Leveraging RSSI and RTT for Accurate Distance Prediction in Bluetooth HC-05 with Multivariate Linear Regression Model

Farid Baskoro
State University of Surabaya, Indonesia
faridbaskoro@unesa.ac.id (corresponding author)

Rifqi Firmansyah
State University of Surabaya, Indonesia
rifqifirmansyah@unesa.ac.id

Wahyu S. Putro
Nanyang Technological University (NTU), Singapore
wahyusas001@e.ntu.edu.sg

Widi Aribowo
State University of Surabaya, Indonesia
widiaribowo@unesa.ac.id

Aristyawan P. Nurdiansyah
State University of Surabaya, Indonesia
aristyawannurdiansyah@mhs.unesa.ac.id

Received: 1 October 2025 | Revised: 17 October 2025, 5 November 2025, and 20 November 2025 | Accepted: 22 November 2025

 DOI: https://doi.org/10.48084/etasr.15256

ABSTRACT

A model for the accurate estimation of the distance between Bluetooth devices using a Multivariate Linear Regression (MLR) approach that integrates Received Signal Strength Indicator (RSSI) and Round-Trip Time (RTT) data is presented in this study. Bluetooth technology, specifically the HC-05 module, is employed for wireless communication between devices, where RSSI and RTT serve as independent variables for distance prediction. The present study aims to address the limitations of using these methods separately, as RSSI is susceptible to environmental factors and signal interference, whereas RTT provides a more accurate measurement but often requires more complex calculations. By integrating both methods using an MLR model, a more robust and accurate distance estimate was achieved. The proposed model exhibited a Mean Squared Error (MSE) of 0.0173, indicating a very small average error in distance predictions, while the R-squared (R^2) value of 0.9986 demonstrated that the model explained 99.86% of the variance in the actual distance data, highlighting its high accuracy. A Root Mean Squared Error (RMSE) of 0.1316 m, or approximately 13.16 cm, indicates that the model's average prediction error is around 13 cm. This approach significantly improves the reliability of Bluetooth-based localization systems and is highly beneficial for applications that require precise distance measurements.

Keywords-bluetooth; RSSI; RTT; estimated distance

I. INTRODUCTION

Bluetooth is a wireless communication technology that facilitates the exchange of data between devices over short distances, eliminating the need for physical cables or connections. Introduced in 1994 by Ericsson, Bluetooth was conceived to replace wired communication between mobile devices and various types of equipment, such as cell phones, computers, and audio devices. Since its inception, Bluetooth has undergone significant advancements and has transformed into a global communication standard that has been widely adopted across diverse electronic devices. These range from wireless headsets and in-car audio systems to Internet of Things (IoT) devices [1, 2]. Among the commonly used

Bluetooth modules, HC-05 stands out for its widespread application in electronic projects. The HC-05 module allows wireless communication between microcontrollers and other Bluetooth-enabled devices, such as smartphones and computers. The HC-05 operates as a serial Bluetooth module, supporting two-way data exchange through serial communication protocols (UART). The primary advantage of the HC-05 module is its seamless integration with various development platforms, including Arduino, Raspberry Pi, and other microcontrollers, owing to its straightforward UART interface. Its compact size, coupled with its ability to provide stable wireless connectivity, makes the HC-05 particularly popular in the development of applications such as remote control, robotics, home automation systems, and other wireless communication-based projects. It is cost-effective, versatile, and easy to use; therefore, the HC-05 has become the preferred choice among developers and hobbyists engaged in the creation of Bluetooth-based systems [3]. A common topic in wireless communication research involving the HC-05 module is distance measurement between Bluetooth devices, typically referred to as RSSI. This method is popular because it is relatively easy to implement and requires no additional devices other than the Bluetooth module itself. However, although RSSI is easy to use in practical applications, there are various challenges and limitations to consider.

