Realtime Monitoring System Towards Waste Generation Management

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Abstract— **Waste management is a significant concern to protect the environment and the population's health. However, due to its uncertainty and high variability, waste generation has dynamic nurture that results in ineffective, inaccurate, and unreliable waste management. Therefore, the existence of the IoT, information systems, and artificial intelligence can help support sustainability and decrease the amount of waste. This research proposes a monitoring system equipped with a forecasting feature and implemented in a mobile application to overcome the limitations of conventional waste management systems. This system is built on two Internet of Things (IoT) architecture nodes with an android-based mobile application interface. Measures the unfilled level of the bin, processes it, and sends it to the database. The data was then computed using Levenberg Marquardt's Artificial Neural Network to predict the height of the garbage. The results of the IoT communication show that the average delay in sending data to the database is 2.886s and 2.912s, with 0% packet loss. The correlation coefficients generated in the Levenberg Marquardt model training process are 0.925 and 0.965. In addition to displaying garbage height data and prediction results, this system application can also display the location of the bin and receive notifications. This monitoring system has also been tested directly on the Undip waste manager using the SUS questionnaire. Based on these tests, the SUS score of 70.2 showed that the application already had good usability.**

Keywords: waste management, IoT, artificial neural network, Levenberg-Marquardt, android.

I. INTRODUCTION

The principle of sustainable development has now become a model, strategy, and reference in all aspects of life with an environmental perspective approved globally to maintain sustainability [1]. According to the United States Green Building Council (USGBC), Green Campus is a community that applies policy in creating and managing eco-friendly and sustainable education in the university area [2]. The Green Campus is intended to be assessed based on environmental, social, and economic, including infrastructure, renewable energy, waste management, water usage, transportation, and environmental education. This competition was participated by more than 900 universities across 80 countries. The scoring points now affect the policies implemented at the university. However, the procedure only covers upstream and downstream processing activities. In contrast, the waste management process consists of a series of activities related to the handling, processing, disposal, or recycling of waste materials. They all have a vital role in ensuring that waste originating from a site is taken out, treated, and disposed of precisely.

If we look at the conventional waste transportation process, it is assumed to be indecisive. First, the cleaning staff must always go around to check and transport the existing waste, whereas the condition of the waste is not always the same at each location. Furthermore, stakeholders cannot directly monitor waste management's condition and the cleaning staff's performance. The best waste transportation is when the vehicle is carried out as needed to prevent scattered waste or excessive waste collection, which can increase costs.

It is necessary to have a system that can monitor and predict the waste's height to increase waste management efficacy. This monitoring system will provide visibility capabilities while collecting historical data, while forecasting offers the basis for implementing, improving, and optimizing waste management operations. This feature will collaborate with the IoT to obtain a real-time waste load monitoring system.

II. RELATED WORK

In previous studies, a bin monitoring system was designed under research entitled "Real-time Smart Garbage Monitoring System Using IOT-Based Fuzzy Logic Method." This research produces output from real-time bin-level data and notifications when the bin is full using Android [3]. However, the waste monitoring system does not yet have location and prediction features as applied in 2 previous studies. According to M. Cubillos [4], an accurate projection of the amount of waste is essential for planning an efficient waste management system. Estimations of future waste generation are the foundation for the sustainable development of waste management infrastructure. Incorrect predictions can lead to widespread problems, such as inadequate or redundant waste disposal infrastructure. That is important because adequate waste management, from collection to disposal systems, can protect human health and the environment and conserve natural resources [5].

Various studies have provided solutions to reduce the impact of waste overflow by utilizing multiple technologies. Some studies have developed LoRa-based IoT for monitoring bins [6]. Bin technology with a mechanical arm that will detect

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the presence of garbage outside the bin [7], even a line follower-based garbage truck [8], has been developed to handle waste generation.

Abbasi M. and Ali E. H. [9] have compared forecasting methods in solid waste management systems. The design and operation of an effective waste generation system require an accurate estimate of the amount of future waste generation. For this reason, this research aims to determine which method is the most accurate to help design and manage waste management systems better. The comparison uses four different algorithms, namely Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), and K-Nearest Neighbour (kNN). After testing, the ANN model's overall efficiency was better, while the others performed better under one condition.

