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Energy Efficient IoT-Based Forest Fire Detection Using LoRaWAN and AI

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Abstract

Forest fires remain a global problem that has a major impact on the economy and health. Indonesia suffered losses of up to Rp. 72.95 trillion due to forest fires in 2019. Internet of Things (IoT) technology can be used for early detection of forest fires, but is constrained by limited network infrastructure and high energy consumption. This study aims to design a smart mitigation device and application for early detection of forest fires using LoRaWAN technology, which does not require an internet connection from the node to the gateway. In addition, an Artificial Intelligence method with adaptive sampling is applied, namely adaptive sampling threshold modeling and reinforcement Q-learning on the gateway to optimize energy use. The method used is Research and Development (R&D), with testing of the effectiveness of the design and descriptive statistical analysis to compare the energy efficiency between LoRaWAN devices with AI and conventional smart mitigation devices. The results of the study show that LoRa-based mitigation devices can cover the entire Jompie Botanical Garden area with a transmission distance of up to 3 kilometers and are 105% more energy efficient than conventional mitigation devices.

Keywords: *smart mitigation; energy efficiency; Internet of Things; Artificial Intelligence; LoRaWAN.*

1. INTRODUCTION

Forest fires are an environmental disaster that continues to be a global challenge because they have a significant impact on ecosystems, health, and the economy. In Indonesia, the economic losses caused by forest fires reached Rp. 72.95 trillion in 2019 (Arumingtyas, 2019). The impact of forest fires also significantly increases health problems for the surrounding community, especially lung health (Grant & Runkle, 2022). Mitigation efforts against forest fires are necessary, but geographical conditions are always a problem because most forests are not supported by road infrastructure, electricity, or internet networks (Gaveau et al., 2021). In forest fire disaster mitigation efforts, the use of technology is needed to facilitate access to early warnings of potential fires. One technology that can be used to monitor forest conditions is the Internet of Things (IoT) for early warning of potential fires (Saputro & Tuslam, 2022). The use of IoT technology in forest fire mitigation offers a potential solution for easy monitoring of forest conditions through a real-time wireless sensor network, but this technology requires an internet network infrastructure for data communication from sensor nodes to mobile servers. In addition, conventional IoT devices also require an adequate energy source to function properly. The next challenge is to optimize IoT devices for forest fire disaster mitigation so that they can reach locations with poor network infrastructure and are also energy efficient. In terms of data transmission technology development, LoRaWAN has excellent potential for sending data from sensor nodes to gateways without requiring an internet network and with a very wide coverage area, making it a potential solution to the network infrastructure constraints in hard-to-reach forests (Avila-Campos et al., 2019). In addition, to optimize energy use in IoT devices for fire disaster mitigation, energy-saving methods are needed to prolong device life. Artificial Intelligence with reinforcement learning modeling can be applied to modern hardware technology based on microcontrollers to optimize data transmission, thereby reducing battery energy consumption (Cai et al., 2023).

The topic of research on forest fire mitigation has emerged in recent times. The use of technology in early detection of forest fires has been widely implemented, one of which is using fuzzy logic and notification integration through Telegram. This system utilizes sensors to measure environmental parameters such as temperature, smoke, and fire. Based on data from the sensors, fuzzy logic determines the level of fire hazard. Each condition is indicated by LEDs and buzzers on the device, and notifications are sent via the Telegram application (Irfanianingrum et al., 2023).

Technological developments in fire mitigation utilize microcontrollers and sensors to collect temperature and smoke data, as well as IoT technology. Data from sensors is sent in real time via NodeMCU 12-F and Arduino Uno to an Android application, enabling remote monitoring by officials or communities living near forests. The implementation of IoT technology is expected to improve rapid response to potential forest fires (Pambudi et al., 2023).