Previous studies using RSSI to measure distance often faced significant environmental influences, such as signal interference, obstacles, and signal reflection, which can cause large fluctuations in RSSI readings [4, 5]. This resulted in unstable RSSI values, ultimately reducing distance estimation accuracy. Additionally, path loss models are often simple and do not take into account more complex environmental variables, such as multipath propagation or changes in field conditions. Another limitation is the instability of the RSSI over longer periods, as Bluetooth signals are highly sensitive to device movement, network interference, and other physical conditions. Moreover, latency or delay in Bluetooth communication can also affect distance measurements, especially in applications requiring quick response times. While RSSI may provide a rough estimate of device distance, these factors make the latter less accurate, especially at greater distances [6-8]. Another method that can be deployed to measure the distance between devices more accurately is Round Trip Time (RTT). RTT utilizes the transmission time from the transmitter to the receiver and back to the transmitter. By measuring this round-trip travel time, the distance between the devices can be calculated more precisely, considering that the speed of the radio wave used in Bluetooth communication is almost the same as the speed of light [9, 10].

Distance measurements using RSSI and RTT of the Bluetooth HC-05-based localization systems often result in different estimates. RSSI measures the signal strength to estimate the distance, whereas RTT measures the time for the signal to return to its device, with each having its advantages and limitations. However, integrating both methods into a single model can improve distance estimation accuracy. This is where MLR plays an innovative role in utilizing both methods simultaneously. By integrating RSSI and RTT as independent variables, MLR can model the linear relationship between these two methods and the actual distance. This approach not only enables more complex modeling but also produces more accurate and reliable distance predictions compared to using only one of the techniques. MLR provides a solution to maximize distance reading accuracy and minimize errors that may occur in Bluetooth-based distance estimation.

II. METHODS

Two devices equipped with HC-05 Bluetooth modules were used to measure the distance between the two devices. Bluetooth was configured as a transmitter, set to be a master, or as a receiver, set to be a slave [11]. The device configured as the master sends a signal to the slave device, which sends it back to the master that measures the RSSI. The received RSSI data were used to estimate the distance between the devices. The device configuration was done by connecting the HC-05 to the appropriate serial port of the microcontroller. The master and slave modes were set using the AT commands on the HC-05 module and RSSI measurements were conducted on both the master-slave devices using the Bluetooth communication protocol [12, 13]. The formula to calculate the distance based on RSSI uses a basic path loss model:

$$\mathrm{RSSI} = 10 \cdot n \cdot \log(d) + A \tag{1}$$

where RSSI is the strength of the received signal, measured in dBm, which depends on the distance d (in m) between the devices, n is the path loss exponent (dimensionless), and A is the reference RSSI at 1 m, measured in dBm. Equation (1) uses a basic path loss model to calculate the signal attenuation as the distance increases.

RTT measurements using the HC-05 module were performed by utilizing serial communication between two devices, one functioning as the master and the other as the slave. The process began by configuring both the HC-05 modules, with the master device sending a data signal in the form of a frame or byte to the slave device via the UART interface. Each HC-05 device was responsible for sending and receiving data through the RX (receive) and TX (transmit) pins, as shown in Figure 1. On the master device, the signal was sent for the first time, marking the time (timestamp) of signal transmission using a timer function on the microcontroller. After the slave device receives the signal from the master, the slave processes the signal and immediately sends a response (ACK) back to the master. The time of this response transmission was also recorded on the master device by noting the timestamp of receiving the response signal. The round-trip travel time of the signal, known as RTT, is obtained by calculating the difference between the reception time and the timestamp. Transmission and reception have a time difference, which results in the RTT value and is calculated using the following basic physics formula:

$$d = \frac{c \cdot \mathrm{RTT}}{2} \tag{2}$$

where d is the distance and c is the speed of light in vacuum (3×10^8 m/s). The signal travel time is divided by two because RTT includes the round-trip travel time between the transmitting and receiving devices.

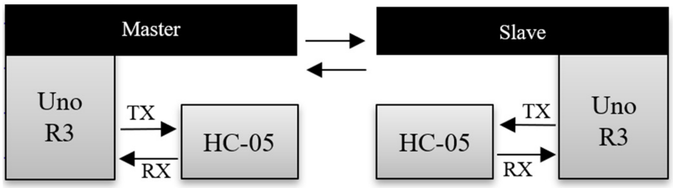

Fig. 1. Master-slave system.

