structure has three fields: the Universally Unique Identifier (UUID), Major value, and Minor value. The UUID is a 16-byte field used to identify a set of beacons, such as the owner, application, or manufacturer. The Major and Minor values are 2-byte fields assigned to iBeacons in order to identify them with greater accuracy. The receiving device used to read the beacons was a Raspberry Pi 3 Model B that was capable of picking-up any beacon signals that were in the area along with their RSSI values and storing the information.

For the Zigbee experiment, four Arduino Unos and four Series 2 2mW Wire Antenna XBees [42] were utilized. Three nodes were set up to act as transmitters and the remaining as the receiver. The XBees were configured to run on the Zigbee Mesh Protocol and operate on the 2.4GHz frequency. Due to the limited processing power of the XBees themselves, and the need for an external power supply, a microcontroller was necessary to control the flow of information and provide power. An Arduino Uno was chosen due to its simple integration with the XBee and low power requirements.

For the LoRaWAN experiment, four Arduinos, each equipped with a Dragino LoRa Shield [43], were used. Three were configured as transmitting devices and one as the receiver. To differentiate the individual transmitters at the receiver, each of the transmitting nodes was configured with their own unique address. The receiving node was configured to continuously read the medium for any messages. If any messages were received, the RSSI was measured, and written to the Arduino serial along with the corresponding node transmitted the message.

