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IMPROVING RSSI-BASED DISTANCE PREDICTION BY UTILIZING ROOM TEMPERATURE AND HUMIDITY VARIANCE FOR INDOOR POSITIONING SYSTEM APPLICATION

DAVID ABRIMAN SIMATUPANG[1], GEDE PUTRA KUSUMA[2]

Computer Science Department, BINUS Graduate Program - Master of Computer Science,

Bina Nusantara University, Jakarta, Indonesia, 11480

E-mail: [1]david.simatupang@binus.ac.id, [2]inegara@binus.edu

ABSTRACT

The development of cellular telephone technology has increased its function from a means of communication into many functions. One of them is in determining the location and distance inside the room using Bluetooth technology. In this technology, the received signal strength indicator (RSSI) of the Bluetooth radio signal is used to estimate the distance between the signal sender and receiver. Due to the fluctuation of the RSSI, the level of measurement accuracy is low so that the development of pre-processing method is carried out to overcome this problem. The proposed RSSI pre-processing method utilizes room temperature and humidity as environmental parameters processed using the Kalman filter (KF), Support vector regression (SVR), and Multilayer Perceptron (MLP). From the evaluation, it is shown the MLP yield the best result with lowest error and highest accuracy of distance prediction and position compared to other methods. Average of the distance prediction evaluation using MLP utilized 4 BLEs with temperature and humidity evaluation test in high temperature-low humidity. The mean absolute percentage error (MAPE) of the MLP is 5.7% and the mean absolute error (MAE) result is 0.124m. For RSSI-based position prediction test in high temperature and low humidity using MLP, it achieved the mean error (ME) of 0.171m, which is lower than without utilizing temperature and humidity with ME of 0.423m. The RSSI-based distance and position prediction models utilizing temperature and humidity gave lower error and higher accuracy compared to the models that did not use temperature and humidity parameter. By utilizing room temperature and humidity using MLP in our research able to improve the accuracy with lesser error for distance prediction and indoor positioning system (IPS) application compared to KF and SVR method.

Keywords: *Room Temperature and Humidity*, *RSSI Distance Prediction, Support Vector Regression, Multilayer Perceptron, Indoor Positioning System*.

1. INTRODUCTION

Indoor positioning system (IPS) is the application or technologies to determine the location and navigate the tracked objects or device that located indoor or inside building. This research is conducted to resolve the limitation of GPS positioning system that cannot determine the location and navigate the tracked objects/ device when its line of sight to satellite is blocked while it inside the room [1], [2], [3]. To overcome this problem, an indoor positioning system development was carried out using several technologies such as infrared, radio frequency identification (RFID), Bluetooth, camera, sound (ultra-sound or audible sound), and Wi-Fi [1]. Bluetooth low energy (BLE), one of wireless technology that required small power which is utilizes small battery (coin battery). BLE send signals independently without external order. Also BLE not required master-slave connection and can be used for many types of receiving devices compared to other technologies [4].

BLE using Bluetooth radio to communicate between devices. From this radio communication, the signal strength can be measured that called received signal strength indicator (RSSI). The RSSI value variance can be affected by the change of transmitter and receiver distance. The RSSI value is so much fluctuated that causing to the low level accuracy of distance and position prediction techniques. To improve this prediction, very important to develop pre-processing techniques to improve the accuracy of the distance and position [5], [6], [7], [8], [9], [10]. It is also necessary to pay attention of environmental conditions. That environmental conditions can be used as an additional parameter in developing pre-processing techniques which is utilize the temperature and humidity to analyze RSSI value [11].

Because of our concern to the environmental changes such as indoor temperature and humidity, so we propose a research that using some pre-processing method combined with environment parameter to achieve better distance measurement that will improve the IPS tracking result. In this research we focus on accuracy improvement that using KF, SVR and MLP with utilizing the room temperature and humidity parameter.

2. RELATED WORKS

Several studies were conducted in the improvement and development of IPS by utilized the BLE advertising nodes. In determining the position of a cellular telephone or receiving device based on the RSSI value that received from several BLEs with the trilateration algorithm [2], [4]. Methods in position prediction ware carried out using the range-based and fingerprinting-based methods [3]. In order to improve distance accuracy and position determination, position prediction was also carried out using several filtering methods. Establishment of fingerprint database and error prediction models (Bluetooth and Wi-Fi) which then make a selection between two signals/ data or use a combination of both as an estimate of the position by determining the threshold limit as a reference [5]. Also the fingerprint cluster and signal weighted Euclidean distance method that used for nonlinear of the received signal strength (RSS) value compare to sender and receiver distance [24]. Used of separate beacon channels (37, 38, and 39) with the best signal quality selection [6]. The used of Kalman filter to reduce noise/ error in RSSI [7], [8], [9], [19], [21], [22]. In reducing the effect of signal fluctuation, Kalman filter is combined with standard deviation classification (hard and light), path-loss model, and android library model [8]. Application of comparisons between mean absolute error (MAE) and root mean square error (RMSE) by various filters techniques to be used, namely simple moving average (SMA), static Kalman filter (KF-ST), dynamic Kalman filter (KF-DN), nonparametric information filter (NI) and particle filter (PF) [9]. To refined the real-time RSSI value, a Gaussian sum filter (GSF) algorithm is used through Wessersien distance (WD)-based clustering Gaussian mixture reduction (GMR) and simulates measurable non-gaussian noise RSSI as a GM distribution model that will be compared with GM-GM another with Bhattacharyya distance (BD), then the position is determined by two scenarios BD-GSF-GM model and the second scenario of the k-NN algorithm with a weight based on BD between the GSF output and GM- GM K-nearest zone distribution [10].

Fluctuate of RSSI value also happen due to environment condition. That generate fluctuation in distance and position prediction in indoor positioning system. That could be due to the different type of objects, size, material and movement. To encounter that problem, the calibration of RSSI respectively to distance, environmental coefficient calculation for each transmitter [29].

It is known that the influence of outdoor temperature and humidity affects the RSSI value of radio signals [11]. Changes in temperature have a negative correlation with the RSSI value, changes in humidity (relative humidity (RH)) have a positive correlation with the RSSI value and changes in absolute humidity (AH) have a negative correlation with the RSSI value. Then the effects of temperature and humidity can be used in this study to be used as environmental parameters to increase the accuracy of the RSSI-based pre-processing techniques in measuring the distance between the radio signal transmitter and receiver.

Also the variation of indoor temperature and humidity affects the RSSI value of wireless modules (Panstamp 2.0 NRG and built-in 868 MHz CC1101 radio ship) [18]. Between temperature and RSSI in distance of sender and receiver ≥ 5m, it show negative correlation. When temperature increasing the RSSI value is decreasing. This experiment also have same correlation when the sender and receiver is closer in 3m distance. For relative humidity (RH) variation with constant room temperature at 23°. The correlation between RH and RSSI is proportional linear. When RH increase the RSSI also increase in 7m distance as well as in closer distance in 3m. The experiment using different indoor temperature show the negative correlation at 22° and 12°C [19].

The best solution to reduce error value was the method that used KF with 6 trilateration method

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based on RSSI from each RSSI beacon. This filtering technique improved accuracy of distance estimation [8].

Refer to some researchers [11], [18], [19], [29] conducted experiment about the effect of environment change to the RSSI value of wireless communication especially temperature and humidity. From these case we try to improve the error value we proposed to combine the pre-processing techniques with environment changes parameter such as room temperature and humidity to check their effect to the RSSI value that will be used for distance and position prediction.

3. THEORY AND METHOD

The pre-processing process is carried out to enhance and improve the distance and position prediction quality with utilize the RSSI value of BLE signal by refining it or often called the filtering process. The pre-processing methods that will be used are the KF, SVR, and MLP.

3.1 RSSI Ranging

RSSI value used to represent the distance between sender and receiver of wireless device using the path-loss model of RSSI value as shown in equation (1) [3], [8], [26], [27]. At first, we need to collect some amount of RSSI value at 1m distance between sender and receiver device (parameter A) as shown in equation (2) [8]. To generate signal propagation (n) of device, it shown in equation (3) and from RSSI value we can calculate the distance as shown in equation (4):

$$RSSI = -(10n \log_{10} d + A) \tag{1}$$

$$A = \frac{1}{t}\sum_{i=1}^{t} RSSI_i \tag{2}$$

$$n = -\left(\frac{RSSI - A}{10 \log d}\right) \tag{3}$$

$$d = 10^{\left(\frac{A-RSSI}{10n}\right)} \tag{4}$$

Where, A is RSSI value at 1m distance, t is number of data, n is signal propagation and d is distance.

3.2 Kalman Filter (KF)

KF is a pre-processing method that used to reduce the fluctuated data input to be a stable series data output. The new data (RSSI) will correlate with previous filtered data that used to reduce the noise close to filtered series of data at each interval time. The fluctuated RSSI data will be predicted by KF to be more stable RSSI value at each time change (interval time) [7] that shown in equation (5), (6), and (7):

x is the RSSI at time step t:

$$x_t = RSSI(t) \tag{5}$$

Below is the KF design:

$$x_t = \dot{A}x_t + \varepsilon \tag{6}$$

Where ε is the noise (processed/ separated).

The model is designed using the relationship between RSSI at time step data and the received RSSI measurement/ calculated results.

$$Z_t = Hx_t + \mathbb{I} \tag{7}$$

Where Z_t is the RSSI measurement/ calculated at time step t. $\mathbb{I}$ is a measurement noise.

Every step of time from $t-1$ to t will be calculated the Kalman filter update, update the Kalman filter process for the RSSI at the time step, Kalman gain and variations for each time step $t-1$ to t show from equations (8), (9), (10), (11), and (12):

$$\hat{x}_t^- = \hat{x}_{t-1}^- \tag{8}$$

$$\bar{P}_t = P_{t-1} + Q \tag{9}$$

$$K_t = P_t^-(P_t^- + R)^{-1} = \frac{P_t^-}{P_t^- + R} \tag{10}$$

$$\hat{x}_t = \hat{x}_t^- + K_t(z_t - \hat{x}_t) \tag{11}$$

$$P_t = (1 - K_t)P_t^- \tag{12}$$

Where $\hat{x}_t^-$ is the predicted result at time step t, $\hat{x}_{t-1}^-$ is the predicted result at time step $t-1$, Q is the covariance of the processed noise, R is the covariance of the measurement noise, P_t^- is the variance of predicted error, P_t is the updated of variance error and K_t is the gain of Kalman in time step t.

3.3 Support Vector Regression (SVR)

SVR origin is from SVM (support vector machine) that supervised learning model used for linear and non-linear classification problems. SVM work to map/ transform the training data from input space to feature space in higher dimensional and make hyper plane for different classification data [31]. To solve the linear and non-linear regression problem that cannot solved by SVM, so that the idea of the SVR methods formulated [31], [32], [33], [34], [35], [39], [40].

SVR is supervised-learning model that built to create new boundary or tube pattern of most training data to be as narrow as possible for optimizing problem and minimize prediction error between predicted and desired result. This boundary should be matching to the continuous value function [13]. Equation (13) is the linear estimation function for support vector regression. T is the training dataset, $\emptyset(x)$ is the nonlinear mapping function that used to mapping the training dataset to $l(l > n)$ dimension feature.

