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Master's Minor Thesis

An Investigation on Received Signal Strength Indicator for Wireless Connection such as Bluetooth in an IoT-based Indoor Environment

Submitted by:

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Abstract

As time has advanced, people have opted for options for handling tasks smartly that consume less time and enhance productivity in any aspect of life. Similarly, many individuals are conscious about doing things smartly even in a household, where people spend a considerable amount of time with their families and loved ones. Consequently, the IoT market is manufacturing more smart products, leading homes to procure more of these smart products. At present, the capability of automated products has improved with the internet, which allows the devices to send data back and forth for awareness and interpretation which is indeed useful for informed decision-making in any home-related scenario.

It has been noted via studies and observation that many smart products are Bluetooth-enabled for convenient wireless connections which will easily ensure data/information exchange in a home-based smart personal area network. However, circumstances have also dictated that initiating Bluetooth connection between devices is another challenge that we all have faced. Alas, exploring the variables and parameters that determine a successful connection is essential.

One such parameter is the Received Signal Strength, which expresses the signal strength of the receiving device. The value that dictates the measurable strength is called the Received Signal Strength Indicator which will be the theme of this empirical study. The experiment involves taking Bluetooth RSSI readings in a household while introducing various variables to observe the changes in the readings. The experiment was conducted at two locations to avoid biases in the readings and to observe a fair relationship between the dependent and independent variables. The independent variables included weather parameters to observe if weather patterns play a significant role in determining a better Bluetooth connection, indoors. For that reason, 1200 samples of Bluetooth RSSI data were collected per scenario and explored to understand its significance of IoT-based indoor localization. Based on the literature review and epistemology it was hypothesized that a Bluetooth Connection is obfuscated due to the interferences, noise, obstacles, and other convolving signals that are present in an IoT-based indoor environment. After exploration of the RSSI readings the null hypothesis and alternative hypothesis were evaluated, and the null hypothesis was proven correct.

***Key Words**: IoT, Smart Homes, Smart Devices, Bluetooth RSSI, Indoor Localisation, and Fiji Weather Patterns*

Declaration of Originality

Statement by Author

I, Deepika Bandhana, declare that this thesis is my own work and that, to the best of my knowledge, it contains no material previously published, or substantially overlapping with material submitted for the award of any other degree at any institution, except where due acknowledgement is made in the text. *(Word Count: ~35,500 words)*

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Statement by Supervisor

The research in this thesis was performed under my supervision and to my knowledge is the sole work of ....

Signature: ………………………….. Date: ………………………..

Name: Professor A B M Shawkat Ali

Designation: Professor

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List of Acronyms

The acronyms that are used in this document are listed as follows.

1. IoT – Internet of Things
2. RSSI – Received Signal Strength Indicator
3. RTI – Retractable Transport Item
4. BLE – Bluetooth Low Energy
5. LE – Low Energy
6. IEEE – Institute of Electrical & Electronics Engineers
7. NFC – Near Field Communication
8. RFID – Radio Frequency Identification
9. MCU – Microcontroller Unit
10. LED – Light Emitting Diode
11. TCP/IP – Transport Communication Protocol/ Internet Protocol
12. MQTT – Message Queuing Telemetry Transport
13. LCD – Liquid Crystal Display
14. GMS – Global System for Mobile Communication
15. ISM – Industrial Scientific Medicine
16. HTTP – Hyper Text Transfer Protocol
17. HTML – Hypertext Markup Language
18. PPE – Personal Protection Equipment

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Chapter 1- Introduction

Chapter 1: Introduction

1.1. Introduction

In this chapter the key technology of this research will be introduced and its application in various scenarios will also be captured to highlight on the significance of this research work under contribution. Afterwards the contribution will be briefly discussed to provide chapter conclusion. So, the Chapter 1 documentation will capture the introduction of the Introduction, then the contribution identified through various sources which is captured in a descriptive nature and Discussion subsection will briefly compare and contrast the contributions of Bluetooth technology, and based on the similarities and differences a possible conclusion will be drawn.

1.2. Significance of Work

While Bluetooth has started dominating most IoT portable ad-hoc devices, especially after the Corona pandemic (Dolan, 2023), it is essential to explore this technology to the fullest to gain understanding in relation to this empirical study which will eventuate into exploring Bluetooth Signals to achieve a successful connection in a household or any indoor environment. A case study shows an IoT-based company assisted Shuferal's farm in building the very first farm-to-store intelligent supply chain IoT-based smart farm in Israel which was achieved by using 1 million reusable transport items that would be transparent from farm to store. Implementation of this technology ensured timely delivery of products to stores and maximum sale of high-quality farm products that will in fact reduce wastage. The piloted Wiliot Technology allowed the retailer - Shuferal to track the location and temperature of the products precisely with the following key points (Wiliot, 2023);

i. The location of each RTI of produce from farm to distribution center to store.
ii. The total time it took for each RTI to travel from farm to store, accurately indicating the time it was picked and the age of the product(freshness).
iii. The total time each RTI spent at each stage of the supply chain: from the field, packing shed, distribution center, transport and to store.

iv. The temperature inside the RTIs at each stage and the total time that RTI temperature was above the temperature at which point freshness was more likely to suffer.

Another article presented a digital and innovative solution to manufacturing industries by facilitating flexible and transparent production and offering swift feedback on new customer needs. The key technology in this context is the usage of low energy (LE) Bluetooth with Internet of Things to identify, locate, track, and monitor applications that are affordable and easy to implement. In manufacturing industries, LE Bluetooth is used as a positioning technology to locate assets in a timely manner to reduce asset loss and optimize indoor asset management, especially in large manufacturing industries. The challenge of this manufacturing company was that it was wasting a lot of time while locating parts, products, orders, racks, and tools in the factory environment which was not documented transparently. So, the company was either re-producing orders or re-purchasing tools for production which was not needed in the first place (blueupbeacons, 2023).

In support of the study a paper titled "Peer to Peer Signal Strength Characteristic between IoT Devices for Distance Estimation" highlights the fact that Bluetooth received signal strength indicator can be used to determine the distance between the IoT devices in an office - based IoT setting. The devices can recognise each other in a wireless body area network but the usage of Bluetooth received signal strength indicator to estimate the distance between peer-to-peer devices in the context is difficult due to the deviation in the index values. So, this paper uses a Low Pass Filter in an office environment to overcome the RSSI deviation values. The experiment is set up to measure the RSSI value from all four directions, East, West, North, and South that is within the wireless body area network and outside of the wireless body area network. Meanwhile, there was no partition in the east direction, so the raw data showed a difference of 23dBm. However, when the low pass filter was applied, the difference came to 1.7dBm, hence the Low pass filter value was used to calculate and determine the distance in the context (Jung, Kang, & Bae , 2014).

As per the conducted research (Jung, Kang, & Bae , 2014), it highlighted various methods that can be used to determine the distance. The first one is using signal strength to determine the distance. In disparity, using RSSI values to calculate distance is not the precise method due to interferences and obstacles that affect the signal strength, so a system could be calibrated to take the RSSI value and evaluate the distance ahead of time in a controlled environment but that too is subjected to uncertainty. Since the usage of RSSI values to calculate distance comes with a low cost, it is yet the most preferable tool. The research also states for proper estimation, it is advisable to use transmission power in relevance to the distance. In support of this claim, the experiment showed that an error of 50cm positioning location was experienced even in an indoor noisy environment. The empirical study was carried out in a 3.5 x 4.5m room with radio frequency, algorithmic parameters, and RSSI value on a mobile device. Similarly, in the Time of arrival method, the distance between the IoT devices should be proportional to the time taken for the signal to travel from one device to another. It uses the phase processing technique in correlation with signal and synchronized time to yield accuracy. Since this technique is mostly used to measure the distance between IEEE 802.15.4 devices, its applicability to Bluetooth signals may be questionable. On the other hand, the Time Difference of Arrival method dictates the difference in time taken for multiple signals from a device to reach another device. This technique is based on different propagation speeds such as ultrasound and radio frequency, and extra hardware. As per the article, the first propagated signal is light-phased, and then the second signal is usually slower. The second signal is propagated at a magnitude of six orders slower. Time Difference of Arrival uses another method which is called Direct Sequence Spread Spectrum modulation, where the difference of distance error is said to be only several centimeters. In practice with ultrasound signals in between three mobile IoT devices, the error was noted to be three centimeters. The acoustic sound produced an error of 23cm between two meters. Though this method proved useful in accuracy, the range of the second signal is limited to 3 - 10m in correspondence with the transmitting power. Another scenario of location systems using distance estimation was the Active Badge system, which finds location from infrared signals. An individual can wear these infrared badges that send unique packets on demand, periodically. The server receives and collects badge data from the infrared sensors in the building, but the infrared signal is limited in range, so diffused infrared signals could be used in fluorescent light or direct sunlight to achieve maximum advantages.

Moreover, Bluetooth LE can operate for years with just a single battery. It offers advantages such as monitoring workers for real-time process control for safety reasons on vehicle collision whilst conditionally monitoring (blueupbeacons, 2023). However, it was noted that energy is often wasted in dense IoT environments due to collision as there are countless devices in a dense IoT environment. Therefore, active mode opportunistic listening was introduced with a large number of tags and a small number of scanning devices (Harris III, Khanna, Tuncay, Want, & Kravets, 2016). The paper also focused on passive advertising using a design called Smart LaBLEs, which is a BLE-enabled, electronic, centralized hub that aggregates multiple advertisements of similar products in a retail environment.

Similarly, BLE is better suited for IoT deployment than in comparison with NFC - Near Field Communication, Bluetooth Classic, ZigBee, and RFID, due to short range distance, complexities in discovery, prohibition, and unfeasibility of installation in mobile devices. The reason why BLE is dominating IoT deployments is because it simplifies the complex discovery mechanism of Bluetooth classic, avoids pairing, and allows short-distance data exchange. Smart LaBLE connects with nearby IoT devices advertising similar product information, aggregates all advertisements, and cancels redundant advertisements. In comparison with Bluetooth Classic, BLE only presents three channels for advertising, this fact may come as a restriction but many channels will cause access delays, these three channels do not carry data but fall in between and outside the frequencies of IEEE802.11 to allow better wireless excess (Harris III, Khanna, Tuncay, Want, & Kravets, 2016).

It also forecasted that future IoT environments will be denser as the number of tags will increase and so will the corresponding scanning devices, which will make the BLE a roadblock. Two possible scenarios were highlighted and based on the scenarios; experiments were carried out. Scenario one : Increasing the density of the scanning device. Scenario two: Dense IoT deployment of advertising devices (Harris III, Khanna, Tuncay, Want, & Kravets, 2016). As per scenario one, the defect lies in the active scanning mode, where the scanning devices request extra information from specific tags, though this mode eases extended data exchange, however, the wireless channels are easily overwhelmed even with few scanning devices. So, opportunistic listening is proposed by leveraging responses from other devices. The second scenario was noted where multiple devices were advertised in the same space using passive scanning mode. As per the paper, significant degradation occurs when the advertising tag increases, so the implementation of a de-centralized aggregation hub for IoT environment called smart LaBels was proposed. The word LaBel is the coinage of the two words, Label and BLE which signified the capabilities of the device. In a dense IoT environment usage of BLE causes collision because of active and passive advertisements. Therefore, a back-off mechanism is proposed to back off from the current perspective device if it's delayed or seems to be delayed, this allows the next device to send an advertisement while avoiding collision at the same time. Additionally, for those devices that have been backed off, the scan responses from these devices will be ignored. Nevertheless, to negate any uncertainties, the back-off algorithm is reset at the start of the listening process (Harris III, Khanna, Tuncay, Want, & Kravets, 2016).

On the other hand, the de-escalation of epidemics and pandemics like COVID-19 highlights the use of BLE, MCU - microcontroller unit, and IoT. As per the experiment, the microcontroller unit has two modules ESP and HC-05. ESP is for Wi-fi connectivity and HC-05 is for Bluetooth connection. HC-05 connects to nearby BLE tags using AT - commands and collects their unique MAC addresses with timestamps and communicates to ESP using Universal Asynchronous Receive Transmitter - UART mode. The ESP then checks the received BLE tags with the information from the database and alerts the nearby IoT devices and the radar applications if the tag is labeled as positive. This process is logged again in the database. The database uses Firebase Authentication to authenticate, retrieve, and store data in real time. Also, the authenticated Scanned BLE tags (healthy person) are notified via messages using Firebase cloud messaging. This system can be connected to other analytical applications for analysis or classified message distribution, the radar application is connected to an alarm to warn the users in that particular area (Chakravarthi, Sathyaseelan, Sathyaseelan, & Sudipta, 2021).

Nevertheless, a study also elaborates on the obstructing factors of Bluetooth devices (Zhou & Liu, 2022). The obstructing factors are communication blockage, signal noise raised by other sources, and vulnerability in application algorithms. This paper iterates experimentation on RSSI-based localization to test the accuracy of the proposed design framework. The proposed framework incorporated an enhanced RSSI-based framework PanoBLE over existing Bluetooth devices.

1.3. Discussions

In discussion, (Wiliot, 2023) highlights the incorporation of Bluetooth RTIs to improve the supply chain from farm to the customer, while (blueupbeacons, 2023) shows that using BLE tags in a manufacturing industry improves productivity, saves time and ensures quality assurance and source (Chakravarthi, Sathyaseelan, Sathyaseelan, & Sudipta, 2021) uses BLE enable medical equipment to identify covid positive patients in a health setting and warn others to provide safety. On the contract, source (Harris III, Khanna, Tuncay, Want, & Kravets, 2016) showed that BLE is a better wireless technology for IoT deployment in comparison with other wireless technology as its battery power is long lasting and the advertising strategy that it uses aims better opportunistic connectivity. Subsequently, to improve the connectivity and bypass the interference, source (Jung, Kang, & Bae , 2014) incorporates low pass filter. Finally, source (Zhou & Liu, 2022) highlights the obstructions that can affect the Bluetooth RSSI in an indoor environment and incorporation of BLE framework improves the RSSI.

1.4. Summary

In conclusion of this chapter, it can be deduced that Bluetooth is an essential application technology when it comes to IoT based indoor automation, so after scrutiny of couple of sources its limitations were also noted, and more sources will be explored and exploited to contribute towards this study. As, this document proceeds, the next section is on a comprehensive Literature Review and thereafter, Methodologies, Results and Analysis, and Conclusion.

Chapter 2 – Literature Review

Chapter 2: Literature Review

2.1. Introduction

In this chapter an extensive literature review will be captured, the literature review is divided into subtopics of Bluetooth, IoT, Stack Protocol, Indoor Localisation and RSSI. The first subtopic which is on Bluetooth that captures the evolution of Bluetooth and its functionalities with its newer version. The second subtopic captures literary articles on the usability of Bluetooth in IoT setting and its advantages and disadvantages. Afterwards, literary sources on stack protocol were scrutinized to observe the communication in between the architectural layers and application concepts of Bluetooth in IoT in detail to see how different applications are conceptualized. The fourth Subtopic is on Indoor Localisation, this subtopic is not directly related to the area of research, but it identifies useful techniques to improve or optimize wireless connection indoors, it also captures literary articles on techniques such as distance estimation, proximity estimation and direction finding and communication protocols such as MQTT for efficient IoT based communication. Lastly, the subtopic on RSSI captures descriptive literature review on various filters such as Kalman filter and discrete filter that can be used to minimize the noise effect that are present in an indoor environment. Afterwards discussion and conclusion will be drawn as well.

2.2 Significance of Work

2.2.1 Bluetooth

Bluetooth was first introduced in 1999 and since then the technology has greatly evolved. Therefore, the list of all the versions of Bluetooth as of today (pcmag, 2022) are iterated as follows for documentation and exploitation.

Bluetooth 1.0 and 1.0B (1999) - These were the first Bluetooth specifications; due to some technical issues these products did not take over the market as it was expected.

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Bluetooth 1.1 (2001) - improvements in terms of reliability and interoperability were observed but as per the article, it was said to be mostly backward compatible.

⇩

Bluetooth 1.2 (2003) - This version of Bluetooth was said to be BDR - Basic Data Rate, which was the first widely used Bluetooth technology. Its adaptive frequency hopping avoided interferences with Wi-Fi and other technologies in the same frequency. The pairing speed also improved.

Bluetooth 2 (2004) - This version was noted to provide enhanced data rate, allowing 3-bit encoding to increase data rate from 1Mbps to 3Mbps. Also, less power was used and interference handing was improved.

Bluetooth 2.1 (2007) - This version had secure simple pairing which allowed secured and faster pairing. Security improvement was noted with mandatory encryption and power usage seemed to be optimized.

Bluetooth 3 + HS (2009) - This version of Bluetooth came with high speed; it started as Bluetooth but later allowed data transmission via Wi-Fi.

Bluetooth 4 (2010) - This version introduced Bluetooth Low Energy (BLE), which was branded as Bluetooth Smart. The BLE device can operate for years without requiring battery replacement. Operating in 2.4 GHz frequency band, this technology can support peer to peer and star topologies.

Bluetooth 4.1 (2013) - Efficient data exchange and better co-existence with LTE frequencies. It maintains connection with less manual intervention and allows the devices to be client and hub at the same time, enabling Bluetooth devices to communicate with each other. Before the introduction of Bluetooth 4.1 the transmission first occurred with the Hub which was an in-built computer and in a stand-alone dongle.

Bluetooth 4.2 (2014) - This version of Bluetooth was specifically designed for Internet of Things, the payload in Bluetooth packets was increased by ten times. Thus lowering the overhead and yielding 2.5 times more data. The IPV6 of Low power wireless personal area network is also supported, hence devices have unique IP addresses. It also offers supporting features such as beacon privacy which prevents retail shops from sensing the user's presence.

Bluetooth 5 (2016) - A robust version with extended battery life that allows outdoor transmission from 50 m - 200m ranges. Location services were optmised as more information could be exchanged prior to establishing a connection. The first set of smartphones to support Bluetooth 5 was Samsung Galaxy S8 and iPhone X and i8.

Bluetooth 5.1 (2019) - Provides tracking accuracy, and generic attribute caching profile enables swift pairing while retaining requirements.

Bluetooth 5.2 (2020) - Its low energy power control features allows adjustable power control that can be requested by peers. The enhanced attribute protocol enables parallel operations between low energy clients and servers.

Bluetooth 5.2 (2020) - Its low energy power control features allows adjustable power control that can be requested by peers. The enhanced attribute protocol enables parallel operations between low energy clients and servers.

Figure 1: Illustration of Bluetooth Evolution

Bluetooth has evolved in such a way that its usability is even noted in trivial applications like mood board (Makhija & Wadhwa, 2019) which was proposed to evaluate group's mood and is designed to aid educators for learning and teaching purposes. It has a portable independent hardware evaluation unit for real-time evaluation. This tool helps the teaching institutes in facilitating a teaching environment and enhancing emotional literacy amongst students via IoT applications. The mood board is a portable hardware tool that facilitates the mood meter, which is displayed using the LED light on a 3X3 matrix of 4 distinguished groups. The Board emulates the 25 different sub-emotions. The liquid crystal displays the current mode on the overall group mode and entries relating to each emotional quadrant. The input to the mood board is received from the mood application via Bluetooth connection.

Moreover, Bluetooth Low Energy in smartphones can communicate with multiple peripherals and based on its underlying layers multiple functionalities are accessible and might not be accessible, so operating systems and security operation centers (SoC) play a significant role when it comes to maximizing the usability of Bluetooth-enabled IoT peripherals (Fürst, Chen, Kim, & Bonnet, 2018).

2.2.2 IoT

It was noted IEEE 802.15.4 and Bluetooth packages such as BLE, Bluetooth Classic - Basic Data Rate - BDR, Enhanced Data Rate 2 - EDR2, Enhanced Data Rate 3 - EDR3 to implement a multimode Wireless Personal Area Network - WPAN trans receiver in a Security Operations Center (SoC) for low power consumption and to allow various options for wireless transfers in IoT environment at the same time (Zolfaghari, et al., 2017).

Another article focuses on the introduction of Bluetooth five standard and how it is a better option for the Internet of Things and future Internet of Things in comparison with Bluetooth Standard four. This paper discusses the advantages of Bluetooth five and the new incorporations that further highlight the importance of it. In contrast, even though Bluetooth has greatly evolved since 1994, there is no limitation on the types of data that need to be transmitted but there are limitations on distance - max 100m, throughput, and transmission rate (Mario Collotta, 2018).

Other concerns such as power consumption, connection with IoT applications and machine-to-machine requires power to carry out the desired task, Wi-Fi also seems to be a viable option for IoT but the power consumption with it is too high, which means a short active time before recharging again. This article also discusses Bluetooth low energy which came through standard 4, an efficient technology to utilize power properly and serve on vehicular systems. This initiated the Bluetooth Special Interest Group to introduce Bluetooth five with its added advantages of range, speed, and broadcasting capabilities. Hence, this article presents information on other wireless technologies in comparison with Bluetooth five for the Internet of Things. As per the article, the Bluetooth five device does not need an AC power supply and as a matter of fact, the device could be installed with a battery. To add on, Bluetooth five comes with sensitivity as well, which has provisions to reduce the data rate hence the power consumption could be saved. It was also noted that the Low-energy Bluetooth connection packet headers and payloads are usually un-coded, and this remains the same with 1Mbps and 2Mbps connections. Similarly, the LE in Bluetooth five uses two data rate links 125kbps and 500kbps with a corresponding symbol per bit rate of eight and two respectively. The symbol indicates tolerance of noise-to-signal ratio, whereas higher symbol bit rate indicates higher tolerance to weak noise-to-signal ratio and yet provides a recoverable data stream. This is made possible via two prominent processes that are carried out at the hardware level. The first step involves forward error correction and then the pattern mapper outlines the bit codes to the input bits. As a result, the spread data provides recovery using forward error correction if a bit error occurs, hence this improves the ability to recover the received bit streams. These steps are especially useful when the signal-to-noise ratio is reduced to a level that the reception data becomes intolerable without the usage of low energy coded mode. From the findings, the advantages and challenges of Bluetooth five are listed as follows (Mario Collotta, 2018).

Advantages of Bluetooth five (Mario Collotta, 2018);

i. Serves greater speed, where the speed is more than Standard four and the air throughput is twice, making it 1400kbps.
ii. Better power consumption which is twice as much than Standard four.
iii. Bluetooth five is also noted to have a better transmission rate outdoors, resulting in a 120m range distance outdoors and an even better throughput rate in comparison with 4.2 standard and IEEE802.15.4 wireless protocols.
iv. Deployment of beacons in an IoT environment using standard five to control it in a mesh structure where the devices can collect data and transmit it to the hub. The scenarios may be experienced with supermarkets, museums, and streetlights, and self-driven cars too.

Challengers of Bluetooth 5 that were noted (Mario Collotta, 2018);

i. Scalability - the number of devices, users and interaction between them seemingly is a problem.
ii. Interoperability - heterogeneity of enabling devices makes it difficult for the platforms.
iii. Efficiency in Communication - Things to be noted for efficient communication: - viable IoT, low-power sensors, wireless transceivers, communication, and machine-to-machine networking.
iv. Security and Privacy - in regard to data mining, data privacy, and providing secure access.
v. Timeliness and freshness of data - ensuring this criterion is met.
vi. Mobility, access, and service continuity - ubiquity of IoT seems to lead to all these challenges.
vii. Practical Naming, resolution, and discovery - where standard five seems to be trumping in this criterion.

This paper also concludes that for simple sensors and actuators operations, a 125kbps connection could be used to obtain the extra range as it comes with the low energy coded mode for higher data transmission as it is advisable to use 500kbps for obvious reasons (Mario Collotta, 2018).

As already noted via research, BLE is known for low power consumption and the data transmission is small and happens infrequently in comparison with other Bluetooth applications. It was also noted that Bluetooth introduced a new radio called Bluetooth Classic (Chang & Consulting, 2014). As per the article, the Bluetooth Classic has 79 channels with 1 MHz bandwidth. The modulation scheme used is quadrature phase shift keying 4PSK or 8PSK Gaussian Frequency shift keying. In addition, BLE also employs GFSK but with 3MHz bandwidth using three channels for advertising out of its 40 channels. The advertising channels are responsible for the discovery, initial communication, and exchange of data. As the role of the advertising channels is very important, BLE is built robustly for those three advertising channels based on the criteria of least interference for wireless signals. The packets that are exchanged in the initial communication are one byte of preamble, four bytes of access code, three bytes of cyclic redundancy code, and a protocol data byte of 2 - 39 bytes. As per the packet size, the smallest impulse of 80Mu/s to longest impulse of 300Mu/s could be transmitted. Hence fulfilling the low duty cycle which is essential for wireless-based networks.