The two measurement results (RSSI and RTT) were integrated deploying MLR. The latter is a statistical calculation that can model the relationship between multiple independent variables and one dependent variable. As an extension of simple linear regression, MLR simultaneously incorporates multiple independent variables to predict the dependent variable, rather than relying on a single predictor. This method enables a greater understanding of the interactions and effects of multiple factors on the outcome of interest [14-16]. The model assumes a linear relationship, where the dependent variable is expressed as a weighted sum of the independent variables, plus an intercept term. MLR allows for more complex modeling of real-world situations, where multiple factors contribute to the outcome. The method works by fitting the following linear equation to the observed data, with the goal of minimizing the difference between the predicted and actual values [17-19]:

$$\hat{y} = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \epsilon \quad (3)$$

where $\hat{y}$ is the dependent variable, denoting the actual distance, and x_1 and x_2 are the independent variables, namely RSSI and RTT. The regression coefficients β_1 and β_2 represent the influence of each variable on the distance estimate. The intercept β_0 denotes the value of the actual distance when both independent variables are zero. The residual ϵ is the difference between the model's predicted and actual observed values. The linear regression model optimizes the coefficients β_0, β_1, and β_2 through a training process using the available data.

The performance of the developed model was evaluated using two main parameters: MSE and R^2. The MSE measures the average squared error between the predicted and actual distances. The R^2 measures the proportion of variation in the data that can be explained by the model. The higher the R^2 value, the better the model explains the variability of the data, and the more accurate the predictions it provides. Evaluation based on these two parameters ensures that the MLR model used in this study performs well in predicting distance with high accuracy.

III. RESULTS AND DISCUSSION

Before testing distances exceeding 1 m, the connectivity between the master and slave devices was first tested at close range to ensure that the devices were properly connected and to verify that the connection between the master and slave remained stable throughout the test, both at a specific distance and under different conditions, such as with or without physical obstructions. This test also aimed to ensure that the initial pairing can be performed quickly and without issues, as well as to evaluate the auto-reconnect capability when the connection is lost, such as when the slave device's power is turned off and then turned back on. This is crucial for applications that require long-term connection stability.

Table I shows that the process of detecting the slave's address by the master was quick, taking less than 3 s, indicating that the slave device was in discoverable mode and easily recognized. The initial pairing was also successfully completed; the LED indicator on the master changed from fast blinking to steady within 3.1 s, in line with the module's specification, which typically requires 2-5 s. The auto-reconnect test demonstrated reliable connectivity, as after the slave’s power was cut for 5 s and then turned back on, the master was able to automatically reconnect without needing to re-pair, with a reconnect time of about 3.2 s.

TABLE I. BLUETOOTH HC-05 CONNECTION AND SIGNAL STRENGTH TESTING

Scenario	Indicator	Observed result	Notes
Slave address detection	AT+INQ on Master finds Slave's unique address	Found in <3 s	Slave in discoverable mode
Initial pairing	Master LED → from fast blinking to steady	Successful, pairing time 3.1 s	In line with HC-05 specifications (2–5 s)
Auto-reconnect setelah reset Slave	Power off Slave for 5 s, then turn back on	Auto-reconnect, reconnect time 3.2 s	No need to re-pair
Check link stability at ±0.5 m	Master sends 50 packets, receives all ACKs	50/50 ACKs received	No packet drops
Check RSSI (optional via BlueZ)	During connection at 0.5 m	≈ −38 dBm, stable (fluctuation ±2 dB)	Strong signal indication
Drop-test at 1 m (LOS)	Re-pairing not required	Link remains connected	RSSI ≈ −41 dBm

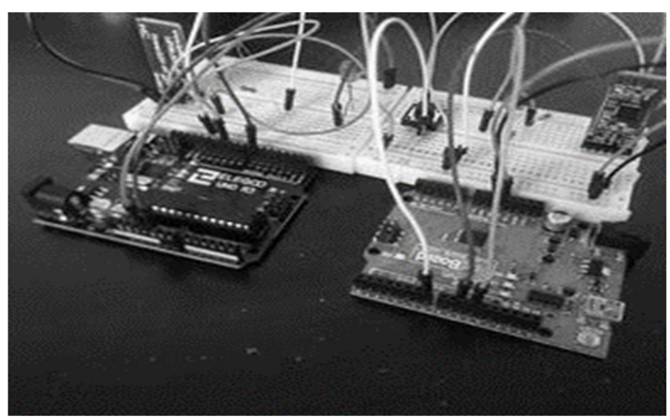

Fig. 2. Pairing devices test

The link stability test at a distance of approximately 0.5 m showed a strong connection. The master sent 50 packets, all of which were successfully received by the slave without any packet loss. The RSSI measurement via the computer host also showed a high signal strength of around -38 dBm with minimal fluctuation, indicating a good link quality at close range. In the drop-test at a distance of 1 m with a line-of-sight condition, the connection remained stable and did not require re-pairing, with RSSI only slightly dropping to -41 dBm, which is still considered very good signal strength. This test is displayed in Figure 2.