Based on the problems above, a system will be built to monitor and predict waste height based on android. This system provides visibility and capabilities while collecting historical data, while forecasting presents the foundation for implementing, improving, and optimizing waste management operations. Monitoring and prediction data will be stored in the Firebase database and displayed through a real-time application. In addition to monitoring and predicting data, the system interface will also display the location of the bin and notification.

III. Methodology

This monitoring system's design for waste generation management consists of several components and supporting processes based on IEEE SA-2413-2019 Standard for an Architectural Framework for The Internet of Things [10]. The standard divides the general IoT architecture into the perception domain, the network domain, and the application domain. As seen in Figure 1 is the following overall system architecture diagram.

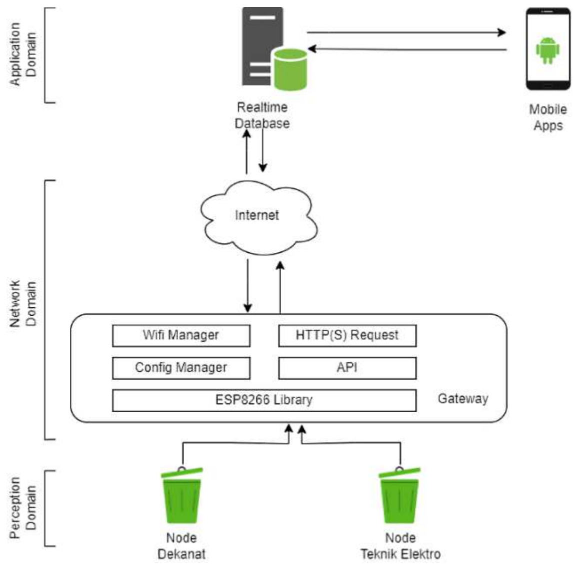


Fig. 1. System architecture of the waste monitoring system

The perception domain is the data retrieval layer, which converts physical quantities into electrical signals. In this research, the ultrasonic sensor HC-SR04 acts as an input unit to *measure the* unfilled level of the bin. The dead band of ultrasonic sensor HC-SR04 is about 47 cm. This dead band is not fixed because there is a variation of waste ingredients. The waste has variations in thickness and interpretation of material such as paper, food, wood, or electrical waste. The default value of the dead band is 500 cm in the Arduino library, but from the trial, the best dead band is only 47 cm. The NodeMCU ESP8266 will perform protocol change, which operates as an IoT Gateway in routing data between IoT devices and cloud servers. ESP8266 allows users to connect to the internet via a Wi-Fi network and send data to the Firebase real-time database by implementing the HTTP/HTTPS protocol. The application domain will be responsible for data processing and service providers. In this case, the data from the database will be displayed through the Android interface.

The design of this waste monitoring system is divided into two designs, i.e., hardware and software design. The hardware components in this system are the Ultrasonic Sensor HC-SR04 which detects the unfilled level of the bin, and the NodeMCU ESP8266 microcontroller, which plays a role in sending data to the database while running the forecasting process.

The forecasting system in this research implements the Artificial Neural Network method with the Levenberg-Marquardt algorithm. The training and testing process is carried out using MATLAB software, and then the mathematical equations from the training process will be implemented in the microcontroller. The process diagram is described in Figure 2.

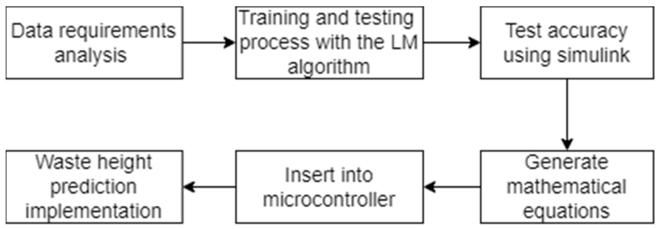


Fig. 2. ANN model design process diagram

The architecture of the Levenberg-Marquardt algorithm method can be described as shown in Figure 3.