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The optimized hyper plane is formed in this dimension [41]:

$$f(x) = w^T \emptyset(x) + b, \quad (13)$$

Subject to:

$T = \{(x_1, y_1), .., (x_n, y_n)\}$,
$i = 1,2, .., n$,
$x_i \in R^p, and\ y_i \in R^n$

Where, w is the l-dimension weight factor and b is the bias. Equation (14) for considering fitting error, C is penalty coefficient ζ_i and ζ_i^* are nonnegative relaxation parameters used to transform the optimized hyper plane to convex quadratic programming problem [41]:

$$\min R(w, b, \zeta, \zeta^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*), \quad (14)$$

Subject to:

$$y_i - f(x_i) \le \varepsilon + \zeta_i, i = 1, \ldots, n$$
$$f(x_i) - y_i \le \varepsilon + \zeta_i^*, i = 1, \ldots, n$$
$$\zeta_{i_i}, \zeta_i^* \ge 0, i = 1, \ldots, n$$

Lagrange multiplier α and α^* at equation (15) introduced to simplify calculation solution of the dual problem [41]:

$$\max R(\alpha_i^*, \alpha_j) = -\frac{1}{2}\sum_{i=1}^{n}\sum_{i=j}^{n}(\alpha_i^* - \alpha_i)\left(\alpha_j^* - \alpha_j\right)\phi^T(x_i)\phi(x_j) + \sum_{i=1}^{n} y_i\,(\alpha_i^* - \alpha_i) - \sum_{i=1}^{n}\varepsilon\,(\alpha_i^* - \alpha_i) \quad (15)$$

Subject to:

$$\sum_{i=1}^{n}(a_i - a_i^*) = 0$$
$$0 \le a_j, a_i^* \le C$$

Equation (16) is the SVR model for the non-linear mapping, after the Lagrange function [41]:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)\,K(x_i, x_j) + b \quad (16)$$

Equation (17) is the kernel function for radial basis function (RBF) that is machine learning most popular kernel function [41]:

$$K_{RBF}(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \quad (17)$$

Where, C is penalty factor and σ is kernel function.

3.4 Multilayer Perceptron (MLP)

Deep learning (DL) also called artificial neural network (ANN) branch of artificial intelligent that inspired from human neuroscience to process non-linear data. ANN consist of some layers that each layer contain some nodes/ neurons. Data received from input layer passing through the hidden layers and the final output at output layer. Each node from one layer as output connected to another node of another layer as input that have weight to be adjusted to fit the activation function output of target when training process [14], [15], [16], [17], [23], [25]. MLP is branch of science artificial neural network (ANN). MLP is a classification model for non-linear data that able solve regression problem to separate not linear data. MLP contain several straight line called perceptron that classified as input data into true and false categories [15]. The structure of how the MLP work to process the information is inspired from human brain. The ability of MLP to predict the continuous as well as the discrete variables, so that MLP have wide usage in different problem. When designing the MLP, number of layers (input, hidden and output) as well activation function need to be decided before processing. Equation (18) and (19) represent the output/ prediction for one hidden layer feed forward neural network defined [16]:

$$\tilde{y} = \delta_2\left(\sum_{i=1}^{m}\left(w_i^{(2)}\,\delta_1\,(X)\right) + b^{(2)}\right) \quad (18)$$

$$zX = \sum_{j=1}^{n}\left(X_j W_{xj}^{(1)}\right) + b^{(1)} \quad (19)$$

Where, $\tilde{y}$ is the MLP model vector of prediction, m is the dataset sample number, n is the dataset features number, X_j is the vector of the j^{th} feature, $w_i^{(2)}$ are the weights between hidden layer and the output layer, $w_i^{(1)}$ are the weights of inputs that connected to hidden layer δ_2 is the output layer activation function. δ_1 is the hidden layer neuron activation function. $b^{(2)}$ and $b^{(1)}$ are the bias vectors in output layer and hidden layer.

For activation function, Leaky-ReLU is applied for inputs to calculate the outputs of all nodes. The output is given by the following equation (20) [36] [37] [38]:

$$\text{Leaky} - \text{ReLU}(x) = \max(kx, x) \quad (20)$$
$$\begin{cases} x, if\ x > 0 \\ kx, if\ x \leq 0 \end{cases}$$

Where, x is the input value, k is approximate constant small value such as 0.01.

3.5 Trilateration Position Prediction

To predict position of the tracked object/ device, the trilateration method used. This method utilize the distance prediction result from at least three known reference position [28]. The object position determines at the center of intersection between at least three spherical surfaces of reference position radii [30]. Equation (21) show the trilateration calculation to:

$$r_1^2 = (x - x_1)^2 + (y - y_1)^2 \quad (21)$$
$$r_2^2 = (x - x_2)^2 + (y - y_2)^2$$
$$\vdots$$
$$r_3^2 = (x - x_n)^2 + (y - y_n)^2$$

Where, r is the radius of each reference point, x_n is the x coordinate of each reference point, y_n is the y coordinate of each reference point and x and y is the target coordinate.

4. METHODOLOGY

4.1 Data Collection

Data collection in this research conducted in one room with dimension 7m x 3m. The collected dataset will be used for calibration and prediction process.

4.1.1 BLE Reference Advertisement Node Setup

The BLE reference or advertisement node that used in this experiment is the BLE iBeacon nRF52832 which is equipped with a temperature and humidity sensor. Bluetooth signal transmission power is set at 0db which is emitted every 100ms. Where the information transmitted is Device Name, MAC Address, Manufacturer Data, and Service Data. The Service Data is contains each BLE iBeacon (BLE reference) temperature and humidity data.

4.1.2 Data Collection System

In this experiment WEMOS LOLIN ESP32 microcontroller used to collect data from BLE reference, which is connected to computer via USB interface. This microcontroller equipped with BT/ BLE and Wi-Fi features so it can receive Bluetooth advertisement data (from BLE reference). This microcontroller was programmed using the Arduino.ide compiler to perform BLE scanning that was active around it to get Device Name, MAC Address, Manufacturer Data, Service Data information and measure the RSSI value as shown in Figure 1.

The Arduino Uno r3 microcontroller used to get the temperature and humidity data close to the BLE receiver device using the BME280 5V sensor (temperature and humidity sensor). This microcontroller was programmed using the Arduino.ide compiler to perform temperature and humidity reading. This sensor is connected to the I2C interface (SDA and SCL pins) which is adjacent to the BLE receiver device (WEMOS LOLIN ESP32). This microcontroller was connected to computer via USB interface to transmit real-time temperature and humidity data during the log data process that shown in Figure 2.

The data log process uses 2 PLX-DAQ Simple Test.xls applications which were carried out every 1-second interval. Where the first application reads and records data from WEMOS LOLIN ESP32 with the following data sequence, namely: Date, Time, Device Name, MAC Address, RSSI, and Service Data. In the second application, it is used to read and record data from the Arduino Uno r3 with the following data sequence, namely: Date, Time, Temperature, and Humidity.

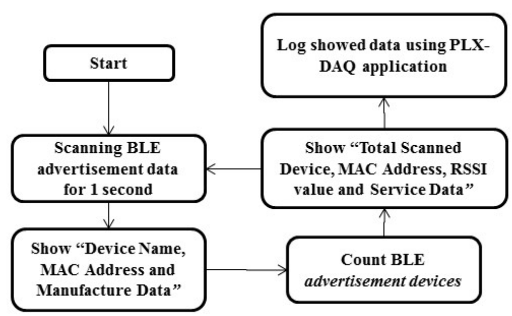

Figure 1: Flowchart of the BLE Advertisement Data Scanning Process on WEMOS LOLIN ESP32

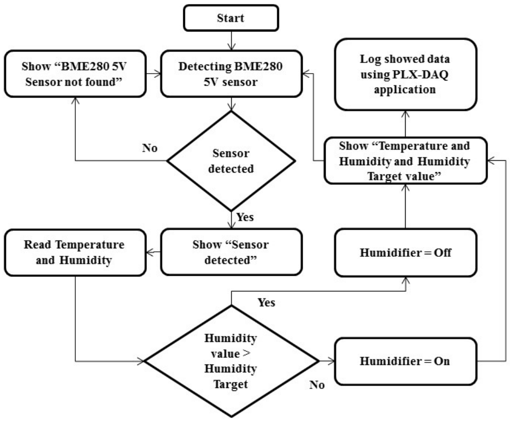

Figure 2: Flowchart of the Process of Reading Temperature and Humidity and Setting Air Humidity on the Arduino Uno r3

4.1.3 Room Temperature and Humidity Controlling System

Room cooling process has been done using a 1HP air conditioner. The temperature setting has been done using a remote control with a target of 16°C (lowest) but the measured temperature was +/-26°C. To get the highest temperature, the air conditioning was turned off and the measured temperature was +/-28°C.

Four humidifiers ware used to adjust room humidity as desired. As shown in Figure 3, the humidity regulator built using the TRIAC circuit. TRIAC circuit used to control the 220VAC input to turn on/ off the humidifiers. The turn on/ off the circuit were controlled by the Arduino Uno r3 microcontroller based on real-time humidity value that shown in Figure 6. The humidity setting ranges were between +/-61% and +/-78% at +/-26°C and +/-68% and +/-81% at +/-28°C.

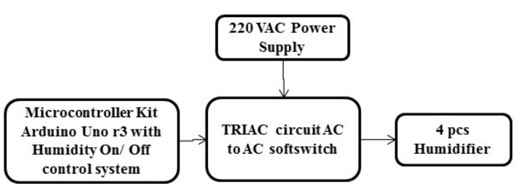

Figure 3: Humidifier Controlling System

4.2 Proposed Method

Figure 4 shows the proposed method for improving the RSSI-based distance prediction using three main distance prediction methods, they are without pre-processing, KF, SVR and MLP with utilizing the room temperature and humidity variance from each BLE reference and BLE receiver. The collected dataset will be used for three stages, they are training (60% dataset), validation (20% dataset) and testing (20% dataset). For each method and stage will be evaluated using MAPE, MAE and ME.

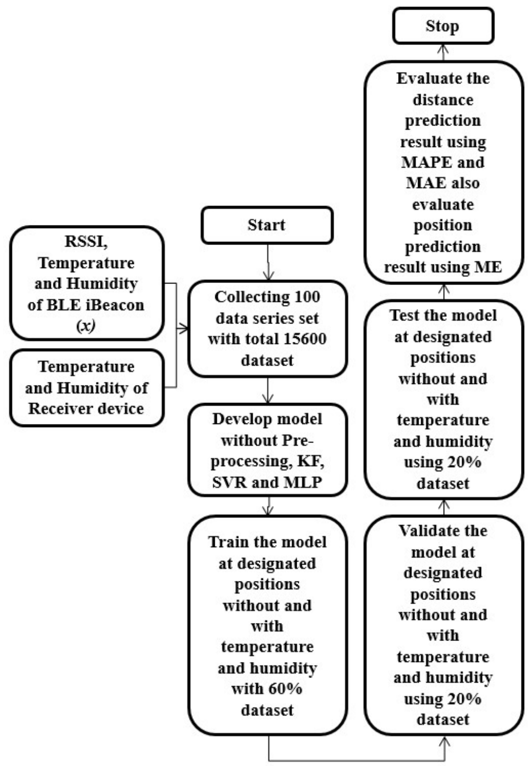

Figure 4: Proposed Methods Overview

4.2.1 Without Pre-Processing

The distance prediction using without pre-processing method was using the RSSI ranging with utilized parameter A and n for the degradation pattern (path-loss) of signal that calculated to raw RSSI value. The calculation of parameter A and n shown in Fig 5 that using all training dataset. The parameter A and n will be used to calculate distance prediction with RSSI value that shown in Fig 6.