The next data collection involved jitter data, which was conducted to evaluate the impact of distance on the stability of the Bluetooth HC-05 connection, with distance testing between the master and slave modules ranging from 1 m to 10 m. The jitter versus distance graph for the HC-05 module in Figure 3 shows a direct relationship between the increasing distance and instability in the data packet travel time. At close range, the jitter remained low, in the range of 5-8 ms, and relatively stable. However, as the distance increased, the signal quality decreased, and the module frequently performed retransmissions, causing greater variations in the travel time. The upward-sloping curve indicates that after reaching distances between 5 and 7 m, instability increases more sharply, reaching over 20 ms at a distance of 10 m. This behavior is characteristic of Bluetooth communication that runs in the 2.4 GHz band, where signal attenuation and potential environmental interference cause fluctuations in the response time.

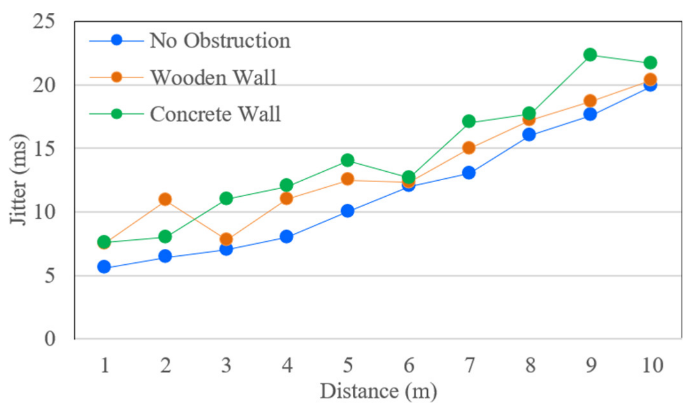

Fig. 3. Jitter versus distance.

Figure 4 shows that both packet loss and packet error rate increased as the distance between the HC-05 master and slave modules increased. At close range, up to about 4 m, the increase in both metrics was still very low, so communication remained reliable. However, starting from 5 m, especially after 6 m, the rate of increase becomes steeper, indicating a decline in connection quality owing to signal attenuation and increasing transmission interference. Packet loss is always higher than the packet error rate because it includes not only corrupted packets but also packets that fail to be delivered at all. This difference shows that most transmission failures at medium to long distances occur because the packets are not received at all, rather than due to data corruption. This indicates that at distances above 7 m, the connection begins to become unstable, and at 10 m, the reliability significantly decreases. Therefore, for applications requiring real-time or reliable communication, the proposed working range should not exceed this range.

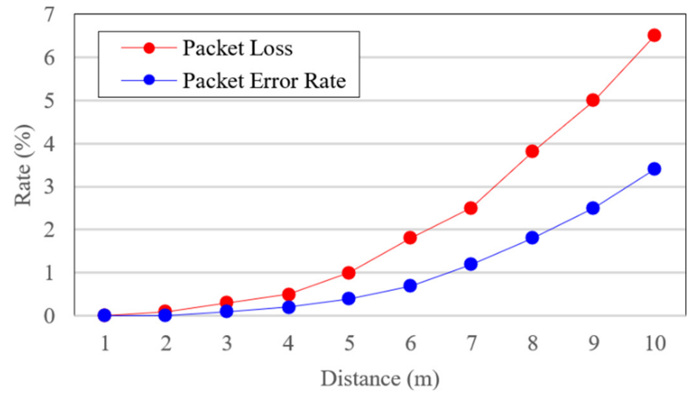

Fig. 4. Packet loss and error rate versus distance.

The disconnect versus the distance graph of the HC-05 module in Figure 5 displays the connection stability limits between the master and slave devices. At close range, up to about 6 m, the connection remained stable without any disconnections, so communication remained reliable. At 7 m, the graph began to show one disconnection per min, indicating that the link was becoming more vulnerable to disconnections. The number of disconnects increased significantly as the distance was extended to 8-10 m, where the connection frequently dropped and required time to reconnect. This trend illustrates that signal strength degradation and increased environmental interference make it difficult for Bluetooth modules like the HC-05 to maintain a stable connection as the distance approaches the specification limits.