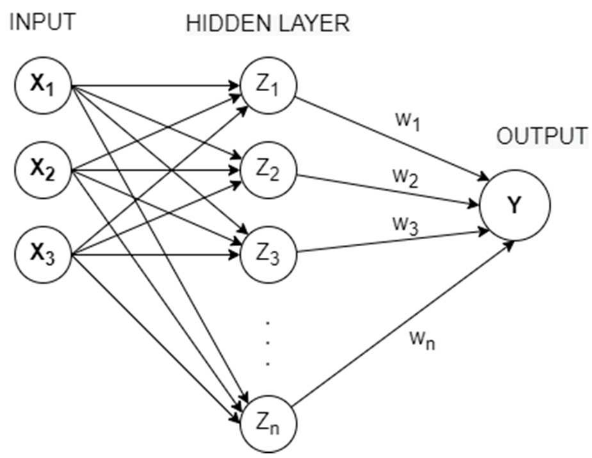


Fig. 3. Levenberg-Marquardt Network Architecture for Waste Height Prediction

The Levenberg-Marquardt network architecture above is used to predict the height of the garbage after 2 hours. The structure can be described as follows:

1. **Input**: 3 units of data symbolized by X1, X2, and X3, representing waste height data every 30 minutes.
2. **Hidden layer:** symbolized by Z1, Z2, Z3, … Zn serves as a liaison between input and output units expressed in weights and activation functions. This research uses three neurons for the "Dekanat Lama" node and six for the "Teknik Elektro" node.
3. **Output**: 1 unit of predictive data symbolized by Y; the result of the hidden layer weights forwarded to the output layer.

The following is an artificial neural network training process using the Levenberg Marquardt algorithm.
Step 1: Initialize parameters (epoch, marquardt parameter, tau factor, MSE target, hidden layer neuron).
Step 2: Calculation of the feedforward to the input unit that receives the input signal. This step is done by adding up the inputs with a weight of 1 and a bias of 1 toward the hidden layer with the activation function's help.
Step 3: Each output value is added with a weighted value of 2 and a biased 2. Then the whole unit is sent to the upper layer with the help of the activation function.
Step 4: Find the error magnitude and MSE of the output layer. This error in the final stage is the final stage of the feedforward calculation. Then compare the MSE value with the target error. If the MSE is still more significant than the target error set at the beginning of the training process, go to step 5.
Step 5: Beginning of the feedback calculation phase. Calculating error information for each output unit, then the results will be sent to the hidden layer of the output for the bias and weight correction process with the help of the activation function.
Step 6: Calculate the error information for each hidden layer unit, and then the results will be sent to the input layer to the hidden layer for the bias and weight correction process.
Step 7: Compile the Jacobian J(x) matrix based on the entire network's weight and bias correction values . This matrix helps obtain new weight and bias corrections in the hidden layer toward the input or the output.
Step 8: Finding the new weight and bias values in the input and output units looking for the difference between the old weights and bias corrections and the new ones.
Step 9: The training will stop if error = target error or if the conditions are met or epoch > epoch.

The Firebase Realtime Database uses the cloud server to store real-time sensor data. Firebase stores data in Javascript Object Notation (JSON) format that does not use queries to enter, update, delete, or add data [11]. In addition, there is also Firebase Authentication which is used for user authentication, and Firebase Cloud Messaging, which is connected to OneSignal for push notifications.

Fig. 4. Firebase Realtime Database Structure

In Figure 4, it can be seen that there are 2 location nodes, namely "Teknik Elektro" and the "Dekanat Lama," which shows the location of the bin. One node is named users, which is used to store user data when registering, and one is called Fetch Time which is used to store the last transport time data. Garbage in real-time will change when the user clicks the "Transport" button on the application.

The following keys are assigned to each location node: distance, percentage, time, and prediction. The distance parameter displays the distance in centimetres between the sensor and the trash. The thickness and cavity of the garbage's structure have resulted in a small mistake in terms of length. The level of garbage fullness can also be represented in percentage form. The data also have a timestamp. Moreover, the prediction field shows the forecasting value of waste capacity every 2 hours.

The data on the firebase will then be displayed through the android interface. Figure 5 is a use case diagram that shows the various activities that the user can perform in this application.