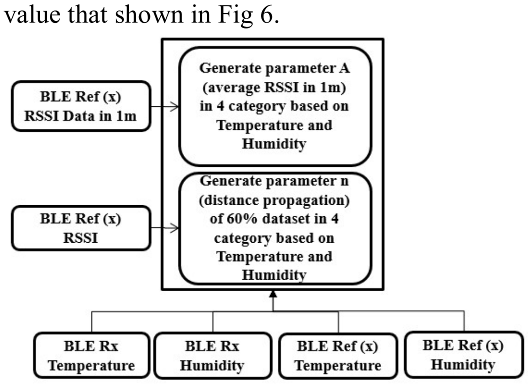

Figure 5: Calculation of Parameter A and n Process

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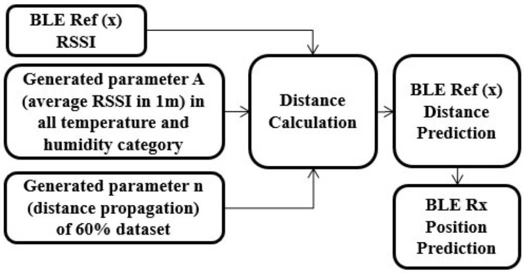

Figure 6: Without Pre-Processing Distance and Position Prediction Process

4.2.2 Kalman Filter

Kalman filter used to filtering the RSSI value, so it will reducing the fluctuation from RSSI value. The parameter A and n used to make signal degradation pattern (path-loss) that will calculated in two ways. There are with all collected dataset and with separated dataset according to temperature and humidity parameter to see the difference based on temperature and humidity changes that shown in Figure 5. The filtered RSSI value using KF, parameter A and n will be used for distance and position prediction that shown in Figure 7 and 8.

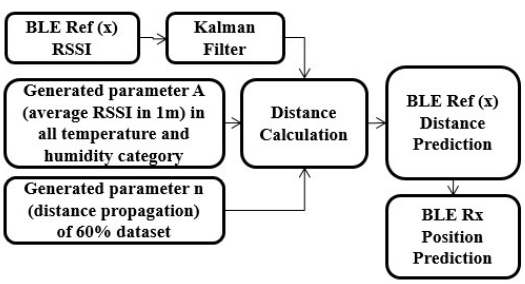

Figure 7: Kalman Filter Distance and Position Prediction Process

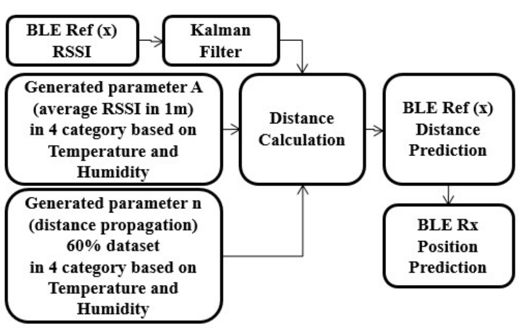

Figure 8: Kalman Filter with 4 Categories of A and n According Temperature and Humidity Distance and Position Prediction Process

4.2.3 Support Vector Regression

SVR used to create regression graph when in the training process utilizing RSSI, temperature and humidity parameter from BLE references and BLE receiver with actual distance parameter as output target. This process shown in Figure 9 and Figure 10. After training process completed the SVR regression graph will be used for distance and position prediction. Each prediction divided into 4 categories. First model utilize 1 BLE without temperature and humidity that have 1 input. Second model utilize 1 BLE with temperature and humidity that have 5 input. Third model utilize 4 BLE without temperature and humidity that have 4 input. Forth model utilize 4 BLE with temperature and humidity that have 14 input.

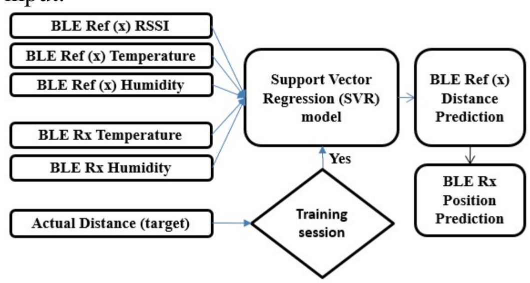

Figure 9: SVR Utilize 1 BLE Distance and Position Prediction Process

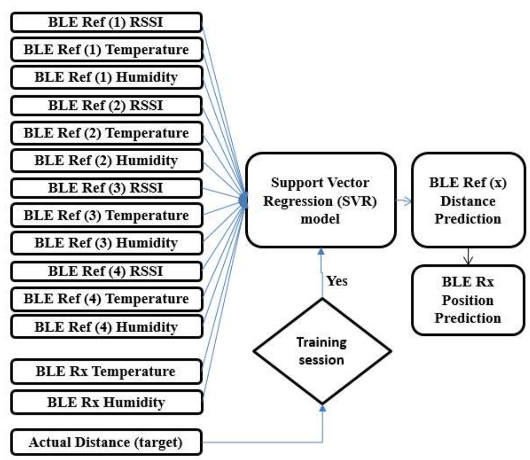

Figure 10: SVR Utilize 4 BLE Distance Prediction Process

4.2.4 Multilayer Perceptron

There are four MLP model developed in this experiment with one input layer, four hidden layer and one output layer. First model utilize 1 BLE without temperature and humidity that have 1 node of input layer. Second model utilize 1 BLE with temperature and humidity that have 5 node of input layer. Third model utilize 4 BLE without temperature and humidity that have 4 node of input layer. Forth model utilize 4 BLE with temperature and humidity that have 14 node of

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input layer. The hidden layer pattern of this model is consist of (36 x 48 x 36 x 10) nodes and for output layer is only 1 node. The actual distance is output target that used while training, validation, testing and evaluation. Each developed MLP model will be trained using training data that shown in Figure 11 and Figure 12. After training process completed the MLP model will be used to distance and position prediction.

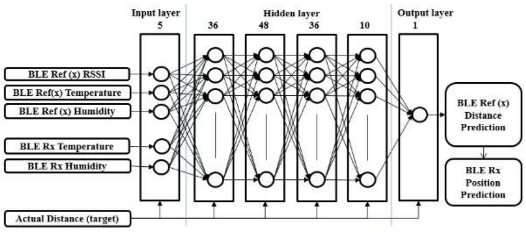

Figure 11: MLP Utilize 1 BLE Distance Prediction Process

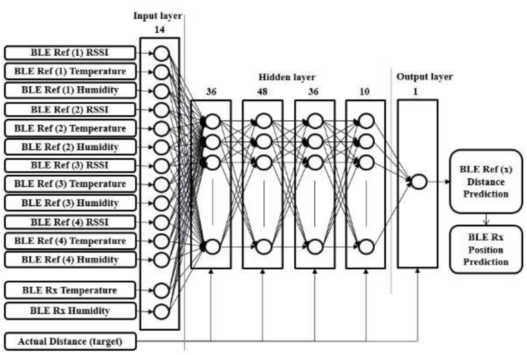

Figure 12: MLP Utilize 4 BLE Distance Prediction Process

4.3 Experimental Design

As shown in Figure 13, prior to data collection, it is necessary to perform temperature and humidity sensor calibration. This calibration conducted to get the correction of BLE references temperature and humidity sensor readings that refer to BME280 5V sensor (BLE receiver). To calibrate the sensors, four BLE iBeacons placed as close as possible to the BME280 5V and collect 600 data in 1 minute.

In this experimental design, we using the living room of a house with a size of 3m x 7m. For BLE reference, we using 4 BLE iBeacons. Figure 14 described the layout or placement of the 4 BLE references, BLE receiver, air conditioner, and 4 humidifiers. The room is not in a prefect square shape. To the west side of the room, there is an open door to the next room which is covered with plastic. To the north of the room, there is a section that juts north to enter two rooms and a toilet.

The orange circle is the BLE references location, yellow circle is the humidifier location and the green circle is the BLE receiver location which is moved every 0.5m. BLE receiver and the BLE reference were set in the same height at 44cm from the floor. 100 data were collected for each location according to Table 1.

Figure 13: BLE iBeacon and BME280 5V Temperature and Humidity Sensor Calibration

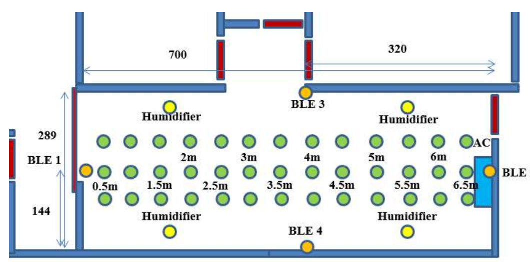

Figure 14: Experimental Design Sensors Placement Setup

Table 1: Data Collection Details

Temperature (°C) and Humidity (%RH)	Dataset collection			X Coordinate (m)												
	Y Coordinate (m)	°C	% RH	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5
	North side (1.945)	+/- 26	61	V	V	V	V	V	V	V	V	V	V	V	V	V
			78	V	V	V	V	V	V	V	V	V	V	V	V	V
			68	V	V	V	V	V	V	V	V	V	V	V	V	V

		+/- 28	**81**	V	V	V	V	V	V	V	V	V	V	V	V	V
	Middle (1.445)	**+/-**	**61**	V	V	V	V	V	V	V	V	V	V	V	V	V
		26	**78**	V	V	V	V	V	V	V	V	V	V	V	V	V
		+/-	**68**	V	V	V	V	V	V	V	V	V	V	V	V	V
		28	**81**	V	V	V	V	V	V	V	V	V	V	V	V	V
	South side (0.945)	**+/-**	**61**	V	V	V	V	V	V	V	V	V	V	V	V	V
		26	**78**	V	V	V	V	V	V	V	V	V	V	V	V	V
		+/-	**68**	V	V	V	V	V	V	V	V	V	V	V	V	V
		28	**81**	V	V	V	V	V	V	V	V	V	V	V	V	V

RSSI, temperature and humidity dataset from all BLEs was collected and divided for training, validation and testing. There is no training needed for the method without pre-processing and Kalman filter. But for SVR and MLP models will be trained to construct trained models. These model will trained in 4 categories, they are model that utilize 1 BLE RSSI without temperature and humidity, 1 BLE RSSI with temperature and humidity, 4 BLE RSSI without temperature and humidity also 4 BLE RSSI with temperature and humidity.

The results of the training model will be used to evaluate the trained data. Also will be used for validation using 20% of data and testing using 20% of data. The validation and testing result will be evaluated as well. Evaluation of measurement results will be carried out with the mean absolute percentage error (MAPE) that shown in equation (22) [17], [20], mean absolute error (MAE) that shown in equation (23) [6], [9], and mean error (ME) for position that shown in equation (24) [20], [24].

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n}\left|\frac{\mathrm{Actual\ Dist}_i - \mathrm{Predicted\ Dist}_i}{\mathrm{Actual\ Dist}_i}\right|}{n} \quad (22)$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}\left|\mathrm{Predicted\ Dist}_i - \mathrm{Actual\ Dist}_i\right|}{n} \quad (23)$$

$$\mathrm{Position\ Dist}_i = \sqrt{(\mathrm{x\ act}_i - \mathrm{x\ pred}_i)^2 + (\mathrm{y\ act}_i - \mathrm{y\ pre}}$$

$$\mathrm{ME} = \frac{\sum_{i=1}^{n}\mathrm{Position\ Dist}_i}{n} \quad (24)$$

Where, $x\ act$ is actual of BLE receiver x coordinate, $x\ pred$ is predicted of BLE receiver x coordinate, $y\ act$ is actual of BLE receiver y coordinate, $y\ pred$ is predicted of BLE receiver y coordinate, n is times of measurement and i is the data sequence.