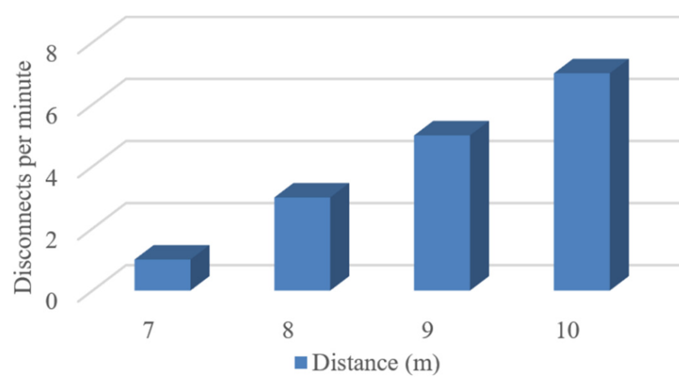

Fig. 5. Disconnect frequency versus distance.

In the absence of obstructions, Bluetooth signals tend to be strong with low latency, allowing for optimal communication. Wooden barriers cause a moderate decrease in signal strength and a slight increase in latency, although communication can still be carried out effectively at medium distances. However, with concrete barriers, the signal is heavily attenuated, with a significant drop in RSSI and a drastic increase in latency, making communication only possible at close range and under specific conditions. Overall, the denser the obstruction, the worse the signal quality and the higher the latency.

Figure 6 portrays the relationship between the signal strength (RSSI) and distance under three different conditions: no obstruction, wooden wall, and concrete wall. In the absence of obstructions, the signal strength decreased steadily as the distance increased, starting at around -40 dBm at 1 m and reaching about -60 dBm at 10 m. This curve shows that signal strength falls off with increasing separation between the transmitter and receiver, which is also consistent with free-space path loss observed in [20].

When a wooden wall existed between the devices, the signal strength decreased more sharply than in the no-obstruction condition. Starting at approximately -40 dBm at 1 m, the signal reached approximately -90 dBm at 10 m. This drop in signal strength can be explained by the interference caused by the wooden wall, which weakens the signal as it passes through the obstruction. Although the signal drop on the wooden wall was greater than that in the no-obstruction condition, its impact was not as significant as that in the concrete wall condition.

When a concrete wall existed between the devices, the signal exhibited the most significant decline. The curve starts at around -40 dBm at 1 m but quickly drops to -110 dBm at 10 m. This is attributed to the concrete wall, which caused a very large attenuation (signal reduction) due to the dense nature of the material blocking the signal. This sharp drop in signal strength reflects how physical obstructions, such as concrete, disrupt signal quality more than lighter materials like wood.

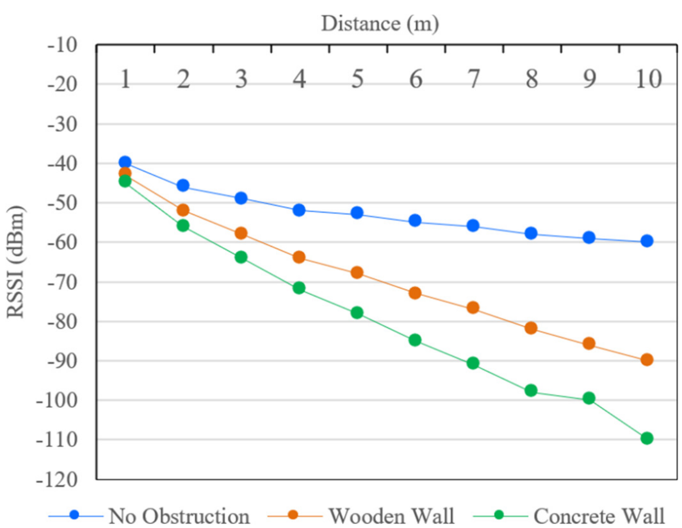

Fig. 6. The effect of obstructions on signal strength.