The use of IoT technology in forest fire mitigation faces obstacles in the form of inadequate internet network infrastructure in the middle of the forest. The latest data communication technology, LoRaWAN (Long Range Wide Area Network), enables long-distance data transmission without an internet connection. Early warning of forest fires using LoRa technology for wireless communication in remote areas enables real-time detection and transmission of fire data, allowing for a rapid response to potential fires (Kavitha et al., 2023).

The effectiveness of IoT device energy use in forest fire mitigation now needs to be developed, given the difficulty of reaching forest locations to routinely recharge batteries. The development of adaptive sampling methods allows for the adjustment of IoT device sampling periods, with the aim of reducing energy consumption while maintaining monitoring quality. A case study conducted on coffee farms in Colombia showed a reduction in current consumption of up to 11% compared to traditional approaches to IoT devices without using this method (Rodriguez-Pabon et al., 2022).

From the description of several previous studies above, it is clear that there is quite a lot of research related to forest fire disaster mitigation by adopting sensor technology and the Internet of Things. However, there has been no specific research discussing the energy efficiency of IoT devices for forest fire mitigation using artificial intelligence adaptive sampling methods and deep reinforcement learning models. As we all know, maintaining IoT device batteries installed in forests requires more time and energy, so the research to be conducted is novel. in the design of IoT Tools and Applications with a combination of technologies to be used, namely the integration of IoT devices for early detection of forest fires with LoRaWAN so that sensor data can be sent to the gateway without an internet network, thereby covering a wider forest area, and implementing the Artificial Intelligence adaptive sampling method to optimize battery energy consumption so that the designed IoT devices are expected to have longer durability compared to conventional IoT devices for early detection of forest fires.

1.1. Problem Statement

Based on the background description, the problem formulation of this research is:

1. How to design an IoT-based Smart Mitigation device for forest fire disaster mitigation by utilizing LoRaWAN and Artificial Intelligence?
2. How effective is the energy consumption and coverage area of Smart Mitigation with the application of LoRaWAN and Artificial Intelligence compared to conventional IoT devices in forest fire disaster mitigation?

1.2. Research Objectives

2. To design an IoT-based Smart Mitigation device for forest fire disaster mitigation by utilizing LoRaWAN and Artificial Intelligence.
3. Evaluate the efficiency of energy use and the coverage area of smart mitigation with LoRaWAN and Artificial Intelligence technology so that it can reach remote locations and the device can last a long time.

2. RESEARCH METHOD

This research requires structured steps in building a smart mitigation system to optimize design time. The method used is R&D (research and development). The R&D research method is used to produce a specific product design or test the effectiveness of a research product (Waruwu, 2024).

2.1. Flowchart

The following is a flowchart of the research stages conducted:

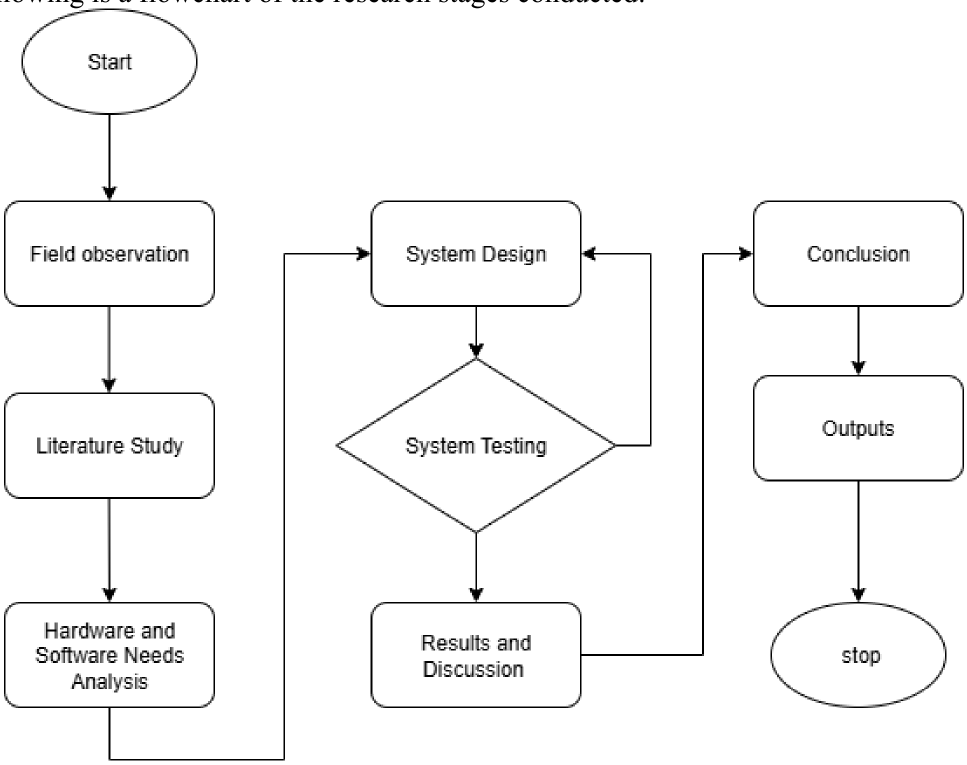

Figure 1. Flowchart of the research stages.

The following is an explanation of the flowchart of the research stages:

a. Field observation

At this stage, the team leader developed a research plan while the members prepared the tools to study the monitoring activities of forestry officials in forest fire prevention. The researchers conducted site surveys and interviews with officials to find out about monitoring activities and constraints. The results were data and information related to the location and forest monitoring activities.

b. Literature review

Next, the research team conducts a joint literature study to understand the theories and technologies that can be applied to the problems formulated. The result of this stage is a hypothesis that becomes an initial statement or answer to the research question.

c. Analysis of hardware and software requirements

In this stage, the team leader analyzed the overall requirements, while team members prepared the research hardware and software. The software included the operating system, programming language, and supporting software (database, text editor). The hardware included device design, domain and hosting, computers, sensors, and microcontrollers for collecting forest condition data. The result of this stage was the fulfillment of all research materials and tools.

d. System design

After identifying hardware and software requirements, the research team designs an integrated system that connects devices to applications via LoRaWAN data transmission to a web server via a gateway. The process begins with assembling the hardware, connecting the sensors to the microcontroller, and installing LoRaWAN. Next, an adaptive sampling-based artificial intelligence algorithm with reinforcement Q-learning is applied for scheduling, classification, and data delivery. Finally, the team designed software in the form of a database and mobile application to display sensor data.

e. System testing

This stage ensures that the designed system runs properly. If there are errors in the system, the hardware and software are redesigned to function properly. Testing uses the blackbox technique, which is very effective in its application in IoT-based devices (Fathoni & Oktiawati, 2021). The main test of this research is to test the device runtime. In addition, testing is also carried out on the data transmission range from the sensor node to the gateway module. Testing will also be carried out by simulating conditions around the sensor with smoke and high temperatures to obtain emergency conditions.

f. Results and Discussion

The results of the system testing will provide insights into the system's application on the research object. The outcomes of this stage include the device's range values and a comparison between conventional smart mitigation devices and smart mitigation devices utilizing LoRaWAN technology and artificial intelligence.

g. Conclusion

Furthermore, the conclusions in the form of research findings will be used to deepen theoretical studies in further research, both by the research team and other researchers.

2.2. Block Diagram

In the design of Smart Mitigation, planning is carried out for the system being developed, as shown in the following block diagram:

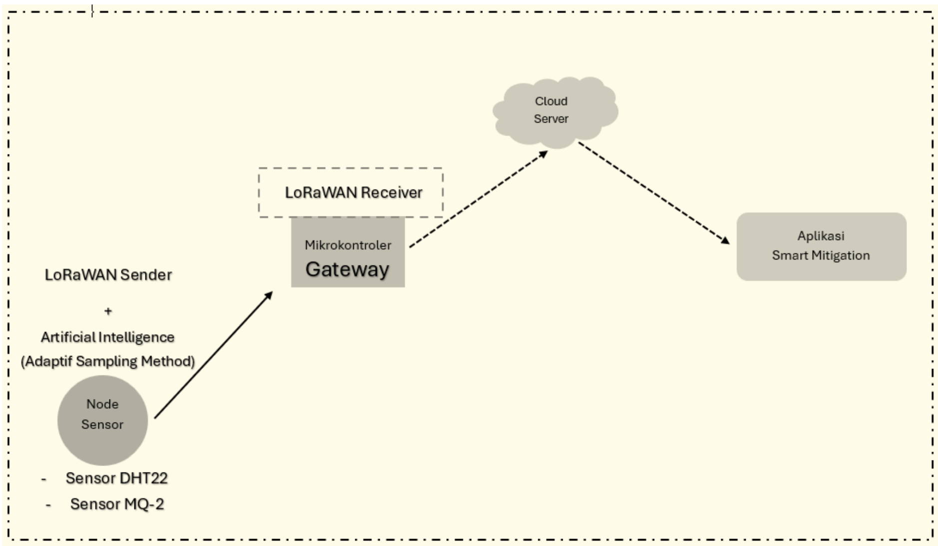

Figure 2. Block Diagram

Figure 3. Block Diagram

In the proposed system, smart mitigation uses two main sensors, namely the DHT22 (temperature) sensor and the MQ-2 (smoke) sensor to monitor forest conditions. Sensor data is transmitted via a LoRaWAN sender and received by a LoRaWAN receiver on the gateway module. The microcontroller at the node is implemented with Artificial Intelligence to detect data anomalies, so that transmission to the web server is more efficient and power usage is more effective according to the detected emergency conditions. The data is then sent via the internet to the web server and displayed on the smart mitigation application, which provides early warning notifications of potential forest fires to the community and forestry officials.

2.3. Location, population, and research sample

The research location is in Pare Pare City within the Jompie Botanical Garden area, a 13.5-hectare urban forest (Aan Ariska Febriansyah, 2023), where the research population consists of 1 forestry official and 3 community members. The sampling technique used is purposive sampling, as this test aims to evaluate the device's performance.

2.4. Data Collection Technique

The first step in data collection is to determine the population that researchers will use as a sample. The purpose of this initial step is to recruit field analysts, forestry officials, and local communities. The second step in data collection is to obtain data from smart mitigation devices that have been tested and displayed in a specially designed mobile application.

2.5. Data Analysis Techniques

This study used a quantitative evaluation method to analyze the runtime of smart mitigation devices that apply LoraWAN and Artificial Intelligence with conventional smart mitigation devices (Rajab et al., 2023).

2.6. State of the Art

In this study, Lorawan and AI technologies are combined directly and simultaneously without separating the contributions of each technology. Currently, there is no specific research discussing the energy efficiency of IoT devices for forest fire mitigation using artificial intelligence, adaptive sampling models, reinforcement learning, and specifically the use of the Q Learning algorithm. As we know, maintaining the batteries of IoT devices installed in forests requires more time and energy, so the research to be conducted is novel. in the design of IoT devices and applications with a combination of technologies to be used, namely the integration of IoT devices for early detection of forest fires with LoRaWAN so that sensor data can be sent to the gateway without an internet network, thereby covering a wider forest area, and implementing the artificial intelligence adaptive sampling method to optimize battery energy consumption so that the designed IoT devices are expected to have longer durability compared to conventional IoT devices for early detection of forest fires.

3. RESULTS AND DISCUSSION

3.1. Device Schematic

The design of the device began with the creation of a schematic for a conventional forest fire mitigation device and a LoRa AI forest fire mitigation device.