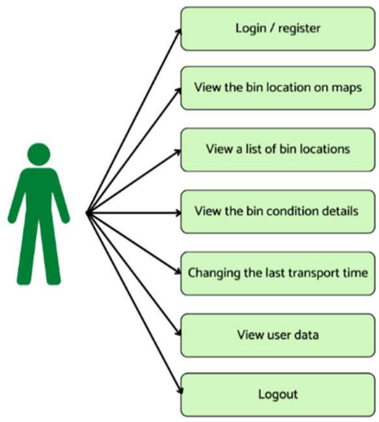


Fig. 5. Use case diagram

IV. Experiments and Results

Figure 6 shows the display of the hardware and data retrieval process. The two components are placed on the bin's lid measuring 20 litres. This system uses a wireless module as an internet connection and a PLN power supply as an electricity supply. As long as the equipment has an electricity supply and internet connection, the waste height data will continue to be recorded every 30 minutes.

Fig. 6. Hardware and data retrieval process

There is a delay in sending data by ESP8266 via a wireless network until the data enters the database. This delay is known as a delay which is the time the packet is travelling. Table 1 shows the delay test on each node.

TABLE I. TEST UPLOAD DATA TO FIREBASE FROM DELAY SIDE

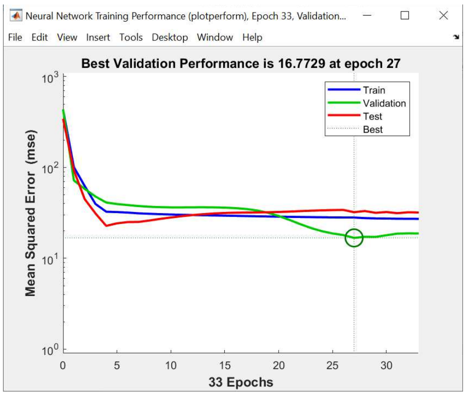
Test	"Dekanat Lama" Node		"Teknik Elektro" Node	
	Sent	*Received*	*Sent*	*Received*
1.	10:28:07.546	10:28:10.492	10:26:30.280	10:26:33.176
2.	10:58:07.578	10:58:10.504	10:56:30.335	10:56:33.352
3.	11:28:07.591	11:28:10.402	11:26:30.407	11:26:33.298
4.	11:58:07.582	11:58:10.470	11:56:30.468	11:56:33.368
5.	12:28:07.589	12:28:10.446	12:26:30.559	12:26:33.415

The delay formula is:

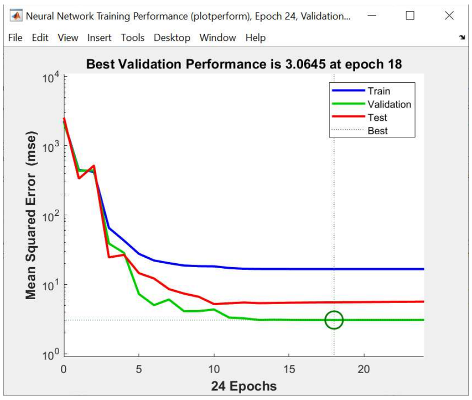
$$Delay = time\ packet\ sent - time\ packet\ received \quad (1)$$

It can be seen that the data communication network is good, with an average delay of the "Dekanat Lama" node of 2,912 seconds and the "Teknik Elektro" node of 2,886 seconds.

The waste forecasting system also tests the model using MATLAB to implement the Levenberg Marquardt Artificial Neural Network algorithm. The success rate of this test is when the prediction results produce the best accuracy and error values for both nodes so that it can be used as a forecasting feature in the waste monitoring application.



(a)

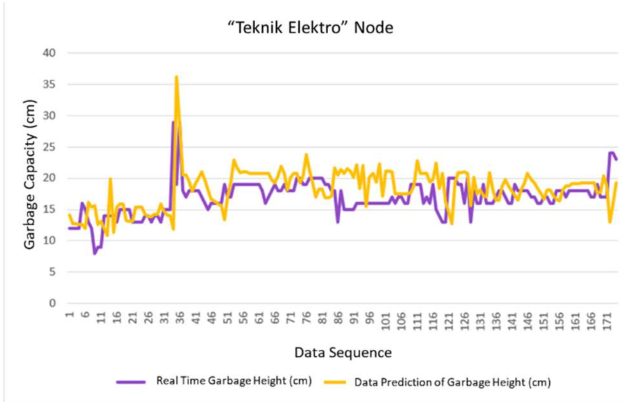


(b)