5. RESULT & DISCUSSION

Table 2-3 show all mean absolute percentage error (MAPE) result and Table 4-5 show all mean absolute error (MAE) result in meter of distance prediction between each BLE references to BLE receiver. Table 6 show all mean error (ME) result of BLE receiver position prediction. These tables show the comparison between 11 pre-processing methods/ models. Also represent the training, validation and testing results for each BLE reference in four temperature and humidity condition. Position of BLE receiver are at x coordinate from 0.5m until 6.5m with interval 0.5m and y coordinate 1.445m.

Table 2 shows the MAPE of four BLEs reference distance prediction in high temperature-high humidity and high temperature-low humidity conditions. In high temperature-high humidity, average of MAPE testing results were 51.7% (without pre-processing), 41.4% (KF), 56.6% (KF with 4 categories A and n), 27.5% (SVR utilize 1 BLE with RSSI only), 22.6% (SVR utilize 1 BLE with RSSI, temperature and humidity), 28.9% (MLP utilize 1 BLE with RSSI only), 19.2% (MLP utilize 1 BLE with RSSI, temperature and humidity), 14.3% (SVR utilize 4 BLE with RSSI only), 14.4% (SVR utilize 4 BLE with RSSI, temperature and humidity), 13.2% (MLP utilize 4 BLE with RSSI only) and 10.0% (MLP utilize 4 BLE with RSSI, temperature and humidity). In high temperature-low humidity, average of MAPE testing results were 47.6% (without pre-processing), 43.1% (KF), 40.7% (KF with 4 categories A and n), 28.7% (SVR utilize 1 BLE with RSSI only), 26.1% (SVR utilize 1 BLE with RSSI, temperature and humidity), 30.6% (MLP utilize 1 BLE with RSSI only), 10.1% (MLP utilize 1 BLE with RSSI, temperature and humidity), 12.7% (SVR utilize 4 BLE with RSSI only), 9.3% (SVR utilize 4 BLE with RSSI, temperature and humidity), 11.3% (MLP utilize 4 BLE with RSSI only) and 5.7% (MLP utilize 4 BLE with RSSI, temperature and humidity).

Table 2: BLE Reference Distance Prediction MAPE of High Temperature - High Humidity and High Temperature - Low Humidity

MAPE*		High Temperature - High Humidity					High Temperature - Low Humidity				
		BLE 1	BLE 2	BLE 3	BLE 4	Avg	BLE 1	BLE 2	BLE 3	BLE 4	Avg
Without Pre-processing	Training	51.3%	35.6%	45.0%	58.9%	**47.7%**	38.3%	35.2%	66.9%	58.1%	**49.6%**
	Validation	49.3%	36.7%	44.2%	68.4%	**49.6%**	38.4%	33.0%	68.1%	57.0%	**49.1%**
	Testing	56.1%	35.8%	52.0%	62.7%	**51.7%**	38.4%	31.0%	58.7%	62.2%	**47.6%**
KF (All)	Training	32.0%	36.1%	37.0%	42.6%	**36.9%**	32.0%	32.7%	56.5%	47.5%	**42.2%**
	Validation	29.8%	36.0%	38.8%	49.4%	**38.5%**	31.9%	31.8%	63.5%	54.4%	**45.4%**
	Testing	36.3%	36.1%	46.2%	46.8%	**41.4%**	34.3%	28.9%	54.2%	54.9%	**43.1%**
KF (4 Categories of A and n)	Training	28.4%	39.6%	71.5%	50.5%	**47.5%**	33.8%	33.4%	51.2%	38.0%	**39.1%**
	Validation	27.3%	40.3%	78.5%	59.0%	**51.3%**	37.2%	33.3%	57.9%	44.4%	**43.2%**
	Testing	34.1%	39.7%	98.3%	54.5%	**56.6%**	39.4%	30.5%	49.2%	43.5%	**40.7%**
SVR 1 BLE with RSSI only	Training	34.4%	37.1%	19.1%	17.8%	**27.1%**	42.4%	29.4%	22.8%	23.8%	**29.6%**
	Validation	33.3%	36.9%	17.2%	18.7%	**26.5%**	40.3%	28.0%	22.6%	23.2%	**28.5%**
	Testing	35.0%	37.8%	19.3%	18.0%	**27.5%**	39.9%	28.4%	23.0%	23.5%	**28.7%**
SVR 1 BLE with RSSI, Temp and Humi	Training	19.4%	27.3%	18.9%	19.6%	**21.3%**	39.6%	30.2%	18.4%	20.3%	**27.1%**
	Validation	20.2%	27.5%	16.4%	20.3%	**21.1%**	37.4%	28.1%	17.4%	19.3%	**25.6%**
	Testing	22.5%	28.0%	18.5%	21.2%	**22.6%**	38.4%	27.9%	18.6%	19.6%	**26.1%**
MLP 1R BLE with RSSI only	Training	41.5%	34.4%	18.5%	19.7%	**28.5%**	49.2%	28.5%	22.7%	25.1%	**31.4%**
	Validation	40.6%	34.8%	17.0%	20.1%	**28.1%**	47.4%	26.8%	22.7%	23.9%	**30.2%**
	Testing	42.1%	34.4%	19.3%	19.8%	**28.9%**	48.1%	27.1%	23.1%	24.0%	**30.6%**
MLP 1 BLE with RSSI, Temp and Humi	Training	15.5%	19.0%	8.5%	12.5%	**13.9%**	7.7%	13.0%	5.8%	9.1%	**8.9%**
	Validation	18.3%	20.9%	10.3%	12.8%	**15.6%**	9.2%	13.6%	6.3%	10.8%	**10.0%**
	Testing	21.0%	25.0%	14.0%	17.0%	**19.2%**	10.1%	14.9%	6.0%	9.3%	**10.1%**
SVR 4 BLE with RSSI only	Training	17.8%	14.9%	10.3%	9.8%	**13.2%**	18.0%	14.8%	9.5%	12.1%	**13.6%**
	Validation	16.7%	13.9%	10.5%	9.1%	**12.6%**	17.3%	15.3%	9.7%	12.0%	**13.6%**
	Testing	21.0%	15.5%	10.9%	9.7%	**14.3%**	15.9%	13.8%	8.8%	12.3%	**12.7%**
SVR 4 BLE with RSSI, Temp and Humi	Training	18.5%	15.0%	8.9%	10.6%	**13.2%**	11.5%	10.9%	7.3%	7.8%	**9.4%**
	Validation	19.7%	16.2%	8.4%	9.3%	**13.4%**	10.0%	11.5%	6.8%	7.9%	**9.0%**
	Testing	21.5%	17.7%	8.9%	9.6%	**14.4%**	11.4%	10.6%	7.0%	8.2%	**9.3%**
MLP 4 BLE with RSSI only	Training	17.8%	13.0%	8.0%	8.2%	**11.8%**	17.8%	10.4%	8.3%	8.5%	**11.2%**
	Validation	18.3%	13.2%	9.5%	8.4%	**12.4%**	17.7%	10.7%	9.6%	9.2%	**11.8%**
	Testing	20.9%	13.7%	9.4%	9.0%	**13.2%**	17.3%	10.4%	8.9%	8.7%	**11.3%**
MLP 4 BLE with RSSI, Temp and Humi	Training	8.1%	8.5%	4.3%	4.4%	**6.3%**	6.3%	5.7%	3.6%	2.8%	**4.6%**
	Validation	10.5%	11.3%	6.3%	5.1%	**8.3%**	6.1%	5.9%	3.8%	3.7%	**4.9%**
	Testing	13.6%	13.1%	7.6%	5.7%	**10.0%**	7.2%	7.0%	4.2%	4.2%	**5.7%**

*The redder color indicates a larger error value, the greener color indicates a smaller error value

Table 3 shows the MAPE of four BLEs reference distance prediction in low temperature-high humidity and low temperature-low humidity conditions. In low temperature-high humidity, average of MAPE testing results were 42.6% (without pre-processing), 36.5% (KF), 35.0% (KF with 4 categories A and n), 25.9% (SVR utilize 1 BLE with RSSI only), 21.4% (SVR utilize 1 BLE

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with RSSI, temperature and humidity), 26.9% (MLP utilize 1 BLE with RSSI only), 20.9% (MLP utilize 1 BLE with RSSI, temperature and humidity), 12.8% (SVR utilize 4 BLE with RSSI only), 10.9% (SVR utilize 4 BLE with RSSI, temperature and humidity), 12.7% (MLP utilize 4 BLE with RSSI only) and 8.3% (MLP utilize 4 BLE with RSSI, temperature and humidity). In low temperature-low humidity, average of MAPE testing results were 43.2% (without pre-processing), 35.9% (KF), 36.4% (KF with 4 categories A and n), 26.0% (SVR utilize 1 BLE with RSSI only), 21.8% (SVR utilize 1 BLE with RSSI, temperature and humidity), 27.9% (MLP utilize 1 BLE with RSSI only), 20.1% (MLP utilize 1 BLE with RSSI, temperature and humidity), 11.1% (SVR utilize 4 BLE with RSSI only), 13.6% (SVR utilize 4 BLE with RSSI, temperature and humidity), 11.1% (MLP utilize 4 BLE with RSSI only) and 7.9% (MLP utilize 4 BLE with RSSI, temperature and humidity).

