IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 9 November 2023, accepted 28 November 2023, date of publication 30 November 2023, date of current version 15 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3338358

RESEARCH ARTICLE

Location Accuracy Optimization in Bluetooth Low Energy (BLE) 5.1-Based Indoor Positioning System (IPS)–A Machine Learning Approach

DASMOND ROY PHILIPS, ERFAN SALAMI, (Member, IEEE), HARIKRISHNAN RAMIAH, (Senior Member, IEEE), AND JEEVAN KANESAN, (Member, IEEE)
Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia
Center for Research in Industry 4.0, Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia

Corresponding author: Jeevan Kanesan (jievan@um.edu.my)

This work was supported in part by the RU Geran-Fakulti Program under Grant GPF056B-2020 and in part by the Private Grant under Grant PV068-2021.

ABSTRACT Indoor Positioning System (IPS) is a technology used to locate and track objects or people inside buildings, by using sensors, wireless networks, or other means to determine their position. IPS has many applications in various fields such as healthcare, retail, logistics, and security. Achieving IPS of high location accuracy is yet to be explored further. In this experimental research, an IPS based on Bluetooth Low Energy (BLE) 5.1 protocol is implemented and two optimization techniques, parameters calibration and application of Machine Learning Algorithm (MLA) are proposed to improve location accuracy. In Stage 1 of this experiment, the measured Root Mean Square Error (RMSE) value before optimization yielded location accuracy of 0.670m. In Stage 2, four different parameters which include elevation angle, tag height, data rate and walking pace are calibrated and tested. Besides, in Stage 2, three different algorithms which include Support Vector Regression (SVR), Decision Tree (DT) and K-Nearest Neighbor (KNN) are evaluated. As a result, parameters calibration decreased RMSE value down to 0.219m. Additionally, among all three MLAs, KNN illustrated the lowest RMSE value of 0.631m. In Stage 3, the lowest RMSE value of 0.015m is obtained by combining parameters calibration and MLA approaches which improved location accuracy up to 98.5%. The developed framework is operational at our industry partner, ams OSRAM's LED wafer fabrication cleanroom facility.

INDEX TERMS Indoor positioning system (IPS), bluetooth low energy (BLE) 5.1, machine learning algorithm (MLA), root mean square error (RMSE).

I. INTRODUCTION

The history of indoor positioning dates to the early 2000s, with the development of systems such as Active Badge, RADAR, and the Where2 Project that used infrared, Wi-Fi, ultrasonic, and Bluetooth technologies. IPS is a technology that enables tracking and locating of people or objects within indoor spaces. IPS uses various sensors to determine the position of the target within a building. The location information is then transmitted to a central system, which can be used to provide location-based services, such as indoor navigation or asset monitoring. Despite the significant progress in IPS technology, one of the major challenges with IPS is their limited accuracy, which is caused by signal attenuation, multipath propagation, and interference. Besides, location accuracy can be affected by the size and complexity of the indoor environment. In this article, we propose a wireless indoor positioning framework to enhance location accuracy based on BLE 5.1 wireless network protocol. BLE 5.1 is a wireless communication standard that has various advantages over previous versions. In 2010, BLE 4.0 was released which reduced power consumption within BLE devices [1]. In 2016, BLE 5.0 was released which added indoor positioning assistance function, positioning distance up to 200m and with

The associate editor coordinating the review of this manuscript and approving it for publication was Riccardo Carotenuto.

less power consumption. In BLE 5.0, the IPS used Received Signal Strength Indicator (RSSI) as parameter to compute positioning via trilateration method. The location accuracy that can be expected from BLE 5.0 is about 2-5m [1], [2]. In 2019, BLE 5.1 was released which included new metrics for positioning, Angle of Arrival (AoA) and Angle of Departure (AoD), that enables Direction Finding feature within BLE devices [3]. With this new addition to the newer BLE 5.1 version, location accuracy down to below 1.0m, known as sub-meter level accuracy can be expected [1], [4]. BLE devices can operate at different transmission power levels, which allows them to transmit at larger distances or conserve battery life [5]. Operating at a high transmission power level reduces noise effects at a larger distance, while operating at a low transmission power level increases the overall lifespan of BLE devices [6]. The contribution of this study is to consolidate two key approaches towards improving location accuracy, which are parameter tuning and machine learning. This work experiments IPS using array of BLE anchors and tags within cleanroom environment, without applying neither parameter tuning nor machine learning in Stage 1. In Stage 2, parameter tuning, and machine learning approach are applied individually, and improvements of location accuracies are evaluated. In Stage 3, parameter tuning, and machine learning approaches are applied in combination, and improvement of location accuracy are compared with the previous stages results. The implemented system in this study uses commercially available readers and tags from BlueIoT. The measured value before applying optimization techniques obtained from software associated with the hardware yielded location accuracy of 0.670m. An elevation angle of 55°, tag height of 2.5m, data rate of 50Hz and slow walking pace at 0.429m/s delivered the lowest RMSE of 0.219m. Among all three MLAs tested, KNN delivered the lowest RMSE value of 0.631m. Applying a combination of parameters calibration and MLAs approaches, resulted in optimization of RMSE value down to 0.015m, improving location accuracy up to 98.5%. The proposed framework has been successfully implemented at our industry partner, ams OSRAM's LED wafer fabrication cleanroom, to track movements of assets within the facility. In summary, in this paper, we:

- Conduct experimental setup for BLE based indoor positioning system within cleanroom environment, which includes hardware and software.
- Collect and analyze location accuracy data before applying neither parameter tuning nor machine learning.
- Collect and analyze location accuracy data after applying parameter tuning and machine learning individually to improve location accuracy.
- Collect and analyze location accuracy data after applying combination of parameter tuning and machine learning to improve location accuracy.
- Compare results obtained from Stage 1, Stage 2 and Stage 3 respectively.
- Identify the best combination approach that yielded the most optimized location accuracy and implement for asset tracking system within the cleanroom environment.
- Develop Graphical User Interface (GUI) to manage the asset tracking system.
- Develop map-view visualization to visualize and monitor the positions of assets within the cleanroom environment.

The rest of the paper is organized as follows: Section II describes related works within IPS field, including some brief introduction to wireless networks, positioning parameters and positioning techniques used in IPS, Section III presents methodology of this work which includes system framework, experimental setup and data collection techniques, Section IV explains the outcome of the experiments whereas Section V summarizes the conclusion of all the experiments conducted in this work.

II. RELATED WORKS

Wireless networks are an important component to establish a connected network between tags and readers within an IPS. Tags are attached onto objects or people to be tracked whereas readers are attached onto walls or ceilings of the indoor environment where the IPS is deployed. Tags transmit wireless signals to nearby readers which will be picked up by readers. There are many types of wireless networks widely used to establish network between the tags and readers to implement IPS, as compared in Table 1 [7], [8], [9], [10]. BLE is one of the wireless networks that is widely used for IPS, mainly due to low cost and low power consumption [10]. In addition, Bluetooth is easier to deploy and implemented as compared to RFID, UWB, ultrasonic and infrared systems [10]. As compared to WiFi system, Bluetooth costs less and uses less energy and offers high precision [10]. The latest released version of BLE technology (BLE 5.1) includes a direction-finding feature which is very useful to achieve high accuracy IPS. In this research, BLE 5.1 is employed to establish wireless network between tags and readers. Positioning parameters refer to raw data that will be processed to determine the position of tags. Various positioning parameters used in IPS along with their respective advantages and disadvantages are shown in Table 2 [2], [7], [8]. Received Signal Strength (RSS) is a measure of power signal's strength measured in dBm or mW. Time of Arrival (ToA) is a measure of time taken for the transmitted signal to be received by readers. Whereas Time Difference of Arrival (TDoA) is a measure of difference in time taken for transmitted signals to be received by readers. Angle of Arrival (AoA) is a measure of signal's angle from where it is received by the readers. In this work, we employ AoA as key parameter for positioning mainly for its less sensitivity towards variations in signal strength as compared to other parameters such as RSSI, ToA or TDoA [2]. As long as the signal is received by receiver, AoA computation for positioning is possible. This

TABLE 1. Wireless networks for IPS.

Wireless Network	Accuracy	Range	Cost	Power Consumption	Advantage	Disadvantage
RFID	Meter Level	5m	Low	Low	Strong penetration, small size	Weak anti-interference ability
Wi-Fi	Meter Level	100m	Medium	Medium	High popularity	Weak anti-interference ability
BLE	Meter Level	50m	Low	Low	Easy to deploy, Directional	Weak anti-interference ability
Infrared	Centimeter Level	5m	High	High	Additional temperature measurement function, Strong concealment	Vulnerable to high temperature, Complex deployment
5G Cellular	Sub-Meter Level	300m	High	High	Low Latency	High equipment requirements
Ultrasonic	Centimeter Level	10m	High	High	N/A	N/A
UWB	Centimeter Level	50m	Medium	Medium	Strong anti-interference ability	Medium popularity

TABLE 2. Positioning parameters for IPS.

Positioning Parameters	Advantages	Disadvantages
RSS	Less complexity	• Less accurate • Highly dependent on Line-of-Sight (LoS)
TOA	Accurate	• Complex • Needs time synchronization
TDOA	Accurate	• Complex • Needs time synchronization
AOA	Very accurate	• Complex • Needs antenna array

TABLE 3. Positioning techniques for IPS.