2.2.3 Stack Protocol

The stack protocol in BLE is structured well to receive IP Communication and reduce power consumption. The design is same in comparison with Bluetooth Classic, whereby the host controller interface separates the host portion which comprises of generic access profile, generic attribute profile, attribute protocol, Security manager, Logical link control, and adaptation protocol from the controller portion which includes Link Layer, physical layer and direct test mode. Now as the IPv6 packets are much larger than BLE, the packets need to be fragmented before transmission and assembled afterward. This process is carried out in the Logical Link Control and Adaptation Protocol. Similarly, Generic Access Profile is responsible for displaying generic procedures for BLE devices during the discovery process and management of connection between the low-energy devices. The security manager ensures the pairing of devices and key distribution, it manages the shifting of workload from the slave device to the master device for efficiency and need-based scenario. Attribute Protocol allows the attribute server to expose attribute values to an attribute client while optimizing small packet sizes. Generic Attribute Profile distinguishes a service framework using attribute framework for discovering services, reading, and writing characteristics value on peer device. This process minimizes the size of data exchanges ensuring energy optimization. The generic access profile plays two roles of central and peripheral functions, whereby the central role allows connection with several multiple devices simultaneously in the peripheral, whereas the peripheral role allows the peripheral to be connected to the single central device but modified later to include many in standard 4.1 to make provisions for Mesh setup (Chang & Consulting, 2014).

IoT (Gore, Kour, Gandhi, Tandur, & Varghese, 2019)in business sectors such as oil-gas, chemical, power, and water has proven to be beneficial while transforming businesses in a progressive direction through informed decision-making and visualization. In a typical situation, IoT in industries functions with a sensor device that is connected to the plants to harness the data to the internet for monitoring and controlling purposes via a gateway using wireless communication. So, this leads to the choice of wireless communication from the various options out there to the best choice, which is BLE to connect sensor nodes to internet-based applications for remote monitoring via a gateway.

The major reason for choosing BLE in this experiment (Gore, Kour, Gandhi, Tandur, & Varghese, 2019) is because the sensor devices were already Bluetooth enabled and the gateway device to relay data to the internet was within a few meters. Also, BLE offered two states for connection which were connected and advertised. In the connected mode, the Generic Attribute Layer exchanges data in a one-to-one connection whereas, in advertising mode, Generic Access Profile layer broadcasts data to any device that is listening. Similarly, BLE remains in sleep mode until and unless a connection is initiated, which is an excellent choice for IoT power-hungry applications. This BLE-based data acquisition system has multiple sensor devices attached to a gateway device, which has an Android-based acquisition system connected via Bluetooth connection. This gateway transfers data to the server via a 3G/4G/802.11 Wi-Fi as this is out of the Bluetooth connection range. The server has analytics embedded in it for analysis, monitoring, and informed decision-making in plant-related matters.

The disadvantage (Gore, Kour, Gandhi, Tandur, & Varghese, 2019) of using Bluetooth connection is that the ad-hoc system requires a lot of manual intervention. Personnel at the field needs to manually connect the sensor device to the gateway to transfer data and terminate the connection to manually connect the next device to initiate a connection for data transfer. So, to fix the defect, the researchers developed a mobile-based autonomous APP mobile application that automatically searches the first device, forms connection, and terminates in pursuit of the next, till all the devices have successfully transferred. This system includes added functionalities that can search for the remaining devices that were not available for data transmission previously. As, the experiment proceeded, the performance of the local BLE communication was investigated using parameters such as the Received Signal Strength Indicator, Transmission latency and power consumption. A mobile application was designed to investigate the efficiency and performance of the system while capturing time for individual data packets from different sensors with timestamps. To achieve efficient results, it was necessary to clarify the parameters in its optimal environment as suited to the situation. RSSI was measured by its power received from the radio signals which were derived from the frames received. The power consumption was measured in joules whereby the specimen gateway's power consumption to acquire data from the sensors needs to be preferably low. The last one is transmission latency, which measures the time the data was transferred from the device and its availability of reception at the gateway. For critical functions and real-time decision making the transmission latency needs to be preferably low. The automated experiment was carried out in a controlled and uncontrolled environment as well, that is indoors and outdoors. The RSSI measurement was noted to be decreasing both in indoor and outdoor environments as the distance increased. The experiment included an estimate of RSSI and the actual results, it was noted from the results that the optimal distance is up to 15 meters indoors and 20 meters outdoors. Likewise, energy consumption significantly increases with distance and as well as latency.

Similarly, implementation of Bluetooth-based local communication on a factory floor (Gandhi, Kour , Tandur, Gore, & Varghese, 2017) to collect real-time data while relaying it to the server for segregation and further analyses to provide real-time information which may be accessible on a mobile device with an augmented reality application to provide a context-based sensitive information to the user. Communication from the server to the mobile devices is via Wi-Fi. Bluetooth seems to be an excellent choice for local communication for IoT.

As per the context (Gandhi, Kour , Tandur, Gore, & Varghese, 2017), the factory floor was divided into three zones to implement nodes that will collect data from its assigned zone. So respectively, three Bluetooth nodes were implemented in each zone that intercommunicated with each other in-order to relay data to the server. Each zone had different types of devices at a distance of 6m that waited for its turn to establish the connection, exchange data, and terminate the connection to initiate connection with the next device, once the data from all the devices are collected by the nodes from its respective zone the preceding node forms connection with the first neighbouring node to collect the data and waits for the next node to initiate connection to eventuate the transfer to the server. If in case any device connection is lost the nodes keep the previous data with the timestamp, but this depends on the memory status of the node as well. The server segregates the data as per the type to receive the data from various devices and transmits it to the respective application software to further allow critical analysis and provide information for decision making. The information is also relayed to smart devices, or any handheld device held by the factory worker, which is enabled with augmented reality features. This enables the worker to access real-time information while holding the smart device to any device in the factory which will provide visually immersive information.

To further evaluate the feasibility of the system a Raspberry Pi boards were installed in the Bluetooth enabled node in zone two and three. For zone one an android table with augmented reality was used as a node which came with camera initiation. Once the camera was initiated the device image or any object that was recognizable by the system produced an augmented reality with tags to provide the user with real-time trends and other information. The augmented reality application was developed using Unity Engine and Viforia Library (Gore, Kour, Gandhi, Tandur, & Varghese, 2019). The exhaustion of fossil fuels and biomass has led to an insufficiency of resources for the future generation and the immediate next generation (T.Shanthi, Anushree, Prabha, & Rajalakshmi, 2017) as well. As automobiles and consumption of fossil fuel increases, it leads to contamination and a rise in diseases. Although, the availability of biomass energy could be utlised to its fullest as it is abundant in nature and disease-free, these resources need to be monitored so that a balance can be maintained. Therefore, this study proposes a system that will monitor the consumption of solar energy for home appliances in an IoT setting. The appliances are installed with current sensors and temperatures as suitable per situation. The data acquisition collects the data and feeds it to the microcontroller for communication via Bluetooth technology for transmission to mobile applications and web servers as well. This way the user has control over power consumption in an IoT-based home, whereby the user can limit or cut off the power supply via distant host if the usage crosses the desired threshold.

The data acquisition is an ATMEGA 328-P system (T.Shanthi, Anushree, Prabha, & Rajalakshmi, 2017) which is aware of the verge value for each appliance, as the power consumption passes the verge value. The mobile application picks and communicates to the user with a sound alert. Which then prompts the user to cut off the supply. The functionality is achieved by use of two major circuits which are current sensor and voltage sensor, the values from these sensors are fed into the performing microcontrollers of Arduino Uno Board.   The simulation is performed using three software which are Proteus 8, Virtual Serial Ports Emulator, and Energy Tracker App. Proteus eight supervises the consumption of current and voltage in real-time with its clock, which is displayed using LCD format together with the date. After this the virtual serial ports emulator needs accessibility to pair the COM ports together so that the value can be transmitted to mobile applications via Bluetooth. The mobile application called the Energy Tracker receives the information from each appliance in the house such as current, voltage, watt, and time as per the experimental context, the appliance may be added with additional programming. Once these steps are completed, a link is used to upload the data to the webserver using IoT concepts and the data can be viewed in the web browser.

On the same note, findings showed that Kodular tools were used to design a smart switch to control IoT home-based appliances without physical intervention (S, 2021). This smart switch is a mobile-based application system that comes with buttons for turning the appliance on and off mode. For reliability purposes as observed in other studies too, MQTT protocol was used. The system also had timer provisions to switch the appliances on and off at a desirable time based on an individual's suitability. The function was achieved by node-red framework. The users can set the timer from anywhere in the world using the mobile device. Additionally, this system comes with a Bluetooth-based modules for receiving files and playing audio.

Also, it mentions a home security system that operates on Bluetooth to control all the appliances in the house. The security system uses Bluetooth module to command the door to open and shut, on a short-range trans receiver. The user locks and unlocks the door through the system via a mobile device, which will even show the status of the door. When a command is sent to open the door, it responds with a confirmation upon action. It vaguely mentions the usage of Bluetooth to operate security cameras in the IoT homes which could be remotely operated via a mobile device (S, 2021). Subsequently, as the literature review proceeds indoor localization will be researched as well.

2.2.4. Indoor Localization

Indoor localization is perhaps the smartest innovation that has been introduced in the realms of IoT Smart homes. This system helps individuals to save a lot of time and effort while making the task a whole lot easier. There are numerous techniques, methods, and alternatives that can be applied for indoor localization using Bluetooth Technology. However, there are three kinds of Bluetooth connections (Bluetooth SIG, 2019), two of which are Bluetooth Proximity and Bluetooth Location Positioning, which are used for point of interest and item finding solutions using proximity technique. The lather one is used for real time location system for locating assets, people, and other mobile resources in factory floor on real-time using trilateration. Bluetooth location positioning is also used for indoor positioning systems, utlising beacon signals and RSSI to locate. This document introduces the third concept of Bluetooth connection which is direction-finding resolution utilizing the Angle of Arrival and Angel of Departure technique. This technique branched out as a need for accuracy of distance, downright to centimeter level in real-time deployment. As determined by the term direction finding from the aviation and nautical industry navigating based perspective, identifying location positioning from the direction of the signal. As per the article, the direction-finding technique is stipulated in Bluetooth 5.1 core specification to aid in location determination. This adds as a plus point in determining the distance using RSSI and trilateration. Direction finding from the Angle of Arrival simply means the receiving device is receiving signals from an angular perspective. The transmitters such as the factor tags transmit direction-finding signal with a single antenna that connects to the receiving device such as the locator in the factory setting has an array of multiple antennas to receive the signal, so as the signal passes through these multiple antennas, this difference of phase distance is sensed by the receiving device. The IQ samples are taken based on the difference of distance sensed by each array and based on this collected sample of data the relative signal direction is determined. The same concept is applied on Angle of Departure, where the transmitting device such as the locator beacon transmits the direction-finding signal, using multiple arrays of antennas to the receiving device such as the mobile phone in an indoor positioning system with a signal antenna to take the IQ sample to determine the relative signal direction. The direction-finding capability of

Bluetooth is meant to enhance item finding, point of Interest Information, real-time location system, and indoor location system solutions.

Further on, two methods were identified via research as of how the indoor locating system could be plausible enough to facilitate are listed as follows (Goh, et al., 2020);

1. A TRICON experiment was carried out where ultra-high frequency RFIDs were implemented in each corner in a 9mx9m room. These RFIDs were said to be operating at 865 - 870 MHz, with a transmitting power of 100mW - 4W operating at a five-meter distance. The 9mx9m room was divided into x-axis and y-axis to identify the location in terms of coordinates. It was noticed that the signal reception significantly improved as the number of RFIDs were increased which acted as neighbors to the nearby tags allowing easier fingerprinting. As per the experiment, the effective range was from 1m -7m distance.
2. The second method pointed out the usage of received signal strength indicator measurement in IoT applications as a primary means of accessing the location. Scientists used both fingerprinting and multi-trilateration approaches for locating mobile devices perche Sony Xepria Sola 2.3 API Android Smart device with Wi-Fi 802.11 capabilities in an indoor environment. The application required the targeted floor plan which should be uploaded with a proper scale and correct position. The map used fingerprinting approaches to collect the data from each doit in terms of identifying the location.

The proposed project (Goh, et al., 2020) conceptualizes these two methods to implement an indoor locating system, provisioning the user to attach Bluetooth tags to effectively locate items while saving person-hours and time lost while manually recovering the misplaced item. The project is divided into two stages: product development and product deployment. In product development, the processes are divided into two stages, which are hardware development and software development. In the hardware development stage, ESP32 is configured to accept and transmit Bluetooth RSSI. The RSSI will be later pushed to the MQTT architecture for binary operations which will eventuate towards software development, where the received signal will be transported to the React Application via SSL connection for processing and multi-literation. The location will be finally viewed or accessed on the webpage.

The system development required combined efforts of the raw data, customized project libraries, window applications like React and MQTT to produce the viewable result. The ESP32 board acts as the hardware which pushes the Bluetooth beacon signal to the local area network via MQTT broker on IoT concepts. MQTT broker publishes this data via its publishing port which is then pushed to the react application for trilateration processing to identify the location. These results will be then published on the webpage. For this experiment, the major part was utilizing MQTT subscription-based TCP/IP protocol for IoT systems and customizing javascript libraries to set up react applications and configure a webpage.

The experiment (Goh, et al., 2020) was carried out in two different environments. One was a 1.5m x 15m indoor corridor and the other one was a 5m x 10m indoor living room. This was done to check the RSSI stability of data packets transmitted from the beacon equipment, which were WGX BLE Beacon and iBeacon protocol. This equipment was set up for a broadcasting power of -4dBm and at an advertising interval of 1000ms. The RSSI was sampled while considering the uncertainties, which included taking the sample data from varied steady sets distance and from a point of mobile varied sets of distance. In scenario one, the choice of equipment was BLE Scanner 4.0 and light blue explorer applications. Scenario two mostly used a couple of ESP32 to collect data for multi-trilateration purposes. Both experiments were carried out with furniture that catered to the noise interferences and obstacles for a real-time situation. Noise interferences from the WIFI Access points were a major cause for the changing RSSI reading.

In addition, IoT (Terán, Aranda, Carrillo, Mendez, & Parra, 2017) home based indoor locating system using Bluetooth low energy which basically required data acquisition system and a central server to form a server-client relationship for the IoT architecture. The proposed system includes BLE beacons for signals, data aggregation and transmission mean, a storage facility, a web-based interface, and cloud services. This system utilizes the simple localizing technique of foot-printing on received signal strength indicators. Foot-printing involves the detection of reference zones inside a closed environment which was tested in a real scenario. Thus, this paper includes the design, implementation, and evaluation of the system. The basic IoT architecture includes four modules. These modules are:

i. Sensors for capturing physical variables.
ii. Embedded systems for interfacing and processing.
iii. Data communication for transmission and connectivity.
iv. Data Analytics for generating insights.

It also incorporates facts such as possible wireless usage for indoor locating systems, which are Wi-Fi, Bluetooth, and GMS frequency bands. Another interesting fact that was noted, after applying the fingerprinting technique to calculate distance, was particle filtering which could be applied to refine and reduce ambiguity. The architecture of the proposed system starts with the data acquisition system acquiring radio frequency via Bluetooth technology to identify the received signal strength and construct a data frame. Afterward, the sensed data is transported to the central server via wireless technology. This central server system includes a local database for storage and a web interface for displaying processed and unprocessed data from the database. The purpose of the central server system is to perform localizing algorithms, store data in the database, and transport the output to the cloud for data analytics to provide browser visualization on any mobile device via an internet connection.

The Acquisition system (Terán, Aranda, Carrillo, Mendez, & Parra, 2017) includes sensing, data aggregation, and data transmission. The central server system includes database management, Socket interface, and web-based Ubiqdots - visualization and data analytics. So, the data acquisition unit accepts signals from the Bluetooth beacons and transports them to the Python-based sensing module, the data from the sensing module passes through the data aggregation module for further processing and finally it passes via the socket module, which marks the exit. This socket module is connected to the central server unit via its socket module on Wi-Fi connection. The Central server socket module distributes received data to the Ubiqdots system for cloud transmission and analytics, also to the database management module, which runs on SQL and C++. The data is stored in the database and sent to the web server for displaying purposes. Ubiqdots were chosen for the experiment as it provides flexibility, ease of use, and gives insights into the positioning of the receiver node. Also, edge computing was conceptualized to perform all the actual computations. As per the processes in the central server system, there are two separate independent processes that are carried out in this unit. The central server management initializes system parameters which include buffer, socket, and variables, then it sends a SQL request to the database to create an entry in the database, once the entry is created the database sends the message back to the central server management. Afterward, it creates and runs the client & server socket to listen to the new frame, once new frames are received an acknowledgment is sent to close the server socket and de-serialize the data frame. The central server management then determines the distance to the beacons, identifies the reference station, and sends SQL request to receive and store data in the database table. The database then sends the SQL confirmation that data has been inserted. The central server management constructs a JSON frame and sends it to the Ubiqdots web server via the sockets. The Ubiqdots web server then receives the JSON frame, updates the dashboard, and waits for the updates. Simultaneously, the central web server closes the Ubiqdot socket once the process has been completed and starts listening to the port for a new frame. The second independent process initiates from the Web Client Browser, to create a request to the database, it checks if the request has been created then this request is sent to the Local Web Server. The Local Web Server receives the HTTP message and serves by creating the query request that is sent to the Database. The database receives SQL Server request Query, accesses the query tables, and sends the query tables back to the Local Web Server. The web server receives the query tables and sends them to the web client browser in HTTP format, where the tables are updated in HTML format. Similarly, the acquisition system management initiates a system parameter request, to open BLE port for scanning available nearby beacons to extract the beacon parameters like RSSI and the current time. The collected data is aggregated, and data frame is created. The data frame is sent to the write socket to check if the frame is received, and if it is received then the socket is closed.

Moreover, findings shows that the respective wireless protocols (Sadowski & Spachos, 2018) and their received signal strength indicator identify the location and more precisely estimate the distance with fewer errors as the received signal strength indicator is receipted with error on the receiving device. This paper also highlights trilateration for estimating localization based on the setup of 3 nodes, which are located at precise coordinates. A mathematical equation is used to calculate or rather estimate the distance of any node. The coordinates are given on the x-axis, y-axis and based on these coordinates the equation to calculate the error is also formulated to achieve accuracy. In Addition, to find a certain power consumption, the transmitting node was plugged into a Monsoon Power Monitor which is capable of accepting 5000 samples per second. So, the average power usage of all the devices in the connected circuit is known all the time plus it also measures the voltage and draws current as well. To specifically identify the power usage of the current wireless technology, the measurement was taken when the nodes were transmitting and then when the nodes were idle. The subtraction of these two measurements was taken as the power of the current wireless operation. The set of wireless technology that was used for this experiment was IEEE 802.11N, BLE 4.0, IEEE 802.15.4 and LoRaWAN.

IEEE802.11N - this technology is widely used for Wireless Local Area Networks, and it operates on a 2.4GHz - 5GHz frequency band. This technology is mostly used for communication and its priority is based on connectivity with high data, which is why it is being preferred for IoT deployments, but it may face challenges as the number of nodes or devices in the network increases (Sadowski & Spachos, 2018). Bluetooth Low Energy - The choice of this technology is mostly due to low power consumption and the cost associated with it. This technology also comes with beacon devices, which could be used to transmit data to nearby BLE-enabled receivers for localization. The most ideal reason for using this technology is because it is an excellent choice for short-range communication.

IEEE802.15.4 - This technology is mostly used for wireless personal area networks for low data rate antennas and is best known for its simplicity, low power usage and secure network capabilities. Since IEEE802.15.4 comes with carrier sense multiple access collision avoidance protocol, the information is controlled, and data loss is avoided. Perhaps, one of the reasons why this option is opted for IoT devices is because it comes with excellent link quality and energy measurement, which makes it easy for RSSI measurement. It also has a greater range than Bluetooth Low energy and supports mesh network. However, peripherals and hardware are required for Wireless Sensor setup, so it is not an excellent choice for IoT deployment. Low Range Wide Area Network - As the term states this network is meant to serve long range on low-frequency band of 915MHz. The distance ranges up to 15000 meters and the waves that are transmitted are often with low frequency, which means larger wavelengths so the signals can pass through the walls, and barriers without any further obstacle. It also utilizes 2.4 GHz frequency band, but it is relatively vacant, so it is not susceptible to external noises and interference. This technology may not be an excellent choice for IoT devices because of the low data rate but in the case of indoor localization, the distance is in proximity, so its low data rate is not an issue. Since its 915MHz is also unlicensed, implying free of use universally. However, the downside of this technology is that it comes with hardware with big antennas which are costly. The article also presents some challenges for indoor localization since it is meant for long-range transmission.

To add on, environmental factors were also considered while carrying out this experiment (Sadowski & Spachos, 2018). So, the experiment was performed in different rooms, with varying settings to serve the real-world scenario which comes with obstacles and interferences. Room 1 was a 10.8m x 7.3m research lab, this room occupied a lot of computers, Wi-Fi, and Bluetooth materials which could interfere with the readings. The second room was a 5.6m x 5.9m meeting room, this room was a direct contrast to the first room as it was mostly empty and occupied tables and chairs. So, this functioned as an environment with low noise and interference. To avoid any further signal interferences, the nodes were placed on the tables at the same height to limit the reflection of the transmitted signals off the ground.

The hardware components that were used for the experiment are listed as follows.

i. IEEE802.11N- 4 Raspberry Pi 3 Model Bs
ii. BLE - 3 Gimbal Series 10 Beacons by Qualcomm, the beacons were configured using iBeacon protocol developed by Apple.
iii. IEEE802.15.4 - 4 Arduino Unos, 4 Series 2 2mW Wire Antenna XBees, XBees were configured to run on ZigBig Mesh protocol operating on a 2.4 GHz frequency band.
iv. LoRaWAN - 4 Arduinos equipped with Dragino LoRa Shield were used. Three of these devices were used as transmitters and one was used as the receiver.

Moreover, a path loss model (Sadowski & Spachos, 2018) was also developed for each of the wireless technologies used in the experiment for different environments. For each of the models, a transmitter and receiver were placed over a range of fixed positions to record their received signal strength indicator. This was done to determine how the signal strength decreased with the ranges. It was noted that a few points over the range of distances were the best fit, so the distance was chosen between 0 - 5 m. 18 points of measurement were taken, nine of them were taken between 0 - 1m, i.e., once every 0.1m, and the other nine measurements were taken from 1m - 5m distance, i.e. once every 0.5m. The RSSI measurement and its corresponding distance were taken and plotted on a fitting curve using MATLAB. As per the graph, it was noted that both environments experienced noise interference but the accuracy for environment two was unstable as the setup was not done accordingly. After this the RSSI measurement was taken for all the wireless technology to determine the distance and the accuracy was calculated using the formula. As per the accuracy formula, Wi-Fi was noted to be the most accurate one, while BLE was second and the ZigBee technology was number three whereas Low Range Wide Area Network was the last one on the accuracy list, overall. Similarly, the power consumption of the devices was also noted, Wi-Fi technology was chewing most power, while Low Range WAN was second, IEEE802.15.4 was third was and Bluetooth Low Energy devices were most efficient with power consumption. In discussion, employing Wi-Fi meant accuracy but it was consuming a lot of power which is not economical, Bluetooth technology was ranked second in accuracy with efficient power management, but the transmission range was restricted even though rechargeable batteries could be used in order to minimize the cost for application context. The Low Range Wide Area Network was associated with excessive power consumption even though it possesses the advantage of stretched range which means nodes could be placed on a stretched plane which was not desirable as per the setting and cost. Lastly, IEEE802.11N was chosen as the most accurate and favorable wireless technology for the setting.