Table 3: BLE Reference Distance Prediction MAPE of Low Temperature – High Humidity and Low Temperature – Low Humidity

MAPE*		Low Temperature-High Humidity					Low Temperature-Low Humidity				
		BLE 1	BLE 2	BLE 3	BLE 4	Avg	BLE 1	BLE 2	BLE 3	BLE 4	Avg
Without Pre-processing	Training	40.0%	41.2%	49.9%	41.4%	**43.1%**	38.3%	35.9%	60.3%	50.8%	**46.3%**
	Validation	37.7%	35.1%	47.9%	40.2%	**40.2%**	39.1%	35.4%	53.7%	48.1%	**44.1%**
	Testing	43.0%	41.1%	47.4%	39.1%	**42.6%**	39.3%	35.2%	47.5%	51.0%	**43.2%**
KF (All)	Training	29.2%	36.3%	39.0%	38.0%	**35.6%**	25.7%	33.3%	51.1%	40.0%	**37.5%**
	Validation	29.5%	33.3%	39.4%	37.5%	**34.9%**	27.5%	33.3%	43.9%	39.6%	**36.1%**
	Testing	32.6%	37.3%	39.8%	36.3%	**36.5%**	29.3%	32.8%	42.6%	39.1%	**35.9%**
KF (4 Categories of A and n)	Training	30.2%	36.6%	30.1%	38.6%	**33.9%**	27.9%	30.9%	48.5%	42.9%	**37.6%**
	Validation	31.0%	33.3%	30.9%	38.3%	**33.4%**	29.3%	30.3%	42.8%	42.5%	**36.2%**
	Testing	33.2%	39.5%	30.1%	37.2%	**35.0%**	31.3%	29.9%	42.4%	42.0%	**36.4%**
SVR 1 BLE with RSSI only	Training	41.9%	31.4%	16.8%	19.1%	**27.3%**	33.1%	28.3%	19.3%	22.2%	**25.7%**
	Validation	41.5%	31.7%	16.4%	18.0%	**26.9%**	33.0%	29.0%	19.0%	22.3%	**25.8%**
	Testing	37.8%	31.1%	17.0%	17.8%	**25.9%**	34.8%	28.7%	17.2%	23.2%	**26.0%**
SVR 1 BLE with RSSI, Temp and Humi	Training	44.8%	20.9%	12.3%	7.0%	**21.2%**	18.2%	25.3%	16.1%	15.4%	**18.8%**
	Validation	44.8%	23.0%	11.9%	7.2%	**21.7%**	18.5%	27.6%	16.3%	15.9%	**19.6%**
	Testing	44.6%	21.6%	11.9%	7.4%	**21.4%**	20.5%	31.8%	15.4%	19.7%	**21.8%**
MLP 1 BLE with RSSI only	Training	42.7%	31.0%	17.4%	20.2%	**27.8%**	38.3%	28.9%	19.4%	23.0%	**27.4%**
	Validation	41.6%	29.7%	16.9%	19.2%	**26.9%**	39.1%	29.3%	19.8%	23.5%	**27.9%**
	Testing	40.9%	30.2%	17.6%	19.1%	**26.9%**	40.7%	28.6%	18.4%	24.0%	**27.9%**
MLP 1 BLE with RSSI, Temp and Humi	Training	14.5%	13.8%	5.4%	3.8%	**9.4%**	9.4%	22.3%	4.9%	6.3%	**10.7%**
	Validation	31.1%	14.5%	5.6%	5.4%	**14.2%**	13.6%	29.2%	9.1%	11.0%	**15.7%**
	Testing	54.9%	14.9%	7.0%	6.8%	**20.9%**	17.0%	29.0%	16.2%	18.3%	**20.1%**
SVR 4 BLE with RSSI only	Training	20.0%	13.4%	9.2%	9.0%	**12.9%**	13.6%	12.4%	8.7%	10.5%	**11.3%**
	Validation	18.9%	13.6%	9.2%	8.3%	**12.5%**	14.0%	13.0%	8.6%	9.7%	**11.3%**
	Testing	19.4%	13.9%	9.2%	8.7%	**12.8%**	13.4%	11.0%	8.8%	11.2%	**11.1%**
SVR 4 BLE with RSSI, Temp and Humi	Training	16.1%	12.1%	5.6%	5.6%	**9.8%**	14.4%	9.9%	6.9%	6.5%	**9.4%**
	Validation	15.2%	13.1%	6.1%	6.0%	**10.1%**	16.6%	12.3%	7.5%	6.3%	**10.7%**
	Testing	17.3%	14.9%	6.0%	5.5%	**10.9%**	21.7%	13.9%	8.5%	10.2%	**13.6%**
	Training	19.2%	12.1%	7.1%	8.2%	**11.7%**	13.6%	10.6%	7.1%	8.5%	**10.0%**

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MLP 4 BLE with RSSI only	Validation	19.8%	13.2%	7.5%	8.1%	**12.2%**	13.8%	11.4%	8.4%	8.6%	**10.6%**
	Testing	20.6%	13.7%	8.1%	8.2%	**12.7%**	15.0%	11.6%	8.1%	9.6%	**11.1%**
MLP 4 BLE with RSSI, Temp and Humi	Training	6.8%	5.5%	3.1%	3.7%	**4.8%**	6.5%	6.3%	3.5%	3.9%	**5.0%**
	Validation	9.3%	8.7%	3.7%	4.5%	**6.5%**	8.2%	6.2%	3.7%	5.5%	**5.9%**
	Testing	12.1%	12.1%	4.3%	4.7%	**8.3%**	11.0%	8.1%	5.2%	7.3%	**7.9%**

*The redder color indicates a larger error value, the greener color indicates a smaller error value

Table 4 shows the MAE of four BLEs reference distance prediction in high temperature-high humidity and high temperature-low humidity conditions. In high temperature-high humidity, average of MAE testing results were 1.413m (without pre-processing), 1.147m (KF), 1.497m (KF with 4 categories A and n), 0.697m (SVR utilize 1 BLE with RSSI only), 0.556m (SVR utilize 1 BLE with RSSI, temperature and humidity), 0.725m (MLP utilize 1 BLE with RSSI only), 0.492m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.321m (SVR utilize 4 BLE with RSSI only), 0.323m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.311m (MLP utilize 4 BLE with RSSI only) and 0.223m (MLP utilize 4 BLE with RSSI, temperature and humidity). In high temperature-low humidity, average of MAE testing results were 1.277m (without pre-processing), 1.178m (KF), 1.161m (KF with 4 categories A and n), 0.719m (SVR utilize 1 BLE with RSSI only), 0.659m (SVR utilize 1 BLE with RSSI, temperature and humidity), 0.738m (MLP utilize 1 BLE with RSSI only), 0.203m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.286m (SVR utilize 4 BLE with RSSI only), 0.199m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.272m (MLP utilize 4 BLE with RSSI only) and 0.124m (MLP utilize 4 BLE with RSSI, temperature and humidity).

Table 4: BLE Reference Distance Prediction MAE of High Temperature-High Humidity and High Temperature-Low Humidity

MAE (meter)*		High Temperature-High Humidity					High Temperature-Low Humidity				
		BLE 1	BLE 2	BLE 3	BLE 4	Avg	BLE 1	BLE 2	BLE 3	BLE 4	Avg
Without Pre-processing	Training	1.794	1.286	0.945	1.385	**1.352**	1.401	1.226	1.381	1.293	**1.325**
	Validation	1.814	1.330	0.949	1.662	**1.439**	1.400	1.164	1.373	1.284	**1.305**
	Testing	1.791	1.318	1.062	1.481	**1.413**	1.409	1.084	1.209	1.406	**1.277**
KF (All)	Training	1.049	1.312	0.742	1.049	**1.038**	1.173	1.147	1.144	1.073	**1.134**
	Validation	0.990	1.325	0.844	1.268	**1.107**	1.162	1.149	1.260	1.226	**1.199**
	Testing	1.175	1.321	0.928	1.162	**1.147**	1.303	1.031	1.110	1.266	**1.178**
KF (4 Categories of A and n)	Training	1.031	1.338	1.529	1.263	**1.290**	1.297	1.225	1.041	0.824	**1.097**
	Validation	1.003	1.362	1.848	1.540	**1.438**	1.372	1.245	1.158	0.965	**1.185**
	Testing	1.196	1.353	2.078	1.363	**1.497**	1.528	1.134	1.012	0.970	**1.161**
SVR 1 BLE with RSSI only	Training	0.994	1.046	0.395	0.338	**0.693**	1.197	0.871	0.469	0.436	**0.743**
	Validation	0.944	1.066	0.362	0.356	**0.682**	1.157	0.843	0.465	0.422	**0.722**
	Testing	0.988	1.060	0.396	0.342	**0.697**	1.142	0.841	0.467	0.426	**0.719**
SVR 1 BLE with RSSI, Temp and Humi	Training	0.648	0.683	0.390	0.363	**0.521**	1.185	0.782	0.372	0.409	**0.687**
	Validation	0.676	0.708	0.347	0.373	**0.526**	1.130	0.719	0.350	0.388	**0.647**
	Testing	0.730	0.726	0.378	0.388	**0.556**	1.177	0.699	0.369	0.391	**0.659**
MLP 1 BLE with RSSI only	Training	1.057	1.069	0.382	0.371	**0.720**	1.209	0.904	0.467	0.459	**0.760**
	Validation	1.027	1.087	0.358	0.380	**0.713**	1.183	0.871	0.464	0.434	**0.738**
	Testing	1.066	1.065	0.395	0.372	**0.725**	1.191	0.855	0.470	0.434	**0.738**
	Training	0.421	0.550	0.178	0.246	**0.349**	0.160	0.301	0.117	0.178	**0.189**

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MLP 1 BLE with RSSI, Temp and Humi	Validation	0.547	0.642	0.215	0.256	**0.415**	0.205	0.252	0.134	0.201	**0.198**
	Testing	0.644	0.704	0.296	0.323	**0.492**	0.232	0.268	0.130	0.183	**0.203**
SVR 4 BLE with RSSI only	Training	0.397	0.398	0.207	0.197	**0.300**	0.420	0.410	0.188	0.225	**0.311**
	Validation	0.370	0.369	0.209	0.183	**0.283**	0.423	0.411	0.191	0.223	**0.312**
	Testing	0.437	0.438	0.215	0.195	**0.321**	0.380	0.372	0.172	0.220	**0.286**
SVR 4 BLE with RSSI, Temp and Humi	Training	0.405	0.407	0.174	0.206	**0.298**	0.253	0.254	0.145	0.157	**0.202**
	Validation	0.408	0.410	0.168	0.185	**0.293**	0.237	0.238	0.133	0.155	**0.191**
	Testing	0.468	0.467	0.169	0.188	**0.323**	0.247	0.248	0.141	0.160	**0.199**
MLP 4 BLE with RSSI only	Training	0.465	0.319	0.154	0.162	**0.275**	0.422	0.321	0.160	0.162	**0.266**
	Validation	0.445	0.364	0.181	0.167	**0.289**	0.441	0.334	0.180	0.172	**0.282**
	Testing	0.490	0.397	0.177	0.178	**0.311**	0.422	0.340	0.168	0.158	**0.272**
MLP 4 BLE with RSSI, Temp and Humi	Training	0.164	0.168	0.095	0.090	**0.130**	0.131	0.127	0.080	0.057	**0.099**
	Validation	0.227	0.255	0.132	0.108	**0.181**	0.121	0.142	0.086	0.075	**0.106**
	Testing	0.308	0.303	0.159	0.121	**0.223**	0.143	0.177	0.091	0.083	**0.124**

*The redder color indicates a larger error value, the greener color indicates a smaller error value

Table 5 shows the MAE of four BLEs reference distance prediction in low temperature-high humidity and low temperature-low humidity conditions. In low temperature-high humidity, average of MAE testing results were 1.264m (without pre-processing), 1.068m (KF), 0.986m (KF with 4 categories A and n), 0.688m (SVR utilize 1 BLE with RSSI only), 0.479m (SVR utilize 1 BLE with RSSI, temperature and humidity), 0.701m (MLP utilize 1 BLE with RSSI only), 0.478m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.296m (SVR utilize 4 BLE with RSSI only), 0.245m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.307m (MLP utilize 4 BLE with RSSI only) and 0.157m (MLP utilize 4 BLE with RSSI, temperature and humidity). In low temperature-low humidity, average of MAE testing results were 1.308m (without pre-processing), 1.082m (KF), 1.107m (KF with 4 categories A and n), 0.713m (SVR utilize 1 BLE with RSSI only), 0.517m (SVR utilize 1 BLE with RSSI, temperature and humidity), 0.739m (MLP utilize 1 BLE with RSSI only), 0.431m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.250m (SVR utilize 4 BLE with RSSI only), 0.305m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.263m (MLP utilize 4 BLE with RSSI only) and 0.184m (MLP utilize 4 BLE with RSSI, temperature and humidity).

