Available *online* at : http://jnte.ft.unand.ac.id/

Jurnal Nasional Teknik Elektro

| ISSN (Print) 2302-2949 | ISSN (Online) 2407-7267 |

Path Loss Prediction Accuracy Based on Random Forest Algorithm in Palembang City Area

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ARTICLE INFORMATION

Received: September 29, 2022
Revised: December 21, 2022
Available online: March 31, 2023

KEYWORDS

Path Loss, Prediction, Drive test, Random Forest, Accuracy

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A B S T R A C T

Path loss is a mechanism where the signal from the transmitting antenna to the receiver in a wireless network is attenuated during transmission across a medium due to external field conditions. In the telecommunication design, precise and efficient calculations are required. Random forest, as a machine learning-based path loss prediction model, is used in this study. Machine learning-based path loss prediction, random forest, has a low level of complexity and a high level of predictability. The data was collected using the drive test method at the Trans Musi busway area on the 4G network in Palembang, South Sumatra, Indonesia. The data ratio comprised 20% of the testing set and the rest of the training set. As a result, it was obtained that the prediction accuracy of 9.24% of mean absolute percentage error (MAPE) and root mean square error (RMSE) was 13.6 decibels (dB). Using hyperparameter tuning for random forest results in optimizing the model used, resulting in accuracy prediction for 8.00% of MAPE and RMSE was 11.8 dB, which is better than the previous results.

INTRODUCTION

The development of communication in a network is something essential. Communication devices are used by individuals or groups that are capable to communicate with others. Commonly, there is the phenomenon of path loss in wireless communication. Path loss is the attenuation (power decrease) as it propagates through the medium from the transmitting antenna (TX) to the receiver (RX) [1]. Additionally, it relies on the environment in which the network is deployed [2]. Path loss is caused by the three main factors, which are reflected, diffracted, and randomly scattered [3]. Other factors can be determined by path loss such as the distance between buildings, the road width, etc. [4], [5].

In the design of telecommunication, it is needed to model path loss. This is due to the path loss prediction model's importance as a tool for radio coverage calculation, base station position determination, frequency allocation, and interference feasibility studies during network development [6]. The empirical models and deterministic models are the two general models commonly used [7]. The empirical model is known as a model based on measurement and statistical analysis. On the other hand, a deterministic model is known as a model which applies propagation mechanisms and analytical techniques for electromagnetic computational modeling [8]. However, models have drawbacks, the empirical model has not obtained good accuracy results in its measurement, while the deterministic model requires high computational and complexity [9], [10]. In this study, we will calculate and evaluate the used path loss model to see how accurate the prediction is with using machine learning–based path loss prediction. Machine learning is a subset of artificial intelligence (AI) that is self – a learning computer process that does not require explicit programming [11].

A recent study [12] showed that path loss models based on machine learning provide more accuracy than empirical models and are even more computationally efficient than deterministic ones. In the study [8], path loss modeling was carried out in the cabin due to the network signal instability which caused the connection speed to be slow and the communication area was not covered properly. In this aircraft cabin, several machine learning–based path loss predictions outperformed one of the empirical models used, namely the long–distance model. This is demonstrated by measuring findings from RMSE in the 2.4 GHz frequency band scenario where machine learning methods such as back propagation neural network (BPNN), support vector regression (SVR), random forest, and AdaBoost are 1.90 decibel (dB), 2.20 dB, 1.76 dB, and 2.12 dB, respectively. While the empirical model used such as the long-distance model is 3.12

https://doi.org/10.25077/jnte.v12n1.1051.2023

dB. In the study [5], drive test measurements were carried out in Nigeria based on a marked route in the 1800 MHz frequency band coverage to obtain path loss data. The empirical models such as Hata, Cost-231, ECC-33, and Egli models are used and evaluated for path loss prediction, the results show these models failed to get the path loss values at each distance. The use of an Artificial Neural Network (ANN) model that has been evaluated based on the mean absolute error (MAE), RMSE, and standard deviation metrics gives the smallest error when compared to the empirical models used. From what is presented, we know that machine learning as a path loss prediction model has very accurate prediction results and more efficient computation.