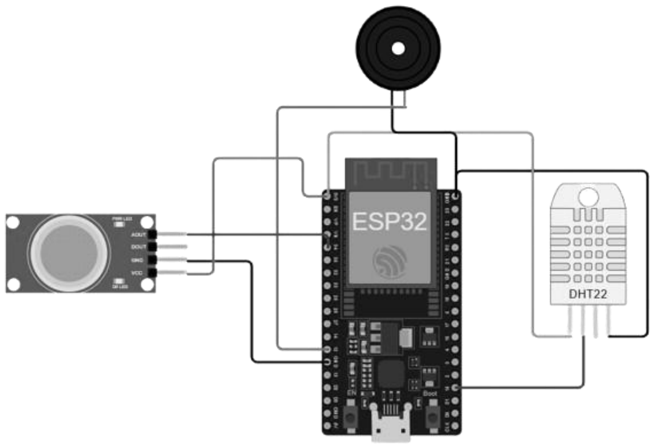

Figure 3. Schematic Conventional device

The design uses an esp32 microcontroller, DHT22 sensor, MQ2 sensor, and Buzzer. On the DHT22 sensor, the data pin is connected to the microcontroller on pin D15, vcc on pin 3v3, and GND on pin GND. For the MQ2 sensor, the data pin is connected to pin D34, the VCC pin to 3V3, and the GND pin to GND. Additionally, a buzzer is connected to the GPIO12 pin and GND.

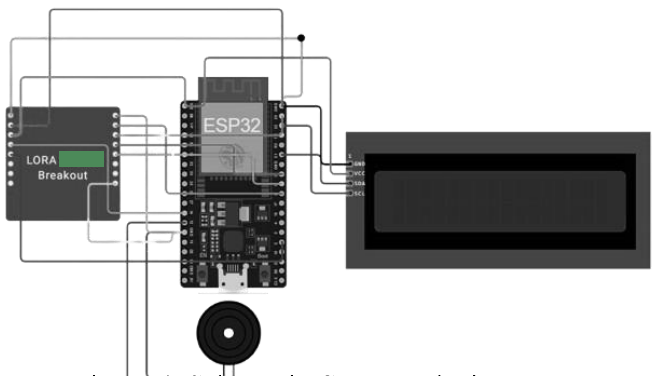

Figure 4. Schematic Gateway device

In the figure, the design was carried out using an ESP32 microcontroller, LoRa SX1278, 16x2 I2C LCD, and a buzzer. The LoRa sx1278 module is connected to the microcontroller with DIO0 on pin D2, RST on pin D15, SCK on pin D18, MISO on pin D19, MOSI on pin D23, NSS on pin D5, VCC on pin 3.3, and GND on GND. For the 16x2 I2C LCD, SDA is connected to pin D21, and SCL is connected to pin D22. For the buzzer, the data is connected to pin D12, and GND is connected to GND.