Table II shows the difference in distance between the RSSI and RTT, which is relatively small, with an error of approximately 5% for each method. However, as the distance increases, the error in the RSSI remains higher, although it tends to stabilize in the range of 2.5-9%. In contrast, the error in RTT showed smaller fluctuations, with the error decreasing as the distance increased. At greater distances, the error in RTT ranges from 0.7% to 5%, indicating that the RTT method is more accurate for measuring distance at longer ranges compared to RSSI.

In MLR, the model integrated the two independent variables, RSSI and RTT, following the mathematical formula in equation (3) to accurately estimate the distance. After the model training, the distance prediction was calculated using the regression formula, resulting in a more accurate distance estimate by simultaneously utilizing both variables.

TABLE II. DISTANCE ESTIMATION

Tape (m)	Distance (RSSI) (m)	Distance (RTT) (m)	Error (RSSI) (%)	Error (RTT) (%)
1	0.95	1.05	5	5
2	1.95	2.05	2.5	2.5
3	2.85	3.1	5	3.3
4	3.8	4.1	5	2.5
5	4.75	5.15	5	3
6	5.65	6.05	5.8	0.83
7	6.5	6.95	7.1	0.7
8	7.4	7.85	7.5	1.8
9	8.25	8.7	8.3	3.3
10	9.1	9.6	9	4

The evaluation results of the MLR model listed in Table III show that the MLR model performs very well in predicting distance based on RSSI and RTT data. An MSE of 0.0173 indicates that the average prediction error of the model is very small. This MSE measures the squared difference between the predicted values by the model and the actual values. The smaller the MSE, the more accurate the predictions generated by the model, which means that this model is capable of predicting the distance with minimal error. The R^2 value of 0.9986 indicates that the model explains 99.86% of the variation in the actual distance data. This shows that the MLR model can explain almost all the variability in the data, which is a strong indicator of its excellent quality. In other words, the MLR model is highly effective in predicting distance by integrating RSSI and RTT. Finally, the RMSE value of 0.1316 provides a more easily understandable representation of the model's average error, as its unit is the same as the predicted data, namely m. An RMSE of 0.1316 m, or approximately 13.16 cm, indicates that the model's average prediction error is around 13 cm. The formulas for calculating MSE, RMSE, and R^2 used in the model evaluation are based on the methodology described in [21], which discusses the application of these evaluation metrics in predictive model analysis.

TABLE III. MLR MODEL EVALUATION

Parameter	Value
MSE	0.0173
R^2	0.9986
RMSE	0.1316
Predicted distance (Test 1)	9.0485
Actual distance (Test 1)	9
Predicted distance (Test 2)	2.1796
Actual distance (Test 2)	2

In the first test, the predicted distance produced by the model was 9.0485 m, which was very close to the actual distance of 9 m. This shows that the model can provide an accurate distance estimate. Similarly, for the second test, the model predicted a distance of 2.1796 m, which was almost identical to the actual distance of 2 m. These results show that the model successfully provided highly accurate estimates for both test data.

Based on the evaluation results presented in Table III, it can be concluded that the MLR model performs very well in predicting distance. The blue line in Figure 7 represents the actual distance measured using a tape measure, which served as a reference for comparison with the other methods. The green line represents the distance predicted using the RSSI method. The RSSI-based prediction tends to approach the actual value, with some differences, especially for higher and lower values, although the error can still be considered small. The red line represents the distance prediction deploying the RTT method. This prediction, while fairly accurate, also demonstrates slight differences at higher values compared to the results from the RSSI method. The yellow line, which represents the distance predicted employing the MLR model, shows results that are very close to the actual distance, with minimal differences.

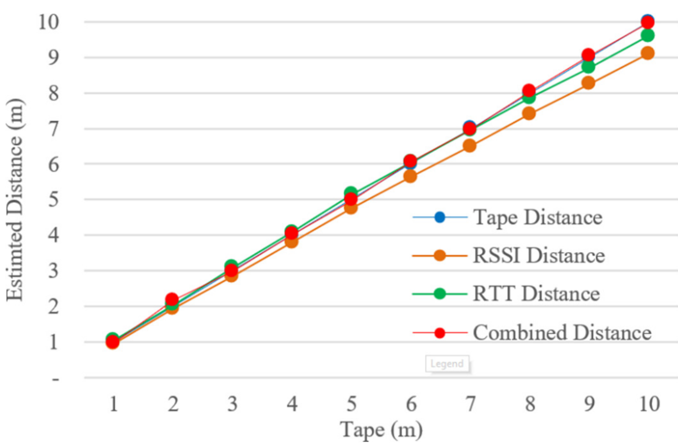

Fig. 7. Comparison of distance estimation using each method.