Table 5: BLE Reference Distance Prediction MAE of Low Temperature-High Humidity and Low Temperature-Low Humidity

MAE (meter)*		Low Temperature-High Humidity					Low Temperature-Low Humidity				
		BLE 1	BLE 2	BLE 3	BLE 4	Avg	BLE 1	BLE 2	BLE 3	BLE 4	Avg
Without Pre-processing	Training	1.533	1.424	1.071	1.027	**1.264**	1.525	1.333	1.395	1.164	**1.354**
	Validation	1.467	1.245	1.056	1.015	**1.196**	1.581	1.350	1.236	1.120	**1.322**
	Testing	1.643	1.391	1.028	0.994	**1.264**	1.582	1.332	1.127	1.189	**1.308**
KF (All)	Training	1.073	1.311	0.855	0.945	**1.046**	0.990	1.234	1.180	0.923	**1.082**
	Validation	1.102	1.210	0.875	0.951	**1.035**	1.087	1.253	1.040	0.927	**1.077**
	Testing	1.165	1.315	0.856	0.935	**1.068**	1.162	1.218	0.999	0.948	**1.082**
KF (4 Categories of A and n)	Training	1.048	1.133	0.666	0.966	**0.953**	0.981	1.308	1.114	1.002	**1.101**
	Validation	1.087	1.038	0.689	0.977	**0.948**	1.059	1.303	1.001	1.011	**1.093**
	Testing	1.120	1.200	0.661	0.963	**0.986**	1.142	1.270	0.980	1.035	**1.107**

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SVR 1 BLE with RSSI only	**Training**	1.169	0.932	0.378	0.385	**0.716**	1.043	0.871	0.418	0.429	**0.690**
	Validation	1.173	0.935	0.365	0.365	**0.710**	1.060	0.910	0.410	0.427	**0.702**
	Testing	1.080	0.928	0.381	0.365	**0.688**	1.122	0.910	0.376	0.445	**0.713**
SVR 1 BLE with RSSI, Temp and Humi	**Training**	1.051	0.461	0.282	0.147	**0.485**	0.424	0.681	0.351	0.312	**0.442**
	Validation	1.058	0.483	0.262	0.150	**0.488**	0.468	0.751	0.351	0.315	**0.471**
	Testing	1.020	0.468	0.268	0.159	**0.479**	0.507	0.845	0.327	0.387	**0.517**
MLP 1 BLE with RSSI only	**Training**	1.115	0.978	0.388	0.398	**0.720**	1.070	0.932	0.416	0.435	**0.713**
	Validation	1.107	0.943	0.372	0.380	**0.700**	1.099	0.963	0.422	0.444	**0.732**
	Testing	1.074	0.960	0.391	0.377	**0.701**	1.165	0.939	0.397	0.453	**0.739**
MLP 1 BLE with RSSI, Temp and Humi	**Training**	0.344	0.232	0.114	0.085	**0.194**	0.225	0.386	0.108	0.138	**0.214**
	Validation	0.761	0.301	0.124	0.115	**0.325**	0.281	0.553	0.207	0.239	**0.320**
	Testing	1.300	0.303	0.153	0.155	**0.478**	0.408	0.545	0.378	0.394	**0.431**
SVR 4 BLE with RSSI only	**Training**	0.417	0.416	0.191	0.187	**0.303**	0.337	0.327	0.173	0.205	**0.260**
	Validation	0.397	0.399	0.187	0.171	**0.288**	0.357	0.342	0.170	0.189	**0.264**
	Testing	0.405	0.407	0.190	0.180	**0.296**	0.311	0.294	0.176	0.217	**0.250**
SVR 4 BLE with RSSI, Temp and Humi	**Training**	0.327	0.330	0.119	0.116	**0.223**	0.275	0.273	0.146	0.135	**0.207**
	Validation	0.332	0.335	0.127	0.122	**0.229**	0.339	0.336	0.156	0.130	**0.240**
	Testing	0.368	0.370	0.128	0.114	**0.245**	0.421	0.414	0.177	0.206	**0.305**
MLP 4 BLE with RSSI only	**Training**	0.429	0.389	0.138	0.167	**0.281**	0.348	0.303	0.139	0.167	**0.239**
	Validation	0.457	0.411	0.147	0.169	**0.296**	0.367	0.326	0.160	0.165	**0.255**
	Testing	0.461	0.439	0.160	0.168	**0.307**	0.372	0.333	0.157	0.189	**0.263**
MLP 4 BLE with RSSI, Temp and Humi	**Training**	0.110	0.111	0.071	0.077	**0.092**	0.120	0.138	0.079	0.081	**0.104**
	Validation	0.161	0.156	0.088	0.092	**0.124**	0.166	0.164	0.079	0.114	**0.131**
	Testing	0.216	0.207	0.104	0.101	**0.157**	0.235	0.240	0.110	0.151	**0.184**

*The redder color indicates a larger error value, the greener color indicates a smaller error value

Table 6 shows the ME of position prediction in high temperature-high humidity, high temperature-low humidity, low temperature-high humidity and low temperature-low humidity conditions. In high temperature-high humidity, ME testing results were 4.381m (without pre-processing), 2.713m (KF), 4.937m (KF with 4 categories A and n), 1.248m (SVR utilize 1 BLE with RSSI only), 0.962m (SVR utilize 1 BLE with RSSI, temperature and humidity), 1.262m (MLP utilize 1 BLE with RSSI only), 0.844m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.503m (SVR utilize 4 BLE with RSSI only), 0.495m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.491m (MLP utilize 4 BLE with RSSI only) and 0.330m (MLP utilize 4 BLE with RSSI, temperature and humidity). In high temperature-low humidity, ME testing results were 3.572m (without pre-processing), 2.805m (KF), 2.548m (KF with 4 categories A and n), 1.231m (SVR utilize 1 BLE with RSSI only), 1.083m (SVR utilize 1 BLE with RSSI, temperature and humidity), 1.240m (MLP utilize 1 BLE with RSSI only), 0.226m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.447m (SVR utilize 4 BLE with RSSI only), 0.269m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.423m (MLP utilize 4 BLE with RSSI only) and 0.171m (MLP utilize 4 BLE with RSSI, temperature and humidity). In low temperature-high humidity, ME testing results were 3.286m (without pre-processing), 2.306m (KF), 2.278m (KF with 4 categories A and n), 1.167m (SVR utilize 1 BLE with RSSI only), 0.802m (SVR utilize 1 BLE with RSSI, temperature and humidity), 1.215m (MLP utilize 1 BLE with RSSI only), 0.930m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.487m (SVR utilize 4 BLE with RSSI only), 0.379m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.485m (MLP utilize 4 BLE with RSSI only) and 0.239m (MLP utilize

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4 BLE with RSSI, temperature and humidity). In low temperature-high humidity, ME testing results were 3.435m (without pre-processing), 2.360m (KF), 2.450m (KF with 4 categories A and n), 1.210m (SVR utilize 1 BLE with RSSI only), 0.821m (SVR utilize 1 BLE with RSSI, temperature and humidity), 1.253m (MLP utilize 1 BLE with RSSI only), 0.585m (MLP utilize 1 BLE with RSSI, temperature and humidity), 0.389m (SVR utilize 4 BLE with RSSI only), 0.479m (SVR utilize 4 BLE with RSSI, temperature and humidity), 0.395m (MLP utilize 4 BLE with RSSI only) and 0.277m (MLP utilize 4 BLE with RSSI, temperature and humidity).

Table 6: BLE Reference Position Prediction ME

ME (meter)*		High Temperature	High Temperature	Low Temperature	Low Temperature
		High Humidity	Low Humidity	High Humidity	Low Humidity
Without Pre-processing	Training	4.172	3.836	3.228	3.998
	Validation	5.095	3.839	2.977	3.407
	Testing	4.381	3.572	3.286	3.435
KF (All)	Training	2.384	2.599	2.150	2.503
	Validation	2.883	3.168	2.174	2.405
	Testing	2.713	2.805	2.306	2.360
KF (4 Categories of A and n)	Training	3.528	2.344	2.078	2.507
	Validation	4.429	2.806	2.091	2.419
	Testing	4.937	2.548	2.278	2.450
SVR 1 BLE with RSSI only	Training	1.240	1.274	1.209	1.160
	Validation	1.218	1.249	1.198	1.189
	Testing	1.248	1.231	1.167	1.210
SVR 1 BLE with RSSI, Temp and Humi	Training	0.869	1.128	0.797	0.673
	Validation	0.896	1.071	0.823	0.743
	Testing	0.962	1.083	0.802	0.821
MLP 1 BLE with RSSI only	Training	1.259	1.277	1.228	1.210
	Validation	1.242	1.245	1.210	1.236
	Testing	1.262	1.240	1.215	1.253
MLP 1 BLE with RSSI, Temp and Humi	Training	0.556	0.251	0.300	0.314
	Validation	0.673	0.222	0.592	0.422
	Testing	0.844	0.226	0.930	0.585
SVR 4 BLE with RSSI only	Training	0.465	0.484	0.495	0.405
	Validation	0.450	0.482	0.479	0.415
	Testing	0.503	0.447	0.487	0.389
SVR 4 BLE with RSSI, Temp and Humi	Training	0.449	0.271	0.338	0.316
	Validation	0.440	0.257	0.344	0.382
	Testing	0.495	0.269	0.379	0.479
MLP 4 BLE with RSSI only	Training	0.435	0.412	0.453	0.366
	Validation	0.456	0.437	0.475	0.388
	Testing	0.491	0.423	0.485	0.395
MLP 4 BLE with RSSI, Temp and Humi	Training	0.190	0.136	0.138	0.144
	Validation	0.265	0.154	0.186	0.193

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	Testing	0.330	0.171	0.239	0.277

*The redder color indicates a larger error value, the greener color indicates a smaller error value

We can observe from MAPE, MAE and ME evaluation results that shown MLP yield gave best distance and position prediction accuracy. The pre-processing method (SVR and MLP) that utilize 4 BLE references giving better distance and position prediction result compared to pre-processing method that utilizes 1 BLE reference. Because of 4 RSSI value from 4 BLE will reduce each other's error. The utilizing temperature and humidity parameters also giving lower error and higher accuracy compared to methods that not utilize temperature and humidity parameters.

Figure 15 – 26 show the graphs that represent the methods testing results for BLE 1 in high temperature-low humidity condition. The BLE receiver position are in x coordinate from 0.5m to 6.5m with 0.5m interval step and y coordinate at 1.445m. Figure 15 shows the graph of raw RSSI vs filtered RSSI using KF. Figure 16 shows the graph of distance prediction using signal path-loss calculation without pre-processing model vs actual distances. Figure 17 shows the graph of distance prediction using signal path-loss calculation with filtered RSSI using KF with same parameter A and n vs actual distances. Figure 18 shows the graph of distance prediction using path-loss calculation with filtered RSSI using KF with various A and n according to various temperature and humidity.