Positioning Techniques	Description	Compatibility
Lateration	Distance between nodes is used	RSS, ToA, TDoA
Angulation	Angle between nodes is used	AoA
Fingerprinting	Paired with RSS for cross-reference	RSS
Dead Reckoning	Uses data from accelerometer or gyroscope	Any
Cell-of-Origin (CoO)	Compares RSSI with threshold limit	RSS

is crucial for high-dense environments such as cleanroom environment where signal fluctuations would be high. Less sensitivity towards signal fluctuations results in less errors which in turn provides higher location accuracy. Positioning techniques refer to methods used to determine the position of an object or person under monitor. Positioning parameters will be used as input data for positioning techniques to calculate the position of the object or person. Various types of positioning techniques used in IPS and their compatibilities are compared in Table 3 [7], [8]. Machine learning algorithms have aided in improving location accuracy in a vast number of previous studies within IPS field. SVR is a machine learning approach where offline training data is used to train the model by dividing the datasets into two or three dimensions, accordingly, depending on two or three inputs respectively, a line for 2-dimensional model or a plane for 3-dimensional model is formed using offline training datasets and tested against online testing datasets [7]. KNN is a supervised machine learning algorithm used for classification and regression problems. This method involves offline training and online testing. Hence, offline training datasets must be prepared to train the model. The dataset is often analyzed for matching patterns among input data. Then, a fine distinguish is made in terms of nearest data points with each other and further data points would fall in other categories accordingly [7]. Regression-based DT machine learning algorithm distinguishes features in training dataset into smaller subsets and trains an appropriate model accordingly. The trained machine learning model is applied onto testing dataset to predict new outputs respectively. This machine learning model helps to segregate the testing dataset according to the learned features from training dataset which subsequently helps to predict new outputs accurately [7]. Table 4 summarizes different machine learning algorithms applied in past related works for IPS. As can be observed in Table 4, SVR, DT and KNN will be experimented in this study mainly for their substantial outcomes on location accuracies.

In the past years, there has been a significant amount of research conducted in the field of IPS to improve location accuracy. Lie et al. [19] experimented BLE based IPS by fine-tuning algorithm using Delta rule and achieved Mean Squared Error (MSE) values of 0.8740m and 1.5385m, employing combination of weighted sum and K-Nearest Neighbor (KNN) with Minkowski distance weight calculation. Ho et al. [20] presented a decentralized BLE-based positioning protocol that does not require training before deployment. The training phase is conducted on-the-go by anchor nodes, by scanning signals transmitted by nearby

TABLE 4. Machine learning algorithms for IPS.

Article	Year	Type	Tools Used	Method	Outcome
[11]	2015	SVR	1. RSSI 2. Statistical Analysis 3. k-Times Continuous Measurement 4. SVR	1. RSSI is acquired. 2. For offline training, RSSI is filtered using statistical analysis. 3. For online testing, RSSI is filtered using k-times continuous measurement. 4. SVM is used to estimate position.	Accuracy: 0.68m
[12]	2018	SVR	1. RSSI 2. Support Vector Machine (SVM) 3. Kalman Filter	1. RSSI is acquired. 2. SVM is employed for position estimation. 3. Kalman filter is used to further smoothen the position data.	RMSE: 0.9385m
[13]	2018	SVR	1. RSSI 2. Custom-Designed Filter 3. Linear Regression (LR) 4. SVR	1. RSSI is acquired. 2. RSSI is filtered using a custom-designed filter. 3. Position estimation by LR and SVR methods. 4. Accuracy of LR and SVR methods are compared.	Accuracy: LR – 0.9m SVR – 0.5m
[14]	2017	DT	1. Wi-Fi RSSI 2. Magnetic Field (MF) Values 3. DT 4. Multi-Layer Perceptron (MLP) 5. Bayesian Network (BN)	1. RSSI and MF values are acquired from database. 2. Fingerprint map is built using the collected RSSI and MF dataset. 3. DT, MLP and BN are used to estimate position.	Accuracy: 4.21m (DT)
[15]	2018	DT	1. RSSI 2. DT 3. Gradient Boosted Algorithm (GBA)	1. RSSI is acquired. 2. Fingerprint map is built. 3. DT and GBA are trained using offline training dataset. 4. DT and GBA are tested against online training dataset.	Accuracy: 55.56% (DT)
[16]	2015	DT	1. RSSI 2. DT 3. Naïve Bayes (NB) 4. BN 5. KNN	1. RSSI dataset is acquired from UJIIndoorLoc indoor positioning database. 2. Radio map is built using training RSSI dataset. 3. Machine learning models are trained using offline training dataset. 4. Machine learning algorithms are tested against online testing dataset.	Accuracy: 99.89% (DT)
[17]	2016	DT	1. RSSI 2. Typical DT (TDT) 3. Optimized DT (ODT)	1. RSSI dataset is acquired. 2. TDT and ODT machine learning models are trained. 3. Improvement from TDT to ODT is determined.	Accuracy: 87.73% (ODT)
[16]	2015	KNN	1. RSSI 2. DT 3. NB 4. BN 5. KNN	1. RSSI dataset is acquired from UJIIndoorLoc indoor positioning database. 2. Radio map is built using training RSSI dataset. 3. Machine learning models are trained using offline training dataset. 4. Machine learning algorithms are tested against online testing dataset.	Accuracy: 86.59% (KNN)
[18]	2021	KNN	1. RSSI 2. Fingerprinting 3. KNN	1. RSSI is acquired. 2. Position estimation by fingerprinting. 3. Position estimation is improved by KNN algorithm. 4. Optimal value of K is determined.	Accuracy: 1.49m (K = 3)

anchors from each other while broadcasting signals. This method achieved an error of 1.5m on average. Bai et al. [21] investigated fingerprinting method using BLE based IPS and achieved an average accuracy of 95.94%. Cheng et al. [22] proposed a modified joint probabilistic data association localization algorithm and achieved location accuracy down to 0.94m. Dong et al. [23] investigated gray wolf algorithm to mitigate Non-Line-of-Sight (NLoS) effects in Ultra-Wideband (UWB) based location system and achieved location accuracy of 16.99cm. Lee et al. [24] studied Simultaneous Location and Mapping (SLAM) technique for location estimation and attained location accuracy of 1.5m. Luo et al. [25] proposed KNN based algorithm with fingerprinting method based on WiFi for location estimation which resulted in average localization error of 1.38m. Van Haute et al. [26] investigated min-max localization algorithm in Time-of-Arrival (ToA) based indoor localization system and achieved average location accuracy of 3.26m. Various MLAs have been used to improve location accuracy in IPS. Another technique that can be used to improve location accuracy of IPS is by increasing the number of readers. Giuliano et al. [27] observed a test case that uses nine receivers obtained lowest estimation error of 84cm, as compared to a smaller number of receivers. Ji et al. [28] observed location error reduced exponentially from 25m down to 10m by increasing number of readers from 10 to 60 units in their study. Duong et al. [29] proved location accuracy is increased from 60% to 71.4% by increasing number of readers from three to four units. Cai et al. [30] proposed a new IPS that uses ultra-wideband (UWB) technology to achieve higher accuracy and lower interference. Another challenge with IPS is their high cost, which is caused by the need for additional hardware installation, such as beacons and sensors. Liu et al. [31] studied a new IPS that uses existing Wi-Fi infrastructure to reduce the cost of IPS deployment. IPS technologies collect personal data, which raises concerns about privacy and security. An et al. [32] investigated a new privacy-preserving IPS that uses secure multi-party computation to protect the location data of users. Different technologies use different protocols and interfaces, which limits the interoperability and scalability of IPS solutions. Fabritz et al. [33] developed a new IPS that uses an open standard to enable interoperability and scalability. BLE is a wireless communication technology that consumes less power than traditional Bluetooth. It is used for indoor positioning by transmitting signals from beacons to readers, which then use the signal strength, time delay or signal angle to estimate the device's location. New IPS that uses a combination of Wi-Fi and BLE technologies to improve the accuracy and reliability of indoor positioning was developed by Zhao et al. [34]. Similarly, Yazıcı et al. [14] investigated a new IPS that uses a hybrid technique integrating several types of sensor measurements and classification algorithms to achieve high accuracy in complex indoor environments. Shi et al. studied various location methods including Artificial Neural Network (ANN), Preprocessed ANN, SVR, Preprocessed SVR, Probabilistic Model (PM) and Preprocessed PM [11]. Among all these location methods, Preprocessed SVR achieved the least average error distance of 0.68m and standing next to Preprocessed SVR is Preprocessed ANN with average error distance of 0.886m. Whereas all other location methods possess an average error distance above 1.0m. Mazlan et al. [35] studied localization performance of Convolutional Neural Network (CNN) method. They used Sensoro SmartBeacon which is developed based on Apple iBeacon protocol standard, that uses Bluetooth 4.0 version and obtained lowest positioning error of 1.2403m. Table 5 compares readily available products for IPS in the market and their respective location accuracies.

TABLE 5. Readily available products for IPS.

Product	Wireless Network	Location Accuracy
Apple iBeacon	BLE	1-3m
Kontakt.io	BLE	1-3m
Quuppa	BLE	0.5-1m
Estimote	UWB	1-3m
Zebra MotionWorks	RFID	1-3m
BlueIoT	BLE	0.1-1m

A cleanroom environment mainly contains metal machines, beams, concretes, other wireless signal interferences, obstructions, human movements and many other factors that heavily affect location accuracy of IPS. In this work, we address improvement towards location accuracy of IPS via two key approaches, parameter tuning and machine learning. For parameter tuning, we test different elevation angles, tag heights, data rate and walking speeds for location accuracy and obtain the best combination of parameters that offer the best location accuracy. For machine learning, we test the system with conventional algorithms, such as SVR, DT and KNN mainly for their lower complexity compared to deep learning algorithms such as Convolutional Neural Network (CNN) or Recurrent Neural Network (RNN) [7], [36] and yet promising results in terms of location accuracy as shown in Table 4. Next, we present a hybrid model by combining parameter tuning and machine learning approaches to improve the location accuracy even further.

III. METHOD

A. EXPERIMENTAL ARCHITECTURE

Fig. 1 shows the experimental architecture of this study. This experiment is divided into three stages where Stage 1 comprises of hardware and software to operate the IPS. In Stage 1, RMSE value is calculated without applying any optimization techniques. Location data that comes out of Stage 1 involves errors sourcing from signal interferences, metal tools, concrete walls, human movement and other possible factors. In Stage 2, two location accuracy optimization techniques are employed individually, parameters calibration and MLA. For parameters calibration, four different parameters are adjusted and experimented to obtain the optimum value for all four parameters that provide the least RMSE value. Likewise, for MLA, three different MLAs are tested, SVR, DT and KNN, and the MLA that provides the least RMSE value is determined. Resultant RMSE value for parameters calibration and MLA are denoted as Result 2 and Result 3 respectively. Finally, the best combination of parameters calibration using the optimum values obtained from Stage 2 and MLA that provide least RMSE value are combined to improve location accuracy even more in Stage 3. Resulting RMSE value is denoted as Result 4 in Stage 3. In the end, Result 1, 2, 3 and 4 are compared and the best approach that delivers lowest RMSE value is determined and applied for the commercial use in ams OSRAM's cleanroom facility.