Another finding shows that Bluetooth low-energy beacon facilitates the Direction of Departure mechanism to accommodate frequency-steered leaky wave antenna which was set in an array for transmission (Poveda-Garcia, Gomez-Alcaraz, Canete-Rebenaque, Martinez-Sala, & Gomez-Tornero, 2020). The Leaky wave array is a passive instrument that is fabricated in an economical FR4 printed circuit board to multiplex differentiated angular directions in space, which is associated with the three periodic advertising channels for transmitting the ID. Therefore, this choice serves as a cheaper option to a much more expensive phase steering array/ beam switching electronics. This mechanism works by connecting the four Bluetooth four modules to the four arrays, which produce an exceptional beacon that produces 12 directional beams which are distributed on an azimuthal plane of 120 degrees horizontally, which is referred to as a field of view. This field of view scans the messages and obtains the corresponding RSSI of the 12 beams from any Bluetooth-enabled IoT device within the azimuthal plane. The estimated relative Direction of Departure using amplitude mono-pulse signal processing allows the distribution of complex In-phase/ Quadrature data acquisition or high computational load. The authors are proposing an angular windowing technique to eliminate angular ambiguities and improve the angular resolution, which reports a root mean squared angular error of 3.7 degrees in the same azimuthal plane. As per the system description, the Bluetooth beacon consists of four Bluetooth low energy modules configured as a scanner which is connected to the 2 - 2 sets of radio frequency leaky wavelength array ports, as of the experiment the BLE modules were connected to a Linux operated laptop for control purposes by running python scripts. The laptop collects data from the BLE beacon modules to approximate the Direction of Departure signals from the BLE unit. This paper also indicates that the BLE beacon signals do not include the advertising channel (37, 38 &39) data in the messages, which is required at the receiver together with the MAC address, payload, and RSSI. So, as a solution to the problem, a BLE beacon is needed which includes the channel data in the advertising message which could be easily retrievable by any of the IoT devices. To suffice this, beacon transmission should be configured together with the transmission channel map. The transmission channel map displays the list of allowed channels either in bulk or individually. The first signal carries channel 37 correspondence together with its payload information and MAC address, which is assigned to a value that identifies the Bluetooth module and supports information about the indication of the channel itself. The configuration is also completed with the inculcation of interval periods and the total amount of advertising messages that eventuate the flood relaying of the messages. This process is repeated for channels 38 and 39 whereby the BLE Scanner with Python script periodically switches to facilitate all four modules to transmit 10 messages every 100milisecond. The mobile application connected to the beacon collects the raw data such as RSSI, Channel number, MAC address, and timestamp via its scanner and forwards the data for Direction of Departure calculation, which is the sole purpose of this experiment. The antenna array is made up of two parallel leaky wavelength arrays which consist of four ports in total, two in opposite directions. The beams are arranged symmetrically on a half-width microstrip LWA technology which serves simplicity, compact shape, direct integration with printed circuit boards, low-cost characteristics, and low profile planar, all these traits seem to be a reasonable ideal for IoT applications.

Furthermore, the three techniques for wireless indoor localization system (Choi & Jang, 2017), namely, fingerprinting, triangulation and Cell-ID; the triangulation technique is useful for locating items in a wide area but its consistency on accuracy changes as it moves to the indoor narrow environment with physical obstacles and signal interferences. The technique of fingerprinting also seems inefficient as it does not point out the precise location but identifies the signal coming from a particular cell. Therefore, a new technique is introduced for accuracy, which utilizes the K-Nearest Neighbors (K-NN) algorithm and moving average filter. This proposed technique when tested under the same conditions as triangulation and fingerprinting showed an accuracy of 86%, whereas the other techniques showed 45.63% and 72.58% respectively.

A matching algorithm is suggested based on the indoor positioning fingerprinting technique, which combines the K-NN algorithm (Choi & Jang, 2017). This algorithm calculates weighted value score and uses moving average filter to find the most similar data, which also increases accuracy for predicting changes in the data. For instance, the fingerprinting technique divides the cell according to its procedure and then determines the cell where the user is located. So, the K-NN algorithm and the moving average filter increase accuracy. K-NN algorithm provides the captured clustered RSSI data to compare with the user's exact location, which outputs the most similar cell. In addition, the moving average filter reduces the error in RSSI. Therefore, as suggested by the authors, the disadvantages of the triangulation method and the low accuracy of the fingerprinting technique could be altered. The prototype starts with measuring the RSSI signal, and based on this signal, the ID and RSSI of the received beacon are identified. The data is separated and trained in the database for fingerprinting. Once the database receives the signal it checks with the existing information and then outputs for matching algorithm whereby K-NN algorithm and moving average filter are applied. The K-NN algorithm arranges the received RSSI data and its ID in ascending order. The top three RSSI data are calculated by the given weighted value and the error is detected by the moving average filter. If the error of the cell is within the accepted value, then the original weighted value is used.

Otherwise, the filter is used to calculate the final value, which outputs the measured positioning. The K-Nearest Neighbors Algorithm is the crowding algorithm that defines distance metrics and provides criteria for deciding which data is classified in which group that intently allows proximity and similarity to be judged. After the distance metric is defined, sequentially, the dataset is segmented for training and further testing. The algorithm is executed to multiple K, after which the optimum K value is tested. Throughout the process, possible RSSI errors and deviations due to the signal variation strength are determined and mapped data of every cell is compared. The highest score is set to minimum difference which becomes a candidate of the user's location. Therefore, the stronger signal receives a better-weighted score. The moving average filter counts the oldest variable by adding a new variable as time lapses. This method is used when the input data is not constant and misleading prediction needs to be reduced. Hence to check the accuracy of the method, a building floor was divided into 24 spaces, called cells which were 3 x 3 m in dimension, individually. These 24 cells were employed with 10 BLE beacons, and 30 sets of signals were collected in five minutes. Subsequently, the accuracy percentage was noted to be 80% for the Cell-ID, 68.81% for the fingerprinting technique, and 25.68% for the triangulation method. So, as the number of beacons increased so did the accuracy of the experiment, thus four more beacons were employed to test the case and the experimented technique showed improvement.

Likewise, a lot of algorithms and parameters have been proposed and implemented for Bluetooth localization, but this paper focuses on RSSI fingerprinting to determine localization (Castillo-Cara, Lovón-Melgarejo, Bravo-Rocca, Orozco-Barbosa, & García-Varea, 2017). It was noted that in an indoor environment, BLE4.0 connections are subjected to fast fading impairment so the RSSI distance model could not be used, instead five BLE4.0 were planted in a lab with a dimension of 9.3m x 6.3m. Two beacons were installed on one side, and the rest of the beacons were installed on the opposite side as they were longer in length. The lab was divided into 15, $1m^2$ grids, consequently, two devices were used as receivers; a smartphone, and a Raspberry Pi with BLE4.0 antenna. In addition, the broadcasting power of the transmitting devices was changed set-wise to observe the performance of the system using symmetric and asymmetric readings. The experiment was divided into three portions one where the propagated signals from the $1m^2$ grid were used for discretizing and these collected

RSSI from all the beacons were further stored in vectors of $< x, y >$ for fingerprinting. The second portion involved applying the supervised learning algorithm where the weighted K-NN algorithm is combined with Support Vector Metrics. From this stage, the RSSI spectrum breaks down the processes into additional three portions where optimal asymmetric transmission power is classified, then the RSSI for each beacon is analyzed and later, the relevance of the BLE4.0 topology is utilized for localization. It was noted that the symmetrical reading showed better performance than the asymmetrical readings. Six different transmission powers were used, and it was noticed that Tx0x03 and Tx0x05 performed better with beacons seven and nine, especially.

It was also noted that the neighboring beacons displayed better readings and peculiarly the farthest beacons too, which was atypical as these beacons were located on the opposite/diagonal ends. Contrastingly, some of the closest beacons displayed the worst RSSI reading which could have been due to fast fading impairment impacts.

Although, Bluetooth RSSI with trilateration could be developed for localization for the visually impaired using methodologies such as Time of Arrival and Time Difference of Arrival to calculate distance but Time or Arrival and Time Distance of Arrival is not suitable for narrow bandwidths like Bluetooth (Aziz, Owens, Khaleeq-uz-Zaman, & Akbar, 2019). So, a new method was proposed in addition to the Kalman filter as RSSI reading is subjected to interferences and obstacles. Therefore, this filter is used to remove any error or uncertainties that may have been introduced due to combining methodologies. In contrast, GPS signals have been used to guide the visually impaired but there are physical obstructions and hazards in the way, so navigation assistance is thoroughly required. The proposed methodology included devices such as Blue Giga WT-12 with an Evaluation board and manufactured Printed Circuit Board. The software was developed in National Instruments LabView, and the experiment was conducted on a 15 x 15 feet grid.

It was noted that for indoor human position sensing, wireless Local Area Networks, Ultra Wide Band, and Radio Frequency Identification have been amalgamated with building information models for emergencies in complex buildings (Aziz, Owens, Khaleeq-uz-Zaman, & Akbar, 2019). In addition, deterministic and probabilistic techniques such as trilateration and fingerprinting are the fundamental techniques in most Indoor Positioning Systems. Consolidated pedestrian dead reckoning and weighted path loss algorithm with a Log-distance path loss model between a router and a client under the extended Kalman filter is another technique to be noted. Moreover, the tailored RSSI fingerprinting model was most widely used in wireless Local Area Networks for location services. Furthermore, the maximum RSSI value was determined by the polynomial for each value and selecting the highest value. It was also observed that RSSI showed fluctuation when the terrain changed from plain to uneven and the sensor position was determined by calculating the point of intersection that was formed by the passing perpendiculars of maximum RSSI points. To check the localization accuracy, the frequency modulation and RSSI for Wi-Fi Vectors were combined. Further on, a room-level low-cost Bluetooth positioning system was developed, which required a beacon that needed to be initialized and wrapped. This beacon needed a lot of on-site time and had the disadvantage of failure in case of a power outage. As per the study, this system was only applicable to where few beacons were required and had a higher tolerance of location determination. Bluepass application was also developed for different indoor environments. Additionally, different characteristics of Bluetooth, such as RSSI, transmission power, link quality, etc., were evaluated, and it concluded that RSSI and link quality could be combined to perform localization. This study (Aziz, Owens, Khaleeq-uz-Zaman, & Akbar, 2019) also stated that only positive values of RSSI could be used to determine the distance between transmitter and receiver but golden receiver power rank could be used, highlighting the precise range of RSSI between the receiver and RSS. Consequently, using the triangulation method to secure localization by using more than three points seems to be difficult but a region-based localization technique was adopted. In relation to the experiment that was carried out on a 15 x 15 feet grid with five Bluetooth modules that were placed at coordinates (0,0), (0,15), (15,0), (15,15), and (7.5,7.5), a total of 25 readings were taken at each coordinate. The Bluetooth module was attached to the evaluation board which in turn was connected to the laptop with software to calculate the distance. The trilateration method was utilized by marking three unique points such as P1, P2, and P3, and the distance between them being D_1,D_2, andD_3. A perpendicular line was drawn at a right angle respectivelyL_1,L_2, and L_3 dividing D_1 into $R_{1,2}$ and $R_{2,1}$, D_2 into $R_{2,3}$ and $R_{3,2}$, and D_3 into $R_{3,1}$ and $R_{1,3}$.

The three linesL_1,L_2, and L_3 connecting at the intersection marked the error region, which could be the region of the desired location.

An optimized strategy is proposed, whereby the Bluetooth technology uses RSSI ranging and positioning algorithm (Shen, Yang, He, & Huang, 2016). Initially, the system uses trilateration to determine all the unknown nodes in the estimated region. Then, in the second part, the region is broken down into different areas, and the RSSI value of the beacon nodes in these centroid areas is determined so the RSSI value at the unknown node could be determined. Finally, the RSSI value that is formed by the beacon node at the unknown nodes and at the centroid of the regions are compared against each other to determine the location of the unknown nodes. The experiment shows 63.3% distance estimation improved compared to the traditional centroid localization.

As per the paper, some of the localization algorithms are three side location, time of arrival, time difference of arrival and RSSI (Shen, Yang, He, & Huang, 2016). Time of Arrival and Time Difference of Arrival are two methods that need higher hardware resources, whereas the RSSI method uses an equation and RSSI value to determine the distance. Moreover, the traditional centroid method is on a triangle where the vertex location information is not accurate, and each vertex has a different influence on location positioning accuracy. The nodes transmit signals forming different RSSI values at the beacon nodes, which provides unreliable distance between the beacon node and the unknown node so the beacon node coordination cannot be calculated by averaging.

Nonetheless, a paper on device-to-device connections between device-to-device devices highlights that to establish the connection, it is essential to determine the distance between the device-to-device devices (Jung J.-y. , Kang, Choi, & Bae, 2015). The applications used to determine the distance between these devices are indispensable items as the distance should be easily calculated while establishing wireless connections. It is also known that several techniques are available to determine the distance but utilizing the RSSI to determine the distance between the two devices seems to be the cheapest method. Therefore, the experiment is based on determining the distance between devices using Bluetooth RSSI in an office wireless body area network (Jung J.-y. , Kang, Choi, & Bae, 2015). Now, Bluetooth RSSI reading also carries errors in the reading, so filters such as Kalman filter were used. The distance between the device-to-device devices in a wireless environment is categorized into several portions where the devices near to the user, within 20cm are recognized via near field communication, wireless body area network classification is used for devices within 1-2m distance, wireless personal area network is meant for the devices in 10 m radius and the wireless local area network can recognize devices till 100m distance. The experiment collected 200 samples of Bluetooth RSSI from a notebook PC using a tablet PC. The standard deviation, mean value, and maximum range value were also calculated. The maximum range value was calculated by subtracting the maximum reading from the minimum reading. Kalman filter was introduced to estimate the state of a discrete time-controlled process that is ruled by a linear stochastic difference equation. The five-step Kalman filter equation introduced the first two steps of error covariance with Kalman gain. From the equation, it was deduced that if the R-value is big, then the estimation value will not be influenced by the measurement value, so the bigger R-value and smaller Q value indeed means the estimation value will be less affected by the measurement value. It was noted that the Kalman filter reduced the measurement errors to 50%, which makes a significant difference. So, in order to test the impact of Kalman filter on RSSI values, academic articles will be explored in continuing future studies and in the upcoming subsection, RSSI specifics will be explored to gain a better understanding of its significance.

2.2.5. RSSI

As per MOKOBlue (mokoblue, 2022), the RSSI for each individual Bluetooth device differs, so it is important to check the index before establishing a connection for a better result. RSSI does not determines the speed of the packet but the strength of the packet. It basically works by transporting the de-authentication packet back to the wireless station which can be re-connected in the network application. The wireless station connects the most suitable access point to the RSSI link, which may link back to the same access point if the range is not deterred or with one range. As noted above, the value of the broadcasting power and the distance determines the signal strength. So, when the broadcasting power is between 2 - 4 dBm then the strength of the signal is between -25 to -100 with a distance ranging from 40 -50m. In addition, the functionality of Bluetooth RSSI is limited to a maximum of five neighboring nodes. Exceeding this number seems to cause performance issues, but the RSSI sensor network seems to have multiple localizing protocols because absolute location is mostly unavailable. The following are some of the key points to improve the strength of the Bluetooth signal.

i. Ensure that the Bluetooth-enabled devices are far from each other.
ii. Make sure that your Wi-Fi router is utilizing different bandwidths.
iii. Check if the sensors and the transmitters are damaged.
iv. Dispose of any material that can impede the Bluetooth signal.
v. Do not simultaneously use more than one Bluetooth device.
vi. Incorporate a USB Bluetooth signal extender on Computers.

Likewise, understanding the RSSI range and manipulating it on the following criteria could prove to be beneficial.

i. Radio Spectrum - the usual radio frequency ranges from 30Hz - 300GHz, and Bluetooth usually use the 2.4GHz band as this supports the ISM (Industrial, Scientific and Medical) frequency band for obvious reasons, and it is considered to be low power. Therefore, it is important to check the coverage and data range to the low-frequency bandwidth as it offers a wide range of facilities, but it does minimize the data bandwidth.
ii. Receiver Sensitivity - indicates the smallest amount of interpreted received Bluetooth signal; with its highest sensitivity, it can connect up to -103dBm. This basically expresses how the sound is heard on a physical layer.
iii. Transmitting Power - basically denotes the power consumed over range. If the transmitting power is higher even over a long distance, then the signal still remains strong, but this chews up the battery power.
iv. Path Loss - radio waves broadcasting through the air over a long distance can result in path loss of the packets due to interferences and obstacles in the path, impacting the strength of the signal.
v. Antenna Gain - The fundamental role of the antenna is to convert the radio waves from the receiver to electrical energy and convert electrical energy to radio waves in the transmitter. The signal strength is affected by antenna,

location and package; hence Bluetooth employs various antenna options from -10dBi - +10dBi.

This article also talks about the challenges of Bluetooth signals, which basically impact their strength and connection.

i. Concrete Physical Barrier - results in a weak Bluetooth connection and cutoff. Metal walls, refrigerators and filling cabinets seem to be the major hindrance.
ii. Wi-Fi and Wireless Device - Wi-Fi routers seem to have similar bandwidth as Bluetooth, so this will serve as an obstacle for Bluetooth connection.
iii. Bluetooth Channel Hopping - Bluetooth is an excellent tool for listening in the context of sharing documents or audio, so while establishing a connection, it can pick up on the interference medium.
iv. Radio Frequency - Unintended radio frequency radiators such as microwaves, electrical railroads, and power lines seem to weaken the strength of the Bluetooth signal, especially if the Bluetooth device is in closer proximity to the equipment.

Correspondingly, proximity estimation seems difficult at times especially in different environments (Rajkiran.S & Balakrishnan., 2015). Although GPS and Wi-Fi triangulation have been used for estimation, it lacks in terms of accuracy and has a cost factor associated with it. In this study, a smartphone Bluetooth is used to find proximity over a shorter distance using Bluetooth RSSI. To improve the accuracy of estimation using RSSI value, atmospheric pressure and light sensors are used. The RSSI values are synced into the clouds every 30s, so the proximity estimation is achieved with accuracy and low cost.

This Bluetooth monitoring application used device RSSI, pressure sensor value, and light sensor value (Rajkiran.S & Balakrishnan., 2015) for proximity estimation. The phone monitor application consists of three modules and the first module inculcated Bluetooth, light and battery divisions. Bluetooth information such as Time, BTID, RSSI, and MAC Address were captured; light time and strength were captured for time division; Battery Time, percentage, and charging were captured for battery divisions. The second module captured Location by GPS, such as Time, Latitude and

Longitude. The third module captured Location by Network Providers such as Time, Latitude and Longitude. These details were stored in the SQLite database and then pushed to GUI Activity. So, overall, all the mobile devices in that particular area connected to the wireless sensor network, and the details collected were used for proximity calculation. The RSSI values were then separated against their Bluetooth and this information was stored on the server for accessibility.

On the contrary, another paper elaborates on different approaches for indoor localization for wireless technology [30] using Bluetooth. Since satellite navigation systems such as GPS and GLONASS are only useful outdoors. Wireless localization is usually resourceful for locating items or identifying tracks in airports, malls, railway stations, production facilities, construction sites and healthcare institutions. This paper highlights on ROCRSSI or MinMax methods, whereby the distance from the wireless node is used to calculate the distance. The basic challenge is identifying the distance from the device based on the signal strength. Therefore, various tools, such as Microsoft Access, R Studio, Octave and Python, are used to estimate the strength of the signal.

Besides, the (Dobrilovic, Z Stojanov, J Stojanov, & M Malic, 2020) technique namely Pedestrian Dead Reckoning, runs on the concept whereby the current location is determined based on the previous location, the current walking length and the current direction. This technique works with iBeacon so BLE version four could be used with RSSI localization determination. The experiment showed that using polynomial and exponential functions, the square mean error ranges from 3.1 - 3.5 m with the highest accuracy. The embedded fitting model is used with the software tools for the experiment.

Furthermore, RSSI information proved useful to safely control the personal protection equipment by limiting and manipulating the power of the tool in the construction area by actively determining the worker-tool distance (Gómez-de-Gabriel, Fernández-Madrigal, Rey-Merchán, & López-Arquillos, 2022). The distance is determined by RSSI information from the BLE located on the rigs with the Bayesian distance locator. The system is meant to reduce instrumentation usage in the workplace and notify risky situations. The prototype is built on accumulated data and distance measurements from the construction sites. (Neburka, et al., 2016) The smart Personal Protection Equipment (PPE) comes with three BLE beacons with placeholders and a beacon enabler, which controls the present sensor. The corresponding smart tool is embedded with BLE receiver, which is connected to the controller, the controller is connected to the safety relay. This safety relay transfers the message to the power tool upon power application. The distance is measured by a beacon with a double statistical filter, which consists of Kalman filter and a discrete filter. The Kalman filter is used to measure the distance between the transmitter and the smart tool receiver. The discrete filter determines the closeness of PPE and smart tool within the possible given threshold. The distance estimation using Bayesian solution consists of two separate filters which minimizes the error. The collocated beacons come with a double estimator for better performance. The filters are used for consecutive RSSI measurements with a 1.15-time constant. The three beacons dynamically take RSSI measurement from the receiver as time increments. The PPE and smart tools are aligned orthogonally for better results.

The behavior of BLE RSSI was experimented in a real office environment and in an anechoic chamber (Neburka, et al., 2016). This was mostly done to study the signal propagation in multipath transmission environment and an ideal no-signal environment. In this ideal environment, the BLE devices were placed in Line-of-sight paradigm. To monitor the communication here, the RN4020 PICtail Plus Daughter Board with a smart Bluetooth module called RN4020 module was used in addition to the high-speed Universal Asynchronous Receiver/Transmitter (UART) protocol. The two modules were kept in the ideal environment through which they were connected to each laptop via USB; these laptops had running programs that captured the real-time RSSI values. In the anechoic chamber, a receiving dipole antenna was also kept capturing the signal which was scrutinized on Real Time Spectrum Analyser R & S FSVR13. As per the experiment, 100 packets were captured and averaged.

A different scenario was noted whereby pathways of a mobile device was created by sensing its RSSI value in an indoor environment in a health setting (Fuad, Deb, Panlaqui, & Mickle, 2022). The algorithm runs by combining the stationary and mobile devices to detect motion on a proximity-based approach in an indoor environment. The pathway is determined for the stationary device with time, the algorithm creates vectors of moving mobile devices such as tail and head vectors in relation to time. So, if the RSSI value of the source is greater than the RSSI value of the destination, then the vector of the stationary device is appended to the tail and vice versa. Now, in order to test this theory, three stationary devices were used, namely S1, S2 and S3, while the drawback that was noticed was that of the pathway from S1 to S3 via S2 and back to S1, but the pathway picked S2 as well while returning to S1. The RSSI value of S2 seemed greater, so this served as a glitch in the algorithm. The algorithm is said to be applicable to at least five stationary devices.

To elaborate further, RSSI application indeed displayed significance on Automatic Gate using Bluetooth technology from a smartphone based on the strength of RSSI (Khreasarn & Hantrakul, 2018). Bluetooth RSSI value is used from a smartphone to open the doors automatically instead of RFIDs and fingerprint signing, which comes with uncertainty. The optimal distance at which the door should open through this implementation was also determined by conducting survey and as per the users, the optimal distance was 2m. Fundamentally, The PN532 NFC RFID module was implemented in the Raspberry pi three which was installed at the door, the module accepts the incoming Bluetooth RSSI from atleast 10 meters which was communicated from the user’s smartphone using MQTT protocol which was also connected to the cloud server bi-directionally. The system also detects the RSSI value once the user has been entered to lock the door afterwards.

On the other hand, A Bluetooth Location Based on kNN Algorithm method was used to capture a set of sampled Bluetooth RSSI values from each location in a 6 x 5m room for indoor localization. The room was divided into 1x1m grid (Wang, Ma, Li, & Wang, 2019). The values were stored in the database tagged as the fingerprint values. The weighted average method was not included per se, as this could have improved the positioning accuracy indeed. The positioning system included setting k in the kNN algorithm then locating and calculating the Euclidean distance of each data. The next step involved sorting the Euclidean distance, selecting k locations with the smallest Euclidean distance, and computing the average of distances to get the location. It was noted that when the k value was set to three, a lot of errors were visible at the 15 locations, but when the k value was changed to six, accuracy improved significantly.

As the findings on Bluetooth RSSI proceeded, a unique system was identified, whereby an Android based smartphone system was designed which used the smartphone's inbuilt accelerometer and barometer with Bluetooth RSSI to estimate indoor distance for walking (Jeon, Kong, Nam, & Yim, 2015). The accelerometer and the phones magnetic sensor could calculate the moving distance in terms of steps. The cumulative error was minimized by including Bluetooth RSSI to determine the moving distance of the users. The designed system also used the inbuilt barometer to determine the level of the building by sensing the altitude change with the change in the atmospheric pressure. The application showed more accuracy as the Bluetooth access points in the buildings increased from for to ten.