Machine learning is a framework that makes predictions using large datasets and a flexible model architecture [13]. There are two types of machine learning, i.e., supervised learning and unsupervised learning. Path loss prediction is a problem that uses a supervised learning algorithm since it is a regression problem due to predicting the target's numerical value [11]. Supervised learning uses labeled data to study the general behavior between input and output [3], [14], [15]. Based on the previous explanation, this study will use machine learning with the type of supervised learning, Random Forest. On the other hand, the data for this study is obtained through the drive test method at the Trans Musi busway area with corridor 5 on the 4G network in Palembang, South Sumatra, Indonesia. In both rural and urban propagation environments, path loss can be predicted using machine learning approaches [16] and Palembang City is an urban propagation environment. Based on [3], [8], [13] that Random Forest as a machine learning–based path loss prediction performs better than other types of supervised learning algorithms. Error metric indicators such as RMSE and MAPE are used to evaluate the path loss prediction performance [3], [17], [18].

METHODOLOGY

Random Forest

Random Forest is an ensemble learning that uses many decision trees [19]. The algorithm works by selecting features naturally based on correlation or any feature selection methodology [13]. Random Forest uses a bagging method that involves extracting numerous bootstrap replicas from the dataset and building multiple decision trees on each replica. Width bootstrap aggregation is to choose a training sample for each tree in which these trees are trained based on that sample [20].

Metrics for Evaluating the Performance Model

Calculating metrics for evaluation is needed to find out how much of a prediction error a model creates. The path loss values obtained from the model prediction will be calculated together with the measured data (actual path loss values). The difference between the measured value and the path loss value predicted by the model is used to calculate. Error metrics such as MAPE and RMSE are used in this study to evaluate the path loss prediction models [20], [21]. The equations for MAPE and RMSE can be expressed as in (1) and (2).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{PL_{actual} - PL_{predicted}}{PL_{actual}}\right| \ x\ 100 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(PL_{actual} - PL_{predicted}\right)^2} \tag{2}$$

Where $i = 1, \ldots, N$ is the test sample index, N is the number of the test samples in total, PL_{actual} is the actual value of path loss, and $PL_{predicted}$ is the predicted value of path loss.

Characteristics of Mean Absolute Percentage Error

In Moreno *et al*. [9], that there are four types of interpretation of MAPE according to Lewis to describe the characteristics of MAPE values in predicting as shown in Table 1.

Table 1. Typical MAPE Interpretation

MAPE (%)	Interpretation
Less than 10	Very Accurate Prediction
10 - 20	Good Prediction
20 - 50	Reasonable Prediction
More than 50	Inaccurate Prediction

As shown in Table 1 above, it can be seen that a model's error can be determined by how great the percentage of results from MAPE is obtained, the smaller the percentage of results from MAPE obtained, the accuracy of a model would be better. Meanwhile, the accuracy of a model would be poor if the percentage of MAPE results obtained is higher.

The Origin of Data

In this study, the data was collected by the Trans Musi busway at corridor 5 in Palembang, South Sumatra, Indonesia. The data is numeric with each column's data type being float and integer. Corridor 5 runs from Sultan Mahmud Badaruddin II Airport to Alang-alang Lebar Terminal purposes.

The Equipment for Data Collection

Equipment that permits data collection is required to get path loss data in the field using the drive test measurement method. The equipment required is classified into three: hardware, software, and additional equipment the details of which are shown in Table 2.

Table 2. List of Data Collection Equipment for Measurement

List of Equipment	
Hardware	Laptop Smartphone
Software	Test Mobile System (TEMS) Investigation Global Positioning (GPS)
Additional Equipment	Universal Serial Bus (USB) Hub Data Cable

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The Step of Data Collection

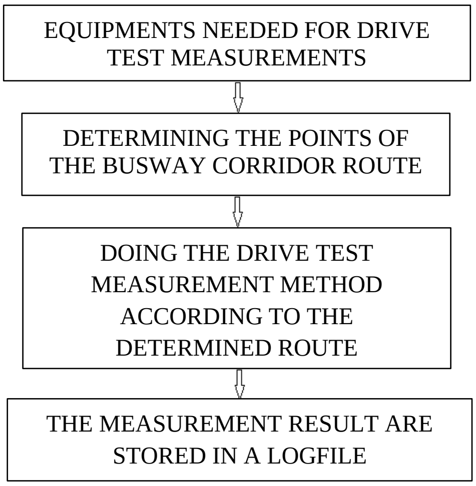


Figure 1. Diagram Block in The Data Collection Step with The Drive Test Measurement Method

As shown in Figure 1 above, this study is using the drive test measurement method for gathering the data. A drive test is a method that involves measuring the complete journey from the departure point to the arrival point. Data collection is in the 4G network area, during path loss data collection on the corridor 5 route, using TEMS Investigation software. It was activated on a laptop that had been connected to a smartphone with turned-on GPS. As previously explained, the route is in corridor 5 of the Trans Musi busway area the starting point is at Sultan Mahmud Badaruddin II Airport and the ending point is at Alang-alang Lebar Terminal can be presented in Figure 2.