B. EXPERIMENTAL SETUP

Firstly, the hardware, including readers and tags, and web-based software (BlueIoT Server Management Software) to run the basic indoor positioning system is acquired from BlueIoT. Next, hardware and software are integrated to form a fully functional indoor positioning system within the allocated cleanroom facility. BLE 5.1 protocol is used as communication medium between readers and tags. Readers are signal receivers that are mounted onto ceilings of the environment whereas tags are signal transmitters that are

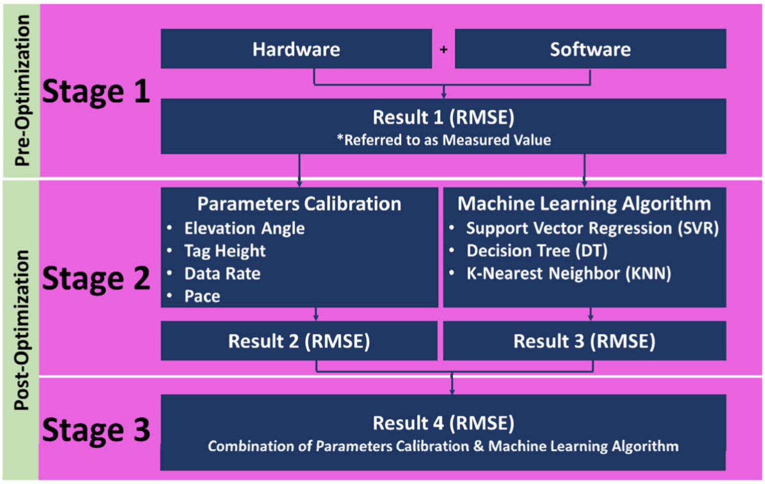
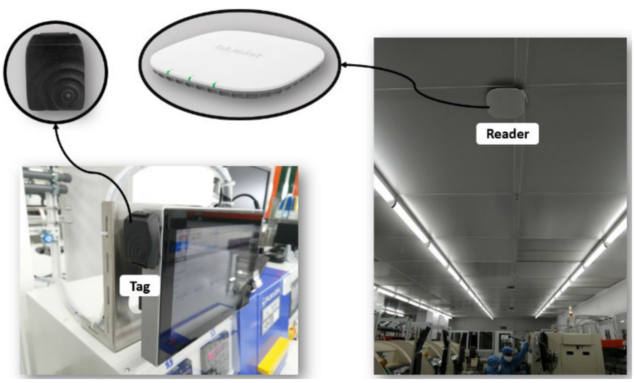


FIGURE 1. Experimental architecture.

attached to the assets that need to be tracked. Fig. 2 shows the actual hardware setup of tags and readers in the cleanroom.



(a) (b)

FIGURE 2. Actual hardware component setup (a) Tag (b) Reader.

In this application, tags are attached onto Panel Computers (PCs) within the cleanroom facility. BlueIoT Server Management Software is a web-based software provided by BlueIoT to operate and manage the hardware including tags and readers, and also to calculate tags' coordinates using angulation method utilizing Angle-of-Arrival (AoA) data. The coordinates calculated by this software are referred to as measured coordinates in this study, meaning these coordinates are highly prone to error and not optimized via neither parameter calibration nor machine learning approach. These measured coordinates are used as input data to MLAs which was made accessible by BlueIoT to our research team through special arrangement. Table 6 shows specifications of hardware including tags and readers used in this work.

C. POSITIONING SYSTEM ARCHITECTURE

The proposed positioning system architecture is illustrated in Fig. 3. The physical layer resembles the array of BLE

TABLE 6. Specifications of tags and readers.

Specifications	Tag	Reader
Model	BlueIoT BT1000-w	BlueIoT BA3000-t
Protocol Standard	BLE 5.1	BLE 5.1
Positioning Technology	AoA	AoA
Frequency Band	(2.4 – 2.4835) GHz	(2.4 – 2.4835) GHz
Transmit Power	0dBm – 20dBm	N/A
Refresh Rate	0.1Hz – 50Hz	N/A
Range	10m	10m
Dimension	(55×40×17) mm	(220×220×32) mm
Power Source	Rechargeable 600mAh Lithium Battery	IEEE 802.3af POE 48V

readers and BLE tags that are present in the cleanroom environment. The proposed framework incorporates Angle-of-Arrival (AoA) as input data used for angulation method. From the physical layer, AoA data is passed to the location module located in the readers. Then, positioning engine software calculates locations of the tags, known as measured XY coordinates. The measured XY coordinates are then stored into database. First, fingerprinting of measured XY coordinates from various locations within the test environment is collected and used to train the machine learning models as part of offline training phase respectively. Trained machine learning models are used to predict new XY coordinates by using live measured XY coordinates as inputs during online testing phase. Newly predicted XY coordinates are then stored in the database. Finally, predicted XY coordinates are visualized on map-view layout for asset tracking.

D. POSITIONING SYSTEM FRAMEWORK

Key modules and interrelations within the proposed asset monitoring system in this work are illustrated in Fig. 4. The diagram illustrates the data flow from start to end including its processing and visualization. The framework is divided into

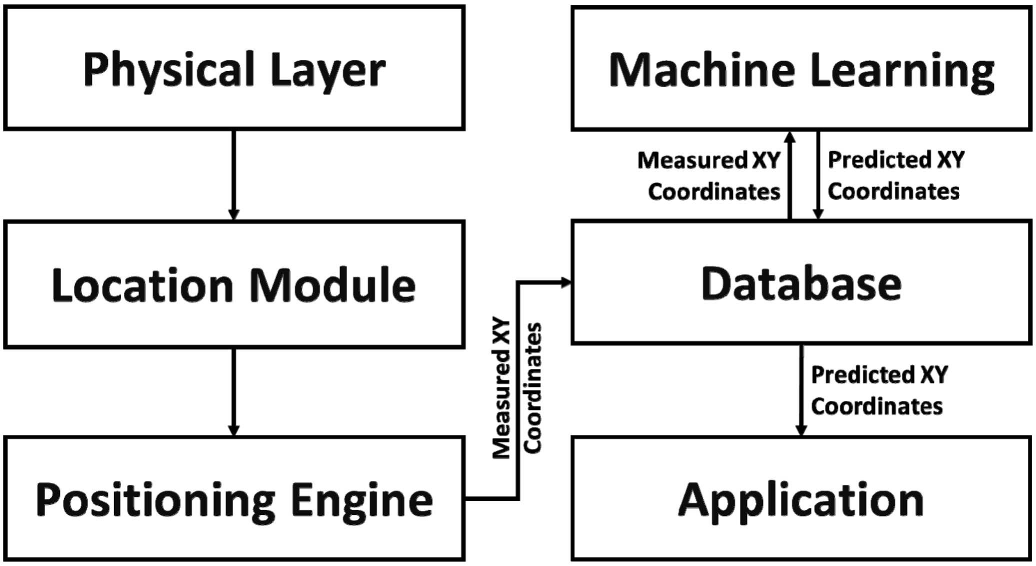


FIGURE 3. Positioning system architecture.

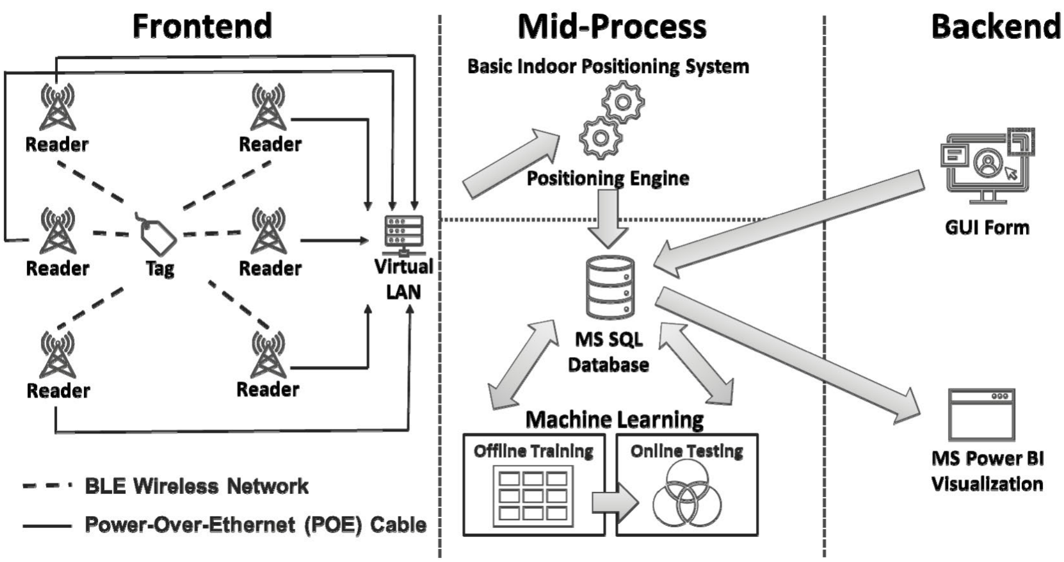


FIGURE 4. Positioning system framework.

three main modules; frontend, mid-process and backend to simplify the asset monitoring mechanism. Frontend module mainly covers the hardware distribution in the asset monitoring system, which covers an array of readers and tags on the assets in the cleanroom. Mid-process module handles all software related processes from position estimation to application of MLAs in the VM server. Backend module includes complementary components for the asset monitoring system that is the Graphical User Interface (GUI) form and map-view visualization on Microsoft Power BI. Fig. 5 shows a snapshot of GUI form developed using Python to manage the asset monitoring system. The GUI form acts as a user interface between users and database of the asset monitoring system to register, de-register, update or search for new or existing tags in the environment. This GUI also helps to keep track of the number of tags present inside the cleanroom and provide visibility to the users at all times. As for communication failure, in case of any BLE tag or receiver lost communication, an email will be triggered to the Person-In-Charge (PIC) with the details of the hardware that lost communication. Fig. 6 shows a snapshot of map-view visualization developed using Microsoft Power BI. The visualization is designed on scatter chart, using the cleanroom layout as the background and x and y coordinates to locate assets within the room. As mouse is hovered onto the blue dots (BLE tags), tag details regarding the assets pop up as shown in Fig. 6. This map-view layout