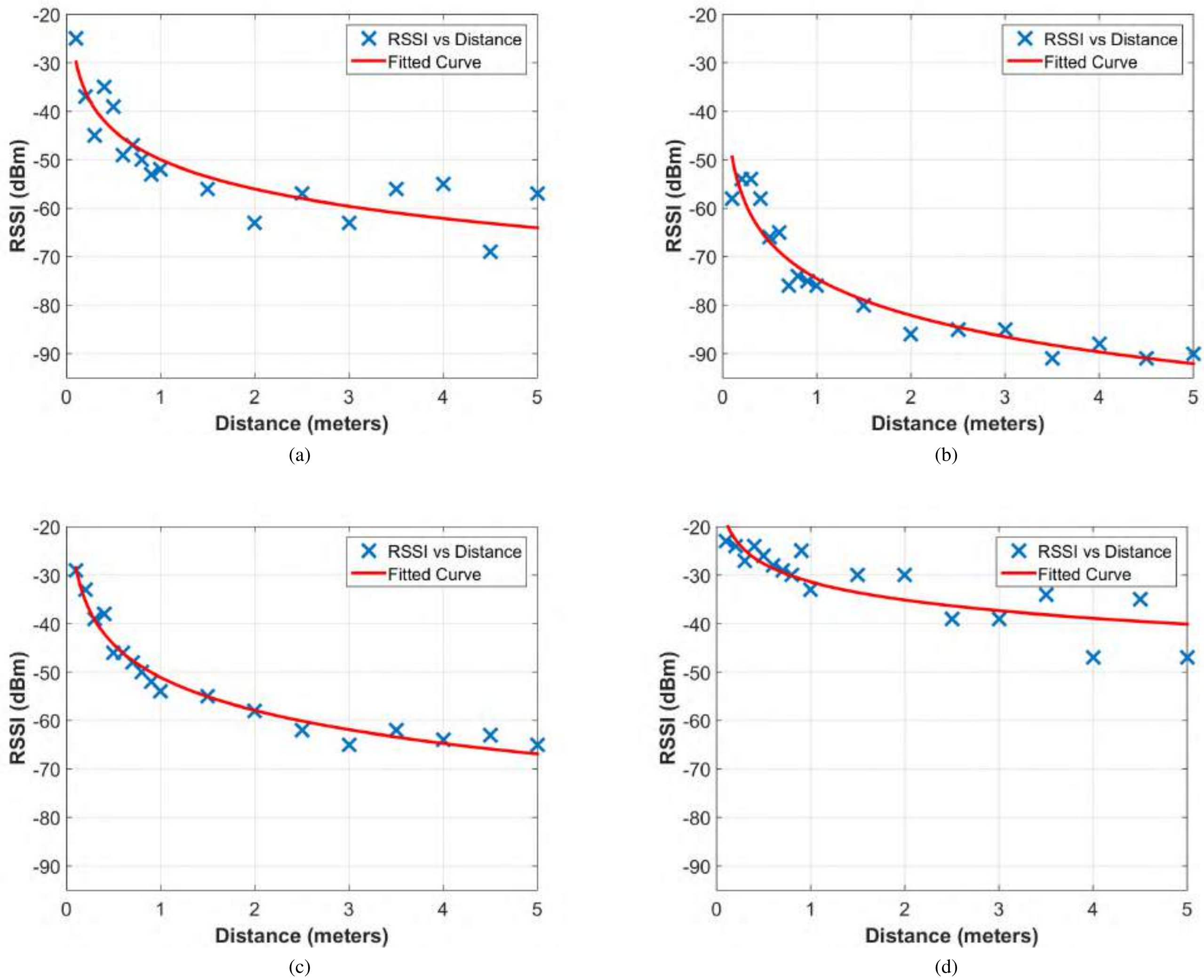

FIGURE 6. Curve fitting for the path loss in environment 1. (a) WiFi. (b) BLE. (c) Zigbee. (d) LoRaWAN.

To perform an equal set of tests between all the experiments, a similar transmit power and interval was required to be used on all the components. In selecting a transmit power, the Series 2 XBees and Gimbal Series 10 Beacons each had a set of configurable power levels that could be selected. Based on the values listed for both components, there was only one common level that could be selected between the two, -10dBm. The Raspberry Pi 3s and LoRa Shields could be programmed with a transmit power and configured with the selected value, hence -10dBm was selected.

In selecting a proper transmit interval, the Gimbal Series 10 Beacons contained a list of times that could be chosen. The Raspberry Pis and Arduinos are microcontrollers and could be programmed with a value. Since any real-time indoor localization system would need to respond quickly to individual movements in an area, a transmit interval of 0.5 seconds was chosen. Broadcasting was done to ensure that if additional receivers were added to the system, each would receive the same signal.

Due to the Arduinos and Raspberry Pis requiring an external power supply to operate, USB cables were connected to wall outlets to provide power. The Gimbal Beacons used internal coin cell batteries and did not suffer from the same requirements.

D. PATH LOSS MODEL

Before any experiment could be performed, the path loss models in the environments for each of the different wireless communication technologies needed to be determined. For each of the systems designed, a single transmitter and receiver were placed over a range of fixed positions and the corresponding RSSI values were recorded.

In order to create these models, the RSSI over a range of distances from the transmitter needed to be measured in the environment to determine how the signal strength decreases. It was determined that points over a range of distances would create the best fit, therefore, distances were selected between 0 to 5 meters. In total eighteen points were taken. Nine points were taken between 0 and 1 meter, once every 0.1 meters.