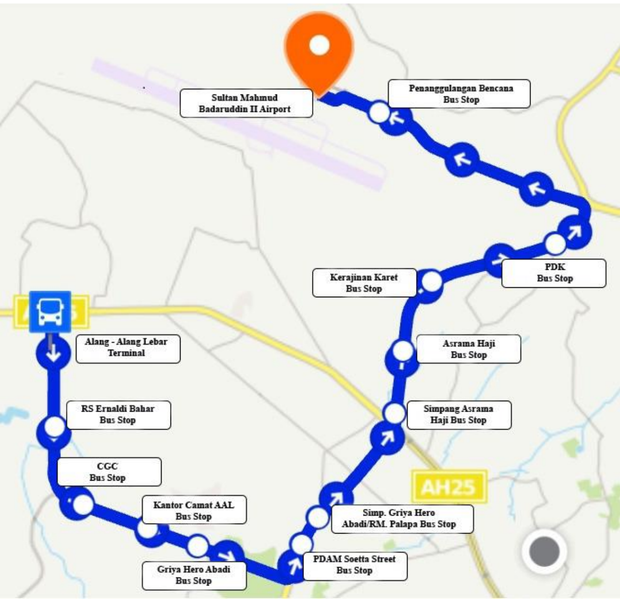


Figure 2. The Selected Route for Data Collection with the Drive Test Method where The Blue Line is The Corridor 5 Route

After collecting data by drive test method, the acquired data is stored in a logfile form. In each route point, we found that the data contains information such as path loss value and related path loss parameters with like building's height, the distance between buildings, road width, the distance between the transmitter antenna and to the receiver, etc.

Data Information Contained

The logfile contains path loss values and related path loss parameters from the drive test measurement method at a fixed distance between buildings of 3 m and the nearby building height of 10 m as shown in Figure 3.

LTE Serving Cell Distance (m)	Frequency (MHz)	Total_Height_of_TX (m)	Total_Height_of_RX (m)	Vertical Angle RX from Mainbeam	Horizontal Angle RX from Mainbaem TX (β)	The road width (m)	PUCCH Path_loss_AllLogs
614.45	1800	42.3	13.2	0.29	76.34	24.32	111
507.26	1800	42.3	13.2	0.28	76.34	24.32	114
507.26	1800	42.3	13.2	0.28	76.34	24.32	117
507.26	1800	42.3	13.2	0.28	76.34	24.32	117
507.26	1800	42.3	13.2	0.28	76.34	24.32	116
507.26	1800	42.3	13.2	0.28	76.34	24.32	120
507.26	1800	42.3	13.2	0.28	76.34	24.32	118
507.26	1800	42.3	13.2	0.28	76.34	24.32	118
507.26	1800	42.3	13.2	0.28	76.34	24.32	111
614.45	1800	63.5	13.2	0.32	34.49	24.32	121
614.45	1800	63.5	13.2	0.32	34.49	24.32	112
614.45	1800	63.5	13.2	0.32	34.49	24.32	111

Figure 3. Sample of Eleven Measurement Data

As shown in Figure 3, the purple label columns are the independent variables and the yellow label column is the dependent variable. The independent variable is a variable that affects the dependent variable. On the other hand, the dependent variable is a variable that is influenced by the dependent variable to be predicted. For more details, Table 3 is shown below which columns are included in the input variable as independent variables and the output variable as a dependent variable.

Table 3. Independent and Dependent Variable

Independent Variable	LTE Serving Cell Distance (m)
	Frequency (MHz)
	Total_Heigh_of_TX (m)
	Total_Heigh_of_RX (m)
	Vertical Angle RX from Mainbeam TX (α)
	Horizontal Angle RX from Mainbeam TX (β)
	The road width (m)
	The nearby buildings height (m)
	The distance between buildings (m)
Dependent Variable	PUCCH Path_Loss All Logs

The parameters that affect path loss in Table 3, are LTE Serving Cell Distance, Frequency, Transmitter and Receiver Antenna Height, Receiver Vertical and Horizontal Angles from the Transmitter Mainbeam, the road width, the height of the nearby building, and the distance between buildings where they are included as independent variables. Path loss value obtained through field measurements (PUCCH Path_Loss All Logs) is a dependent variable.