IV. CONCLUSIONS

In the present study, a Multivariate Linear Regression (MLR) model is proposed for accurate distance estimation using Bluetooth HC-05 modules. The MLR model integrates the Received Signal Strength Indicator (RSSI) and Round-Trip Time (RTT), providing highly accurate distance predictions. The model exhibited a Mean Squared Error (MSE) of 0.0173, which indicates that the average error between the predicted and actual distances was very small, suggesting that the model is capable of generating highly precise predictions. This low MSE also indicates that the difference between the predicted and actual values is almost undetectable in the tested data. Furthermore, the MLR model showed an R-squared (R^2) value of 0.9986, which demonstrates that 99.86% of the variation in the actual distance data can be explained by the model. Thus, the proposed model is very effective at capturing the relationship between RSSI with RTT as independent variables and the actual distance as dependent variable, reflecting the former's ability to explain most of the variability in the test data.

The implications of this approach can be applied to the development of localization systems in complex environments, such as in shopping malls, airports, or large office buildings, where high accuracy in distance estimation is crucial. The MLR model can also serve as a foundation for future research that could integrate more variables or adapt this technique/be adapted to other wireless technologies, ultimately improving the performance of localization systems and distance measurement overall.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to all parties who provided support and assistance throughout the research process. This research was conducted independently without involving funding from any party. Therefore, all costs and resources used in this study were fully covered by the authors. The authors also appreciate every contribution in the form of suggestions, critiques, and ideas provided by colleagues and peers at the State University of Surabaya, whose input was invaluable. We hope that this research will contribute to the advancement of knowledge and technology.

The dataset of this study is available from the corresponding author upon reasonable request (request link: https://bit.ly/3X6hGwV).

REFERENCES

[1] I. F. Tabib, "A review of Bluetooth Technology," *ResearchGate*, 2023, https://doi.org/10.13140/RG.2.2.35146.99522.

[2] R. Shi, "The world of the Bluetooth," in *Third International Conference on Electronics and Communication; Network and Computer Technology (ECNCT 2021)*, Harbin, China, Mar. 2022, vol. 12167, pp. 161–167, https://doi.org/10.1117/12.2628460.

[3] N. Rajeswari, H. M. Breesam, N. A. Dawod, C. Bharath, C. Vivek, and K. Pavanchand, "IOT-based Smart Surveillance Robotic Car using HC05," in *2024 International Conference on Augmented Reality, Intelligent Systems, and Industrial Automation (ARIIA)*, Manipal, India, Dec. 2024, pp. 1–6, https://doi.org/10.1109/ARIIA63345.2024.11051986.

[4] D. Suresh, P. V. Joshi, and P. Parandkar, "Mitigating Relay Attacks in Vehicle Access Systems Using BLE and UWB," *Engineering, Technology & Applied Science Research*, vol. 15, no. 5, pp. 26965–26970, Oct. 2025, https://doi.org/10.48084/etasr.12581.

[5] R. Ramirez, C.-Y. Huang, C.-A. Liao, P.-T. Lin, H.-W. Lin, and S.-H. Liang, "A Practice of BLE RSSI Measurement for Indoor Positioning," *Sensors*, vol. 21, no. 15, Jan. 2021, Art. no. 5181, https://doi.org/10.3390/s21155181.

[6] S. Barai, D. Biswas, and B. Sau, "Estimate distance measurement using NodeMCU ESP8266 based on RSSI technique," in *2017 IEEE Conference on Antenna Measurements & Applications (CAMA)*, Tsukuba, Japan, Dec. 2017, pp. 170–173, https://doi.org/10.1109/CAMA.2017.8273392.

[7] M. Omer and G. Y. Tian, "Indoor distance estimation for passive UHF RFID tag based on RSSI and RCS," *Measurement*, vol. 127, pp. 425–430, Oct. 2018, https://doi.org/10.1016/j.measurement.2018.05.116.

[8] G. Li, E. Geng, Z. Ye, Y. Xu, J. Lin, and Y. Pang, "Indoor Positioning Algorithm Based on the Improved RSSI Distance Model," *Sensors*, vol. 18, no. 9, Sept. 2018, Art. no. 2820, https://doi.org/10.3390/s18092820.