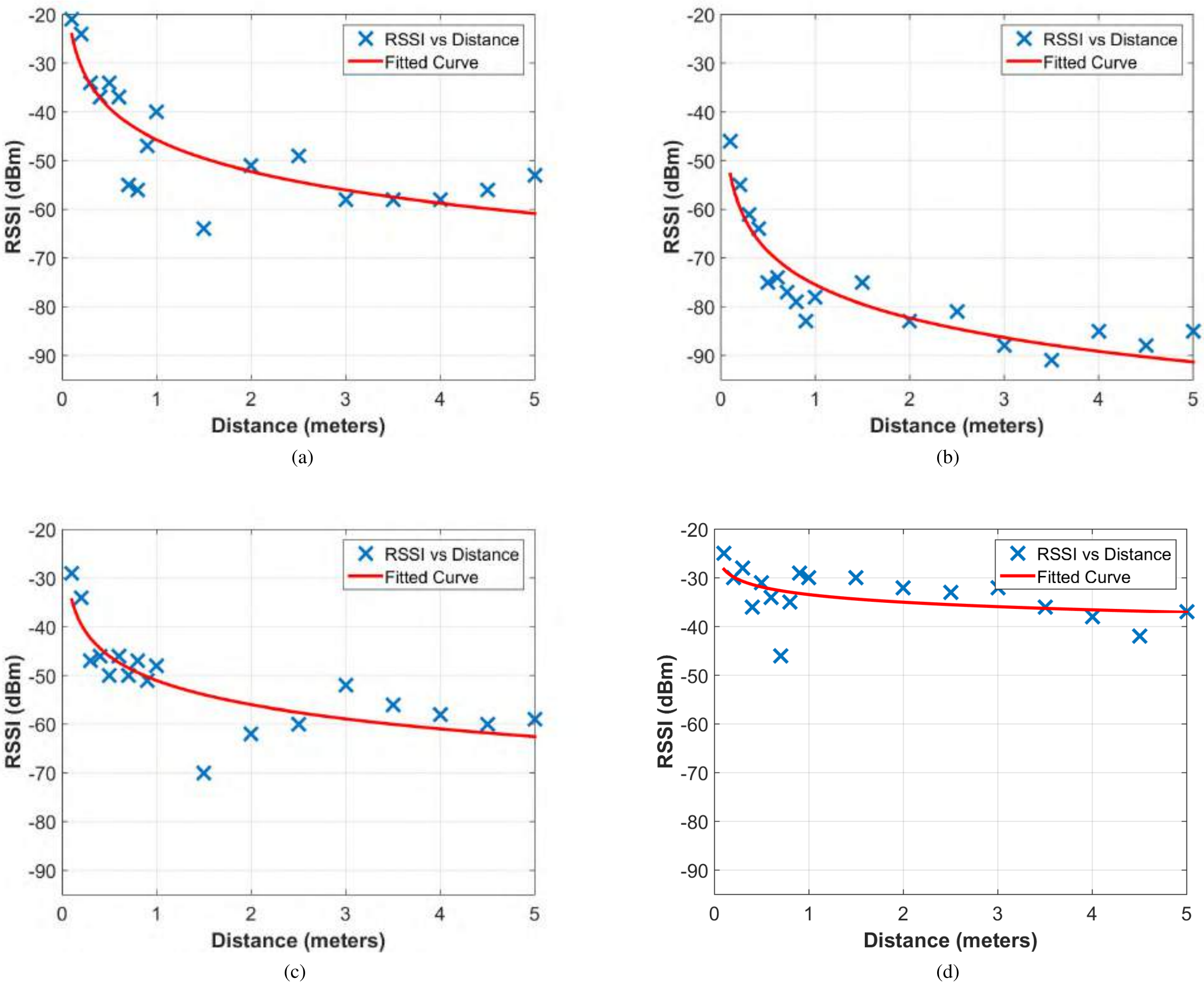

FIGURE 7. Curve fitting for the path loss in environment 2. (a) WiFi. (b) BLE. (c) Zigbee. (d) LoRaWAN.

TABLE 2. Parameters used in converting RSSI to distance using the path loss model in environment 1.

	WiFi	BLE	Zigbee	LoRaWAN
n	2.013	2.511	2.261	1.246
C	-49.99	-75.54	-51.1	-31.38
R^2	0.8123	0.9697	0.8123	0.7065

TABLE 3. Parameters used in converting RSSI to distance using the path loss model in environment 2.

	WiFi	BLE	Zigbee	LoRaWAN
n	2.162	2.271	1.653	0.5196
C	-45.73	-75.48	-51.01	-33.44
R^2	0.85	0.6915	0.7177	0.2521

While the remaining nine points were taken between 1 and 5 meters, once every 0.5 meters. After all the points were measured, the distance vs. RSSI was plotted and Matlab's curve fitting function was used to estimate a model based on Eq. (1).

The curve fitting for the path loss in Environment 1 and Environment 2 are shown in Fig. 6 and Fig. 7 respectively. The values for the path loss exponent, n, constant, C, and the coefficient of determination, R^2, are shown in Tables 2 and 3 for Environments 1 and 2 respectively.

It is clear that the two environments experienced noise and interference. Based on the R^2 values determined, Environment 2 seemed to experience much more variation in RSSI readings as the models created do not match as nicely as those in Environment 1. Hence, it is expected that the accuracy in Environment 2 be lower than in Environment 1.