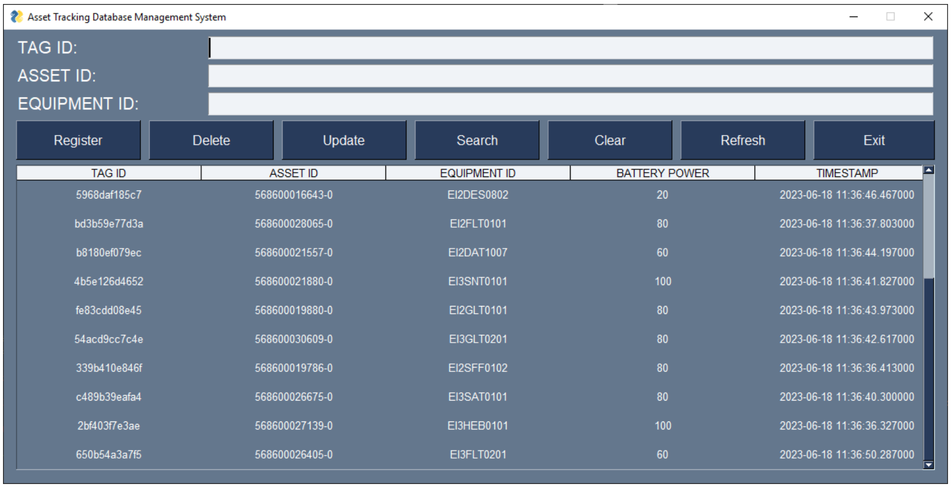


FIGURE 5. GUI form developed on python.

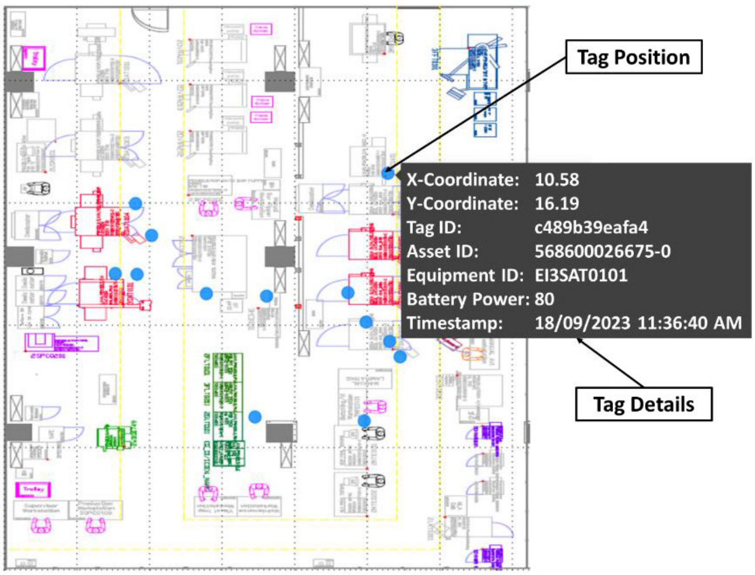


FIGURE 6. Developed map-view visualization using microsoft power BI – Tag position & details.

is published onto the host company's shared internal site for employees' access.

E. DATA COLLECTION

Fig. 7 shows 3-D model of the cleanroom to depict location of readers placed in the facility along with their respective coverage area. The coverage area for every reader is two times the ceiling height. This means, each reader offers, 3m $\times$ 2 = 6m radius of coverage. With that, every reader is placed 6m apart from each other to maximize coverage with minimal readers. Three readers are deployed along each line in the room that consists of two operation lines, which requires a total of six readers for full coverage. Dashed lines in Fig. 8 represent the data collection routes based on cleanroom layout shown in Fig. 9 for online testing phase. Route B travels right under location of readers installed on the ceilings of the cleanroom, and Route A and C are 0.6m apart from Route B. The purpose of adding Route A and C in this experiment is to study the behavior of the location accuracy when the tag position is deviated about 0.6m away from the perpendicular position from readers. For online testing, measured coordinates of Route A, B and C are collected from BlueIoT Server Management Software, by walking over the routes with the tag from start point to end point and recorded in the database. Fig. 9 shows the simplified cleanroom layout. Square gridlines denote the coordinate system where each grid measures 0.6m by 0.6m. X-axis and Y-axis represent the actual width and length, accordingly, starting from (0,0) as the origin point up to (14.5,23) as the maximum point. For offline training, coordinates with

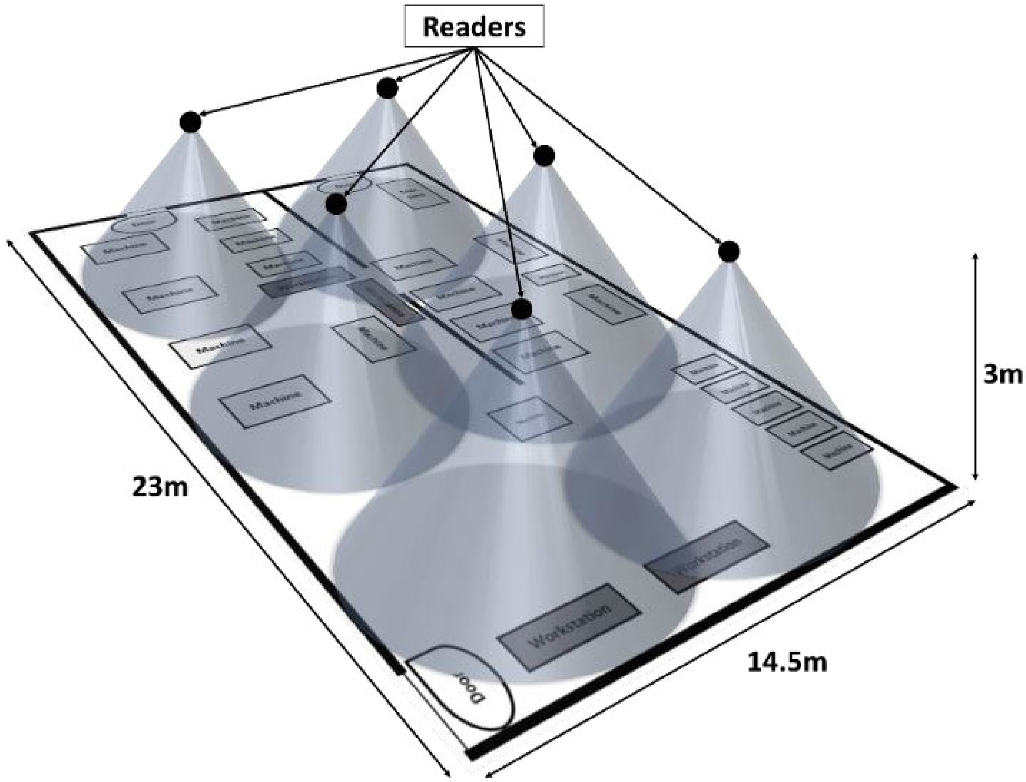


FIGURE 7. 3-D model of the cleanroom with readers.

respect to square gridlines formed are acquired and recorded within the database. The actual and measured coordinates are then used as input data to train the machine learning models accordingly.

Test cases for test runs are shown in Table 7. Every test case is repeated 3 times with all 3 different routes each, which gives a total of nine test runs for every test case and the results are averaged to increase reliability and minimize the error within collected data. Elevation angle and data rate are adjusted in the BlueIoT Server Management Software. Tag height is adjusted by sticking the tag onto the person's body according to tag heights from floor as mentioned in Table 7. Walking speed is measured using a speedometer on smartphone and kept constant throughout every test run. First, three different elevation angles are tested by keeping other testing parameters constant. Then, the best elevation angle that delivers lowest RMSE value is used as constant parameter for subsequent test cases. This pattern is repeated for other test cases in other testing parameters until all 12 test cases are complete. Finally, test case that give lowest RMSE value is infused with machine learning approach. As for MLAs, SVR, DT and KNN have been experimented in this study. To evaluate the performance of machine learning algorithms, the dataset was divided into two parts: an 80% training set and a 20% testing set. The training set was used to train the algorithms, while the testing set was used to evaluate their performance. Based on the testing outcome, model parameters that presents outcomes of neither underfitting nor overfitting are selected to be used in the final stage of the experiment. For SVR, 'RBF' kernel, C value of four, and epsilon value of 0.01 is used. For DT, maximum depth of tree is set at five levels. For KNN, the number of neighbors to use for regression is set at four. The best machine learning algorithm that gives lowest RMSE value is determined from this experiment. Finally, test cases of parameter tuning and machine learning algorithm that give lowest RMSE value when implemented separately, are merged and implemented together to study the improvement on location accuracy. Hence, location accuracy is optimized via three approaches in this study, through parameter tuning only, machine learning approach only and both parameters tuning and machine learning approach combined. All results are presented in the next section accordingly.

IV. ACCURACY OPTIMIZATION AND COMPARISON

This study focuses on parameters calibration and machine learning approaches to optimize location accuracy. For parameters calibration approach, the impacts of elevation angle, data rate, tag height and pace are tested with different settings respectively. For machine learning approach, SVR, DT and KNN are experimented. Detailed parameter calibration and MLAs used are discussed and their improvements before and after applications are compared in this section.