Results and Discussion

Relationship between Path Loss and Transmitter Antenna to Receiver Distance

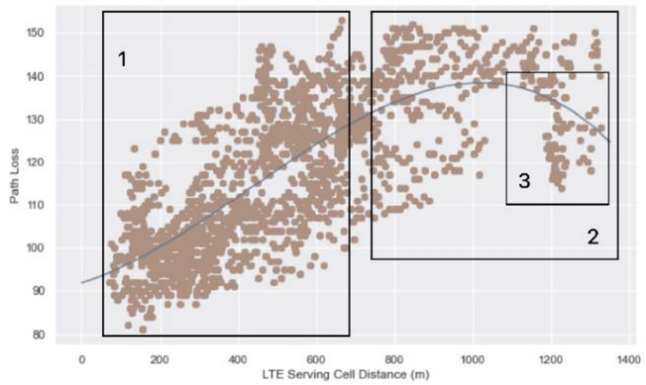
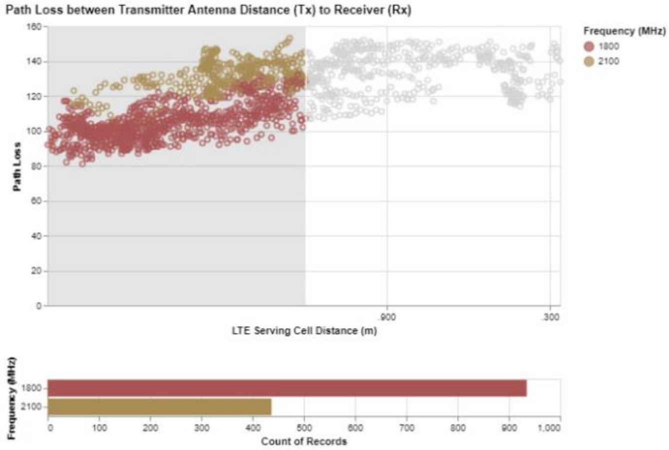
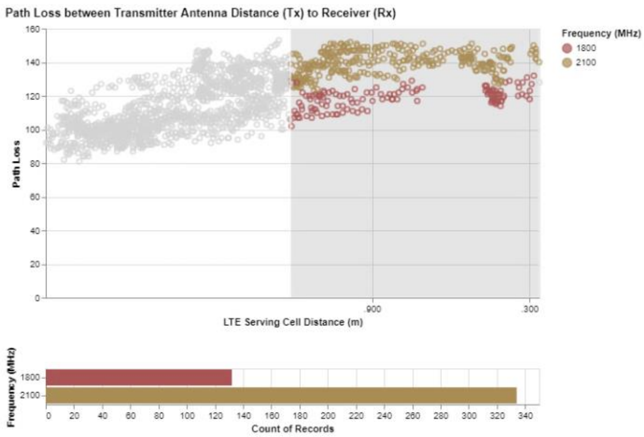


Figure 4. Graph of The Relationship between Path Loss and Transmitter Antenna to Receiver Distance

According to Figure 4, the path loss value is affected by the distance between the transmitting antenna (TX) to the receiver (RX). The path loss tends to increase as the distance between the transmitting antennas (TX) to the receiver (RX) increases. However, it can be seen from the graph, there are a lot of data points that are very close to each other. Likewise, there are quite a lot of data points but they are not too close to each other. Then, we also found data points at the end of which the path loss value at that point is low, even though the path loss will increase as the distance between the transmitting antennas (TX) to the receiver (RX) increases. In this regard, we have not confirmed whether the data points that are quite close to one another are genuinely numerous which are shown through the black box number 1 in Figure 4, or whether the data points that appear to be few are numerous which are shown through the black box number 2 in Figure 4. Furthermore, we have to find out why several data points converge at the end which is shown through the black box number 3 in Figure 4 whose path loss should increase as the distance between the transmitting antennas (TX) to the receiver (RX) increases. The following observations and analyses are shown in Figure 5(a) and Figure 5(b) below.