A client-side and a server-side Android application were designed to accept data from the access point and calculate the RSSI value, which can be transported to the server side to be stored as meta-data for further calculations such as location positioning using the trilateration method (Mussina & Aubakirov, 2014). As noted by the paper, BLE signal is subjected to interferences and when signals are attenuated due to these interferences, it takes a multipath to propagate. So, filters were designed such as mode, median, single direction outlier removal, feedback and shifting filters. The mode filter picks out the value which has the most frequent occurrence. The Median filter arranges the RSSI values in a list then picks the middle one, whereas the single direction outlier removal filter captures 10 RSSI values where by the mean and standard deviation of these RSSI values aformula opened and passed through the formula of ($RSSI_{mean} - 2\,x\,RSSI_{std}$), any RSSI which is below the product is eliminated and then re-calculated again as preprocessed RSSI. The feedback filtering utilizes formula($RSSI = \alpha\, x\, RSSI_n + (1 - \alpha) x\, RSSI_n - 1$). The Shifting filter is similar to feedback filter, the only difference is that it includes rounds, and each round includes a period of three seconds.

Lastly, another idea was captured, that involved creating a working system which locates seniors in a smart home, and this location positioning method was noted to have a precision distance of 0.4m (Thaljaoui, Val, Nasri, & Brulin, 2015). The experiment is divided into two phases whereby phase one captures the RSSI value between the BLE ibeacon transmitter (x3) and receiver (iPhone). Phase two involves estimating the distance using an inter ring-locating algorithm. The formula in phase one of the experiment was also noted for signal propagation modeling, whereby n is the path loss index. The formula to calculate RSSI, distance and path loss are listed as follows for future utilization.

i. $RSSI(d) = RSSI(d_0 - 10\ x\ n\ x\ \log\left(\frac{d}{d_0}\right)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$

ii. $Distance = 10\ \left(\frac{RSSI(d_0) - RSSI(d)}{10\ x\ n}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (2)$

iii. $Path\ Loss(n) = \left(\frac{RSSI(d_0) - RSSI(d)}{10\ x\ \log\left(\frac{d}{d_0}\right)}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$

Furthermore, another study (Lopes, Sara Paiva, Habib Rostami, Ahmad Keshavarz, & Azin Moradbeikie, 2022) displayed that location estimation could also be improved by observing the impact of weather conditions on the network gateway, and evaluation of the results could possibly improve the RSSI-based distance estimation for localisation purposes. Although, improving localisation is not the core objective of this research but investigation of RSSI will serve as a contribution to localisation estimation in Fiji for future development.

Alternatively, another finding (Adao, Helmerich, Voigt, Moldenhauer, & Neumann, 2017) showed that changes in RSSI reading can be seen by monitoring the humidity of a concrete building. Concrete is the core source of material to construct buildings in the pacific and as per observation most of the commercial building and homes in Fiji are constructed using concrete. This study (Adao, Helmerich, Voigt, Moldenhauer, & Neumann, 2017) highlights those buildings are also constructed using low-quality concrete, which means the constructed building might not be of high quality, besides prolonged weather conditions play a huge role in further deteriorating the quality of a building. It was noted as it rains the water content in the building walls increases and the RSSI reading is impacted, resulting in a weaker RSSI. Similarly, as the water content in the walls decreases the RSSI improves significantly. It was also noted that the damping effect of the walls is not proportional to water content in the wall by linear means but rather exponentially. This indicates that the changes in the RSSI reading could be only observed when the water content in the walls is high.

Additionally, studies have also highlighted that temperature and relative humidity influence the strength of the signals outdoors, which raises the question of whether these variables affect the signal strength in an indoor environment. So, an experiment was conducted in a 9m x 9m laboratory to observe if room temperature and internal relative humidity have any impact on the RSSI. The results were analysed with linear regression, and it was noted that these variables are subjected to variations such as temporal and spatial resulting an impact on the link quality which induces fluctuation in RSSI readings. Thus, it was concluded that the relative humidity and room temperature has an impact on RSSI (Guidara, Fersi, Derbel, & Jemaa, 2018).

Consequently, an investigation will be conducted in Fiji to explore the behavior of RSSI with the following research methodology.

2.3. Discussions

From the thorough literature review that is captured above, it was noted that Bluetooth is the best wireless option for indoor IoT deployment in comparison with other wireless technologies such as IEEE802.15.4, LoRaWAN, and IEEE802.11N, as it is economical, more accurate and power efficient. The BLE version of Bluetooth is exceptionally better in comparison with other versions of Bluetooth as it is more economical in terms of device uptime and power consumption. The Bluetooth connection is determined by the strength of the connection or indicator of RSS. In addition, to improve Bluetooth RSSI connection indoors between devices the RSSI plays a huge part and the RSSI is subjected to inferences, obstacles and noise effects which can deteriorate the connection strength, at the same time the RSSI is also subjected to multi-fading effect and multi path effect which diverges the signal reception, leading a weaker connection indoors. It was also noted that weather also plays a significant role in determining a better wireless connection, so weather parameters need to be exploited to observe its impact on RSSI.

2.4. Summary

Thus, from this chapter it can be concluded that Bluetooth is the best wireless option for IoT deployment, and it is subjected to interferences, obstacles, multi path fading effect and weather parameters which deteriorates the signal strength in an IoT based indoor environment.

Chapter 3 – Research Methodology

Chapter 3: Research Methodology

3.1.Introduction

This chapter presents the research methodology of the titled research that initiated with literature review to develop the null hypothesis and alternative hypothesis while considering epistemology and ideology as well. The alternative hypothesis is a contradiction of the null hypothesis, in case the null hypothesis is proven incorrect in this experiment. Thereafter, the experiment was carried at two different sites, Tavua and Suva. RSSI samples were collected from both the sites with RSSI BLE analyser application, and RSSI reading was recorded on Excel sheets for further analysis.

3.2.Significance of Work

In this section the research methodology steps will be listed that were carried out in different phases, and each phase is listed as follows in a sequential manner.

3.2.1. Literature Review – Phase One

Literature Review was performed on Journal articles from prominent databases such as IEEE Xplore, IEEE Transaction, Science Direct, and Google Scholar to scrutinize and identify the possible techniques, methods, and work that has been done in this area of study to collaborate ideas and provide further insights. Based on the research, a problem area was identified, and the hypothesis was developed.

i. Null Hypothesis: Bluetooth Connection is obfuscated due to the interferences, noise, obstacles, and other convolving signals that are present in an IoT-based indoor environment which was hypothesized based on Epistemology and Literature review done so far.
ii. Alternative Hypothesis: Bluetooth Connection may not be obfuscated due to the interferences, noise, obstacles, and other convolving signals that are present in an IoT-based indoor environment which was hypothesized based on the contradiction of the null hypothesis.

This hypothesis served as an insight to setup an experiment to investigate on wireless connections such as Bluetooth in an indoor environment in Fiji, various independent variables were introduced to observe its impact on the RSSI reading.

3.2.2. Experiment – Phase Two

An empirical experiment will be conducted to collect Bluetooth RSSI data from two different locations listed as follows.

a. Remotes of Tavua – Malele Stage three, Coordinates :17°29'58.6"S 177°53'32.9"E
b. Suburb of Suva – Caqiri, Nasinu, Coordinates: 18°05'47"S 178°29'06" E
c. Dimensions of the Indoor Locations with pictures are iterated as follows.
    i. Tavua Room 1 - 5m x 3m

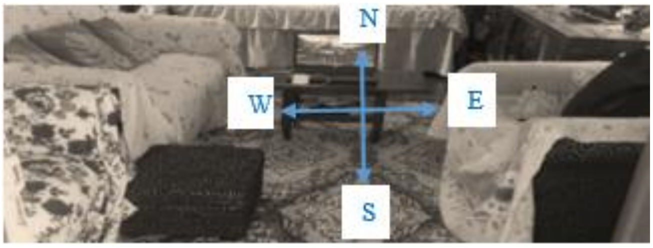

Figure 2: HP Laptop and Samsung Galaxy Ear buds are setup at a height of 40 cm.

    ii. Tavua Room 2 - 3.2m x 2.4m

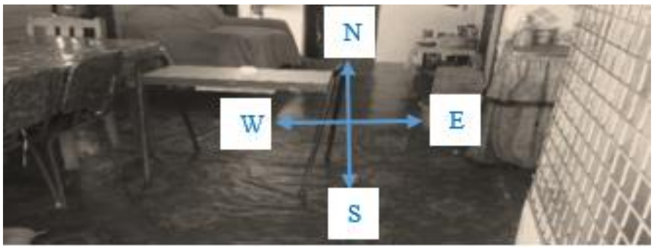

Figure 3: Samsung Galaxy Earbuds are setup at a height of 90cm.

    iii. Tavua Partitioned Space - 5.9m x 2.5m

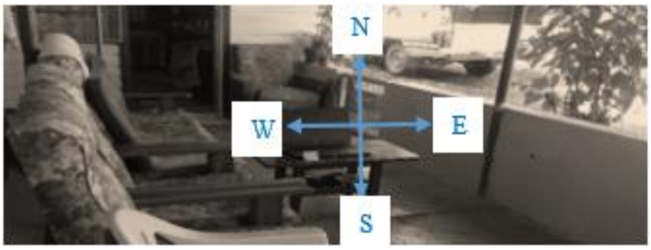

Figure 4: HP Laptop and Samsung Galaxy Ear buds are setup at a height of 40cm, facing South.

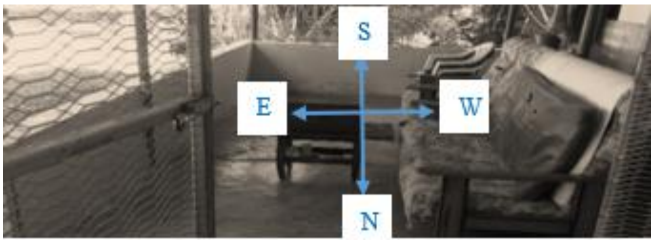

Figure 5: HP Laptop and Samsung Galaxy Ear buds are setup at a height of 40cm, from North Direction

iv. Suva Room1 - 3.125m x 2.22m

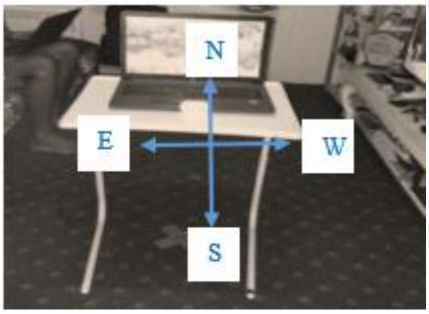

Figure 6: Experiment Setup in Caqiri Nasinu displaying distance mark of 1m Interval.

d. Equipment Setup – A HP laptop with Bluetooth adapter and a pair of Samsung Galaxy Earbuds with the Earpods were setup on a 40cm and a 90cm furniture respectively in different scenarios. These two devices were the designated receivers, and the transmitter was a Samsung Galaxy Android phone with installed BLE Analyser - an application that captures the receivers RSSI Value. This application displays the receiver's MAC address, the unfiltered RSSI value of the corresponding device, which keeps on jumping, and the Average value, which was the intended collected data from the maximum and minimum RSSI values that were displayed on the final column as per the snapshot given below.

Figure 7: BLE Analyser App

The BLE Analyser App displays the Devices detected, their jumping RSSI values, Average values, which are the target data for this experiment and the minimum and maximum value of the jumping RSSI value that calculates the average value. The RSSI reading was calculated along its Mac address, although most Mac addresses were unrecognized and peculiarly new Mac addresses popped up in new sets of readings, it was not considered for analysis.

3.2.3. Data Collection – Phase Three

1. The data was mostly collected in a quantitative manner, as listed in the Excel sheets on different days while noting the changing distance and independent variables involved. Approximately 1200 samples of data were collected from each location. So approximately, 4800 samples of data were collected from four locations. Local Weather patterns were also noted for the days on which the experiment was conducted, as this hypothetically affects the RSSI readings.

2. The following independent variables were introduced in the experiment to observe its impact on the RSSI reading that was taken in an indoor environment.
    i. Distance – Based on the dimensions of the room the reading was collected from 4 directions, respectively North, South, East and West.
    ii. Room Temperature – Room temperature was collected from an application called a Thermometer. The temperature was taken before collecting the RSSI data.
    iii. Atmospheric Pressure – Data was provided by the Fiji Meteorological Services
    iv. Amount of Sunshine – Data was provided by the Fiji Meteorological Services
    v. Amount of Rainfall – Data was provided by the Fiji Meteorological Services
    vi. Relative Humidity – Data was provided by the Fiji Meteorological Services
    vii. Height of Transmitter – The transmitter aka. Samsung Galaxy phone was held at different height/distance from the ground to check if the changing height had any impact on the RSSI reading.

These collected data were used for analysis in the upcoming section.

3.2.4. Data Analysis – Phase Four

The collected data was analyzed qualitatively and quantitatively using two relevant techniques in excel.

i. Correlation co-efficient – To Identify the relationship and predict the future.
ii. Linear Regression - It defines a cause-and-effect relationship.

Based on these two analyses a possible conclusion will be drawn with facts as the document proceeds to the next section.

3.3. Discussions

The research methodology was carried out in four phases to show that the experiment was academically carried out in a sequential matter and to prove that this research is entirely an academic work. The concepts that are used in this research is referenced from other academic sources. The four phases that are iterated above shows transparency and ensures that the required academic work is qualitative and quantitative in nature. The experiment was carried out at two different sites to prove ideas developed through epistemology and ideology to observe consistency and variation so that a relationship or a contradiction could be identified.

3.4. Summary

Thus, it can be concluded from this chapter that the research methodology that was developed ensures feasibility and consistency of the required research work. Also, the developed null hypothesis and the alternative hypothesis is critical and academic in nature. The experimental outcome of the empirical research work will be captured in the next chapter.

Chapter 4 – Experimental Outcomes

Chapter 4: Experimental Outcomes

4.1. Introduction

In this chapter, the experimental outcome of the empirical experiment that was carried out are captured accordingly. The data that was collected and analyzed using Microsoft excel and two different techniques were used to determine the relationship between the variables. These techniques are Correlation Co-efficient and Linear Regression. The Correlation Co-efficient are summarized in the tables listed in subsection 4.2.1 and the experimental outcome of Liner Regression are listed under subsection 4.2.2.

The flow diagram given below summaries the presentation of experimental outcome for easier understanding.

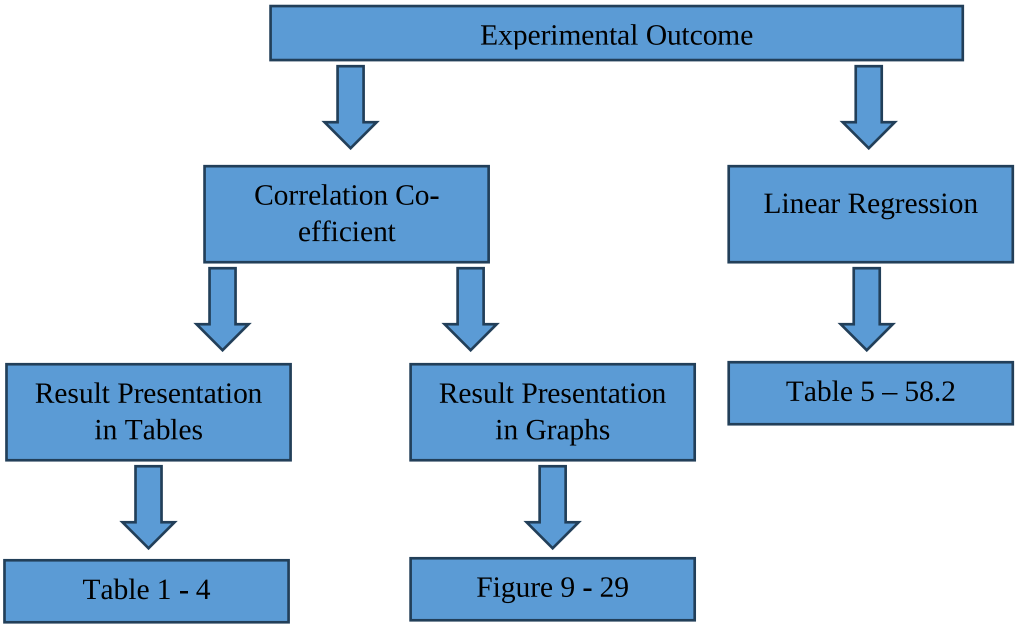

Figure 8: Flow Diagram of Experimental Outcome Result Presentation

1.2. Significance of Work

1.2.1. Correlation Co-efficient

The following section displays the Correlation Co-efficient results accordingly for Device 1 and Device 2 in four different sites where the experiment was carried out. In this subsection the summary of the experimental outcomes related to correlation co-efficient were only captured in tables. Table 1 provides a summary of correlation co-efficient for Room 1 in Tavua. Table 2 provides a summary of correlation co-efficient for unpartitioned space in Tavua. Table 3 provides a summary of correlation co-efficient for Room 1 in Suva. Table 4 provides a summary of correlation co-efficient for Room 2 in Tavua. The tables below capture the correlation value with its dependent and independent parameter and its relationship.

Table 1: Correlation Co-efficient for Room 1 – Tavua

Correlation	*Value*	*Relationship*
Distance Vs. RSSI (Device 1)	*0.143*	Weak Positive
Distance Vs. RSSI (Device 2)	*0.059*	Weak Positive
RSSI (Device 1) Vs. Room Temperature	*0.125*	Weak Positive
RSSI (Device 2) Vs. Room Temperature	0.234	Weak Positive
Height Vs. RSSI (Device 1)	*-0.099*	Weak Negative
Height Vs. RSSI (Device 2)	-0.345	Weak Negative
Relative Humidity Vs. RSSI (Device 1)	-0.099	Weak Negative
Relative Humidity Vs. RSSI (Device 2)	-0.298	Weak Negative
Distance Vs. Room Temperature	0.002	Weak Positive
RSSI (Device 1) Vs. Room Temperature Vs. Distance	0.143	Weak Positive
RSSI (Device 2) Vs. Room Temperature Vs. Distance	0.143	Weak Positive
Air Temperature Vs. RSSI (Device 1)	0.087	Weak Positive
Air Temperature Vs. RSSI (Device 2)	0.322	Weak Positive
Atmospheric Pressure Vs. RSSI (Device 1)	0.180	Weak Positive
Atmospheric Pressure Vs. RSSI (Device 2)	0.431	Positive
Atmospheric Pressure Vs. Relative Humidity	-0.379	Weak Negative
Atmospheric Pressure Vs. Air Temperature	-0.939	Weak Negative
RSSI Vs. Atmospheric Pressure Vs. Relative Humidity	0.224	Weak Positive
RSSI Vs. Atmospheric Pressure Vs. Air Temperature	0.180	Weak Positive
Rainfall Vs. RSSI (Device 1)	-	Could not achieve a value.
Rainfall Vs. RSSI (Device 2)	-	

Table 2: Correlation Co-efficient for Un-partitioned Space – Tavua

Correlation	Value	Relationship
Distance Vs. RSSI (Device 1)	*0.080*	Weak Positive
Distance Vs. RSSI (Device 2)	*0.027*	Weak Positive
RSSI (Device 1) Vs. Room Temperature	*-0.213*	*Weak Negative*
RSSI (Device 2) Vs. Room Temperature	0.366	Weak Positive
Height of Transmitter Vs. RSSI (Device 1)	*0.273*	*Weak Negative*
Height of Transmitter Vs. RSSI (Device 2)	0.355	Weak Positive
Relative Humidity Vs. RSSI (Device 1)	0.347	Weak Positive
Relative Humidity Vs. RSSI (Device 2)	-0.251	Weak Negative
Distance Vs. Room Temperature	0.012	Weak Positive
RSSI (Device 1) Vs. Room Temperature Vs. Distance	0.083	Weak Negative
RSSI (Device 2) Vs. Room Temperature Vs. Distance	0.078	Weak Positive
Atmospheric Pressure Vs. RSSI (Device 1)	-0.098	Weak Negative
Atmospheric Pressure Vs. RSSI (Device 2)	0.084	Weak Positive
Air Temperature Vs. RSSI (Device 1)	-0.270	Weak Negative
Air Temperature Vs. RSSI (Device 2)	0.419	Positive
Atmospheric Pressure Vs. Relative Humidity	-0.610	Negative
Atmospheric Pressure Vs. Air Temperature	0.282	Weak Positive
RSSI Vs. Atmospheric Pressure Vs. Relative Humidity	0.427	Positive
RSSI Vs. Atmospheric Pressure Vs. Air Temperature	0.271	Weak Positive
Rainfall Vs. RSSI (Device 1)	-	Could not achieve a value
Rainfall Vs. RSSI (Device 2)	-	

Table 3: Correlation Co-efficient for Room 1 – Suva

Correlation	Value	Relationship
Distance Vs. RSSI (Device 1)	*0.013*	*Weak Positive*
Distance Vs. RSSI (Device 2)	*0.012*	*Weak Positive*

RSSI (Device 1) Vs. Room Temperature	*-0.017*	*Weak Negative*
RSSI (Device 2) Vs. Room Temperature	-	Could not achieve a value
Height of Transmitter Vs. RSSI (Device 1)	*-0.680*	*Negative*
Height of Transmitter Vs. RSSI (Device 2)	-	Could not achieve a value
Relative Humidity Vs. RSSI (Device 1)	-0.300	Weak Negative
Relative Humidity Vs. RSSI (Device 2)	-	Could not achieve a value
Distance Vs. Room Temperature	0.002	Weak Positive
RSSI (Device 1) Vs. Room Temperature Vs. Distance	0.014	Weak Negative
RSSI (Device 2) Vs. Room Temperature Vs. Distance	-	Could not achieve a value
Atmospheric Pressure Vs. RSSI (Device 1)	0.633	Positive
Atmospheric Pressure Vs. RSSI (Device 2)	-1.225	Anomaly
Air Temperature Vs. RSSI (Device 1)	0.386	Weak Positive
Air Temperature Vs. RSSI (Device 2)	-	Could not achieve a value
Atmospheric Pressure Vs. Relative Humidity	0.186	Weak Positive
Atmospheric Pressure Vs. Air Temperature	-0.007	Weak Negative
RSSI Vs. Atmospheric Pressure Vs. Relative Humidity	0.713	Fairly Positive
RSSI Vs. Atmospheric Pressure Vs. Air Temperature	0.742	Fairly Positive
Amount of Rainfall Vs. RSSI (Device 1)	-0.680	Negative

Table 4: Correlation Co-efficient for Room 2 – Tavua

Correlation	Value	Relationship
Distance Vs. RSSI (Device 1)	*-0.012*	*Weak Negative*
Distance Vs. RSSI (Device 2)	*-0.031*	*Weak Negative*
RSSI (Device 1) Vs. Room Temperature	*-0.270*	*Weak Negative*
RSSI (Device 2) Vs. Room Temperature	0.167	Weak Positive

Height Vs. RSSI (Device 1)	*-0.148*	*Weak Positive*
Height Vs. RSSI (Device 2)	2.418	Anomaly
Relative Humidity Vs. RSSI (Device 1)	-0.409	Negative
Relative Humidity Vs. RSSI (Device 2)	-0.167	Weak Negative
Distance Vs. Room Temperature	4.779	Anomaly
RSSI (Device 1) Vs. Room Temperature Vs. Distance	0.013	Weak Positive
RSSI (Device 2) Vs. Room Temperature Vs. Distance	0.031	Weak Positive
Atmospheric Pressure Vs. RSSI (Device 1)	-0.166	Weak Negative
Atmospheric Pressure Vs. RSSI (Device 2)	-0.167	Weak Negative
Air Temperature Vs. RSSI (Device 1)	0.035	Weak Positive
Air Temperature Vs. RSSI (Device 2)	0.167	Weak Positive
Atmospheric Pressure Vs. Relative Humidity	9.014	Anomaly
Atmospheric Pressure Vs. Air Temperature	0.131	Weak Positive
RSSI (Device 1) Vs. Atmospheric Pressure Vs. Relative Humidity	0.441	Positive
RSSI (Device 1) Vs. Atmospheric Pressure Vs. Air Temperature	0.170	Weak Positive
Amount of Rainfall Vs. RSSI (Device 1)	-0.150	Weak Negative
Amount of Rainfall Vs. RSSI (Device 2)	-	

As this document proceeds, correlation coefficient plots are interpreted to highlight the changes and variations.