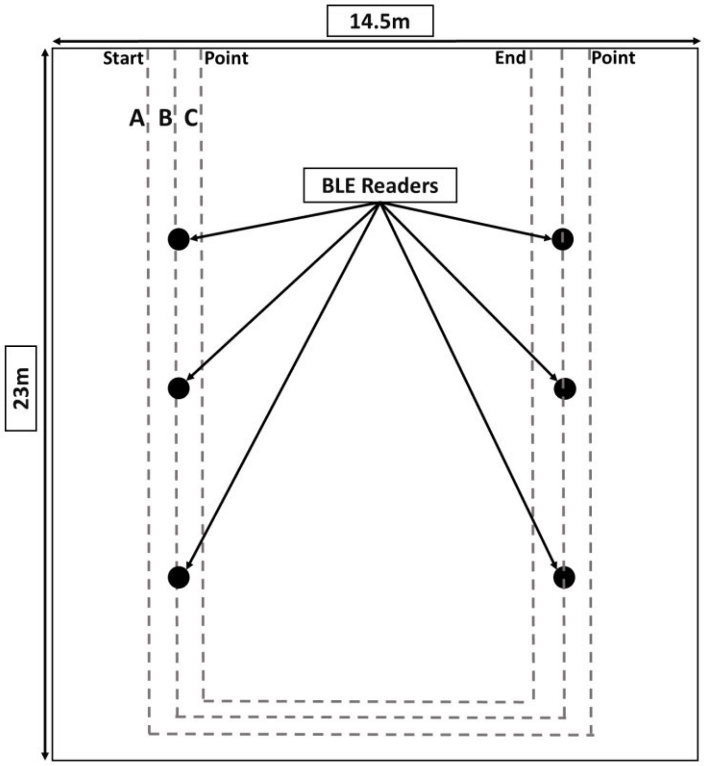


FIGURE 8. Data collection routes.

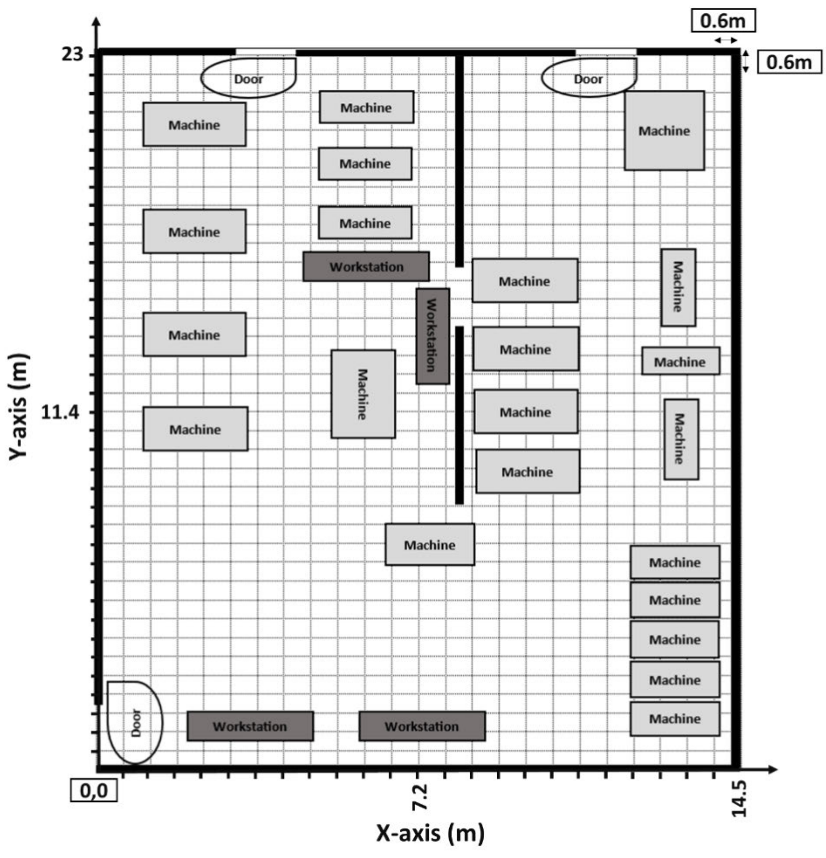


FIGURE 9. Coordinate system illustrated on simplified cleanroom layout.

TABLE 7. Test cases for test runs.

Test Case	Elevation Angle (°)	Tag Height (m)	Data Rate (Hz)	Walking Speed (m/s)
1	21	2.5	50	0.429
2	55	2.5	50	0.429
3	89	2.5	50	0.429
4	55	0.5	50	0.429
5	55	1.5	50	0.429
6	55	2.5	50	0.429
7	55	2.5	5	0.429
8	55	2.5	10	0.429
9	55	2.5	50	0.429
10	55	2.5	50	0.429
11	55	2.5	50	0.857
12	55	2.5	50	1.286

A. IMPACT OF ELEVATION ANGLE

Elevation angle is the angle of measurement from the readers. Different elevation angles (21°, 55° and 89°) were tested to study the response of location accuracy towards different elevation angles. RMSE values are calculated for every elevation angle and the elevation angle with lowest RMSE value is determined. Elevation angle can be visualized as shown in Fig. 10.

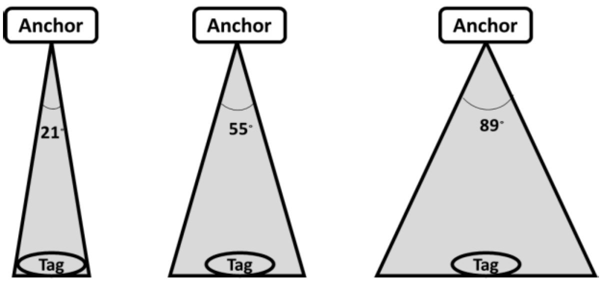


FIGURE 10. Elevation angles.

Elevation angle of 55° has lower fluctuations in terms of readings as compared to elevation angle of 21° according to Fig. 11 (a). Fig. 11 (b) shows that the elevation angle of 55° has lower RMSE value as compared to elevation angles of 21° and 89° respectively. Fig. 11 (c) compares cumulative distribution functions (CDFs) obtained from different elevation angles. Elevation angle of 55° outperforms other experimented angles by achieving 90% of its RMSE values below 0.3m. According to Table 8, elevation angle of 55° delivers the least average RMSE value of 0.258m as compared to elevation angles of 21° and 89° with average RMSE values of 0.332m and 0.3m respectively.

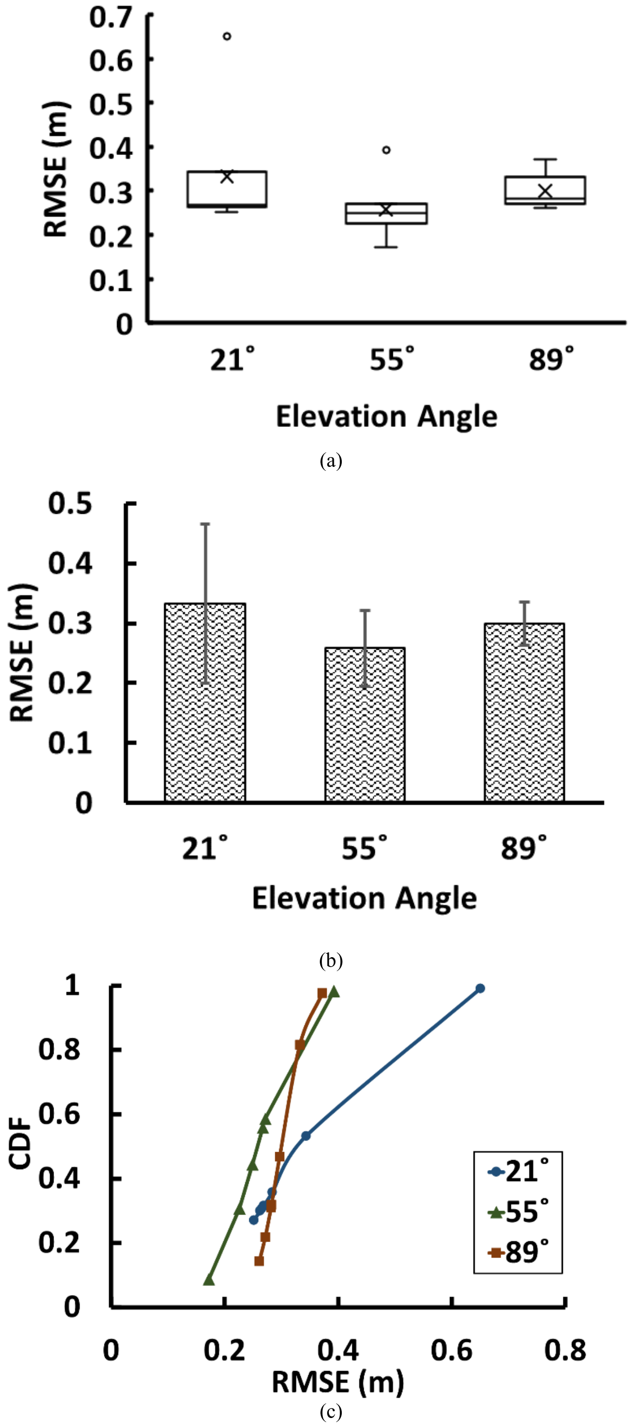


FIGURE 11. Elevation angle impact (a) Boxplot of RMSE (b) Bar graph of RMSE (c) Cumulative distribution function (CDF) Graph of RMSE.

B. IMPACT OF TAG HEIGHT

Tag height refers to the distance between ground level and tag which potentially influences location accuracy. Different tag heights (0.5m, 1.5m and 2.5m) were tested to study the response of location accuracy towards different tag heights. RMSE values are calculated for every tag height and the tag height with lowest RMSE value is determined. Tag height can be visualized as shown in Fig. 12.

According to Fig. 13 (a), tag height of 2.5m delivers the lowest RMSE value. From Fig. 13 (b), same pattern can be observed that tag height of 2.5m gives lowest RMSE value as compared to tag heights of 0.5m and 1.5m

TABLE 8. Mean and standard deviation of RMSE for elevation angle.

Elevation Angle (°)	21	55	89
Mean RMSE (m)	0.332	0.258	0.3
Standard Deviation	0.133	0.063	0.036

TABLE 9. Mean and standard deviation of RMSE for tag height.

Tag Height (m)	0.5	1.5	2.5
Mean RMSE (m)	0.398	0.288	0.271
Standard Deviation	0.196	0.03	0.046

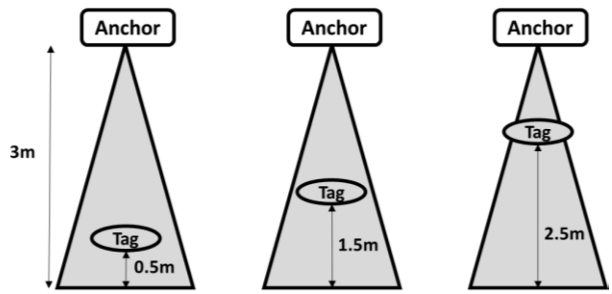


FIGURE 12. Tag heights.

respectively. Fig. 13 (c) compares cumulative distribution functions (CDFs) obtained from different tag heights. Tag height of 2.5m outperforms other experimented tag heights by achieving 90% of its RMSE values below 0.3m. It can be observed that tag height of 2.5m delivers the least average RMSE value of 0.271m as compared to tag heights of 0.5m and 1.5m with average RMSE values of 0.398m and 0.288m respectively, according to Table 9.