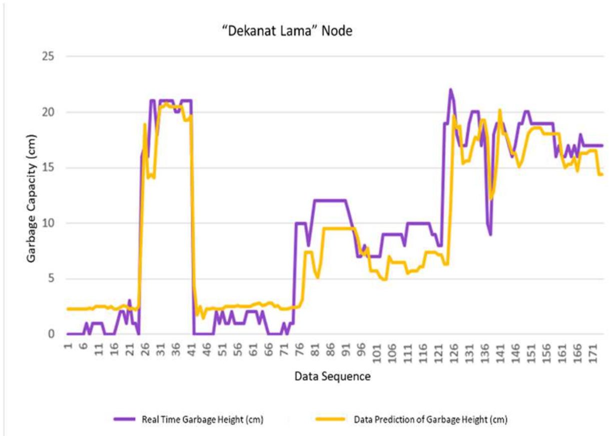
Fig. 7. Performance Curves Training for Nodes (a) "Teknik Elektro" (b) Dekanat Lama

Figure 7 shows the best training performance for the "Teknik Elektro" node and the "Dekanat Lama". Training stops after the best performance from the epoch with the lowest validation error. At the "Teknik Elektro" node, the best training data occurs in the 27th epoch with an MSE value of 16.7729. The best training from the "Dekanat Lama" node happened in the 18th epoch with an MSE of 3.0645.

This test was carried out for four days by comparing the actual sensor catch data with the predicted results. The aim is to determine the prediction model's accuracy and performance after it is applied to the monitoring system. The test result data is shown in the attachment. The graph in Figure 8 (a) compares the garbage height at "Teknik Elektro" Node to the chart of "Dekanat Lama" node in Figure 8 (b).



(a)



(b)

Fig. 8. Comparison of Prediction Data and Sensor Data (a) "Teknik Elektro" Node (b) "Dekanat Lama" Node

In Figure 8, it can be seen that the comparison of the predicted data with the actual data on the two nodes has almost the same pattern. Furthermore, it can be concluded that forecasting using the Artificial Neural Network method is appropriate and can be applied using waste height data every 30 minutes.

TABLE II. COMPARISON OF PREDICTION DATA WITH SENSOR DATA

Nodes	Comparison	Sensor Data (cm)	Prediction Data (cm)	Error (cm)	Square error (cm)
"Teknik Elektro"	Minimum	8	10.88	2.88	
	Maximum	29	36.19	7.19	
	Average	16.86	18.26	2.62	13.04
"Dekanat Lama"	Minimum	0	1.46	1.46	
	Maximum	22	20.82	2.82	
	Average	10.17	9.29	2.17	8.96

Table 2 shows that the average error generated in the "Teknik Elektro" node test is 2.62 cm, and the "Dekanat

Lama” node is 2.17cm. The intermediate level of squared error at the “Teknik Elektro” node is 13.04 cm, and at the “Dekanat Lama”, the node is 8.96 cm. The results of this bin-level forecasting can be used as a reference for determining policies and decisions for stakeholders so that they can form programs that can reduce waste generation regularly.

On the software side, it can be seen in Figure 9, which are some of the interfaces of the waste monitoring system. The first image shows the main page that provides information on the location of the bins and the percentage of the capacity of each node. The second image shows the detailed information of a particular selected node, for example, FT's “Dekanat Lama”. On this page, the user can get more information about the condition of the bins at the “Dekanat Lama” of FT. The report includes the forecasting results of the unfilled level, the time of the last transport, a button to confirm the garbage transport, and a button to send a notification. Moreover, the third image displays when the application gets a push notification.