1.2.2. Correlation Co-efficient Plotting
Location: Tavua, Room 1 - Device 1

Graph of Distance vs. RSSI data

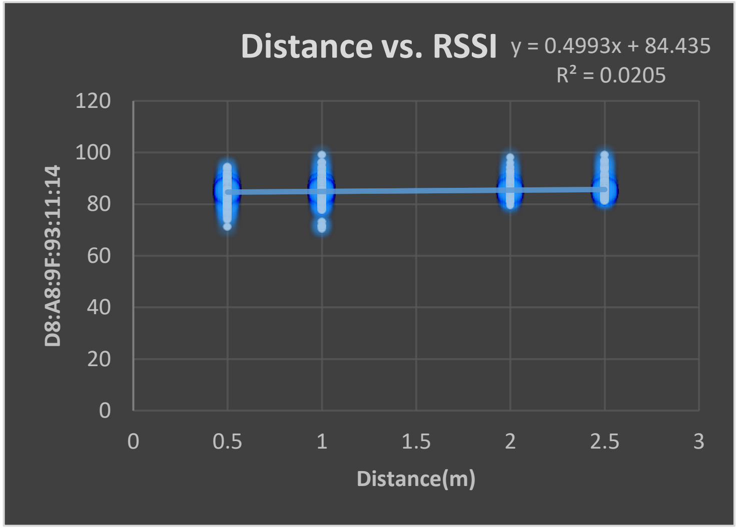

Figure 9: Graph of Distance vs. RSSI Data

As seen above, the RSSI reading at 0.5m distance, displays a better set of RSSI which is between -*(70 to < 100)*. The RSSI reading at 1m is between - *(70 –100)*. The RSSI reading at 2m and 2.5m distance is mostly > - *(80)*.

Graph of Air Temperature vs. RSSI data

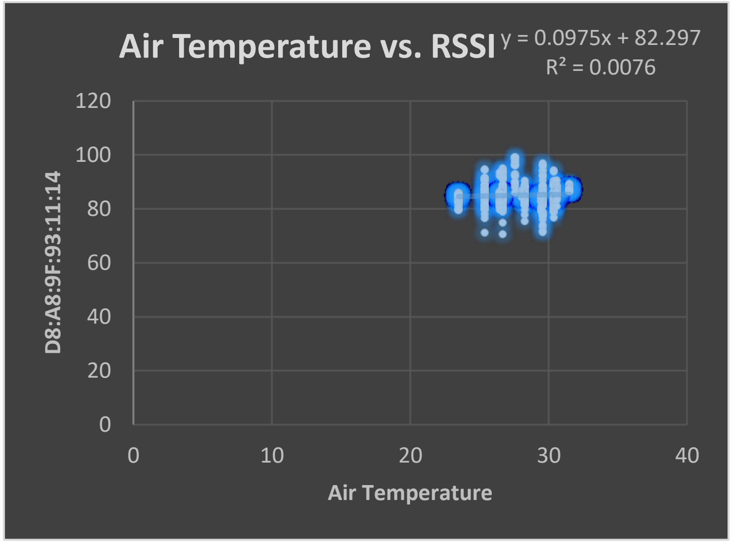

Figure 10: Graph of Air Temperature vs. RSSI data

The Air Temperature below 25℃ shows consistency in terms of RSSI range, the RSSI reading is mostly between -*(80 – 90)*. Above 25℃ the air temperature is mostly evenly distributed between -*(80 – 100)*. This reading was mostly taken in May, when the weather is slightly cooler in Fiji. Also, Fiji has only two seasons, which are the hot and rainy seasons and the cool and dry seasons. So huge temperature variations are not observed.

Graph of Room Temperature vs. RSSI

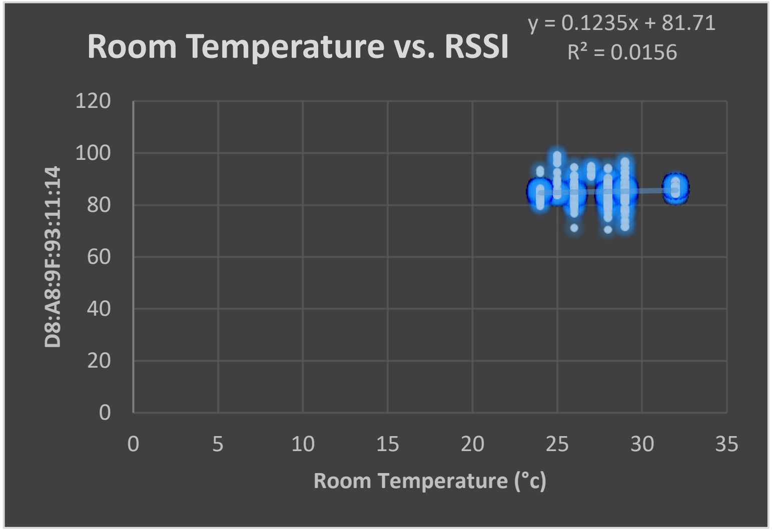

Figure 11: Graph of Room Temperature vs. RSSI

The RSSI reading with Room Temperature displayed a similar pattern as Air Temperature for Device 1

Graph of Relative Humidity vs. RSSI data

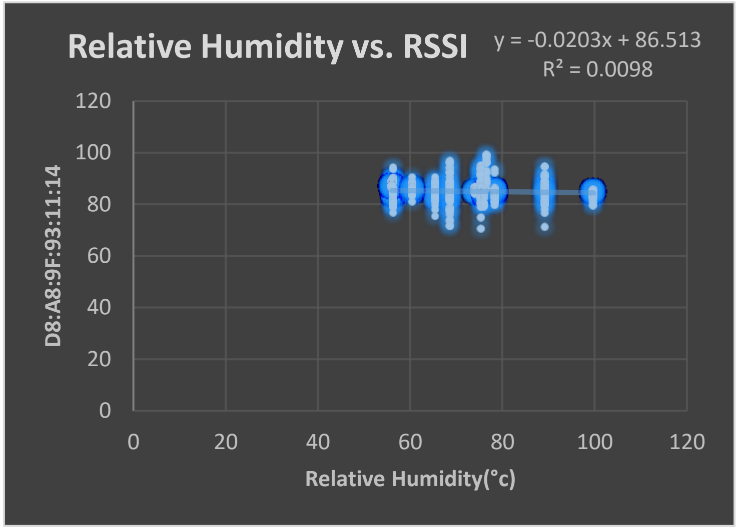

Figure 12: Graph of Relative Humidity vs. RSSI data

The RSSI reading with Relative Humidity shows that the RSSI is mostly between -*(70 to < 100)*

Location: Tavua, Unpartitioned Space

Correlation Plotting

Graph of Atmospheric Pressure vs. RSSI data

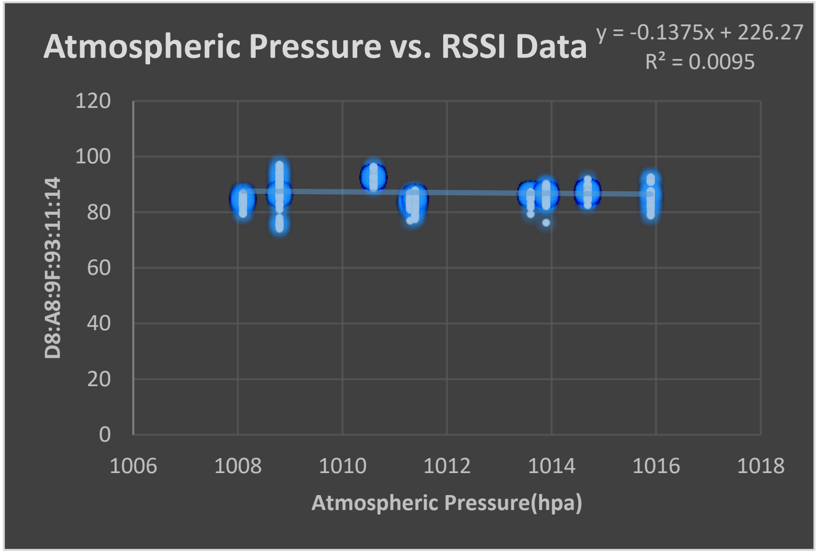

Figure 13: Graph of Atmospheric Pressure vs. RSSI data

The RSSI reading with Atmospheric Pressure in an un-partitioned space, mostly displayed a neutral visual, as the RSSI readings were mostly between

-(80 - < 100)

Graph of Air Temperature vs. RSSI Data

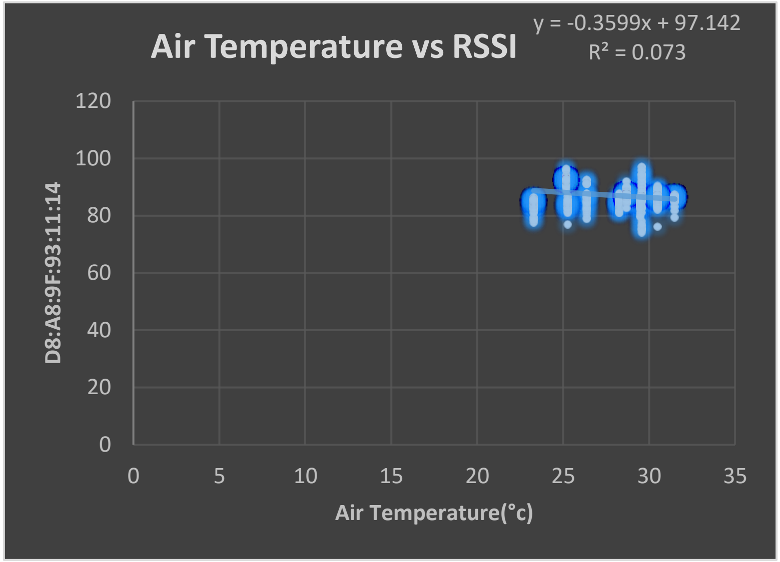

Figure 14: Graph of Air Temperature vs. RSSI Data

The RSSI reading with Air Temperature in an unpartitioned space displayed a similar pattern as seen in Room 1.

Graph of Relative Humidity vs. RSSI data

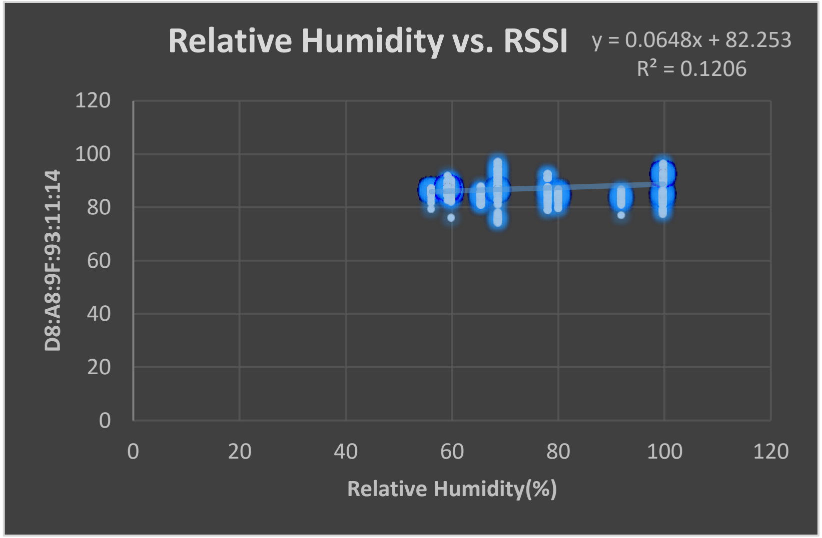

Figure 15: Graph of Relative Humidity vs. RSSI data

The RSSI reading with Relative Humidity in an unpartitioned space displayed a reading of ~ - *(80 - < 100)* between 50% - 100% Relative Humidity.

Graph of Transmitter Height vs. RSSI data

Figure 16: Graph of Transmitter Height vs. RSSI data

The RSSI reading with Height of Transmitters in an unpartitioned space showed that as the height of the Transmitter increased so did the RSSI, which was mostly ~ - *(>80)*. The heights of the Transmitter at 0.2m and 1.4m showed almost the same reading.

Graph of Room Temperature vs. RSSI Data

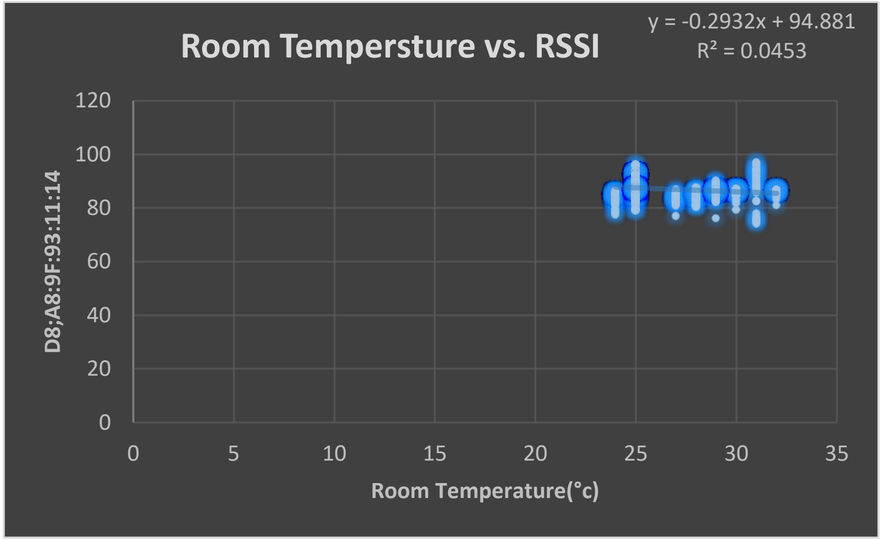

Figure 17: Graph of Room Temperature vs. RSSI

The RSSI reading with Room Temperature in an unpartitioned space displays that most readings are between ~ - *(80 - < 100)* for room temperature ranging from below 25℃ to slightly above 30℃.

Location: Room 1, Suva – Device 1

Graph of Distance vs. RSSI

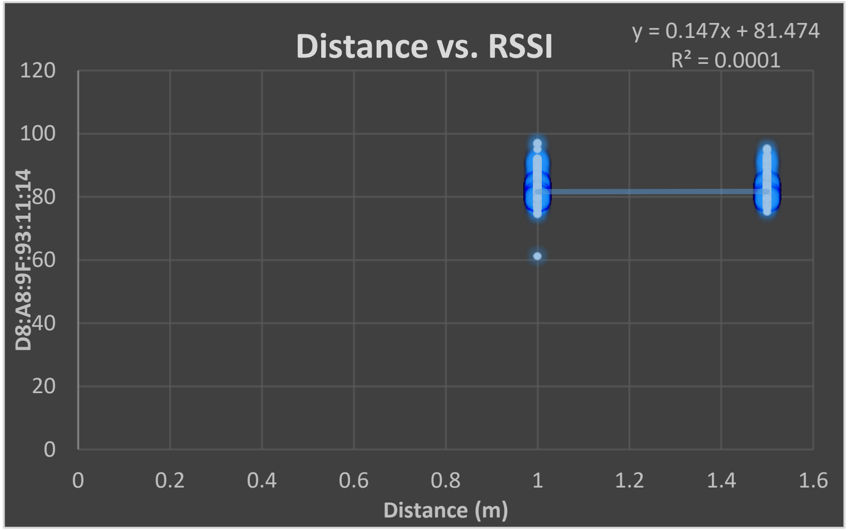

Figure 18: Distance vs. RSSI

The RSSI reading with Distance in Room 1 Suva displayed that the reading is between ~ - *(70 - 100).*

Graph of Atmospheric Pressure vs. RSSI data

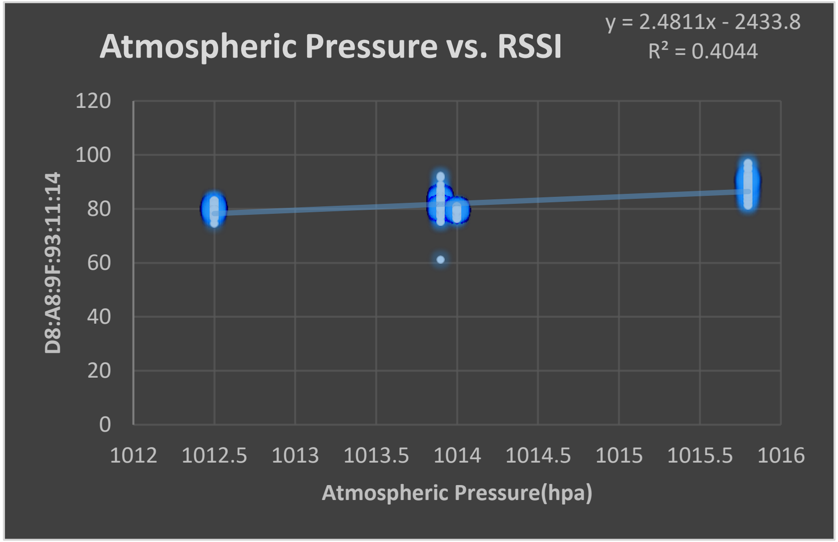

Figure 19: Atmospheric Pressure vs. RSSI

The RSSI reading with Atmospheric Pressure in Room 1 Suva displayed that mostly the RSSI reading at 1012.5 is between ~ - (<80 - <85). The RSSI reading at 1014 is between ~ - (<80 - <95). The RSSI reading for >1016 is mostly between ~ - (<80 - 100)

Graph of Relative Humidity vs. RSSI Data

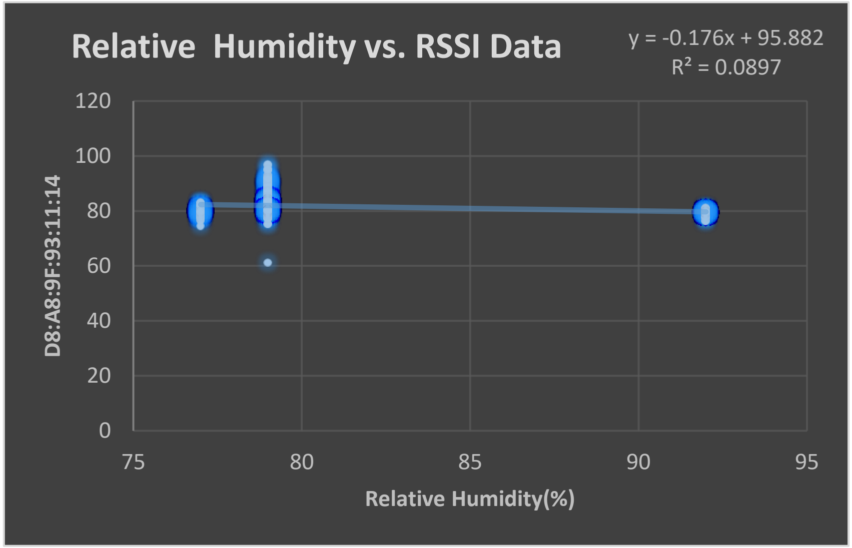

Figure 20: Graph of Relative Humidity vs. RSSI Data

The RSSI reading with Relative Humidity >*80 %* is between ~ - (<80 - 100), relative humidity >90% is ~ -(80).

Graph Air Temperature vs. RSSI Data

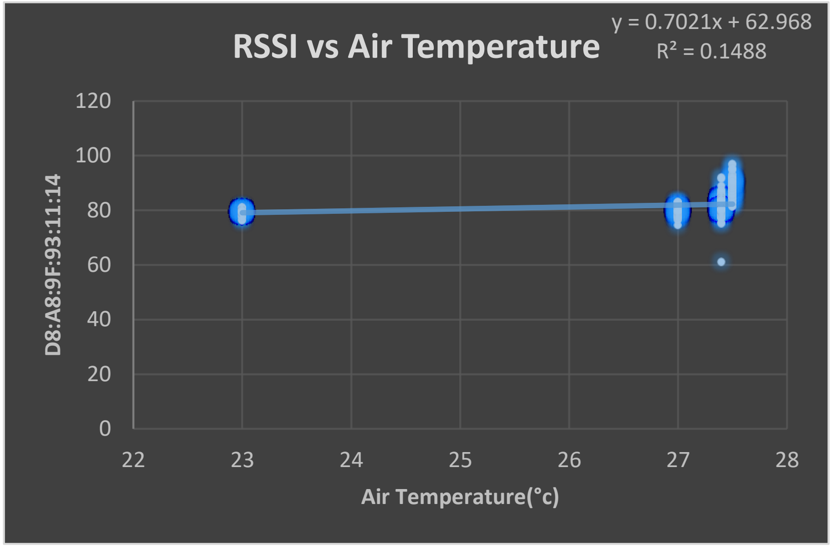

Figure 21: Graph Air Temperature vs. RSSI

The RSSI reading with Air Temperature in Room 1 Suva displays reading between ~ -(<80 - 100) at 27℃. The RSSI reading at 23℃ shows a reading of mostly -80.

Graph of Height of Transmitter vs. RSSI Data

Figure 22: Height of Transmitter vs. RSSI

The RSSI reading with Height of Transmitter in an un-partitioned space display, at Height of 0 the RSSI reading is between ~ *-(80 - 100)*. At height of 1m the RSSI reading ranged from slightly < *-(80)* to slightly < -(100). The RSSI reading with the Height of Transmitter a little below 1.2m displayed RSSI reading between *-(70 – 90*). At 1.35m the RSSI reading ranges from ~-(75 – 85)

Graph Room Temperature vs. RSSI

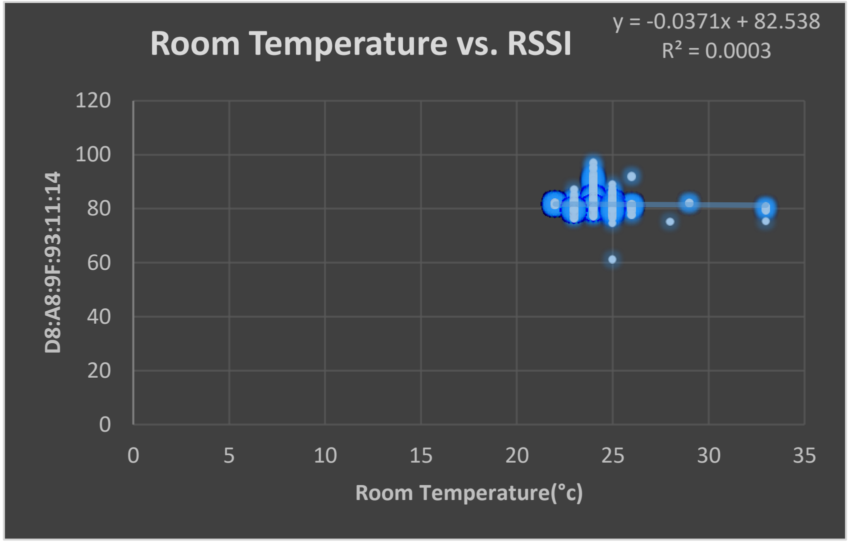

Figure 23: Room Temperature vs. RSSI

The RSSI reading with Room Temperature in an unpartitioned space displays few instances of outliers above the room temperature of 25℃ . The RSSI reading between room temperature of above 20℃ to 26℃ is between ~-(<80 - 100)

Location: Room 2, Tavua

Device 1

Graph of Distance vs. RSSI

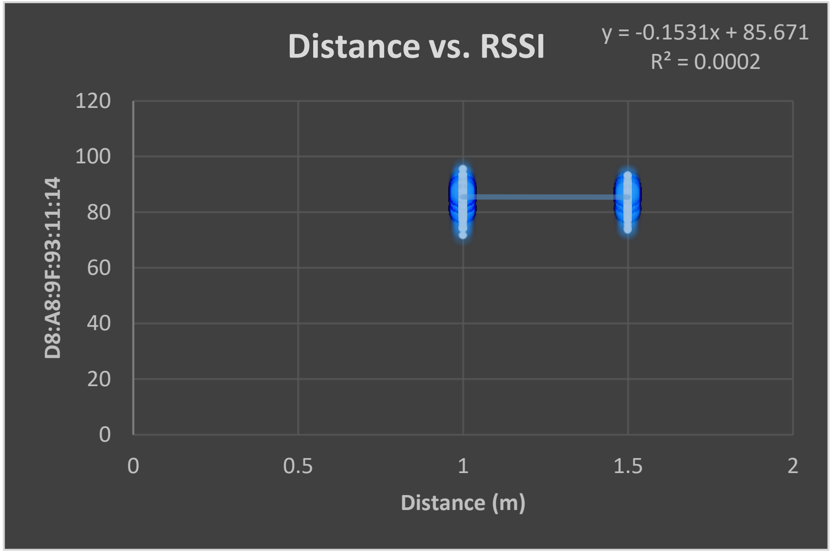

Figure 24: Graph of Distance vs. RSSI data

The RSSI reading with Distance in Room 2 Tavua displays a range of ~ - *(70 - 100)* at a Distance of 1m. The RSSI reading at ~1.3m displays a range of ~-*(75 - 100)*.