C. IMPACT OF DATA RATE

Data rate refers to frequency of data published by tags to anchors per second. Different data rates (5Hz, 10Hz and 50Hz) were tested, to study the response of location accuracy towards different data rates. According to Fig. 14 (a), data rate of 50Hz possesses lowest fluctuations in terms of readings as compared to data rates of 5Hz and 10Hz respectively. Fig. 14 (b) shows that data rate of 50Hz delivers the least average RMSE value as compared to data rates of 5Hz and 10Hz respectively. Fig. 14 (c) compares cumulative distribution functions (CDFs) obtained from different data rates. The data rate of 50Hz outperforms other experimented data rates by achieving more than 90% of its RMSE values below 0.3m. It can be observed that data rate of 50Hz gives the best result with the least average RMSE value of 0.265m as compared to data rates of 5Hz and 10Hz with average RMSE values of 0.327m and 0.283m respectively, according to Table 10.

TABLE 10. Mean and standard deviation of RMSE for data rate.

Data Rate (Hz)	5	10	50
Mean RMSE (m)	0.327	0.283	0.265
Standard Deviation	0.13	0.041	0.023

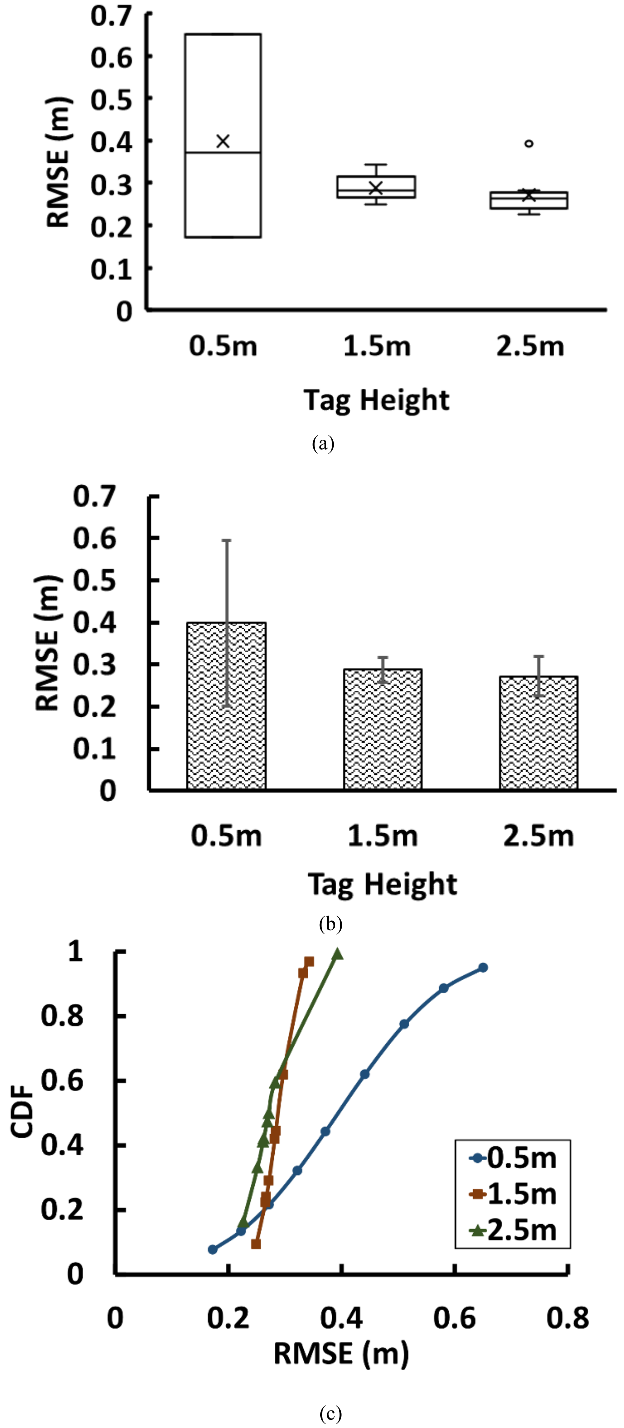


FIGURE 13. Tag height impact (a) Boxplot of RMSE (b) Bar graph of RMSE (c) Cumulative distribution function (CDF) graph of RMSE.

D. IMPACT OF PACE

Walking pace plays a crucial role in affecting location accuracy. To study the response of different walking paces towards location accuracy, wide range of readings collected at slow, moderate and fast paces respectively. Shao et al investigated the effects of different walking speeds on particle transmission within cleanroom [37]. Walking speeds investigated in

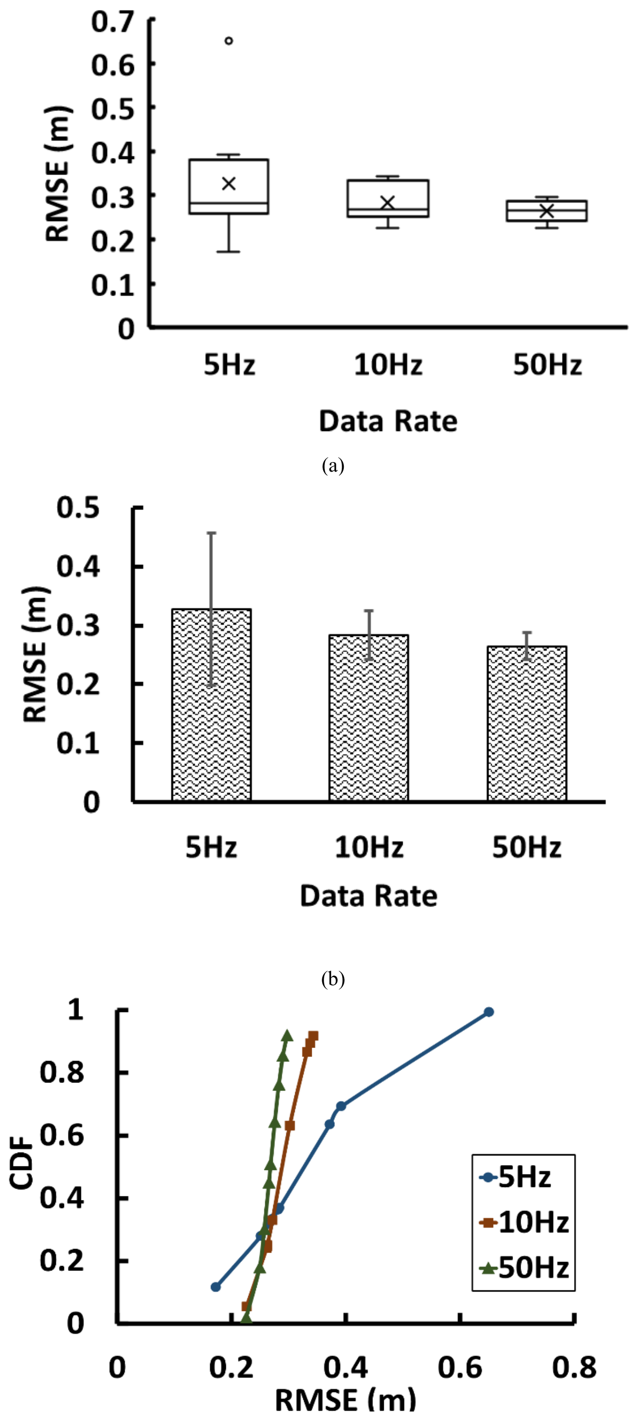


FIGURE 14. Data rate impact (a) Boxplot of RMSE (b) Bar graph of RMSE (c) Cumulative distribution function (CDF) graph of RMSE.

this study, as shown in Table 11, are 0.429m/s for slow, 0.857m/s for moderate and 1.286m/s for fast walking paces which are in good agreement with those of Shao et al [37]. RMSE values are calculated for every pace and the lowest RMSE value is determined accordingly. Pace is controlled and monitored throughout data collection using a stopwatch to ensure uniform paces. Pace speed is calculated at the end of data collection by dividing distance travelled by time taken to complete each test run. Fig. 15 shows that the slow pace delivers the least average RMSE value as compared to moderate and fast paces. This is because, as data is collected while walking slowly, more data gets captured in the system, which results in larger training dataset that eventually results in lower RMSE value. The speeds of respective paces are as shown in Table 11. From Table 11, it can be observed that slow pace gives the best result with the least average RMSE value of 0.178m as compared to moderate and fast paces with average RMSE values of 0.225m and 0.254m respectively. The difference between speeds is consistent and approximately 0.428m/s, which increases reliability of the results obtained. Slow pace provides the highest location accuracy, with lowest RMSE value.

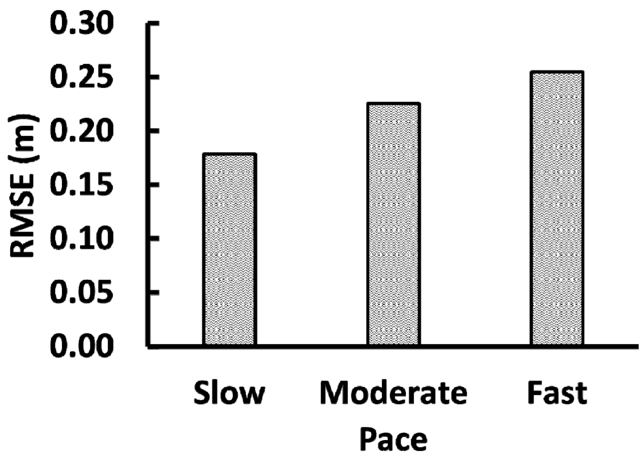


FIGURE 15. Bar graph of RMSE for pace.

TABLE 11. Speed and RMSE for different paces.