E. EXPERIMENTAL PROCESS

In total, nine tests were performed in each of the two environments at varying distances and locations in order to determine how positioning the nodes would affect the localization accuracy. In each of the tests, the location of all the nodes was recorded along with the measured RSSI values.

TABLE 4. Error between estimated and actual positions in environment 1 (meters).

Distance (m)	Test Point	Actual Coordinates		Error			
		M	N	WiFi	BLE	Zigbee	LoRaWAN
1	D_1	0.500	0.000	0.158	0.133	0.431	0.326
	D_2	0.500	0.500	0.122	0.015	0.335	0.701
	D_3	0.667	0.333	1.005	0.182	1.838	0.783
	Average			**0.428**	**0.110**	**0.868**	**0.603**
3	D_1	1.500	0.000	2.633	1.173	1.222	0.392
	D_2	1.500	1.500	0.379	0.050	0.806	0.294
	D_3	2.000	1.000	0.469	0.791	0.795	1.358
	Average			**1.160**	**0.671**	**0.941**	**0.681**
5	D_1	2.500	0.000	1.376	2.406	0.187	1.665
	D_2	2.500	2.500	0.476	0.118	0.393	0.873
	D_3	3.333	1.667	0.967	1.082	1.933	1.225
	Average			**0.939**	**1.202**	**0.838**	**0.846**

TABLE 5. Error between estimated and actual positions in environment 2 (meters).

Distance (m)	Test Point	Actual Coordinates		Error			
		M	N	WiFi	BLE	Zigbee	LoRaWAN
1	D_1	0.500	0.000	0.139	0.447	0.408	0.490
	D_2	0.500	0.500	0.193	0.989	0.350	0.081
	D_3	0.667	0.333	0.182	0.199	0.480	0.236
	Average			**0.171**	**0.545**	**0.413**	**0.269**
3	D_1	1.500	0.000	0.530	1.461	1.528	1.473
	D_2	1.500	1.500	0.515	0.544	0.503	0.255
	D_3	2.000	1.000	1.283	0.657	0.176	3.138
	Average			**0.776**	**0.888**	**0.736**	**1.622**
5	D_1	2.500	0.000	0.515	2.227	1.248	2.364
	D_2	2.500	2.500	0.729	0.020	2.185	0.939
	D_3	3.333	1.667	0.284	1.053	1.317	4.831
	Average			**0.509**	**1.100**	**1.583**	**2.711**

Once the RSSI values were measured for all the tests for each of the wireless communication technologies, a distance could then be calculated that approximated the position of the receiver relative to each of the transmitting nodes. Using Eq. (1) and the corresponding parameters found in Tables 2 and 3, an appropriate distance can be determined for each of the wireless communication methods for each of the testing environments.

To evaluate the accuracy between all the systems, using Eq. (7), the MSE between the estimated and actual node position was found. The results of this calculation can be seen in Tables 4 and 5 for Environments 1 and 2, respectively. Finally, for all the experiments performed, an average was taken to find the overall error per environment along with the overall error from all the experiments performed. The results can be seen in Fig. 9 with the numeric values and the average error for each wireless technologies for the environment tested in along with the overall error, in Table 6.

VI. RESULTS AND DISCUSSION

In this section, the experimental results are presented, followed by a discussion. All the experimental data collected are also available in [24].

A. LOCATION ESTIMATION RESULTS

The error between estimated and actual position for Environment 1 and Environment 2, is shown in Table 4 and Table 5, respectively. Experimental results showed that WiFi is the most accurate system overall. Deviating off of the actual receiver position by 0.664 meters on average, shown in Table 6.

TABLE 6. Average error in positions (meters).

Wireless Technology	Environment 1	Environment 2	Overall
WiFi	0.843	0.486	0.664
BLE	0.661	0.844	0.753
Zigbee	0.882	0.911	0.896
LoRaWAN	0.846	1.534	1.190

In Environment 1, WiFi produced an error of 0.843 meters, while in Environment 2 it was 0.486 meters. The next highest overall (based on the tests performed) was BLE, with an overall error of 0.753 meters. In Environment 1, WiFi produced the second highest accuracy being beat by BLE which produced an error of 0.661 meters. In Environment 2, WiFi demonstrated to be the best technology, with BLE following with an error of 0.844 meters.