Graph of Atmospheric Pressure vs. RSSI Data

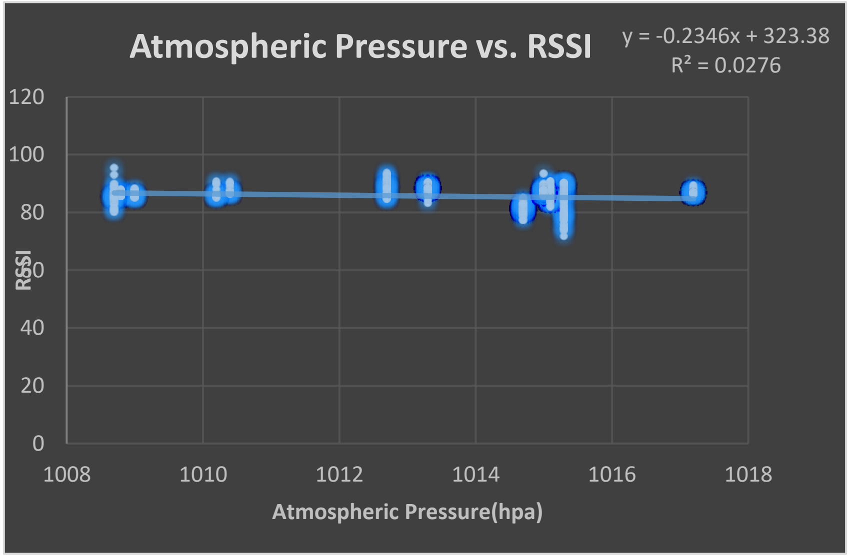

Figure 25: Graph of Atmospheric Pressure vs. RSSI

The RSSI reading with Atmospheric Pressure in Room 2 Tavua displayed mostly reading above ~-*(80)*.

Graph of Air Temperature vs. RSSI

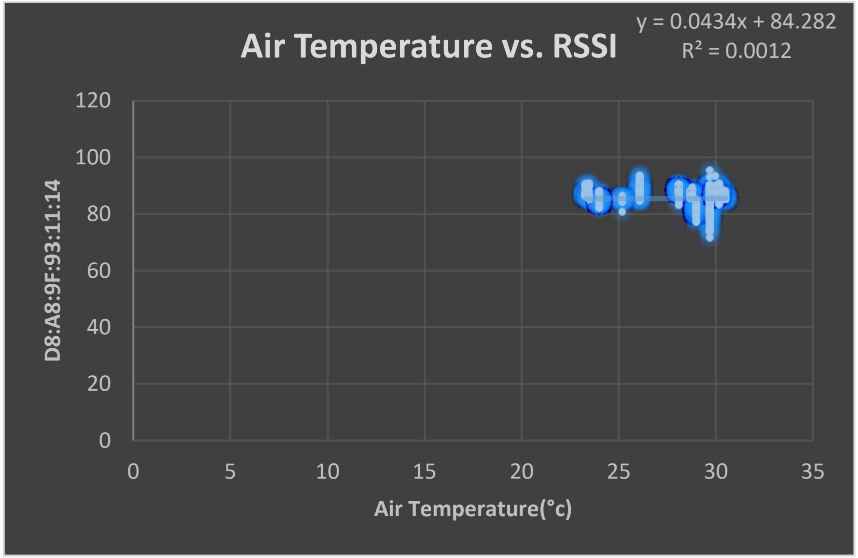

Figure 26: Graph of Air Temperature vs. RSSI

The RSSI reading with the Height of the Transmitter in Room 2 displays a similar observation with Un-partitioned space in Tavua.

Graph of Relative Humidity vs. RSSI

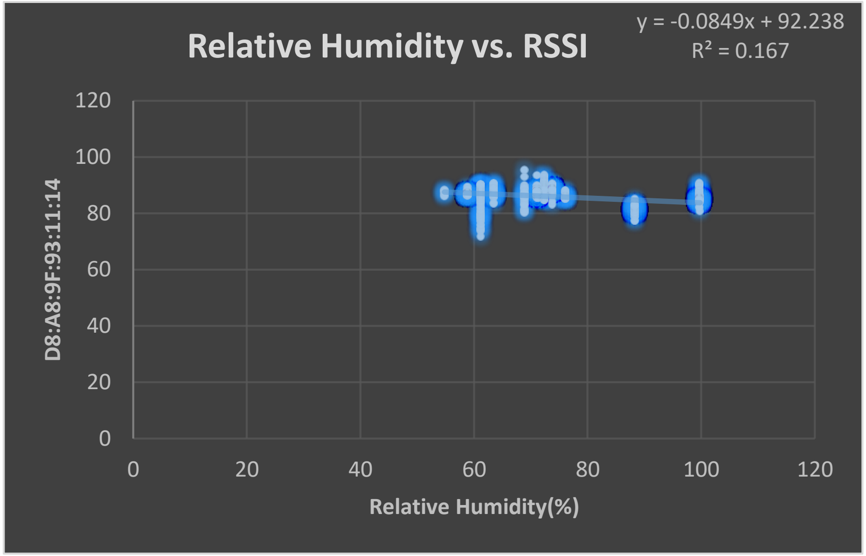

Figure 27: Graph of Relative Humidity vs. RSSI

The RSSI reading with Relative Humidity in Room 2 Tavua displays that most RSSI readings fall between 60% to 80% relative humidity and these readings are mostly in between ~*-(80 - 100).*

Graph of Height of Transmitters vs. RSSI Data

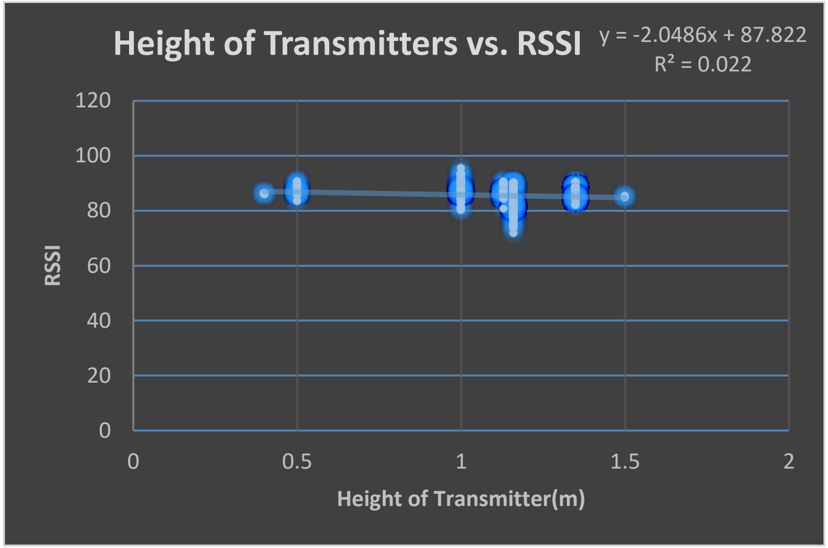

Figure 28: Graph of Height of Transmitters vs. RSSI Data

The RSSI reading with Height of Transmitters in Room 2 Tavua displays that most readings are collected between ~-*(80 -100)* at different heights such as 0.4m, 0.5m, 1m, ~1.2m, 1.37m and 1.5m.

Graph of Room Temperature vs. RSSI

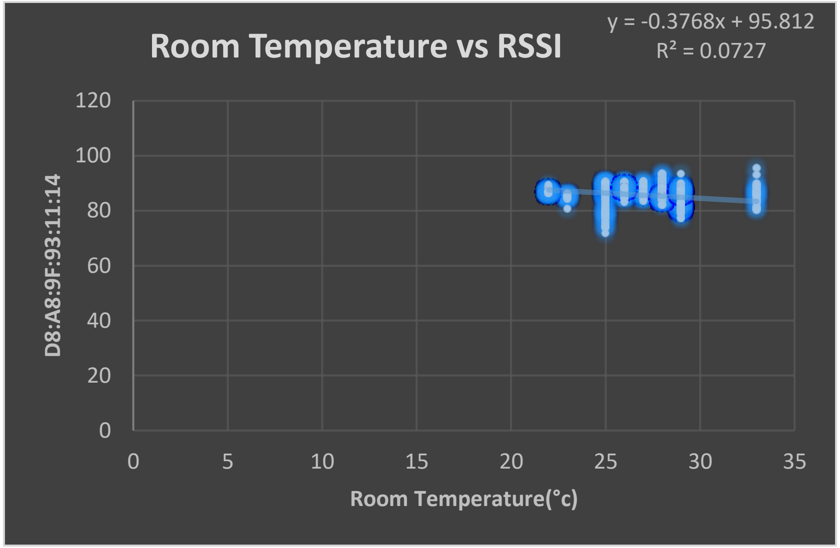

Figure 29: Room Temperature vs RSSI

The RSSI reading with Room Temperature in Room 2 Tavua displays that most reading is between ~-*(80 -100)* for air temperature ranging from *above* 20℃ to below 30℃.

From the above correlation, the co-efficient table and graph show a lot of discrepancies; a clear relationship could not be identified, so Linear Regression will be utilised to observe the cause and effect between the independent and dependent variables. Therefore, in the following sub-section, an alternate tool will be referred to successfully determine a cause and effect between the variables.

4.2.3. Linear Regression

In this subsection, the results of linear regression calculation that was performed in Microsoft Excel are captured to determine the cause and effect between the dependent and independent parameters. As per the scenario of dependent and independent parameters, three tables provide details of regression indicators, which were selected based on their significance to analyse and draw conclusions. These three tables are Regression Statistics, Anova Details and Linear Graph Statistics. The key terms that are used in linear regression are listed as follows.

Essential Key Terms (Svetlana Cheusheva, 2023);

i. Multiple R – it denotes the correlation coefficient; it indicates the strength of the relationship between the dependent and independent variable. As stated above the values between -1 – 1, indicate either a positive relationship, no relationship, or a negative relationship.
ii. R Square – literally means coefficient determination, which indicates goodness of fit and how many points' fall on the regression line. Generally, a rounded value of 0.95 indicates a good fit.
iii. Adjusted R Square – This value is adjusted based on the number of introduced independent variables. So, it is only useful when multiple independent variables are used.
iv. Standard Error – A smaller value indicates comparative precision in the regression model or the goodness of fit. It also displays the aggregate distance of the data points from the regression line.
v. Observations – This specifies a number of values.
vi. Degree of Freedom (df) – number of degrees of freedom related with the sources of variance.
vii. Smaller Square (SS) – it indicates the totality of squares. The smaller the residual SS compared with the total SS, the better the model fits the data.
viii. Mean Square (MS) – is the mean square.
ix. F – F-static or F-test for null hypothesis. It is mostly used to test the overall significance of the model.
x. Significance F - provides statically significant reliable results, if the value is less than 0.05 % then the model is acceptable, if the value is more than 0.05% then another independent variable needs to be selected.

Device 1

Location: Room 1, Tavua

RSSI Data vs. Distance - Summary Output

The table below displays the summary output of the Regression Analysis of RSSI Data vs. the Distance of Device 1 from Room 1 in Tavua.

Table 5: RSSI Data vs. Distance Regression Statistics

Regression Statistics	
Multiple R	0.143
R Square	0.021
Adjusted R Square	0.020
Standard Error	2.591
Observations	1210

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 1 in Tavua.

Table 5.1: RSSI Data vs. Distance Anova

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	170.448	170.448	25.357	5.488
Residual	1208	8120.027	6.722		
Total	1209	8290.475			

Table 5.2: RSSI Data vs. Distance Statistics on Linear Graph

The table below displays the Statistics on Linear Graph of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 1 in Tavua.

	Coeff-icient	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	84.432	0.145	582.648	0	84.148	84.716	84.148	84.716
Vari-able 1	0.500	0.099	5.036	5.488	0.306	0.700	0.306	0.700

The table displays the summary output of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 1 in Tavua.

RSSI Data vs. Air Temperature - Summary Output

Table 6: RSSI Data vs. Air Temperature Regression Statistics

Regression Statistics	
Multiple R	0.088
R Square	0.008
Adjusted R Square	0.007
Standard Error	2.610
Observations	1210

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 1 in Tavua.

Table 6.1: RSSI Data vs. Air Temperature ANOVA Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	63.431	63.431	9.314	0.002
Residual	1208	8227.044	6.810		
Total	1209	8290.475			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 1 in Tavua.

Table 6.2: RSSI Data vs. Air Temperature Linear Graph Statistics

	Coe-ffi-cient s	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	82.2 94	0.909	90.5 54	0	80.511	84.077	80.511	84.077
Variab-le 1	0.01 0	0.032	3.05 2	0.002	0.0349	0.160	0.035	0.160

The table below displays the summary output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 1 in Tavua.

RSSI Data vs. Relative Humidity - Summary Output

Table 7: Data vs. Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	0.100
R Square	0.010
Adjusted R Square	0.009
Standard Error	2.607
Observations	1210

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 1 in Tavua.

Table 7.1: Data vs. Relative Humidity Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	81.601	81.601	12.010	0.001
Residual	1208	8208.874	6.795		
Total	1209	8290.475			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 1 in Tavua.

Table 7.2: Data vs. Relative Humidity Linear Graph Details

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	86.514	0.427	202.665	0	85.677	87.351	85.676	87.351
Variable 1	-0.020	0.006	-3.465	0.001	-0.0319	-0.009	-0.0319	-0.009

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 1 in Tavua.

RSSI Data vs. Atmospheric Pressure - Summary Output

Table 8: RSSI Data vs. Atmospheric Pressure Regression Statistics

Regression Statistics	
Multiple R	0.180
R Square	0.032
Adjusted R Square	0.032
Standard Error	2.577
Observations	1210

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 1 in Tavua.

Table 8.1: Data vs. Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	267.867	267.867	40.339	3.024
Residual	1208	8022.609	6.641		
Total	1209	8290.475			

The table below displays the Liner Graph Statistics of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 1 in Tavua.

Table 8.2: Data vs. Atmospheric Pressure Linear Graph Details

	Coef-fi-cients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	-105.943	30.075	-3.523	0.0004	-164.948	-46.939	-164.948	-46.939
Varia-ble 1	0.189	0.030	6.351	3.024	0.130	0.247	0.130	0.247

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 1 in Tavua.

RSSI Data vs. Room Temperature - Summary Output

Table 9: RSSI Data vs. Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.125
R Square	0.016
Adjusted R Square	0.015
Standard Error	2.600
Observations	1210

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 1 in Tavua.

Table 9.1: Data vs. Room Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	129.597	129.597	19.183	1.300
Residual	1208	8160.878	6.756		
Total	1209	8290.475			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 1 in Tavua.

Table 9.2: Data vs. Room Temperature Linear Graph Statistics

	Coe-ffic-ients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	81.701	0.770	106.103	0	80.190	83.212	80.190	83.212
Varia-ble 1	0.124	0.028	4.380	1.300	0.0683	0.1780	0.068	0.179

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Height of Transformer of Device 1 from Room 1 in Tavua.

RSSI Data vs Height of Transformer - Summary Output

Table 10: RSSI Data vs Height of Transformer Regression Statistics

Regression Statistics	
Multiple R	0.0985
R Square	0.010
Adjusted R Square	0.010
Standard Error	2.607
Observations	1210

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Height of Transformer of Device 1 from Room 1 in Tavua.

Table 10.1: RSSI Data vs Height of Transformer Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	80.436	80.436	11.835	0.001
Residual	1208	8210.039	6.796		
Total	1209	8290.475			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transformer of Device 1 from Room 1 in Tavua.

Table 10.2: RSSI Data vs Height of Transformer Linear Graph Statistics

	Coe-ffic-ients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	85.898	0.255	336.488	0	85.396	86.398	85.396	86.398
Variab-le 1	-0.801	0.233	-3.440	0.001	-1.258	-0.344	-1.258	-0.344

Location: Un-partitioned Space – Tavua

RSSI Data vs. Distance - Summary Output

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Distance of Device 1 from Un-partitioned Space in Tavua.

Table 11: RSSI Data vs. Distance Regression Statistics

Regression Statistics	
Multiple R	0.080
R Square	0.006
Adjusted R Square	0.006
Standard Error	3.239
Observations	1204

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Distance of Device 1 from Un-partitioned Space in Tavua.

Table 11.1: RSSI Data vs. Distance Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	81.030	81.030	7.725	0.006
Residual	1202	12607.639	10.489		
Total	1203	12688.669			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 1 from Un-partitioned Space in Tavua.

Table 11. 2: RSSI Data vs. Distance Linear Graph Statistics

	Coeff-icients	*Stan-dard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	86.615	0.182	476.042	0	86.258	86.972	86.258	86.972
X Varia-ble 1	0.346	0.124	2.780	0.006	0.102	0.590	0.102	0.590

RSSI Data vs. Atmospheric Pressure - Summary Output

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Un-partitioned Space in Tavua.

Table 12: RSSI Data vs. Atmospheric Pressure Regression Statistics

Regression Statistics	
Multiple R	0.100
R Square	0.010
Adjusted R Square	0.010
Standard Error	3.23
Observations	1204

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Un-partitioned Space in Tavua.

Table 12.1: RSSI Data vs. Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	120.638	120.638	11.538	0.001
Residual	1202	12568.031	10.456		
Total	1203	12688.670			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Un-partitioned Space in Tavua.

Table 12.2: RSSI Data vs. Atmospheric Pressure Linear Graph Statistics

	Coeffic-ients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	226.274	40.988	5.521	4.138	145.858	306.690	145.858	306.690
X Variab-le 1	-0.138	0.040	-3.400	0.0007	-0.217	-0.0581	-0.217	-0.058

RSSI Data vs. Air Temperature - Summary Output

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Un-partitioned Space in Tavua.

Table 13: RSSI Data vs. Air Temperature Regression Statistics

Regression Statistics	
Multiple R	0.213
R Square	0.045
Adjusted R Square	0.044
Standard Error	3.175
Observations	1204

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Un-partitioned Space in Tavua.

Table 13.1: RSSI Data vs. Air Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	574.649	574.649	57.019	8.510
Residual	1202	12114.02	10.078		
Total	1203	12688.67			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Un-partitioned Space in Tavua.

Table 13.2: RSSI Data vs. Air Temperature Linear Graph Statistics

	Coefficient	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	94.881	1.0412	91.124	0	92.838	96.924	92.838	96.924
X Varia-ble 1	-0.293	0.039	7.551	-8.51	-0.369	-0.217	-0.369	-0.217

RSSI vs Relative Humidity - Summary Output

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Un-partitioned Space in Tavua.

Table 14: RSSI Data vs. Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	0.347
R Square	0.121
Adjusted R Square	0.120
Standard Error	3.047
Observations	1204

The table below displays the Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Un-partitioned Space in Tavua.

Table 14.1: RSSI Data vs. Relative Humidity Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1530.700	1530.700	164.896	1.837
Residual	1202	11157.969	9.283		
Total	1203	12688.669			

The table below displays the Linear Graph Statistics of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Un-partitioned Space in Tavua.

Table 14.2: RSSI Data vs. Relative Humidity Linear Graph Statistics

	Coeff-icien-ts	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	82.253	0.384	214.380	0	81.500	83.006	81.500	83.006
X Variab-le 1	0.0648	0.005	12.841	1.837	0.0549	0.0747	0.055	0.0747

RSSI Data vs Height of Transmitters - Summary Output

The table below displays the Summary Output of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Un-partitioned Space in Tavua.

Table 15: RSSI Data vs Height of Transmitters Regression Statistics

Regression Statistics	
Multiple R	0.273
R Square	0.074
Adjusted R Square	0.074
Standard Error	3.126
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Un-partitioned Space in Tavua.

Table 15.1: RSSI Data vs Height of Transmitters Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	944.813	944.813	96.703	5.31
Residual	1202	11743.86	9.770		
Total	1203	12688.67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Un-partitioned Space in Tavua.

Table 15. 2: RSSI Data vs Height of Transmitters Linear Graph Statistics

	Coeffi-cients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	84.148	0.308	272.817	0	83.543	84.753	83.543	84.753
X Vari-able 1	2.790	0.284	9.834	5.31	2.233	3.347	2.233	3.347

RSSI Data vs Room Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Un-partitioned Space in Tavua.

Table 16: RSSI Data vs Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.213
R Square	0.045
Adjusted R Square	0.044
Standard Error	3.175
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Un-partitioned Space in Tavua.

Table 16. 1: RSSI Data vs. Room Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	574.649	574.649	57.019	8.51
Residual	1202	12114.02	10.078		
Total	1203	12688.67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Un-partitioned Space in Tavua.

Table 16.2: RSSI Data vs. Room Temperature Linear Graph Statistics

	Coeffic-ients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	94.881	1.041	91.125	0	92.838	96.924	92.838	96.924
X Varia-ble 1	-0.293	0.039	-7.551	8.51	-0.370	-0.217	-0.370	-0.217

RSSI Data vs Amount of Rainfall - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Amount of Rainfall of Device 1 from Un-partitioned Space in Tavua.

Table 17: RSSI Data vs Amount of Rainfall Regression Statistics

Regression Statistics	
Multiple R	0.0685
R Square	0.005
Adjusted R Square	0.004
Standard Error	3.241
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Amount of Rainfall of Device 1 from Un-partitioned Space in Tavua.

Table 17.1: RSSI Data vs Amount of Rainfall Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	59.569	59.569	5.670	0.017
Residual	1202	12629.1	10.507		
Total	1203	12688.67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Amount of Rainfall of Device 1 from Un-partitioned Space in Tavua.

Table 17.2: RSSI Data vs Amount of Rainfall Linear Graph Statistics

	Coeffic-ients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	87.049	0.093	931.846	0	86.866	87.232	86.866	87.232
X Vari-able 1	0	0	65535	-	0	0	0	0

Location: Room 2 Tavua

RSSI Data vs Distance - Summary Output

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 2 in Tavua.

Table 18: RSSI Data vs Distance Regression Statistics

Regression Statistics	
Multiple R	0.013
R Square	0.0002
Adjusted R Square	-0.0007
Standard Error	2.885
Observations	1241

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 2 in Tavua.

Table 18.1: RSSI Data vs Distance Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.613	1.613	0.194	0.660
Residual	1239	10316.02	8.326		
Total	1240	10317.63			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 2 in Tavua.

Table 18.2: RSSI Data vs Distance Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	85.671	0.414	207.14 1	0	84.860	86.482	84.860	86.483
Varia-ble 1	-0.153	0.347	-0.440	0.660	-0.835	0.529	-0.834	0.529

RSSI Data vs. Atmospheric Pressure - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 2 in Tavua.

Table 19: RSSI Data vs. Atmospheric Pressure Regression Statistics

Regression Statistics	
Multiple R	0.166
R Square	0.028
Adjusted R Square	0.0268
Standard Error	2.846
Observations	1241

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 2 in Tavua.

Table 19.1: RSSI Data vs. Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	284.6063	284.6063498	35.14664	3.95974E-09
Residual	1239	10033.03	8.097682309		
Total	1240	10317.63			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 2 in Tavua.

Table 19.2: RSSI Data vs. Atmospheric Linear Graph Statistics

	Coeffic-ients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	323.433	40.135	8.059	1.8	244.692	402.173	244.692	402.173
Varia-ble 1	-0.235	0.040	-5.928	3.96	-0.312	-0.157	-0.312	-0.157

RSSI Data vs Air Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 2 in Tavua.

Table 20: RSSI Data vs Air Temperature Regression Statistics

Regression Statistics	
Multiple R	0.035
R Square	0.001
Adjusted R Square	0.0004
Standard Error	2.884
Observations	1241

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 2 in Tavua.

Table 20.1: RSSI Data vs Air Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	12.817	12.817	1.541	0.215
Residual	1239	10304.82	8.317		
Total	1240	10317.63			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 2 in Tavua.

Table 20.2: RSSI Data vs Air Temperature Linear Graph Statistics

	Coeffic-ients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	84.280	0.980	85.984	0	82.357	86.203	82.357	86.203
Vari-able 1	0.043	0.035	1.241	0.215	-0.025	0.112	-0.025	0.112

RSSI Data vs. Relative Humidity - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 2 in Tavua.

Table 21: RSSI Data vs. Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	0.409
R Square	0.167
Adjusted R Square	0.166
Standard Error	2.634
Observations	1241

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 2 in Tavua.

Table 21.1: RSSI Data vs. Relative Humidity Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1723.727	1723.727	248.513	3.63
Residual	1239	8593.908	6.936		
Total	1240	10317.63			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 2 in Tavua.

Table 21.2: RSSI Data vs. Relative Humidity Linear Graph Statistics

	Coeffic-ients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	92.240	0.434	212.298	0	91.388	93.092	91.388	93.092
Varia-ble 1	-0.0850	0.005	-15.764	3.63	-0.0955	-0.074	-0.095	-0.074

RSSI Data vs. Height of Transmitters - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Room 2 in Tavua.

Table 22: RSSI Data vs. Height of Transmitters Regression Statistics

Regression Statistics	
Multiple R	0.150
R Square	0.022
Adjusted R Square	0.022
Standard Error	2.853
Observations	1241

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Room 2 in Tavua.