Pace	Speed (m/s)	RMSE (m)
Slow	0.429	0.178
Moderate	0.857	0.225
Fast	1.286	0.254

E. IMPACT OF MACHINE LEARNING APPROACH

Based on Table 12, measured values have accuracy of 78.1%. This low percentage can be explained by the interferences that are available in the cleanroom facility, such as employee movements, signal interferences, metal machines, beams, concrete walls and other factors. In order to optimize location accuracy and minimize the effect of interferences and noises, machine learning algorithms are employed and tremendously increased location accuracy. Different machine learning techniques (SVR, DT and KNN) are applied and tested in this study to improve the location accuracy and to determine the best machine learning algorithm that delivers lowest RMSE value. The results are compared against the measured XY coordinates (pre-optimized by MLAs) to study the improvement on location accuracy before and after applying MLAs. According to Fig. 16, all machine learning techniques that were experimented in this study improve location accuracy, as RMSE values of all 3 machine learning techniques are lower than measured data. Among the 3 machine learning techniques applied, KNN offers the highest location accuracy of 98.5%, with the least RMSE value of 0.015m as compared to SVR and DT as shown in Table 12. KNN possess the highest improvement percentage of 20.4% as compared to SVR and DT with improvement percentages of 12.1% and 12.5% respectively. Therefore, KNN is the best machine learning technique for this application. In a study conducted by Sthapit et al., RMSE value achieved using SVR method was 0.5m which is comparatively higher than RMSE value obtained using SVR method in this research, which is 0.098m [13]. Bozkurt et al., study shows location accuracy of 99.89% and 86.59% that were obtained using DT and KNN methods respectively [16]. In the present study, location accuracy obtained for DT and KNN methods are 90.6% and 98.5% respectively. KNN method shows better result in terms of location accuracy compared to the research conducted by Bozkurt et al. [16] whereas DT performs lower which could be due to differences in the testing environment as the experiment in this study is conducted in a high-dense manufacturing environment whereas the other research uses readily available dataset adapted from UJIIndoorLoc dataset, as input rather than actual experimental dataset. KNN method delivers lowest RMSE value with highest location accuracy among other machine learning techniques assessed in this research, and as compared to other works demonstrating that KNN is the best machine learning algorithm for this application.

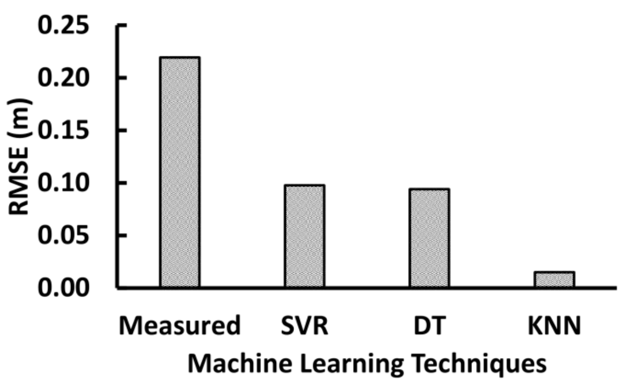


FIGURE 16. Bar graph of RMSE for machine learning techniques.

F. COMPARISON OF PRE-OPTIMIZATION AND POST-OPTIMIZATION OF PARAMETERS

Parameters calibration is crucial to optimize location accuracy. Test runs are performed before and after calibrating the parameters. Pre-optimization parameter settings are elevation angle of 21°, tag height of 0.5m, data rate of 5Hz and fast walking pace. Post-optimization parameter settings

TABLE 12. Measured data vs machine learning results.

Machine Learning Technique	RMSE (m)	Location Accuracy (%)	Improvement (%)
Measured	0.219	78.1	N/A
SVR	0.098	90.2	12.1
DT	0.094	90.6	12.5
KNN	0.015	98.5	20.4

are elevation angle of 55°, tag height of 2.5m, data rate of 50Hz and slow walking pace. The results are shown in Fig. 17 and tabulated on Table 13. Pre-optimized and post-optimized datasets are used to train the machine learning models respectively, and the resulting RMSE values are calculated accordingly. Fig. 17 illustrates that post-optimization RMSE values are much lower than pre-optimization RMSE values, which demonstrates location accuracy has been optimized after parameters calibration. Parameters optimization has a great impact on performance of measured data as well as MLAs result. According to Table 13, location accuracy improvements contributed by parameters optimization on measured data is 67.3%, SVR is 87.05%, DT is 36.6% and KNN is 97.6%. Evidently parameters calibration greatly impacts location accuracy and performance of MLAs.

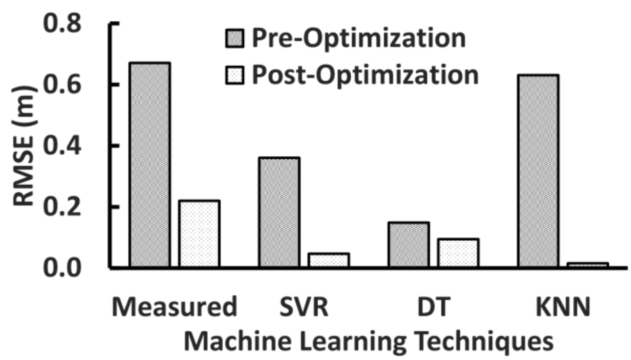


FIGURE 17. Bar graph of pre-optimization and post-optimization of parameters.

TABLE 13. Pre-optimization vs post-optimization of parameters.

Parameters Optimization	Measured	SVR	DT	KNN
Pre-Optimization RMSE (m)	0.670	0.361	0.148	0.631
Post-Optimization RMSE (m)	0.219	0.047	0.094	0.015
Improvement (%)	67.3	87.05	36.6	97.6

V. CONCLUSION AND FUTURE WORK

This study presents an IPS with improved location accuracy that has been developed, implemented and successfully operational at our industry partner, ams OSRAM's LED manufacturing cleanroom, to track movements of assets within the facility. Before applying neither parameter tuning nor machine learning approach, the RMSE value of the IPS is 0.670m. Upon applying parameters tuning only (elevation angle of 55°, tag height of 2.5m, data rate of 50Hz, slow-paced movement), location accuracy is improved by 67.3% and lowest RMSE value of 0.219m is achieved. Upon applying machine learning algorithm only, lowest RMSE value achieved is 0.148m which is using DT algorithm, which improves location accuracy by 36.6%. Finally, upon combining both parameters tuning and machine learning approaches, lowest RMSE value of 0.015m is obtained, by using elevation angle of 55°, tag height of 2.5m, data rate of 50Hz, slow-paced movement and KNN algorithm. Applying parameters calibration and machine learning algorithm have optimized location accuracy by up to 98.5%, which shows improvement of 20.4%. The developed asset monitoring framework is currently implemented on one production floor, comprised of two production lines. Considering the performance, reliability and maintenance cost of the overall framework, our industry partner is eager to proliferate this asset monitoring framework to other production floors, and other plants as well. The developed asset monitoring framework is tested in an actual cleanroom environment where production runs on 24/7 basis, with the existence of equipment, employee movements and signal interferences, that has helped to tailor this framework to adapt to the environment that it is currently implemented in. The current setup can be replicated in another room with the same dimension. For rooms with different dimensions, the same framework can be replicated by customizing the number of readers accordingly. Moreover, this developed asset monitoring system is highly recommended to track human assets (employees) to study hotspot areas of employees and mainly for contact tracing in pandemic era. Furthermore, this framework is highly reliable to study space utilization within an indoor environment that helps space optimization. In parallel to the Malaysian Government's initiative towards Fourth Industrial Revolution (4IR), this developed asset monitoring framework is a steppingstone that can be thrived to other sectors and industries as part of asset management system.

REFERENCES

[1] I. Gouzouasis, S. Papaharalabos, M. A. Nasa, and P. Karlsson, "A novel antenna system for direction finding applications using BLE 5.1 technology," in *Proc. 17th Eur. Conf. Antennas Propag. (EuCAP)*, Mar. 2023, pp. 1–5.

[2] N. Paulino and L. M. Pessoa, "Self-localization via circular Bluetooth 5.1 antenna array receiver," *IEEE Access*, vol. 11, pp. 365–395, 2023.

[3] M. Qian, K. Zhao, A. Seneviratne, and B. Li, "Performance analysis of BLE 5.1 new feature angle of arrival for relative positioning," *Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.*, vol. 3, pp. 155–161, Apr. 2022.

[4] G. Pau, F. Arena, Y. E. Gebremariam, and I. You, "Bluetooth 5.1: An analysis of direction finding capability for high-precision location services," *Sensors*, vol. 21, no. 11, p. 3589, May 2021.

[5] A. Barua, M. A. Al Alamin, M. S. Hossain, and E. Hossain, "Security and privacy threats for Bluetooth low energy in IoT and wearable devices: A comprehensive survey," *IEEE Open J. Commun. Soc.*, vol. 3, pp. 251–281, 2022.

[6] U. M. Qureshi, Z. Umair, and G. P. Hancke, "Evaluating the implications of varying Bluetooth low energy (BLE) transmission power levels on wireless indoor localization accuracy and precision," *Sensors*, vol. 19, no. 15, p. 3282, Jul. 2019.

[7] A. Nessa, B. Adhikari, F. Hussain, and X. N. Fernando, "A survey of machine learning for indoor positioning," *IEEE Access*, vol. 8, pp. 214945–214965, 2020.

[8] R. Ali, R. Liu, Y. He, A. Nayyar, and B. Qureshi, "Systematic review of dynamic multi-object identification and localization: Techniques and technologies," *IEEE Access*, vol. 9, pp. 122924–122950, 2021.

[9] X. Zhu, W. Qu, T. Qiu, L. Zhao, M. Atiquzzaman, and D. O. Wu, "Indoor intelligent fingerprint-based localization: Principles, approaches and challenges," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 4, pp. 2634–2657, 4th Quart., 2020.

[10] H. Yao, H. Shu, X. Liang, H. Yan, and H. Sun, "Integrity monitoring for Bluetooth low energy beacons RSSI based indoor positioning," *IEEE Access*, vol. 8, pp. 215173–215191, 2020.

[11] K. Shi, Z. Ma, R. Zhang, W. Hu, and H. Chen, "Support vector regression based indoor location in IEEE 802.11 environments," *Mobile Inf. Syst.*, vol. 2015, Sep. 2015, Art. no. 295652.