(a)



(b)

Figure 5. Graph of The Relationship between Path Loss and The Distance between Transmitter Antenna to Receiver

The path loss at each point of the distance between the transmitting antennas to the receiver consists of two types of frequency bands, using 1800 MHz and 2100 MHz frequency bands (refer to Figure 5 (a) and (b)). In Figure 5 (a), there are a lot of data points close to each other, and it is evident that there is more path loss in the 1800 MHz frequency than path loss in the 2100 MHz frequency band. On the other hand, there are data points in Figure 5 (b) that are not too near to one other, it indices that there is more path loss in the 2100 MHz frequency band than path loss in the 1800 MHz frequency band in that range. In addition, Figure 5 (b) shows that there is a path loss in the 1800 MHz frequency band at the end where there are data points that are close to each other, which is a form of a question on the black box number 3 in Figure 4.

Feature Selection

To obtain good and accurate results in predicting, it is needed to choose the best features from the independent variables to the dependent variable. In this study, a heatmap is used to see the correlation between the independent and dependent variables. The correlation score between each independent variable and the dependent variables is shown in Table 4.

https://doi.org/10.25077/jnte.v12n1.1051.2023

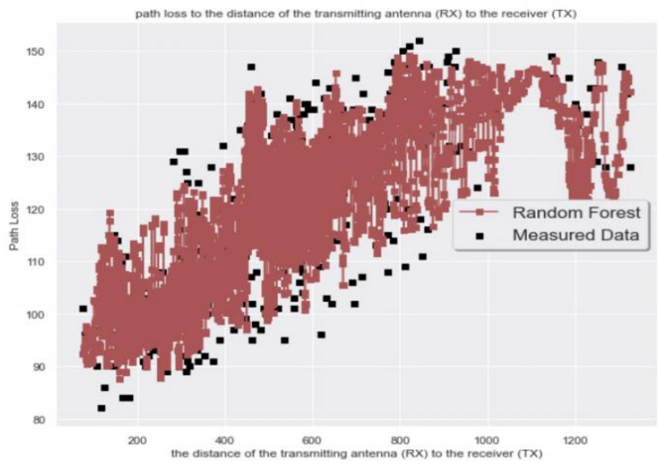
Table 4. The Correlation Score of The Independent Variable on the Dependent Variable

	PUCCH Path Loss_All Logs
LTE Serving Cell Distance	0.7
Frequency	0.81
Total Heigh of TX	0.25
Total Heigh of RX	0.057
Vertical Angle RX from Mainbeam TX	0.012
Horizontal Angle RX from Mainbeam TX	0.02
The Road Width	-0.16
The Nearby Buildings Height	0.16

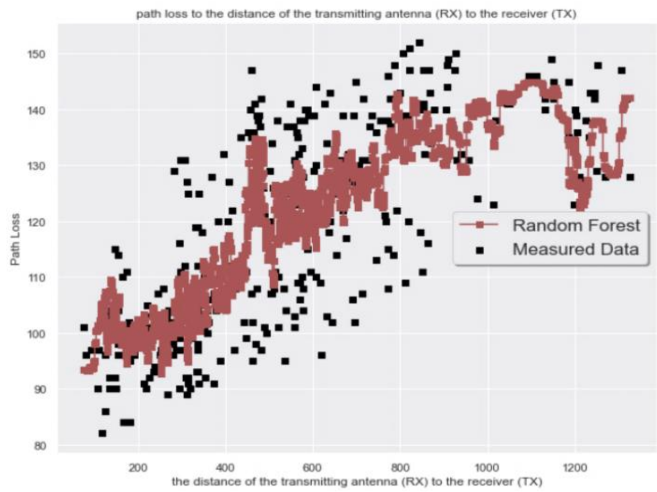
Based on Table 4 above, the dependent variable (PUCCH Path Loss_All Logs) shows a very strong correlation with independent variables such as Long-Term Evolution (LTE) Serving Cell Distance and Frequency. LTE Serving Cell Distance gets a correlation score of 0.7 and Frequency gets a correlation score of 0.81. We determine the correlation score through a graphical method called Heatmap. The heatmap will display the attributes score for each class (variables) in a two-way matrix. In short, the similarity of a pattern at the same time is what determines the correlation value. The high correlation score does not necessarily have a causal relationship. From Table 4 above, both LTE Serving Cell Distance and Frequency have a high correlation with PUCCH Path Loss_All Logs. LTE Serving Cell Distance is the distance between the transmitter antennas with the receiver which proves that the greater the distance between the two, the greater the path loss would be obtained due to factors such as more obstacles. From those, we can indicate that both variables have a causal relationship. Frequency and PUCCH Path Loss_All Logs have a strong correlation but they do not have a causal relationship. It was discovered that there were two types of frequency bands, they are 1800 MHz and 2100 MHz. Based on the data, it shows that the path loss values at each location along the busway corridor are under the two types of frequency bands, they are 1800 MHz and 2100 MHz which are only categorized and there is no causal relationship with path loss. Through this causal analysis, we would train a random forest algorithm to make it a trained model for predicting path losses by using the LTE Serving Cell Distance variable as an input variable.