[9] G. Arslan, "Improving accuracy of round-trip time (RTT) in high accuracy distance measurements (HADM)," US12245182B2, Mar. 04, 2025.

[10] M. A. Attar, N. Yadav, A. R. Singh, V. Jeyakumar, S. Gandham, and R. F. Spadaro, "Round trip time (RTT) measurement based upon sequence number," US10116531B2, Oct. 30, 2018.

[11] A. Hashmi, "A Novel Drone-based Search and Rescue System using Bluetooth Low Energy Technology," *Engineering, Technology & Applied Science Research*, vol. 11, no. 2, pp. 7018–7022, Apr. 2021, https://doi.org/10.48084/etasr.4104.

[12] K. Sangrit, J. Karnjana, S. Laitrakun, K. Fukawa, S. Fugkeaw, and S. Keerativittayanun, "Distance Estimation Between Wireless Sensor Nodes Using RSSI and CSI with Bounded-Error Estimation and Theory of Evidence for a Landslide Monitoring System," in *2021 13th International Conference on Information Technology and Electrical*

Engineering (ICITEE), Chiang Mai, Thailand, Oct. 2021, pp. 40–45, https://doi.org/10.1109/ICITEE53064.2021.9611887.

[13] Seiya H. *et al.*, "RSSI-Based Distance Estimation Enhanced by Interference Signals," *IEICE Proceedings Series*, vol. 74, no. A3L-D-3, pp. 101–104, Nov. 2020.

[14] M. Slawski, E. Ben-David, and P. Li, "Two-Stage Approach to Multivariate Linear Regression with Sparsely Mismatched Data," *Journal of Machine Learning Research*, vol. 21, no. 204, pp. 1–42, 2020.

[15] C. G. Manriquez-Padilla, I. Cueva-Perez, A. Dominguez-Gonzalez, D. A. Elvira-Ortiz, A. Perez-Cruz, and J. J. Saucedo-Dorantes, "State of Charge Estimation Model Based on Genetic Algorithms and Multivariate Linear Regression with Applications in Electric Vehicles," *Sensors*, vol. 23, no. 6, Jan. 2023, Art. no. 2924, https://doi.org/10.3390/s23062924.

[16] D. ALabdeh, B. Omidvar, A. Karbassi, and A. Sarang, "Study of speciation and spatial variation of pollutants in Anzali Wetland (Iran) using linear regression, Kriging and multivariate analysis," *Environmental Science and Pollution Research*, vol. 27, no. 14, pp. 16827–16840, May 2020, https://doi.org/10.1007/s11356-020-08126-3.

[17] P. V. Mahesh, S. Meyyappan, and R. K. R. Alla, "A New Multivariate Linear Regression MPPT Algorithm for Solar PV System with Boost Converter," *ECTI Transactions on Electrical Engineering, Electronics, and Communications*, vol. 20, no. 2, pp. 269–281, June 2022, https://doi.org/10.37936/ecti-eec.2022202.246909.

[18] B. C. Haas, A. E. Goetz, A. Bahamonde, J. C. McWilliams, and M. S. Sigman, "Predicting relative efficiency of amide bond formation using multivariate linear regression," *Proceedings of the National Academy of Sciences*, vol. 119, no. 16, Apr. 2022, Art. no. e2118451119, https://doi.org/10.1073/pnas.2118451119.

[19] A. Pavlov and M. Holovchenko, "Modified Method of Constructing a Multivariate Linear Regression Given by a Redundant Description," *Bulletin of National Technical University "KhPI". Series: System Analysis, Control and Information Technologies*, vol. 2, no. 8, pp. 3–8, Dec. 2022, https://doi.org/10.20998/2079-0023.2022.02.01.

[20] H. A. Obeidat *et al.*, "An Indoor Path Loss Prediction Model Using Wall Correction Factors for Wireless Local Area Network and 5G Indoor Networks," *Radio Science*, vol. 53, no. 4, pp. 544–564, Apr. 2018, https://doi.org/10.1002/2018RS006536.

[21] T. O. Hodson, "Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not," *Geoscientific Model Development*, vol. 15, no. 14, pp. 5481–5487, July 2022, https://doi.org/10.5194/gmd-15-5481-2022.