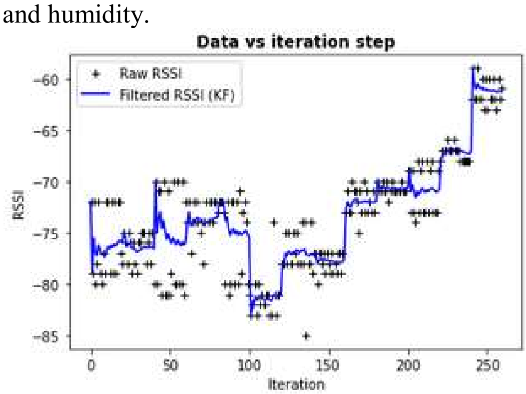

Figure 15: Raw RSSI vs filtered RSSI using KF

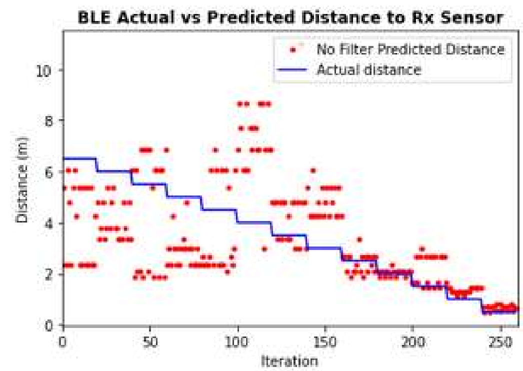

Figure 16: Without Pre-Processing Model Distance Prediction

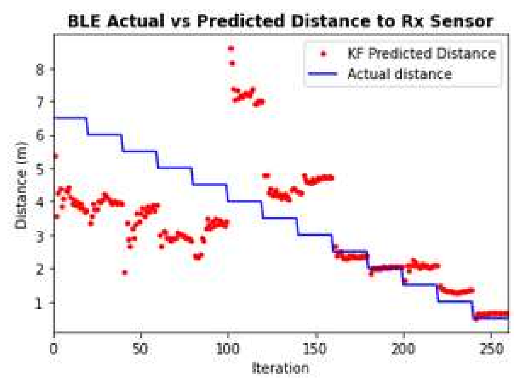

Figure 17: KF Model Distance Prediction

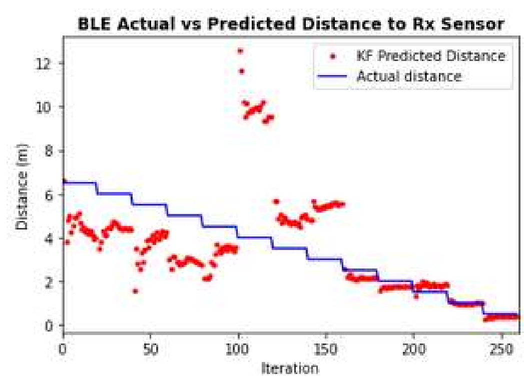

Figure 18: KF with 4 Categories of A and n according temperature and humidity Model Distance Prediction

Figure 19 shows the graph of distance prediction using SVR with 1 BLE not utilized temperature and humidity parameters vs actual distances. Figure 20 shows the graph of distance prediction using SVR with 1 BLE utilized temperature and humidity parameters vs actual distances.

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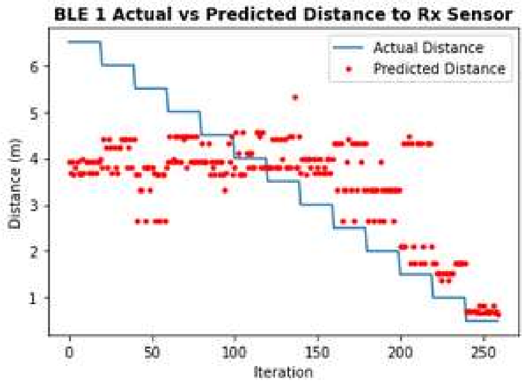

Figure 19: SVR Utilize 1 BLE without Temperature and Humidity Model Distance Prediction

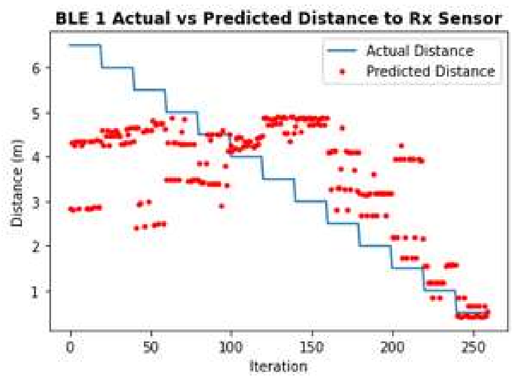

Figure 20: SVR Utilize 1 BLE with Temperature and Humidity Model Distance Prediction

Figure 21 shows the graph of distance prediction using MLP with 1 BLE not utilized temperature and humidity parameters vs actual distances. Figure 22 shows the graph of distance prediction using MLP with 1 BLE utilized temperature and humidity parameters vs actual distances.

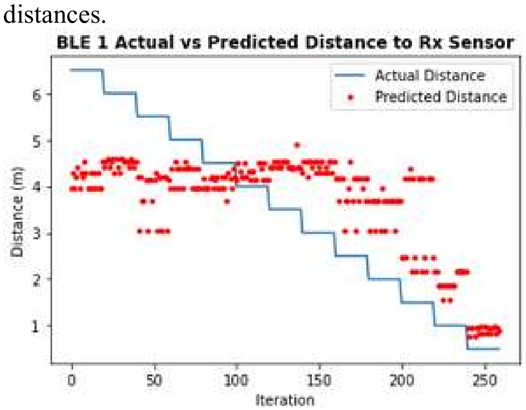

Figure 21: MLP Utilize 1 BLE without Temperature and Humidity Model Distance Prediction

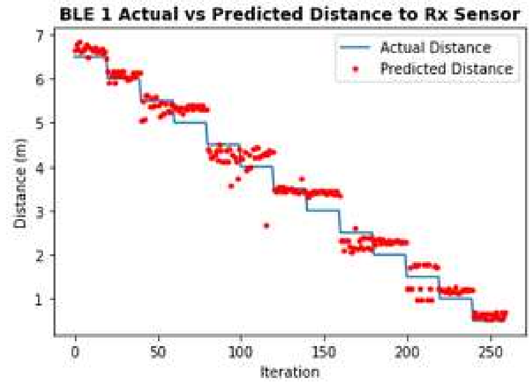

Figure 22: MLP Utilize 1 BLE with Temperature and Humidity Model Distance Prediction

Figure 23 shows the graph of distance prediction using SVR with 4 BLE not utilized temperature and humidity parameters vs actual distances. Figure 24 shows the graph of distance prediction using SVR with 4 BLE utilized temperature and humidity parameters vs actual distances.

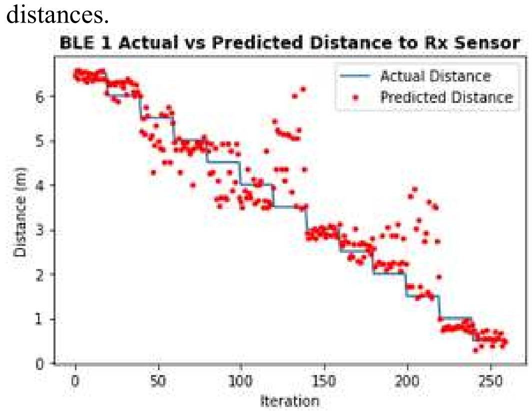

Figure 23: SVR Utilize 4 BLE without Temperature and Humidity Model Distance Prediction

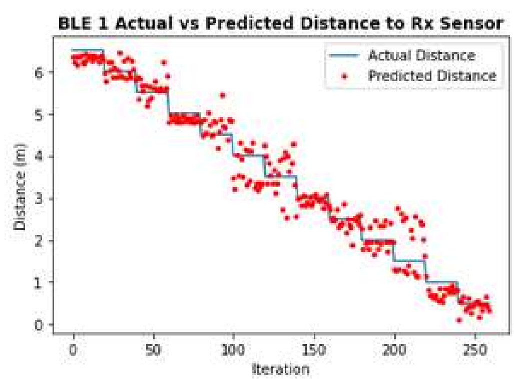

Figure 24: SVR Utilize 4 BLE with Temperature and Humidity Model Distance Prediction

Figure 25 shows the graph of distance prediction using MLP with 4 BLE not utilized temperature and humidity parameters vs actual distances. Figure 26 shows the graph of distance prediction using MLP with 4 BLE utilized temperature and humidity parameters vs actual distances.

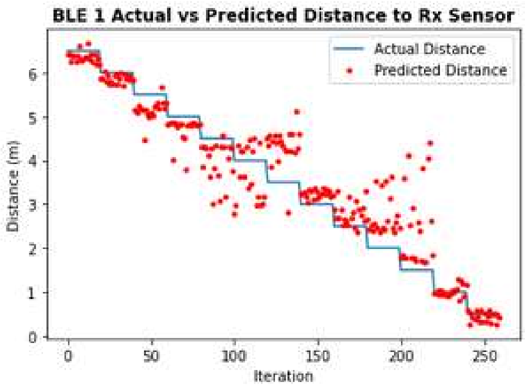

Figure 25: MLP Utilize 4 BLE without Temperature and Humidity Model Distance Prediction

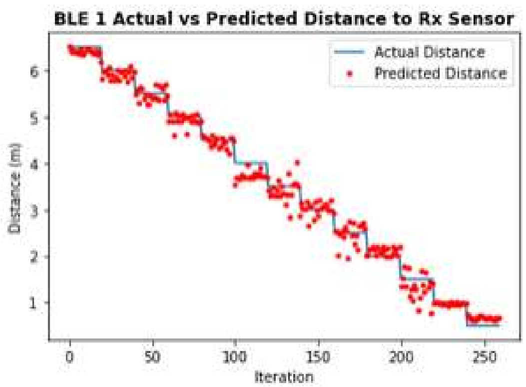

Figure 26: MLP Utilize 4 BLE with Temperature and Humidity Model Distance Prediction

From the visual graphs of distance prediction, the MLP method that utilizes 4 BLE with temperature and humidity parameters (Figure 26) shows the best distance prediction results (red dots) which results are closest to the actual distances (blue line) that compared to others methods. The method without pre-processing (Figure 16) shows the highest distance prediction errors resulting from fluctuation of RSSI values. Both KF methods (Figure 17 and 18) show better distance prediction than the model without pre-processing, but the error is getting higher when the distance between BLE reference and receiver is getting farther. SVR method that utilize 1 BLE with temperature and humidity parameters (Figure 20) gives slightly lesser error compare to the method without temperature and humidity parameters (Figure 19). Both of these methods resulting lesser error compare to both KF methods. MLP method that utilize 1 BLE with temperature and humidity parameters (Figure 22) shows lesser error compare to the method without temperature and humidity parameters (Figure 21). This also shown in SVR method that utilize 4 BLE with temperature and humidity parameters showing better distance predictions (Figure 24) than without temperature and humidity parameters (Figure 23). MLP method that utilize 4 BLE without temperature and humidity parameters (Figure 25) shows some distance prediction error which have higher error to actual distance compare to the model that utilize temperature and humidity parameters (Figure 26).

Figure 27 - 37 show the graphs of position prediction results using trilateration model. These graphs are model of testing results for high temperature and low humidity condition with x coordinate from 0.5m until 6.5m with interval 0.5m and y coordinate 1.445m. Figure 27 shows the graph of position prediction using signal path-loss calculation without pre-processing model vs actual position. Figure 28 shows the graph of position prediction using signal path-loss calculation with filtered RSSI using KF with same parameter A and n vs actual position. Figure 29 shows the graph of position prediction using path-loss calculation with filtered RSSI using KF with various A and n according to various temperature and humidity vs actual position.