Path Loss Prediction Model Performance

The performance of a machine learning–based path loss model, random forest, using the corridor 5 route dataset which was divided into 20% for the test dataset and 80% for the training dataset. The corridor 5 busway was split into training data to train the model and test data is used to determine whether the built model is already correct or not. The results can be presented in Figure 6.



(a)



(b)

Figure 6. Path Loss Prediction Performance using Random Forest (a) Without Hyperparameter Tuning, and (b) with Hyperparameter Tuning

Figure 6(a) shows the predictive performance of the random forest model as a predictor using 20% of the test dataset and 80% of the training dataset, which is 9.34% MAPE and 13.6 dB RMSE. Based on the prediction performance of the model, the optimization of the prediction model is currently being used by tuning the hyperparameters as shown in Figure 6(b). In Figure 6(b), hyperparameter tuning is used in the Random Forest algorithm where a specific set of parameter values is entered before the learning process of a model begins. We use a library called RandomisedSearchCV to tune the hyperparameters which using this library will look for the best values from a set of parameters. Once the optimal value has been obtained, all that is left to do is insert the value into each parameter. As the results, this study gets prediction accuracy results with 8.00% MAPE and 11.8 dB RMSE.

Model Prediction Accuracy Results

Based on the prediction performance that has been obtained, the prediction accuracy results will be listed in Table 5.

Table 5. Prediction Accuracy Results

Metric	Without Hyperparameter Tuning	With Hyperparameter Tuning
MAPE (%)	9.34	8.00
RMSE (dB)	13.6	11.8

Table 5 shows the accuracy results for each metric before and after hyperparameter tuning have a significant result. The MAPE obtained was 9.34% previously, then after hyperparameter tuning the MAPES value obtained at 8.00%. Based on the MAPE interpretation according to Lewis in Table 1, prediction models like Random Forest are included in the category of model interpretation with very accurate prediction because the MAPE results are less than 10%. The previous RMSE result was 13.6 dB, but the value after tuning the hyperparameter is 11.8 dB, which indicates that the model has been improved.

CONCLUSIONS

From this study, it can be concluded that Random Forest as a supervised machine learning algorithm in predicting path loss can be proposed. As a result, the RMSE even though hyperparameter tuning has not been carried out on the model, the result is still good. Before the hyperparameter tuning, the MAPE and RMSE obtained were 9.34% and 13.6 dB, respectively. Then, the MAPE and RMSE become 8.00% and 11.8 dB which indicates the optimization of the model after hyperparameter tuning. Through the graph of the relationship between the path loss and the distance between the transmitter antenna (TX) to the receiver (RX) that each data points are in the 1800 MHz and 2100 MHz frequency bands. Additionally, the type of frequency bands followed by the increasing distance between the transmitter antennas (TX) to the receiver (RX) affects the path loss value obtained.

As for further study, Exploratory Data Analysis (EDA) is crucial and should be improved on the data used so that when used to predict path loss with the proposed method, it is believed to be even better. Furthermore, it is also required to compare the performance of various models of machine learning–based path loss prediction models to determine which predictor for predictive path loss has the highest level of prediction accuracy.

ACKNOWLEDGMENT

We would like to acknowledge our gratitude to our late colleague Mr. Reza Firsandaya Malik for his guidance and advice and finally, we made this paperwork possible. He was also part of the research team before this paper was written and contributed a lot.

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NOMENCLATURE

i	meaning of i is the test sample index
N	meaning of N is the number of the test samples in total
PL_{actual}	meaning of PL_{actual} is the actual value of path loss
$PL_{predicted}$ value	meaning of $PL_{predicted}$ is the predicted of path loss
m	meaning of m is meter and it is the International Standard (SI) base unit of length
α	meaning of α is the vertical angle
β	meaning of β is the horizontal angle
%	meaning of how big is the result of the average absolute error in percentage
dB	meaning of dB is decibel and it serves as the standard for measuring standard strength

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