Table 22.1: RSSI Data vs. Height of Transmitters Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	230.928	230.928	28.366	1.19
Residual	1239	10086.71	8.141		
Total	1240	10317.63			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Room 2 in Tavua.

Table 22.2: RSSI Data vs. Height of Transmitters Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	85.692	0.089	960.225	0	85.517	85.868	85.517	85.867
Varia-ble 1	-0.067	0.013	-5.326	1.19	-0.092	-0.042	-0.092	-0.042

RSSI Data vs. Room Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 2 in Tavua.

Table 23: RSSI Data vs. Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.270
R Square	0.073
Adjusted R Square	0.072
Standard Error	2.78
Observations	1241

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 2 in Tavua.

Table 23.1: RSSI Data vs. Room Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	750.489	750.489	97.193	4
Residual	1239	9567.146	7.722		
Total	1240	10317.63			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 2 in Tavua.

Table 23.2: RSSI Data vs. Room Temperature Linear Graph Statistics

	Coeffic-ients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	95.812	1.050	91.279	0	93.752	97.871	93.752	97.871
Varia-ble 1	-0.377	0.038	-9.859	4	-0.452	-0.302	-0.452	-0.302

Location: Room 1 Suva

RSSI Data vs Distance - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 1 in Suva.

Table 24: RSSI Data vs Distance Regression Statistics

Regression Statistics	
Multiple R	0.012
R Square	0.0001
Adjusted R Square	-0.0007
Standard Error	2.973
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 1 in Suva.

Table 24.1: RSSI Data vs Distance Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.448	1.448	0.164	0.686
Residual	1204	10644.85	8.841		
Total	1205	10646.29			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 1 from Room 1 in Suva.

Table 24.2: RSSI Data vs Distance Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	81.474	0.432	188.438	0	80.626	82.322	80.626	82.322
X Varia-ble 1	0.147	0.363	0.405	0.686	-0.566	0.860	-0.566	0.860

RSSI Data vs Atmospheric Data - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 1 in Suva.

Table 25: RSSI Data vs Atmospheric Data Regression Statistics

Regression Statistics	
Multiple R	0.636
R Square	0.404
Adjusted R Square	0.404
Standard Error	2.295
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 1 in Suva.

Table 25.1: RSSI Data vs Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4305.354	4305.354	817.489	1.2
Residual	1204	6340.939	5.266		
Total	1205	10646.29			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 1 from Room 1 in Suva.

Table 25.2: RSSI Data vs Atmospheric Linear Graph Statistics

	Coeffic-ients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	-2433.84	87.979	-27.664	8.5	-2606.45	-2261.23	-2606.45	-2261.23
X Varia-ble 1	2.481098	0.0868	28.592	1.2	2.311	2.651	2.311	2.651

RSSI Data vs Relative Humidity - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 1 in Suva.

Table 26: RSSI Data vs Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	0.300
R Square	0.090
Adjusted R Square	0.090
Standard Error	2.837
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 1 in Suva.

Table 26.1: RSSI Data vs Relative Humidity Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	955.040	955.040	118.650	2.04
Residual	1204	9691.253	8.049		
Total	1205	10646.29			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Relative Humidity of Device 1 from Room 1 in Suva.

Table 26.2: RSSI Data vs Relative Humidity Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	95.882	1.310	73.219	0	93.313	98.452	93.313	98.452
X Varia-ble 1	-0.176	0.016	-10.893	2.04	-0.208	-0.144	-0.208	-0.144

RSSI Data vs Air Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 1 in Suva.

Table 27: RSSI Data vs Air Temperature Regression Statistics

Regression Statistics	
Multiple R	0.386
R Square	0.149
Adjusted R Square	0.148
Standard Error	2.743
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 1 in Suva.

Table 27.1: RSSI Data vs Air Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1584.664	1584.664	210.551	4.34
Residual	1204	9061.63	7.526		
Total	1205	10646.29			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 1 from Room 1 in Suva.

Table 27.2: RSSI Data vs Air Temperature Linear Graph Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	62.968	1.290	48.827	9.1	60.438	65.498	60.438	65.498
X Variable 1	0.702	0.048	14.510	4.34	0.607	0.797	0.607	0.797

RSSI Data vs Amount of Rainfall - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Amount of Rainfall of Device 1 from Room 1 in Suva.

Table 28: RSSI Data vs Amount of Rainfall Regression Statistics

Regression Statistics	
Multiple R	0.013
R Square	0.0002
Adjusted R Square	-0.0007
Standard Error	2.973
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Amount of Rainfall of Device 1 from Room 1 in Suva.

Table 28.1: RSSI Data vs Amount of Rainfall Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.852615	1.852	0.210	0.647
Residual	1204	10644.44	8.8409		
Total	1205	10646.29			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Amount of Rainfall of Device 1 from Room 1 in Suva.

Table 28.2: RSSI Data vs Amount of Rainfall Linear Graph Statistics

	Coeffic-ients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	81.646	0.0856	953.585	0	81.478	81.814	81.478	81.814
X Varia-ble 1	0	0	65535	-	0	0	0	0

RSSI Data vs Height of Transmitters - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Room 1 in Suva.

Table 29: RSSI Data vs Height of Transmitters Regression Statistics

Regression Statistics	
Multiple R	0.682
R Square	0.466
Adjusted R Square	0.465
Standard Error	2.173
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Room 1 in Suva.

Table 29.1: RSSI Data vs Height of Transmitters Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4958.98	4958.98	1049.812	4.1
Residual	1204	5687.314	4.724		
Total	1205	10646.29			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 1 from Room 1 in Suva.

Table 29.2: RSSI Data vs Height of Transmitters Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	88.029	0.207	425.876	0	87.623	88.434	87.623	88.434
X Varia-ble 1	-6.226	0.192	-32.401	4.1	-6.603	-5.850	-6.603	-5.849

RSSI Data vs Room Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 1 in Suva.

Table 30: RSSI Data vs Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.017
R Square	0.0003
Adjusted R Square	-0.0005
Standard Error	2.973
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 1 in Suva.

Table 30.1: RSSI Data vs Room Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.059	3.059	0.346	0.556
Residual	1204	10643.23	8.840		
Total	1205	10646.29			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 1 from Room 1 in Suva.

Table 30.2: RSSI Data vs Room Temperature Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	82.538	1.520	54.328	0	79.557	85.519	79.557	85.519
X Varia-ble 1	-0.0371	0.063	-0.588	0.556	-0.161	0.087	-0.161	0.087

Device 2

Location: Room 1, Tavua

RSSI Data vs. Distance - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 1 in Tavua.

Table 31: RSSI Data vs. Distance Regression Statistics

Regression Statistics	
Multiple R	0.004
R Square	1.463
Adjusted R Square	-0.0008
Standard Error	42.697
Observations	1211

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 1 in Tavua.

Table 31.1: RSSI Data vs. Distance Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	32.263	32.263	0.018	0.894
Residual	1209	2204043	1823.03		
Total	1210	2204075			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 1 in Tavua.

Table 31.2: RSSI Data vs. Distance Linear Graph Statistics

	Coeffic-ients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	37.918	2.384	15.901	7.65	33.239	42.596	33.240	42.596
X Varia-ble 1	0.218	1.637	0.133	0.894	-2.994	3.430	-3.000	3.430

RSSI vs. Air Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Tavua.

Table 32: RSSI vs. Air Temperature Regression Statistics

Regression Statistics	
Multiple R	0.733
R Square	0.537
Adjusted R Square	0.537
Standard Error	29.056
Observations	1211

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Tavua.

Table 32.1: RSSI vs. Air Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1183345	1183345	1401.609	2.5
Residual	1209	1020730	844.276		
Total	1210	2204075			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Tavua.

Table 32.2: RSSI vs. Air Temperature Linear Graph Statistics

	Coeffi-cients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-339.310	10.118	-33.536	7.4	-359.161	-319.46	-359.161	-319.46
X Variable 1	13.336	0.356	37.438	2.5	12.637	14.035	12.637	14.035

RSSI vs. Relative Humidity - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Tavua.

Table 33: RSSI vs. Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	0.717
R Square	0.514
Adjusted R Square	0.514
Standard Error	29.756
Observations	1211

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Tavua.

Table 33.1: RSSI vs. Relative Humidity Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1133608	1133608	1280.313	8
Residual	1209	1070467	885.415		
Total	1210	2204075			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Tavua.

Table 33.2: RSSI vs. Relative Humidity Linear Graph Statistics

	Coeffici-ents	*Stand-ard Error*	*t Stat*	*P-valu e*	*Lower 95%*	*Upp er 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	209.834	4.873	43.0 64	2.4	200.27 4	219. 394	200.2 74	219.394
X Variab-le 1	-2.399	0.067	- 35.7 82	8	-2.53	- 2.26 7	-2.530	-2.267

RSSI vs. Atmospheric Pressure - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Tavua.

Table 34: RSSI vs. Atmospheric Pressure Regression statistics

Regression Statistics	
Multiple R	0.046
R Square	0.002
Adjusted R Square	0.001
Standard Error	42.652
Observations	1211

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Tavua.

Table 34.1: RSSI vs. Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4632.698	4632.698	2.546524	0.111
Residual	1209	2199443	1819.225		
Total	1210	2204075			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Tavua.

Table 34.2: RSSI vs. Atmospheric Pressure Linear Graph Statistics

	Coeffi-cients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	-755.54794	497.398	-1.519	0.129	-1731.41	220.312	-1731.41	220.312
X Variab-le 1	0.784	0.491	1.596	0.111	-0.180	1.747	-0.180	1.747

RSSI vs Rainfall - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Tavua.

Table 35: RSSI vs Rainfall Regression Statistics

Regression Statistics	
Multiple R	0.033
R Square	0.001
Adjusted R Square	0.0002
Standard Error	42.674
Observations	1211

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Tavua.

Table 35.1: RSSI vs Rainfall Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2445.002	2445.002	1.342	0.247
Residual	1209	2201630.207	1821.034		
Total	1210	2204075.209			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Tavua.

Table 35.2: RSSI vs Rainfall Linear Graph Statistics

	Coeffi-cients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	38.190	1.226	31.143	7.963	35.784	40.595	35.784	40.595
X Variab-le 1	0	0	65535	-	0	0	0	0

RSSI vs Height of Transmitter - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 2 from Room 1 in Tavua.

Table 36: RSSI vs Height of Transmitter Regression Statistics

Regression Statistics	
Multiple R	0.147
R Square	0.022
Adjusted R Square	0.021
Standard Error	42.232
Observations	1211

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 1 in Tavua.

Table 36.1: RSSI vs Height of Transmitter Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	47735.03	47735.03	26.764	2.69
Residual	1209	2156340	1783.573		
Total	1210	2204075			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 1 in Tavua.

Table 36.2: RSSI vs Height of Transmitter Linear Graph Statistics

	Coefficie-nts	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	58.535	4.116	14.222	1.47	50.460	66.610	50.460	66.610
X Varia-ble 1	-19.431	3.756	-5.173	2.69	-26.800	-12.062	-26.800	-12.062

RSSI vs Room Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 37: RSSI vs Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.737
R Square	0.544
Adjusted R Square	0.543
Standard Error	28.843
Observations	1211

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 37.1: RSSI vs Room Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1198282.401	1198282.401	1440.380	3.378
Residual	1209	1005792.808	831.921		
Total	1210	2204075.209			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 37.2: RSSI vs Room Temperature Linear Graph Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-284.473	8.542	-33.302	4.261	-301.232	-267.714	-301.232	-267.714
X Variable 1	11.901	0.314	37.952	3.378	11.286	12.517	11.286	12.517

Location: Un-partitioned Space, Tavua

RSSI vs. Distance - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Un-partitioned Space in Tavua.

Table 38: RSSI vs Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.004
R Square	1.31
Adjusted R Square	-0.001
Standard Error	38.571
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 38.1: RSSI vs Room Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	23.388	23.388	0.0157	0.900
Residual	1202	1788206	1487.692		
Total	1203	1788229			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 38.2: RSSI vs Room Temperature Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	24.784	2.167	11.437	7.93	20.532	29.035	20.532	29.035
X Varia-ble 1	-0.186	1.482	-0.125	0.900	-3.094	2.722	-3.094	2.722

RSSI vs Atmospheric Pressure - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Tavua.

Table 39: RSSI vs Atmospheric Pressure Regression Statistics

Regression Statistics	
Multiple R	0.219
R Square	0.048
Adjusted R Square	0.047
Standard Error	37.635
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Tavua.

Table 39.1: RSSI vs Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	85715.46	85715.46	60.516	1.56
Residual	1202	1702513	1416.401		
Total	1203	1788229			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Tavua.

Table 39.2: RSSI vs Atmospheric Pressure Linear Graph Statistics

	Coefficie-nts	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	3735.651	477.054	7.831	1.06	2799.7	4671.601	2799.7	4671.601
X Varia-ble 1	-3.666	0.471	-7.780	1.56	-4.591	-2.741	-4.591	-2.741

RSSI vs Air Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Tavua.

Table 40: RSSI vs Air Temperature Regression Statistics

Regression Statistics	
Multiple R	0.329
R Square	0.108
Adjusted R Square	0.107
Standard Error	36.429
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Tavua.

Table 40.1: RSSI vs Air Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	193095.9	193095.9	145.506	1.04
Residual	1202	1595133	1327.066		
Total	1203	1788229			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Tavua.

Table 40.2: RSSI vs Air Temperature Linear Graph Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	170.310	12.129	14.041	1.38	146.513	194.106	146.513	194.106
X Variable 1	-5.198	0.431	-12.063	1.04	-6.043	-4.352	-6.043	-4.352

RSSI vs. Relative Humidity - Output Summary

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Tavua.

Table 41: RSSI vs. Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	0.495
R Square	0.245
Adjusted R Square	0.244
Standard Error	33.520
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Tavua.

Table 41.1: RSSI vs. Relative Humidity Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	437692.1	437692.1	389.553	2.48
Residual	1202	1350537	1123.575		
Total	1203	1788229			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 1 in Tavua.

Table 41.2: RSSI vs. Relative Humidity Linear Graph Statistics

	Coeffic-ients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	-56.551	4.221	-13.397	3	-64.833	-48.270	-64.833	-48.270
X Varia-ble 1	1.095	0.0555	19.737	2.48	0.986	1.204	0.986	1.204

RSSI vs. Rainfall - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Tavua.

Table 42: RSSI vs. Rainfall Regression Statistics

Regression Statistics	
Multiple R	0.018
R Square	0.0003
Adjusted R Square	-0.0005
Standard Error	38.565
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Tavua.

Table 42.1: RSSI vs. Rainfall Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	569.425	569.425	0.383	0.536
Residual	1202	1787659	1487.237		
Total	1203	1788229			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Tavua.

Table 42.2: RSSI vs. Rainfall Linear Graph Statistics

	Coeff-icients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	24.550	1.111	22.089	5.0543	22.370	26.731	22.370	26.731
X Vari-able 1	0	0	65535	-	0	0	0	0

RSSI vs. Height of Transmitter - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 1 in Tavua.

Table 43: RSSI vs. Height of Transmitter Regression Statistics

Regression Statistics	
Multiple R	0.219
R Square	0.0480
Adjusted R Square	0.0471
Standard Error	37.635
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 1 in Tavua.

Table 43.1: RSSI vs. Height of Transmitter Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	85697.17	85697.17	60.50284	1.57
Residual	1202	1702532	1416.416		
Total	1203	1788229			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 1 in Tavua.

Table 43.2: RSSI vs. Height of Transmitter Linear Graph Statistics

	Coef-ficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	-3.077	3.714	-0.829	0.407	-10.363	4.209	-10.364	4.209
X Varia-ble 1	26.573	3.416	7.778	1.57	19.870	33.275	19.870	33.275

RSSI vs. Room Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 44: RSSI vs. Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.110
R Square	0.012
Adjusted R Square	0.011
Standard Error	38.336
Observations	1204

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 44.1: RSSI vs. Room Temperature Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	21747.12	21747.12	14.800	0.0001
Residual	1202	1766482	1469.619		
Total	1203	1788229			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Tavua.

Table 44.2: RSSI vs. Room Temperature Linear Graph Statistics

	Coef-ficients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	72.731	12.573	5.784	9.27	48.062	97.399	48.062	97.399
X Varia-ble 1	-1.804	0.469	-3.847	0.0001	-2.723	-0.884	-2.723	-0.884

Location: Room 1, Suva

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 1 in Suva.

RSSI vs. Distance - Summary Output

Table 45: RSSI vs. Distance Regression Statistics

Regression Statistics	
Multiple R	0.0001
R Square	2.06
Adjusted R Square	-0.001
Standard Error	0.236
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 1 in Suva.

Table 45.1: RSSI vs. Distance Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.38	1.38	2.48	0.996
Residual	1204	67	0.056		
Total	1205	67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 1 in Suva.

Table 45.2: RSSI vs. Distance Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	1.167	0.0071	164.782	0	1.153	1.181	1.153	1.181
X Varia-ble 1	1.48	0.0003	0.00498	0.996	-0.0006	0.00066	-0.0006	0.0006

RSSI vs. Atmospheric Pressure - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Suva.

Table 46: RSSI vs. Atmospheric Pressure Regression Statistics

Regression Statistics	
Multiple R	1.419
R Square	2.015
Adjusted R Square	-0.0008
Standard Error	0.236
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Suva.

Table 46.1: RSSI vs. Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.35	1.35	2.43	0.100
Residual	1204	67	0.0556		
Total	1205	67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 1 in Suva.

Table 46.2: RSSI vs. Atmospheric Pressure Linear Graph Statistics

	Coeffic-ients	*Stand-ard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	1.167	9.044	0.129	0.897	-16.576	18.910	-16.576	18.910
X Vari-able 1	3.568	0.009	4	1	-0.018	0.018	-0.018	0.018

RSSI vs. Relative Humidity - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Suva.

Table 47: RSSI vs. Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	65535
R Square	-5.7
Adjusted R Square	-0.0008
Standard Error	0.236
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Suva.

Table 47.1: RSSI vs. Relative Humidity Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	-3.8	-3.8	-6.9	-
Residual	1204	67	0.0556		
Total	1205	67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 1 in Suva.

Table 47.2: RSSI vs. Relative Humidity Linear Graph Statistics

	Coeffi-cients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	1.167	0.109	10.715	1.19	0.95	1.380	0.953	1.380
X Varia-ble 1	2.4	0.001	1.79	1	-0.003	0.003	-0.003	0.003

RSSI vs. Air Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Suva.

Table 48: RSSI vs. Air Temperature Regression Statistics

Regression Statistics	
Multiple R	1.4
R Square	1.95
Adjusted R Square	-0.0008
Standard Error	0.236
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Suva.

Table 48.1: RSSI vs. Air Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.31	1.31	2.35	0.100
Residual	1204	67	0.056		
Total	1205	67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 1 in Suva.

Table 48.2: RSSI vs. Air Temperature Linear Graph Statistics

	Coeffici-ents	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	1.167	0.111	10.521	7.96	0.949	1.384	0.949	1.384
X Varia-ble 1	7.64	0.004	1.84	1	-0.008	0.008	-0.008	0.008

RSSI vs. Rainfall - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Suva.

Table 49: RSSI vs. Rainfall Regression Statistics

Regression Statistics	
Multiple R	0.041
R Square	0.002
Adjusted R Square	0.0009
Standard Error	0.236
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Suva.

Table 49.1: RSSI vs. Rainfall Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.114	0.114	2.056	0.152
Residual	1204	66.886	0.056		
Total	1205	67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 1 in Suva.

Table 49.2: RSSI vs. Rainfall Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	1.167	0.007	171.896	0	1.153	1.180	1.153	1.180
X Varia-ble 1	0	0	65535	-	0	0	0	0

RSSI vs Height of Transmitters - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 2 from Room 1 in Suva.

Table 50: RSSI vs Height of Transmitters Regression Statistics

Regression Statistics	
Multiple R	1.46
R Square	2.12
Adjusted R Square	-0.0008
Standard Error	0.236
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 2 from Room 1 in Suva.

Table 50.1: RSSI vs Height of Transmitters Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.42	1.42	2.55	1
Residual	1204	67	0.056		
Total	1205	67			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transmitters of Device 2 from Room 1 in Suva.

Table 50.2: RSSI vs Height of Transmitters Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	1.167	0.022	52.002	0	1.123	1.211	1.123	1.211
X Vari-able 1	2.99	0.021	1.44	1	-0.041	0.0410	-0.0410	0.0410

RSSI vs. Room Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Suva.

Table 51: RSSI vs. Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.012
R Square	0.0001
Adjusted R Square	-0.0007
Standard Error	22.910
Observations	1206

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Suva.

Table 51.1: RSSI vs. Room Temperature Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	91.361	91.361	0.174	0.677
Residual	1204	631923.2	524.853		
Total	1205	632014.6			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 1 in Suva.

Table 51.2: RSSI vs. Room Temperature Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	11.603	11.707	0.991	0.322	-11.364	34.571	-11.364	34.571
X Vari-able 1	-0.203	0.486	-0.417	0.677	-1.1560	0.751	-1.156	0.751

Location: Tavua, Room 2

RSSI vs. Atmospheric Pressure - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 2 in Tavua.

Table 52: RSSI vs. Atmospheric Pressure Regression Statistics

Regression Statistics	
Multiple R	0.158
R Square	0.025
Adjusted R Square	0.024
Standard Error	22.854
Observations	1242

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 2 in Tavua.

Table 52.1: RSSI vs. Atmospheric Pressure Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	16610.71	16610.71	31.802	2.11
Residual	1240	647664.8	522.310		
Total	1241	664275.5			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Atmospheric Pressure of Device 2 from Room 2 in Tavua.

Table 52.2: RSSI vs. Atmospheric Pressure Linear Graph Statistics

	Coeffici-ents	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	-1810.75	322.279	-5.619	2.38	-2443.03	-1178.48	-2443.03	-1178.48
X Varia-ble 1	1.79225	0.318	5.639	2.11	1.169	2.416	1.169	2.416

RSSI vs. Distance - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 2 in Tavua.

Table 53: RSSI vs. Distance Regression Statistics

Regression Statistics	
Multiple R	0.0002
R Square	5.94
Adjusted R Square	-0.0008
Standard Error	23.145
Observations	1242

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 2 in Tavua.

Table 53.1: RSSI vs. Distance Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.039	0.039	7.37	0.993
Residual	1240	664275.5	535.706		
Total	1241	664275.5			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Distance of Device 2 from Room 2 in Tavua.

Table 53.2: RSSI vs. Distance Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	6.719	3.316	2.026	0.043	0.212	13.225	0.212	13.225
X Vari-able 1	-0.024	2.786	-0.009	0.993	-5.490	5.443	-5.490	5.443

RSSI vs. Air Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 2 in Tavua.

Table 54: RSSI vs. Air Temperature Regression Statistics

Regression Statistics	
Multiple R	0.224
R Square	0.050
Adjusted R Square	0.050
Standard Error	22.556
Observations	1242

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 2 in Tavua.

Table 54.1: RSSI vs. Air Temperature Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	33397.29	33397.29	65.643	1.28
Residual	1240	630878.2	508.773		
Total	1241	664275.5			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Air Temperature of Device 2 from Room 2 in Tavua.

Table 54.2: RSSI vs. Air Temperature Linear Graph Statistics

	Coeffici-ents	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	-55.186	7.664	-7.201	1.04	-70.222	-40.150	-70.222	-40.150
X Varia-ble 1	2.2153	0.273	8.102	1.28	1.679	2.752	1.679	2.752

RSSI vs. Relative Humidity - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 2 in Tavua.

Table 55: RSSI vs. Relative Humidity Regression Statistics

Regression Statistics	
Multiple R	0.390
R Square	0.152
Adjusted R Square	0.151
Standard Error	21.317
Observations	1242

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 2 in Tavua.

Table 55.1: RSSI vs. Relative Humidity Anova Details

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	100793.3	100793.3	221.806	2.83
Residual	1240	563482.2	454.421		
Total	1241	664275.5			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Relative Humidity of Device 2 from Room 2 in Tavua.

Table 55.2: RSSI vs. Relative Humidity Linear Graph Statistics

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	58.27613	3.516113	16.57402	6.98E-56	51.37795	65.17432	51.37795	65.17432
X Variable 1	-0.64903	0.043579	-14.8932	2.83E-46	-0.73452	-0.56353	-0.73452	-0.56353

RSSI vs. Rainfall - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 2 in Tavua.

Table 56: RSSI vs. Rainfall Regression Statistics

Regression Statistics	
Multiple R	0.134
R Square	0.018
Adjusted R Square	0.017
Standard Error	22.937
Observations	1242

Table 56.1: RSSI vs. Rainfall Anova Details

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 2 in Tavua.