Following closely behind BLE, in third, was Zigbee which resulted in an overall error of 0.896 meters. Zigbee was found to have the worst accuracy in Environment 1, deviating off by 0.882 meters, while it achieved the third highest accuracy in Environment 2 deviating by 0.911 meters. Lastly, performing the worst overall was LoRaWAN, with an overall error of 1.190 meters. LoRaWAN was found to have the second worse performance in Environment 1 with an

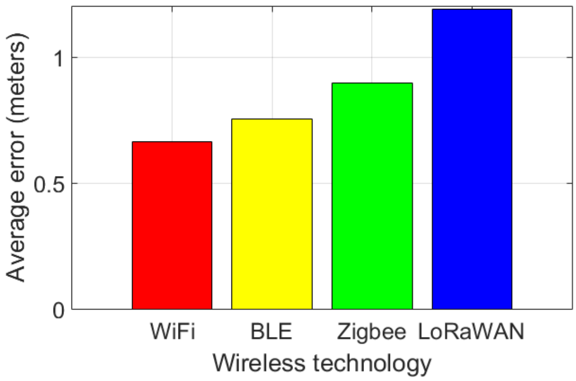

FIGURE 8. Average error of wireless technologies in both environments.

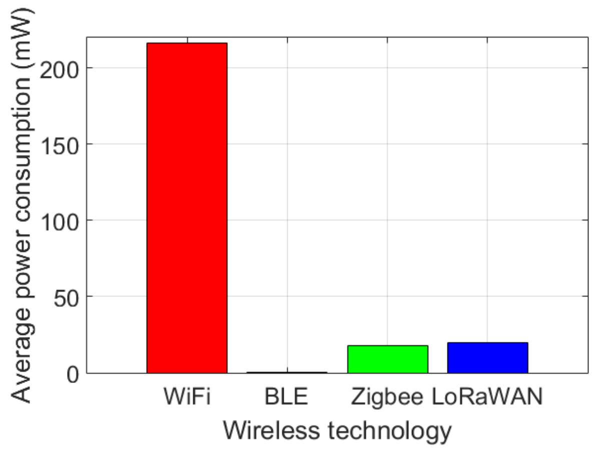

FIGURE 9. Average power consumption of wireless technologies.

error of 0.846 meters, while being the worst in Environment 2, producing an error of 1.109 meters.

Overall, three out of the four systems performed better in Environment 1, resulting due to the large space that allowed for signals to travel farther distances and not be as concentrated in the room. WiFi was found to function better in the second environment due to the lower amount of WiFi signals that would cause interference. Within Environment 1 and a distance of 1 meters, the test point D_3, in the centre of all the devices, had the worst performance. However, when the distance was increased to 3 and 5 meters, the test point D_1, at the edge of the triangle, had the worst performance. This was found to be due to the high interference at this position between the two transmitting devices.

In terms of accuracy, the most accurate results were produced at the smallest distance of 1 meter. In Environment 1 BLE had the best results, while in Environment 2 WiFi had the best results. However, as the distance increased, the error did as well. On the other hand, in both environments WiFi was the most accurate when large distances were used such as 5 meters. While it performed relatively well at small distances as well. LoRaWAN performed adequately in Environment 1, but its performance dropped significantly in Environment 2, which was a smaller room with a lower amount of interference, but a large amount of reflection.

B. POWER CONSUMPTION

In order to measure the power consumption for the different wireless technologies, two tests were performed.

- In the first test, the transmitting device was connected to a power monitor which transmitted normally as per the experiments performed.
- The second test had the same transmitting device, but was configured to be idle by disabling the device to no longer transmit any information.

Once the two values were found, they were subtracted to find just the power that is consumed by the antenna of the wireless technology that is being tested.