[12] H. Torii, S. Ibi, and S. Sampei, "Indoor positioning and tracking by multi-point observations of BLE beacon signal," in *Proc. 15th Workshop Positioning, Navigat. Commun. (WPNC)*, Oct. 2018, pp. 1–5.

[13] P. Sthapit, H.-S. Gang, and J.-Y. Pyun, "Bluetooth based indoor positioning using machine learning algorithms," in *Proc. IEEE Int. Conf. Consum. Electron. Asia (ICCE-Asia)*, Jun. 2018, pp. 206–212.

[14] A. Yazici, S. B. Keser, and S. Gunal, "Integration of classification algorithms for indoor positioning system," in *Proc. Int. Conf. Comput. Sci. Eng. (UBMK)*, Oct. 2017, pp. 267–270.

[15] L. Chanama and O. Wongwirat, "A comparison of decision tree based techniques for indoor positioning system," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2018, pp. 732–737.

[16] S. Bozkurt, G. Elibol, S. Gunal, and U. Yayan, "A comparative study on machine learning algorithms for indoor positioning," in *Proc. Int. Symp. Innov. Intell. Syst. Appl. (INISTA)*, Sep. 2015, pp. 1–8.

[17] S. B. Keser and U. Yayan, "A case study of optimal decision tree construction for RFKON database," in *Proc. Int. Symp. Innov. Intell. Syst. Appl. (INISTA)*, Aug. 2016, pp. 1–6.

[18] N.-S. Duong and T.-M. Dinh, "On the accuracy of iBeacon-based indoor positioning system in the iOS platform," in *Proc. 18th Int. Multi-Conf. Syst., Signals Devices (SSD)*, Mar. 2021, pp. 58–62.

[19] M. M. K. Lie and G. P. Kusuma, "A fingerprint-based coarse-to-fine algorithm for indoor positioning system using Bluetooth low energy," *Neural Comput. Appl.*, vol. 33, no. 7, pp. 2735–2751, Apr. 2021.

[20] Y. H. Ho and H. C. B. Chan, "Decentralized adaptive indoor positioning protocol using Bluetooth low energy," *Comput. Commun.*, vol. 159, pp. 231–244, Jun. 2020.

[21] L. Bai, F. Ciravegna, R. Bond, and M. Mulvenna, "A low cost indoor positioning system using Bluetooth low energy," *IEEE Access*, vol. 8, pp. 136858–136871, 2020.

[22] L. Cheng, Y. Li, M. Xue, and Y. Wang, "An indoor localization algorithm based on modified joint probabilistic data association for wireless sensor network," *IEEE Trans. Ind. Informat.*, vol. 17, no. 1, pp. 63–72, Jan. 2021.

[23] M. Dong, Y. Qi, X. Wang, and Y. Liu, "A non-line-of-sight mitigation method for indoor ultra-wideband localization with multiple walls," *IEEE Trans. Ind. Informat.*, vol. 19, no. 7, pp. 8183–8195, Jul. 2023.

[24] S. Lee, B. Kim, H. Kim, R. Ha, and H. Cha, "Inertial sensor-based indoor pedestrian localization with minimum 802.15.4a configuration," *IEEE Trans. Ind. Informat.*, vol. 7, no. 3, pp. 455–466, Aug. 2011.

[25] J. Luo, Z. Zhang, C. Wang, C. Liu, and D. Xiao, "Indoor multifloor localization method based on WiFi fingerprints and LDA," *IEEE Trans. Ind. Informat.*, vol. 15, no. 9, pp. 5225–5234, Sep. 2019.

[26] T. Van Haute, B. Verbeke, E. De Poorter, and I. Moerman, "Optimizing time-of-arrival localization solutions for challenging industrial environments," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1430–1439, Jun. 2017.

[27] R. Giuliano, G. C. Cardarilli, C. Cesarini, L. Di Nunzio, F. Fallucchi, R. Fazzolari, F. Mazzenga, M. Re, and A. Vizzarri, "Indoor localization system based on Bluetooth low energy for museum applications," *Electronics*, vol. 9, no. 6, p. 1055, Jun. 2020.

[28] M. Ji, J. Kim, J. Jeon, and Y. Cho, "Analysis of positioning accuracy corresponding to the number of BLE beacons in indoor positioning system," in *Proc. 17th Int. Conf. Adv. Commun. Technol. (ICACT)*, Jul. 2015, pp. 92–95.

[29] N. S. Duong, V. T. A. Trinh, and T. T. M. Dinh, "Bluetooth low energy based indoor positioning on iOS platform," in *Proc. IEEE 12th Int. Symp. Embedded Multicore/Many-Core Systems Chip (MCSoC)*, Sep. 2018, pp. 57–63.

[30] Z. Cai, L. Zhao, C. Su, J. Lu, T. Jin, and Z. Zhou, "Design and implementation of area positioning system based on UWB," in *Proc. Int. Conf. Microw. Millim. Wave Technol. (ICMMT)*, Aug. 2022, pp. 1–3.

[31] Z. Liu, X. Wang, Z. Chen, M. Zhao, S. Zhang, and J. Li, "3D-fingerprint augment based on super-resolution for indoor 3D WiFi localization," in *Proc. 13th Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2021, pp. 1–5.

[32] J. An, Z. Wang, X. He, X. Gui, J. Cheng, and R. Gui, "Know where you are: A practical privacy-preserving semi-supervised indoor positioning via edge-crowdsensing," *IEEE Trans. Netw. Service Manage.*, vol. 18, no. 4, pp. 4875–4887, Dec. 2021.

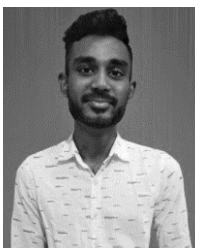
[33] C. Fabritz, M. Abdelrahim, S. Wirsz, and T. Wang, "Open specification for indoor-navigation," in *Proc. IEEE 11th Int. Conf. Semantic Comput. (ICSC)*, Jan. 2017, pp. 354–359.

[34] P. Zhao, L. Wang, Y. Tian, L. Guo, and B. Lu, "WiFi-Bluetooth dual modal indoor positioning system using adaptive range filter," in *Proc. 7th Int. Conf. Big Data Comput. Commun. (BigCom)*, Aug. 2021, pp. 60–67.

[35] A. B. Mazlan, Y. H. Ng, and C. K. Tan, "A fast indoor positioning using a knowledge-distilled convolutional neural network (KD-CNN)," *IEEE Access*, vol. 10, pp. 65326–65338, 2022.

[36] N. K. Chauhan and K. Singh, "A review on conventional machine learning vs deep learning," in *Proc. Int. Conf. Comput., Power Commun. Technol. (GUCON)*, Sep. 2018, pp. 347–352.

[37] X. Shao, K. Hashimoto, L. Fang, A. K. Melikov, K. G. Naydenov, and C. Rasmuseen, "Experimental study of airborne particle transmission through the doorway of a cleanroom due to the movement of a person," *Building Environ.*, vol. 183, Oct. 2020, Art. no. 107205.



DASMOND ROY PHILIPS received the bachelor's degree (Hons.) in electrical and electronics engineering from UTP, in 2020. He is currently pursuing the master's degree with the University of Malaya (UM), Kuala Lumpur, Malaysia. He is tied to the Faculty of Engineering, UM. His research interests include indoor positioning systems (IPS) and machine learning approach to improve location accuracy of IPS. He joined UM, in July 2021, and acting as a Research Postgraduate Student till date, for the ongoing research. He completed his secondary school studies with the High School Bukit Mertajam (HSBM), in 2014. Then, in 2015, he joined the University of Technology Petronas (UTP) for foundation studies in engineering. As working experience, he was with Western Digital Corporation as an Equipment Engineer, from December 2020 to July 2021. Then, in July 2021, he joined UM and is collaborating with Osram for the research project.

ERFAN SALAMI (Member, IEEE) received the B.Eng. degree (Hons.) in mechatronics engineering from UCSI University, Malaysia, in 2012, the M.Sc. degree in aerospace engineering from UPM University, Malaysia, in 2015, and the Ph.D. degree in aerospace engineering from the University of Malaya (UM), Malaysia, in 2021. He is currently a Postdoctoral Research Fellow with the Department of Electrical Engineering, University of Malaya. His main research interests include image processing, the IoT applications, smart manufacturing, asset monitoring, object detection, deep learning applications, bio-mimetic micro aerial vehicles (BMAV), unmanned aerial systems (UAS), and urban air mobility (UAM).

HARIKRISHNAN RAMIAH (Senior Member, IEEE) received the B.Eng. (Hons.), M.Sc., and Ph.D. degrees in electrical and electronic engineering, with a focus on analog and digital IC design from Universiti Sains Malaysia, Malaysia, in 2000, 2003, and 2008, respectively. In 2002, he was with Intel Technology Sdn. Bhd., performing high-frequency signal integrity analysis. In 2003, he was with SiresLabs Sdn. Bhd., Cyberjaya, Malaysia, working on 10-Gb/s SONET/SDH transceiver solution. He is currently a Professor with the Department of Electrical Engineering, University of Malaya, Kuala Lumpur, Malaysia, working in the area of RF integrated circuit (RFIC) and RF energy harvesting circuit design. He has authored or coauthored several articles in technical publications. His main research interests include analog-integrated circuit design, RFIC design, VLSI system design, and radio frequency energy harvesting power management module design. He is a member of the Institute of Electronics, Information and Communication Engineers. He was a recipient of the Intel Fellowship Grant Award, from 2000 to 2008. He had received continuous international research funding in recognition of his work, from 2014 to 2018, such as the Motorola Foundation Grant. He is also a Chartered Engineer of the Institute of Electrical Technology and a Professional Engineer registered under the Board of Engineers Malaysia.

JEEVAN KANESAN (Member, IEEE) received the degree in electrical engineering from Universiti Teknologi Malaysia, in 1999, and the M.Sc. and Ph.D. degrees from Universiti Sains Malaysia, Penang, in 2002 and 2006, respectively. He was an Engineer with Carsem Semiconductor, Ipoh. He was a Research and Development Engineer with Intel, Penang, for two and a half years. He joined the Department of Electrical Engineering, Universiti Malaya, in 2008. He has published more than 70 peer-reviewed journals. His research interests include optimization and machine learning.