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	11888.99	11888.99	22.598	2.23
Residual	1240	652386.5	526.118		
Total	1241	664275.5			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Rainfall of Device 2 from Room 2 in Tavua.

Table 56.2: RSSI vs. Rainfall Linear Graph Statistics

	Coeffici-ents	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	8.122	0.717	11.326	2.29	6.715	9.528	6.715	9.528
X Varia-ble 1	-0.481	0.101	-4.754	2.23	-0.680	-0.282	-0.680	-0.282

RSSI vs. Height of Transmitter - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 2 in Tavua.

Table 57: RSSI vs. Height of Transmitter Regression Statistics

Regression Statistics	
Multiple R	0.032
R Square	0.001
Adjusted R Square	0.0002
Standard Error	23.133
Observations	1242

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 2 in Tavua.

Table 57.1: RSSI vs. Height of Transmitter Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	690.342	690.342	1.29	0.256
Residual	1240	663585.2	535.149		
Total	1241	664275.5			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Height of Transmitter of Device 2 from Room 2 in Tavua.

Table 57.2: RSSI vs. Height of Transmitter Linear Graph Statistics

	Coeffici-ents	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	2.627	3.638	0.722	0.470	-4.510	9.7639	-4.510	9.764
X Varia-ble 1	3.575	3.148	1.136	0.256	-2.600	9.750	-2.600	9.751

RSSI vs. Room Temperature - Summary Output

The table below displays Summary Output of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 2 in Tavua.

Table 58: RSSI vs. Room Temperature Regression Statistics

Regression Statistics	
Multiple R	0.299
R Square	0.090
Adjusted R Square	0.089
Standard Error	22.087
Observations	1242

The table below displays Anova Details of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 2 in Tavua.

Table 58.1: RSSI vs. Room Temperature Anova Details

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	1	59377.55	59377.55	121.72	4.6
Residual	1240	604898	487.821		
Total	1241	664275.5			

The table below displays Linear Graph Statistics of Regression Analysis of RSSI Data vs. Room Temperature of Device 2 from Room 2 in Tavua.

Table 58.2: RSSI vs. Room Temperature Linear Graph Statistics

	Coeffic-ients	*Standa-rd Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Inter-cept	98.474	8.343	11.803	1.51	82.107	114.842	82.107	114.842
X Varia-ble 1	-3.351	0.304	-11.033	4.6	-3.947	-2.756	-3.947	-2.756

4.3. Discussions

The summarized correlation coefficient data are presented in the table to identify and determine a possible relationship between dependent and independent variables. The linear regression data were also displayed in 3 tables for each scenario to observe a possible cause and effect between the independent and dependent variables. It was noted that the tables with correlation coefficient displayed a lot of disparity, while the correlation co-efficient linear plotting seemed trivial. So, this technique cannot be used alone to determine any sort of relationship. On the other hand, the Linear Regression data was presented in a detailed manner, and it also captures the correlation coefficient value, which is a favorable technique compared to the latter one to determine a possible cause and effect between the variables.

4.4. Summary

From this chapter, it can be concluded that a possible cause and effect could be identified between the dependent and independent variables through Linear Regression. Nonetheless, the co-efficient correlation and linear regression data will be further analyzed in the upcoming chapter to derive a valid conclusion for this research work.

Chapter 5 – Discussions

Chapter 5: Discussions

5.1. Introduction

In this chapter, the Linear Regression experimental outcome will be further analysed. The output from the 3 tables will be summarized and streamlined so that conclusive statements can be derived. As this chapter proceeds, the comparison analysis between Correlation Co-efficient and Linear Regression will be captured for understanding and its purpose of application. Afterwards the Multiple R value, which is the correlation co-efficient value and the standard error for Device 1 and 2 will be highlighted respectively to derive a narrowed precise statement. On the same note, the average RSSI for each location is also analysed to understand the overall behavior of the RSSI as per each room based on its susceptibility of different weather patterns. Subsequently, the limitations and shortcomings of this research work are also highlighted as more work needs to be done to find a regress solution to optimize the wireless connections such as Bluetooth in an indoor environment.

5.2. Significance of Work

To analyze the data in Excel, it was important to understand the underlying concept of these analytical techniques. The fundamentals of correlation co-efficient are listed as follows (Svetlana Cheusheva, 2023);

- If the value is 1 then it is a strong positive relationship
- If the value is -1 then it is a strong negative relationship
- If the value is 0 then there is no relationship at all
- If the value is closer to zero (0.1 – 0.4), then there is a weak positive relationship.
- If the value is closer to zero (- 0.1 – - 0.4), then there is a weak negative relationship.

In addition, Multivariate Correlation was also performed to see how two independent variables affect the dependent variable which is slightly different from basic correlation co-efficient computation. In excel, the following formula (Charles Zaiontz, 2023) was used to calculate the multivariate correlation as this yields the maximum degree of liner relationship (Jensen, 2006);

$$R_{z.xy} = \sqrt{\frac{r_{xz}^2 + r_{yz}^2 - 2r_{xz}r_{yz}r_{xy}}{1 - r_{xy}^2}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (4)$$

The value of this formula was mostly used to measure the strength of the relationship and it was mostly observed that a weak positive and a weak negative as per correlation co-efficient experimental outcome relationship was observed. So, the application of a multi-variate relationship is not highly favoured in this case.

Moreover, Linear Regression was also performed to observe how the independent variable(s) affect the dependent variable. Nonetheless, the below table displays the comparison between Linear Regression and Co-efficient calculation that possibly relates to the use of these tools in the analysis of the gathered data (Mara Calvello, 27 April 2023).

Table 59: Comparison between Linear Regression and Co-efficient

	Correlation	Regression
Usable scenarios	To identify the direct relationship between two variables	To predict or clarify the numeric reaction
Able to quantify the direction of the relationship	☑	☑
Able to quantify the strength of the relationship	☑	☑
Able to show cause and effect	☒	☑
Able to predict and optimize	☒	☑
X and Y interchangeable?	☑	☒
Uses a Mathematical Relationship	☒	$y = b(x) + a$

5.2.1. Linear Regression

In this subsection regression analysis will be displayed as per scenario with dependent and independent variables. The Regression data are listed below in tabular form. The table given below displays the comparison analysis derived from the above-tabulated Linear Regression data, which captures the location of the experiment, parameters, Multiple R, R Square, Significant F and Standard Error.

Table 60: Regression Comparison

Regression Comparison					
Location	**Parameters**	**Multiple R**	**R Square**	**Significant F**	**Standard Error**
Device1 Tavua – Room 1	RSSI Data vs. Distance	0.143	0.021	2.593	5.488
	RSSI Data vs. Air Temperature	0.087	0.008	2.610	0.002
	RSSI Data vs. Relative Humidity	0.992	0.010	2.607	0.0005
	RSSI Data vs. Atmospheric Pressure	0.180	0.032	2.577	3.022
	R SSI Data vs. Room Temperature	0.125	0.016	2.600	1.29
	RSSI Data vs. Height of Transformers	0.098	0.010	2.607	0.0006
Un-Partitioned Space	RSSI Data vs. Distance	0.080	0.006	3.239	0.006
	RSSI Data vs. Atmospheric Pressure	0.100	0.010	3.233	0.0007
	RSSI Data vs. Air Temperature	0.213	0.045	3.175	8.51
	RSSI vs. Relative Humidity	0.347	0.121	3.047	1.834
	RSSI Data vs. Height of Transmitters	0.273	0.075	3.126	5.31

	RSSI Data vs. Room Temperature	0.213	0.045	3.175	8.51
	RSSI Data vs. Amount of Rainfall	0.069	0.005	3.241	0.017
Tavua – Room 2	RSSI Data vs. Distance	0.013	0.0002	2.885	0.660
	RSSI Data vs. Atmospheric Pressure	0.167	0.028	2.846	3.960
	RSSI Data vs. Air Temperature	0.035	0.001	2.884	0.215
	RSS.I Data vs. Relative Humidity	0.409	0.167	2.634	3.63
	RSSI Data vs. Height of Transmitters	0.150	0.022	2.853	1.19
	RSSI Data vs. Room Temperature	0.270	0.073	2.779	4
Suva Room 1	RSSI Data vs. Distance	0.012	0.0001	2.973	0.686
	RSSI Data vs. Atmospheric Pressure	0.636	0.404	2.295	1.2
	RSSI Data vs. Relative Humidity	0.300	0.090	2.837	2.04
	RSSI Data vs. Air Temperature	0.386	0.149	2.744	4.34

	RSSI Data vs. Amount of Rainfall	0.013	0.0002	2.973	0.647
	RSSI Data vs. Height of Transmitters	0.682	0.466	2.173	4.1
	RSSI Data vs. Room Temperature	0.017	0.0003	2.973	0.556
Device 2 Tavua Room 1	RSSI Data vs. Distance	0.004	1.464	42.697	0.894
	RSSI vs. Air Temperature	0.733	0.537	29.056	2.5
	RSSI vs. Relative Humidity	0.717	0.514	29.756	8
	RSSI vs. Atmospheric Pressure	0.046	0.002	42.655	0.111
	RSSI vs. Rainfall	0.033	0.001	42.673	0.247
	RSSI vs. Height of Transmitters	0.147	0.022	42.232	2.69
	RSSI vs. Room Temperature	0.737	0.544	28.843	3.378
Un-partitioned Space	RSSI vs. Distance	0.004	1.31	38.571	0.900
	RSSI vs. Atmospheric Pressure	0.219	0.048	38.635	1.56
	RSSI vs. Air Temperature	0.329	0.108	36.429	1.04

	RSSI vs. Relative Humidity	0.495	0.245	33.520	2.48
	RSSI vs. Rainfall	0.018	0.0003	38.565	0.536
	RSSI vs. Height of Transmitters	0.219	0.048	37.635	1.57
	RSSI vs. Room Temperature	0.110	0.012	38.336	0.0001
Suva Room 1	RSSI vs. Distance	0.0001	2.06	0.236	1
	RSSI vs. Atmospheric Pressure	1.420	2.015	0.236	1
	RSSI vs. Relative Humidity	65535	-5.7	0.236	-
	RSSI vs. Air Temperature	1.4	1.95	1	-
	RSSI vs. Rainfall	0.413	0.002	0.236	0.152
	RSSI vs. Height of Transmitters	1.46	2.12	0.236	1
	RSSI vs. Room Temperature	0.012	0.0001	22.910	0.677
Tavua, Room 2	RSSI vs. Atmospheric Pressure	0.158	0.025	22.854	2.11
	RSSI vs. Distance	0.0002	5.9	23.145	0.993

	RSSI vs. Air Temperature	0.224	0.050	22.556	1.28
	RSSI vs. Relative Humidity	0.390	0.152	21.317	2.83
	RSSI vs. Rainfall	0.133	0.018	22.937	2.23
	RSSI vs. Height of Transmitters	0.032	0.001	23.133	0.256
	RSSI vs. Room Temperature	0.299	0.089	22.087	4.6

Tables 61 and 62 display the decisive remarks derived from the readings from the above table. Especially Multiple R and Standard Error for Device 1 and Device 2 respectively.

Table 61: Multiple R and Standard Error for Device 1

	Device 1	
Location	**Multiple R**	**Standard Error**
Tavua Room 1	1. RSSI vs. Relative Humidity displays a strong positive relationship. 2. Distance, Air Temperature, Atmospheric Pressure, Room Temperature and Height of the Transmitter display a weak positive relationship.	1. Air Temperature, Relative Humidity and Height of Transformers show a small value, which means more precision. 2. Distance, Atmospheric Pressure, and Room Temperature display a relatively large value, which means less precision.
Un-partitioned Space	1. Distance, Atmospheric Pressure, Air Temperature, Relative Humidity, Height of Transmitters, Room	1. Distance, Atmospheric Pressure and amount of rainfall show a small value

	Temperature, and Amount of Rainfall display a weak positive relationship.	which means more precision. 2. Air Temperature, Relative Humidity, Height of Transmitters and Room Temperature show a large value which means less precision
Tavua Room 2	1. Distance, Atmospheric Pressure, Air Temperature, Relative Humidity, Height of Transmitters, and Room Temperature overall display a weak positive relationship.	1. Distance and Air Temperature show a small value, so the values are precise. 2. Atmospheric Pressure, Relative Humidity, Height of Transmitters and Room Temperature display a larger value which means more precision
Suva Room 1	1. Distance, Relative Humidity, Air Temperature, Amount of Rainfall and Room Temperature display a weak positive relationship. 2. Atmospheric Pressure and Height of Transmitters display a perfect positive relationship.	1. Distance, Room Temperature and amount of rainfall display a smaller value, which is precise. 2. Atmospheric Pressure, Relative Humidity, Air Temperature and Height of Transmitters display a larger value which is not precise.

Table 62: Multiple R and Standard Error for Device 2

	Device 2	
Location	**Multiple R**	**Standard Error**
Tavua Room 1	1. Air Temperature and Relative Humidity display a perfect positive relationship. 2. Distance, Atmospheric Pressure, Rainfall and Height of Transmitters display a weak positive relationship.	1. Air Temperature, Relative Humidity, Height of Transmitter and Room Temperature display a larger value which means less precision. 2. Distance, Atmospheric Pressure and Rainfall display a smaller value which means more precision.
Un-partitioned Space	1. Distance, Atmospheric Pressure, Air Temperature, Rainfall, Height of Transmitters and room temperature displayed a weak positive relationship. 2. Relative Humidity displays a fair positive relationship.	1. Distance, Rainfall and Room Temperature display a small value, which means less precision. 2. Atmospheric Pressure, Air Temperature, Relative Humidity and Height of Transmitters display a larger value which means less precision.
Tavua Room 2	1. Atmospheric Pressure, Distance, Air Temperature, Relative Humidity, Rainfall, Height of Transmitters and Room Temperature display a weak positive relationship.	1. Relative Humidity and Air Temperature give no value and return a functional error. 2. Rainfall and Room Temperature display a smaller value. 3. Distance, Atmospheric Pressure and Height of Transmitters display a larger

		value which means less precision.
Suva Room 1	1. Atmospheric Pressure, Air, Relative Humidity, Air Temperature and Height of Transmitters displayed some inconsistencies. 2. Distance and Room Temperature displayed a weak positive relationship. 3. Rainfall displays an almost fair relationship.	1. The height of Transmitters displays a smaller value which means precision. 2. Atmospheric Pressure, Distance, Air Temperature, Relative Humidity, Rainfall and Room Temperature display a larger value which means less precision.

In addition to Table 61 and Table 62, the following remarks will also be applied to determine a clear conclusive statement.

- R Square – Overall, R square readings display a weak goodness of fit for all locations for both devices.
- Significant F
  - In order for the values to be statistically significant, the values should be 0.05% but the range of values from this experimental setup is from 0.23 – 43%, which is not desirable.

The following table shows possible conclusion derivation from Tables 61 and 62.

Table 63: Conclusive Statement based on Multiple R and Standard Error

Device	Location	Independent variable in support of Hypothesis	Explanation
Device 1	Tavua Room 1	Relative Humidity Multiple R: 0.99210822 Error: 0.000548222	By Linear Regression, the Multiple R deduces relationship is positively strong which means if the relative humidity reading increases in value so will the RSSI value. Also, the error value for this relationship is relatively smaller, so

			RSSI vs. relative humidity supports the hypothesis.
Device 2	Suva Room 1	Rainfall Multiple R: 0.41293 Error: 0.151821	By Linear Regression, the Multiple R deduces the relationship is positively fair which means if the rainfall reading increases in value, then there will be significant changes in the RSSI value. Also, the error value for this relationship is relatively smaller, so RSSI vs. Relative humidity goes in support of the hypothesis.

5.2.2. Average RSSI Reading per location:

The below list of data shows the average reading for Device 1, which was the dominant equipment in terms of the collection of RSSI values. It was noted that indoor rooms displayed average RSSI value which is relatively better compared to the RSSI reading which was taken in an unpartitioned space. Peculiarly, it was expected that RSSI reading in Suva would be better when compared to RSSI reading in the West, but the experiment outcome showed a contradiction in the reading. The average reading for Device 1 in Suva showed disparity as it was expected that the reading should be higher in comparison with Tavua. To add on, the smaller room in Tavua displayed a weaker average RSSI value as it can be suspected that the signals are subjected to multi-path fading effect which reduces the strength of the signal. In contrast, partitioned and unpartitioned rooms highlighted those interferences and obstacles increased if the partitions of a room were removed. Finally, it was noted that devices are always competing to establish connections, and the dominance of the device is determined with better RSS indicator against other devices, and as per observation Device 1 was dominant in comparison with Device 2 so to avoid biases, the average values of Device 1 was analysed that is listed as follows:

i. Device 1 Tavua Room 1 - -85.12867769
ii. Device 1 Tavua Un-partitioned Space - -87.12152951

iii. Device 1 Suva - -81.71352697

iv. Device 1 Tavua Room 2 - -85.56172442

5.2.3. Limitation and Short Comings

The shortcomings of this research were that the data was provided by The Fiji Meteorological Services on a daily and hourly basis but the weather details that were provided were not precise in terms of the location. Since Fiji is a relatively small geographical country, the provided details were considered for the experiment as this was the only alternative available. Additionally, the rainfall details were biased so a clear relationship between Rainfall and RSSI reading could not be observed. Furthermore, the RSSI reading and room temperature were collected from a mobile application, so uncertainty was also expected while taking the room temperature and RSSI. To add on, the experiments were also carried out in smaller rooms that were practically smaller in dimensions, specifically less than 10m. There is a possibility that the RSSI reading could behave differently in a room with a bigger dimension of more than 10m. Additionally, the reading taken in Suva was biased in terms of duration as it was taken for a period of less than a week, so a sufficient amount of rainfall was not observed. The unpartitioned space specimens were only taken from Tavua so a fair comparison could not be performed.

5.3.Discussions

In order to highlight the significance of the titled research work in Fiji, the experimental outcome by Linear Regression was vigorously analysed by presenting the comparison between the application of Correlation Co-efficient and Linear Regression and how Linear Regression is a better tool in this scenario. The Linear Regression Summary shows that for Device 1 in Room 1 Tavua, there is a possible cause and effect relationship between RSSI and Relative Humidity. This shows if the Relative Humidity changes in value, then a noticeable change will be observed in the RSSI reading as well. On the same note, another conclusive statement was also developed, by Linear Regression it was observed that for Room 1 in Suva, when the amount of rainfall changes possible changes are reflected on RSSI reading.

5.4.Summary

To conclude the discussion chapter, it was noted that via Linear regression it was possible to derive a conclusive statement to conclude that the titled research that was carried out. The experimental outcome analysis was in favour of the null hypothesis, and the average reading per room presented more insights into the investigation. It was noted that independent weather variables such as Rainfall and Relative Humidity induce possible change in the dependent variable, which is the RSSI reading. The shortcomings and limitations of the research were also noted so that it can serve as an awareness for future research that may be carried out by the academic society. As the document proceeds, the next chapter will introduce the research conclusion of this entire document.

Chapter 6 - Conclusions

Chapter 6: Conclusions

6.1. Introduction

In this chapter, the entire research work that is captured in this document will be concluded. The documented research was initiated with the introduction chapter that highlighted the use of key technology – Bluetooth in an indoor based IoT setting. Case studies were scrutinized on the application of this technology in different parts of the world, and since it is ready in most devices, this wireless technology needs to be further exploited to improve connectivity indoors. In Chapter 2, a thorough literature review was performed on various subtopics such as Bluetooth, IoT, Stack Protocol, Indoor Localisation and RSSI to explore ideas and their application in different scenarios. From this thorough literature review and application of epistemology, the null hypothesis and the alternative hypothesis were established. In chapter 3, the research methodology was highlighted that presented the four phases in which the empirical investigation was carried out. These four phases were Literature review, Experimental Setup, Data collection and data analysis. Afterwards, in Chapter 4, the experimental outcome of the recorded data was displayed using two tools which were correlation coefficient and linear regression. The correlation co-efficient calculation and linear plotting seemed trivial in nature so the second tool was applied to see if any significant impact could be observed. Eventually, in Chapter 5, the linear regression data was further summarized and analysed to derive a conclusive statement, and it was noted that the conclusive derivative statements were in support of the null hypothesis, whereas the alternative hypothesis remained insignificant. Henceforth, the next subsection will present the contribution of this entire research document.

6.2. Significance of Work

This entire research document referenced various case studies, online sources, journals, academic literary articles to explore and contribute ideas towards this research which was carried out in Fiji to support the forecasted idea on the adaptability of IoT construction in the near future to automate activities and task and bring forth productivity in terms of time, money, energy and manpower. In the case studies, the possible use of Bluetooth-enabled RTIs was noted in smart farms to improve the supply chain from farm to customers. Another applicable case was also noted where BLEs were used to monitor the productivity in a manufacturing industry. As the document proceeds to the literature review, the evolution of Bluetooth was emphasized with its added functionality in each version. The Bluetooth application with IoT was also noted in couple of scenarios and comparison was also made with different wireless technologies and BLE was an economical option from the various wireless technologies that was compared. The Stack protocol mostly presented significance in the communication between the Bluetooth layers and in an IoT setting. As more sources were researched, localization performances were identified too. These performances were direction finding, indoor localization and proximity estimation and it utilized techniques such as Trilateration, multi-Trilateration, Triangulation, Angle of Arrival, Angle of Departure, Time of Arrival and Time Difference of Arrival and so forth. As the Literature review was explored in depth, it was noted that signals are susceptible to inferences, obstacles, noise and multi path fading effect and consequently, the effect could be reduced with certain filters such as Kalman filter, discrete filter, and algorithms like kNN. Finally, articles were explored on RSSI to understand its nature before the development of the null hypothesis. The RSSI literary review highlighted how weather parameters have a possible impact on its indicator, which can deteriorate the signal and cause a poor connection. So, an investigatory experiment was carried out and the results were analysed to derive a research conclusion. While conducting the experiment, uncertainties and biases were noted, such as application uncertainties, data collection period, the exposure of certain parameters like rainfall and sunlight, and data precision in terms of location. Nevertheless, conclusive statements were derived with its short coming and limitations which will be documented in the proceeding subsection.

6.3. Discussions

As noted above the entire research document has contributed greatly towards the titled research in terms of literature review which was the basis of the null hypothesis and alternative hypothesis. The null hypothesis was critically established after reviewing literary sources on Bluetooth connections in IoT environments and their application indoors. It was noted that the signal indicator deteriorates with interference, noise, and obstacles. The signals are also subjected to multi path fading effect due to closer walls in a narrow room. Since the idea was to investigate how signals can be optimized, so it was essential to identify the factors that deteriorate the signals, but an alternative hypothesis was also developed to oversee in case the experimental finding presented a contradiction. Fortunately, it was noted with Linear regression that the null hypothesis was proven correct, and it can be deduced that Bluetooth Connection is obfuscated due to the interferences, noise, obstacles, and other convolving signals that are present in an IoT-based indoor environment which was hypothesized based on Epistemology and Literature review of this research work. It was observed that the average RSSI reading in an unpartitioned space was slightly higher, so it can be concluded that interference increased as the room partitions were removed.

6.4. Conclusions

It can be concluded that the null hypothesis is proven correct as the Bluetooth Connection is obfuscated due to the interferences, noise, obstacles, and other convolving signals that are present in an IoT-based indoor environment. It was noted that parameters like the amount of rainfall and relative humidity have an impact on RSSI reading via the conducted empirical experiment. As witnessed, the amount of rainfall and RSSI reading in Suva displayed a strong positive relationship by correlation coefficient and linear regression. Similarly, relative humidity versus RSSI reading in Tavua displayed a fairly positive relationship by correlation coefficient and linear regression. This means that with excessive rainfall, the RSSI indicator will be higher, and it will be difficult to detect the transmitting device during scanning or even in the connecting phase. On the same note, if the relative humidity increases, the connection quality will deteriorate. This finding can be considered useful for device energy management and prolonged device uptime. However, it can also be deduced that the RSSI reading slightly deteriorates outside the room setting as the average RSSI reading for un-partitioned space is slightly higher than the average RSSI reading for rooms that are indoors.

6.5. Future Work:

The purpose of this research work was to optimize the Bluetooth connection in an IoT based indoor environment. The research that was carried out highlighted that signals are subjected to interferences, and few parameters were identified that impact the signal quality. These identified parameters or weather variables were rainfall and relative humidity. Now, since these variables have been identified, there is a need to find a possible solution that can negate the subjected interferences. So, it was noted via literature review that filters could be designed to reduce the noise effect of the contaminated signals. Therefore, Future work will be carried out to explore filters such Kalman and Discrete and kNN algorithm that could cancel out the noise effect of rainfall and relative humidity.

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