When measuring the power consumption of the transmitters, the power usage proved to be consistent over the course of the experiments. It was found that the amount of power consumed was the result of the set transmit power and interval. The distance between the transmitter and receiver played no part in the amount of power consumed. As a result the average power consumption could easily be found and recorded. The results of the measured power values can be seen in Fig. 9. When measuring the power consumption, the transmit power for all the devices tested was set to be -10dBm and the transmit interval was set to 0.5 seconds. If a higher transmission power is utilized, or a faster transmit interval is set, the power consumption of the device would increase.

Based on the values found, WiFi consumes the largest amount of power utilizing 216.71mW. LoRaWAN consumed the second largest amount of power using 19.53mW on average. Zigbee was third, which on average consumed 17.68mW of power. BLE used the least amount of power, consuming only 0.367mW.

C. DISCUSSION

The experimental results revealed useful insights. In terms of accuracy, WiFi produced estimates that were closest to the actual receiver position, deviating by 0.664 meters. However, WiFi was also found to use the largest amount of power which would not be suitable for use in a system that requires batteries to function.

One the other hand, BLE had the second highest accuracy of 0.753 meters. The BLE beacons were also the system that also consumed the least amount of power, but it had the lowest transmission range of all the devices tested. In addition, due to the low current draw of BLE, rechargeable batteries could be used in order to power the device, which could help in reducing the total cost of the system. The major disadvantage with using BLE for localization, is that it would not be suitable for covering a large area due to its poor transmission range therefore, additional devices would be required.

LoRaWAN had a slightly larger error of 1.190 meters and had a much higher power consumption, because of this, rechargeable batteries cannot be used. However, LoRaWAN has a very high transmission range which would greatly limit the number of nodes that could be required in an environment, which would reduce the total cost.

Interestingly, for three out of the four wireless communication technologies tested, results in the second testing environment produced much larger errors than when compared to the results produced in the first testing environment. Since the second environment had zero transmitting devices in the room, it was expected that the overall error would be lower when testing in it. A major difference between the two testing environments was in the number of windows present. Environment 1 had four small windows while Environment 2 had one big window that was covering most of the outer wall. Since glass does not reflect transmitted signals effectively, in Environment 2, most of the signals would be reflected and sent outward out of the room. While in Environment 1 the signals did not have such an opportunity and were concentrated in the room.

However, even thought results in Environment 2 were larger, tests performed in both environments followed similar trends with respect to the errors determined. It was found that the errors are much lower when the transmitters were placed 1 meter apart than when 5 meters apart. The greater accuracy at lower distances could be attributed to the path loss model that was used to convert the RSSI values to distances. Since the signal strength decreases the greatest in the first meter from the transmitter, a more accurate distance can be found in this small area. When comparing test points it was found that D_2 was the most accurate for all of the wireless technologies no matter the distance between the transmitters. Since D_2 is located in the center of all the transmitters, similar signal strengths occurred at that point, which were converted to similar distances. The worst point for testing was found to be D_1, which was located along the edge of the triangle created between the transmitters. Often it would be expected that the signal strength from two transmitters to be similar and the third be smaller, but this would not occur and would seem to follow different patterns caused by the reflections of signals off other obstacles.

According to the experimental results, for an indoor localization system, BLE is a promising candidate. The other three technologies had much higher power consumptions and are used for transmitting information between devices. BLE was designed for small networks in the IoT. Hence, energy consumption was a priority which allowed for a longer network run time. This is the main advantage of BLE technology that is also useful when it comes to indoor localization systems.

VII. CONCLUSION

In this work, we compared WiFi, BLE, Zigbee, and LoRaWAN for use in an indoor localization system. By using three transmitting nodes broadcasting information, along with a single receiver, trilateration could be performed to determine an approximate receiver location. Through experimentation, WiFi proved to be the most accurate, deviating off the actual receiver position by 0.664 meters on average. WiFi was followed by BLE, which produced an error of 0.753 meters. BLE was also found to use the lowest amount of power, consuming 0.367 mW on average. For transmission range, LoRaWAN, the technology that was designed to transmit at a lower frequency of 915MHz, had the furthest transmission range when running at its maximum transmission power. The experimental results can be used as an indicator for the selection of a proper indoor localization system in smart buildings. All the data collected through experimentation are publicly available online [24].

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