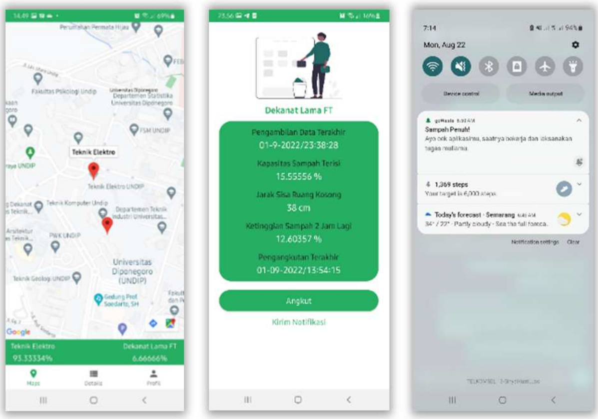


Fig. 9. Display of the waste monitoring application

Two tests were carried out at the waste monitoring system interface: alpha and beta. Alpha testing is done by the black box method to determine the functionality of the system application. Table 3 shows the results of alpha testing on this purpose system.

TABLE III. COMPARISON OF PREDICTION DATA WITH SENSOR DATA ANDROID APPLICATION FUNCTIONALITY TEST RESULTS

Trials	Form Test	Test result	
		Samsung A32	Oppo A12
1	Installing applications on android devices.	Succeed	Succeed
2	Showing the splash screen	Succeed	Succeed
3	Login	Succeed	Succeed
4	Register	Succeed	Succeed
5	Showing Main Menu	Succeed	Succeed
6	Tap *Bottom navigation*	Succeed	Succeed
7	Showing List of Bin Locations	Succeed	Succeed
8	Displaying Detailed Bin Information	Succeed	Succeed
9	Show Profile Menu	Succeed	Succeed
10	*Push Notification*	Succeed	Succeed
11	Logout	Succeed	Succeed
12	User Session	Succeed	Succeed

Beta testing aims to determine the usability of the application. This test was conducted using the System Usability Scale (SUS) questionnaire on 13 respondents who were the target users of this application. Table 3 is the result of the calculation of the SUS questionnaire obtained from the respondents.

Based on the results of the SUS questionnaire involving 13 respondents in Table 2, it can be seen that each respondent's score on ten questions. This value is the result of the value that has been processed using the SUS calculation, where the original value for the odd number question has been reduced by one, and the value for the even number question is the result of subtracting five minus the actual value. After that, each respondent's score is added up and multiplied by 2.5 to get the score for each respondent. Furthermore, the final SUS score is calculated by dividing the total score and the number of respondents. In this test, a SUS score of 70.2 is obtained, which means it is in the excellent category or above the average (mean = 68) [12].

TABLE IV. SUS QUESTIONNAIRE RESULTS

Respondent	Questions										Amount	Score (Amount x 2,5)
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*		
1	4	4	4	4	4	0	0	0	4	0	24	60
2	2	3	2	4	3	3	3	3	2	2	27	67.5
3	2	2	2	2	2	1	1	2	2	3	19	47.5
4	3	0	4	0	4	4	4	4	4	0	27	67.5
5	1	4	4	3	4	4	4	4	4	0	32	80
6	4	1	3	1	4	2	4	3	3	0	25	62.5
7	2	2	3	3	3	2	3	3	3	2	26	65
8	4	4	4	3	4	1	4	4	3	3	34	85
9	4	4	4	4	4	4	4	4	4	4	40	100
10	3	4	4	3	4	4	4	4	4	3	37	92.5
11	3	3	4	2	4	4	2	4	2	3	31	77.5
12	3	3	3	1	2	2	1	3	3	0	21	52.5
13	3	1	3	2	2	1	4	3	2	1	22	55
											Total score	912.5
											Average score (SUS Score)	70.2

V. CONCLUSION

IoT real-time data communication in the waste monitoring system has proper real-time data communication. That denotes the average delay at the “Teknik Elektro” and “Dekanat Lama” nodes, which is relatively small, i.e., 2.8886 seconds and 2.912 seconds. In the results of the prediction of the waste height using the LM method, ANN also has a small error, i.e., the “Teknik Elektro” node is 2.62 cm, and the “Dekanat Lama” node is 2.17 cm. The difference in error prediction results from the two nodes is due to the different historical data learning patterns at each location. While alpha testing the waste monitoring system interface using the black box method on seven smartphones with other specifications, it was found that the application features can run on all devices. Furthermore, based on the analysis of usability testing using the SUS questionnaire on 13 respondents who are part of the waste management at Diponegoro University, the SUS score of 70.2 means that the usability of this application is quite good.

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