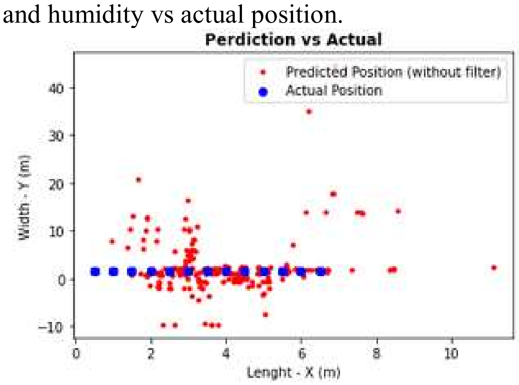

Figure 27: Without Pre-Processing Model Position Prediction

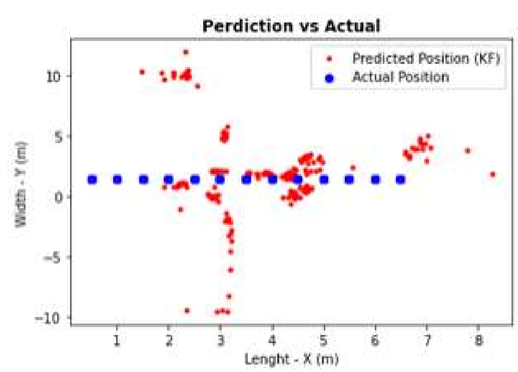

Figure 28: KF Model Position Prediction

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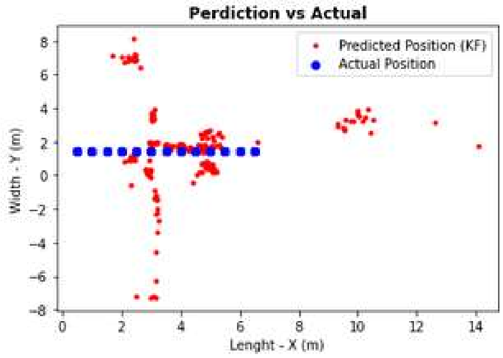

Figure 29: KF with 4 Categories of A and n according temperature and humidity Model Position Prediction

Figure 30 shows the graph of position prediction using SVR with 1 BLE not utilized temperature and humidity parameters vs actual positions. Figure 31 shows the graph of position prediction using SVR with 1 BLE utilized temperature and humidity parameters vs actual positions.

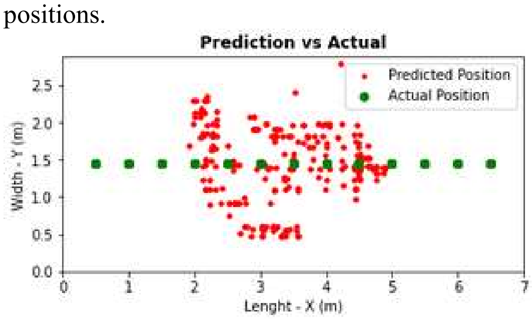

Figure 30: SVR Utilize 1 BLE without Temperature and Humidity Model Position Prediction

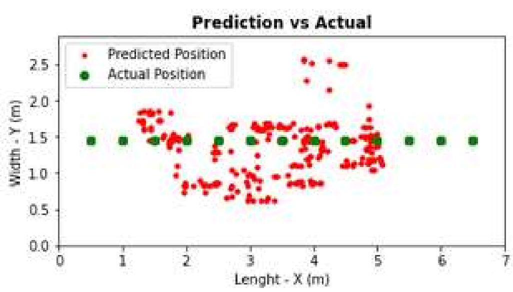

Figure 31: SVR Utilize 1 BLE with Temperature and Humidity Model Position Prediction

Figure 32 shows the graph of position prediction using MLP with 1 BLE not utilized temperature and humidity parameters vs actual positions. Figure 33 shows the graph of position prediction using MLP with 1 BLE utilized temperature and humidity parameters vs actual positions.

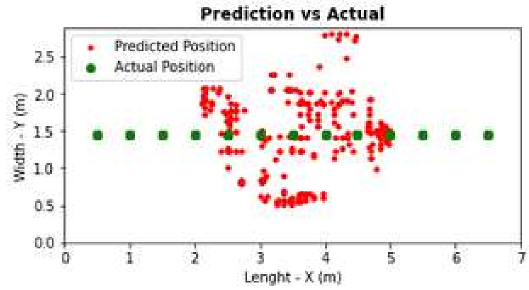

Figure 32: MLP Utilize 1 BLE without Temperature and Humidity Model Position Prediction

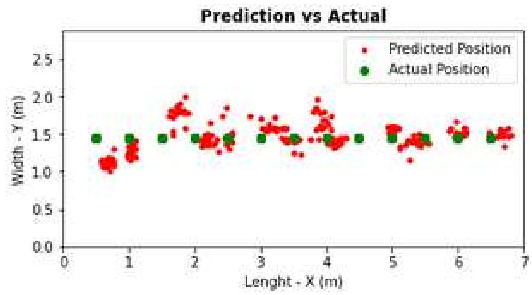

Figure 33: MLP Utilize 1 BLE with Temperature and Humidity Model Position Prediction

Figure 34 shows the graph of position prediction using SVR with 4 BLE not utilized temperature and humidity parameters vs actual positions. Figure 35 shows the graph of position prediction using SVR with 4 BLE utilized temperature and humidity parameters vs actual positions.

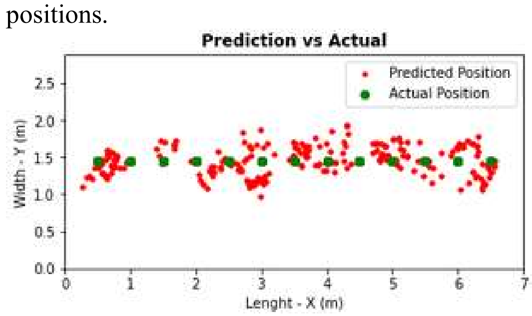

Figure 34: SVR Utilize 4 BLE without Temperature and Humidity Model Position Prediction

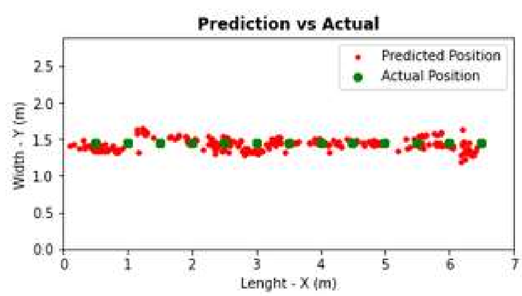

Figure 35: SVR Utilize 4 BLE with Temperature and Humidity Model Position Prediction

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Figure 36 shows the graph of position prediction using MLP with 4 BLE not utilized temperature and humidity parameters vs actual positions. Figure 37 shows the graph of position prediction using MLP with 4 BLE utilized temperature and humidity parameters vs actual positions.

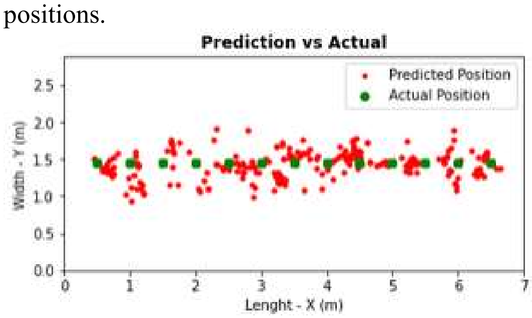

Figure 36: MLP Utilize 4 BLE without Temperature and Humidity Model Position Prediction

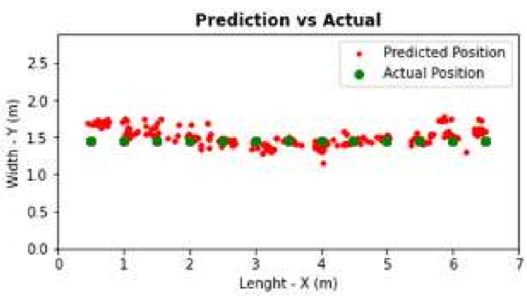

Figure 37: MLP Utilize 4 BLE with Temperature and Humidity Model Position Prediction

From the visual graph of position predictions, the MLP method that utilize 4 BLE with temperature and humidity parameters (Figure 37) shows the best position predictions (small red dots) which closer to the actual positions (big green dots) that compared to others methods. The method without pre-processing (Figure 27) shows the highest error. The both KF methods (Figure 28 and 29) shows better position predictions compare to method without pre-processing. SVR method that utilize 1 BLE with temperature and humidity parameters (Figure 31) compared to without temperature and humidity parameter (Figure 30) show slightly lesser error. These methods give lesser error compared to both KF models. MLP method that utilize 1 BLE with temperature and humidity parameters (Figure 33) shows lesser error compared to method without temperature and humidity parameters (Figure 32). This also shown in SVR model that utilize 4 BLE with temperature and humidity parameters shows better position predictions (Figure 35) compared to method without temperature and humidity parameters (Figure 34). The MLP method utilize 4 BLE without temperature and humidity parameters (Figure 36) shows some position prediction error which have higher error to actual distance compared to the method that utilize temperature and humidity parameters (Figure 37).

6. CONCLUSION & FUTURE WORKS

From this experiment, the distance and position prediction using without pre-processing method shows the highest error due to the distance and position prediction results calculated with fluctuated raw RSSI values. The best distance and position prediction method was MLP method that shown most accurate distance and position predictions then followed by SVR method. The KF method with same parameter A and n compared to KF model with 4 categories parameter A and n, gave similar distance prediction result and error for both model. The without pre-processing method compared to KF method gave more stable distance prediction result with lesser error, but gave lower accuracy compared to SVR and MLP methods.

From this experiment, the room temperature and humidity parameter help to increase the distance prediction accuracy, that shown from comparison between all methods that utilized RSSI, temperature and humidity parameters with the methods that only utilize RSSI parameter. The error in MLP method that utilized 1 BLE with RSSI, temperature and humidity parameters gave smaller errors (shown in MAPE, MAE and ME result) compared to MLP method that utilized 1 BLE with RSSI parameter only. This also shown in MLP method that utilized 4 BLE with RSSI, temperature and humidity parameter that gave smaller error compared to the MLP method that utilized RSSI parameter only. The pre-processing method (SVR and MLP) that utilize 4 BLE references gave better distance and position prediction result compare to pre-processing method that utilize 1 BLE reference. Because of 4 RSSI value from 4 BLE will reduce each other's error. This not only happen in MLP methods, SVR methods also gave the same comparison result.

By utilizing room temperature and humidity in RSSI-based distance prediction using MLP, successfully give the best result with high accuracy and lower error compared to other prediction method in this experiment such as KF and SVR. The temperature and humidity used as input parameter along with RSSI value to the MLP model in training process with 60% dataset, 20% dataset for validation and 20% for testing. The result shown not so much different error between training, validation and testing process error. That shown the consistent and stable result of the trained model. So this method can be used to give less error for the distance and position prediction and future research.

For future research development, the RSSI-based distance prediction utilize room temperature and humidity variance system could be utilize more sensitive temperature and humidity sensor that could increase the prediction accuracy due to in this experiment the inbuilt temperature and humidity sensor at BLE reference giving 0 decimal temperature and humidity reading. Also can develop the system using hybrid model, such as KF combined with SVR (machine learning) or KF combined with MLP (deep learning). Also can analyze and construct some models of the room shapes, walls, materials, atmospheres and object movements that could affect the RSSI reading value.

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