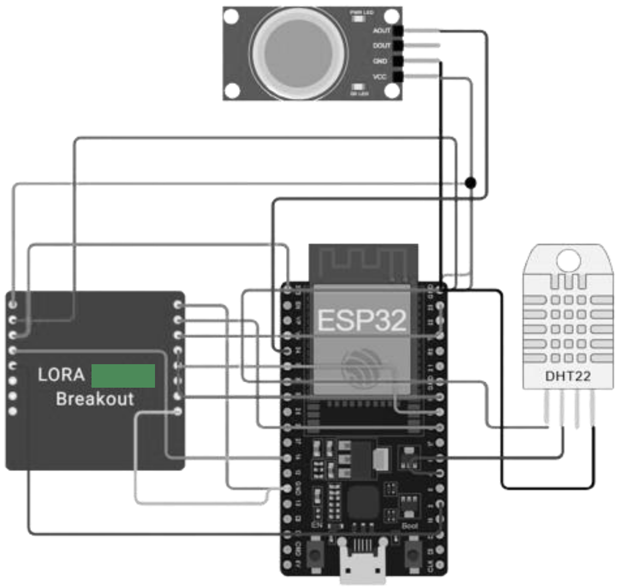

Figure 5. Schematic LoRA AI device

In the image, the design was made using an esp32 microcontroller, DHT22, MQ2, and LoRa sx1278 module. On the DHT22 sensor, the data pin is connected to the microcontroller on pin D4, vcc on pin 3v3, and GND on pin GND. For the MQ2 sensor, the data pin is connected to pin D34, VCC to pin 3V3, and GND to pin GND. The LoRa SX1278 module is connected to the microcontroller with DIO0 on pin D2, RST on pin D15, SCK on pin D18, MISO on pin D19, MOSI on pin D23, NSS on pin D5, VCC on pin 3.3, and GND on GND.

3.2. Application Design Results

In this study, the ThinkSpeak platform was used to display data from the sensors. The image shows three fields for displaying data. Field 1 displays the temperature value, Field 2 displays the humidity value, and Field 3 displays the gas or smoke value. In the Thinkspeak application, two different channels were created to display sensor data from conventional fire mitigation devices and fire mitigation devices with LoRa and AI.

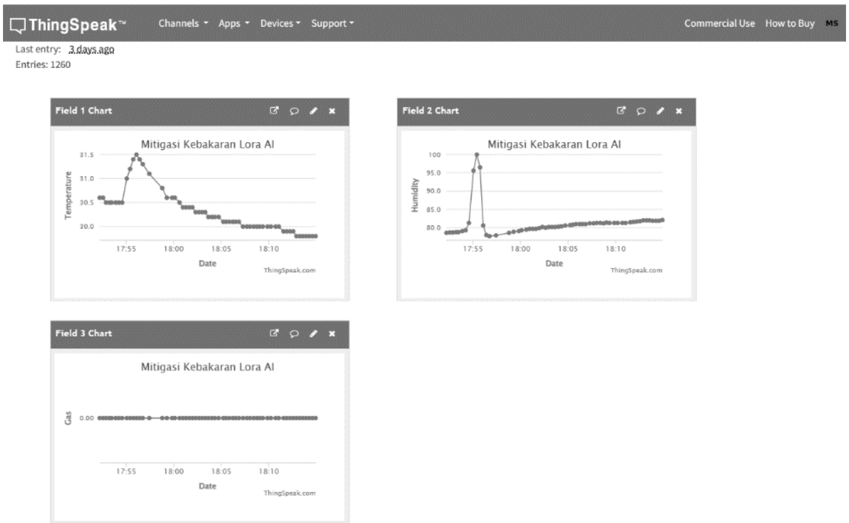

Figure 6 . Data View in Thinkspeak

3.3. Blackbox Testing

In the Blackbox testing, testing scenarios were conducted on both devices.

Table 1. Blackbox Testing for Conventional Mitigation Device

No	Test Scenario	Expected Output	Status
1	The DHT22 sensor detects humidity	Data appears on the application	Yes
2	The DHT22 sensor detects temperature	Data is displayed on the application	Yes
3	The MQ 2 sensor detects smoke	Data displayed on the application	Yes
4	Buzzer activates during data transmission	Buzzer sounds	Yes
5	DHT22 sensor detects humidity changes	The graph on the app changes	Yes
6	The DHT22 sensor detects changes in temperature	The graph on the app changes	Yes
7	The MQ 2 sensor detects smoke changes	The graph on the app changes	Yes

In the table. Testing was conducted on a system equipped with a DHT22 sensor to measure air temperature and humidity, an MQ-2 sensor to detect smoke, and a buzzer to provide an audible warning if data was successfully sent to the cloud. The testing was conducted by observing whether each sensor could work properly and display its data in the application. The blackbox testing method means that the testing only focuses on the functions visible to the user, without looking at how the system works internally.

The table shows that all 7 test scenarios were successful, marked with a "Yes" status for each test. The sensors successfully read environmental data and sent it to the application to be displayed in graph form. The system also proved capable of detecting changes in environmental conditions, such as changes in humidity or the presence of smoke, and then responding appropriately. These perfect test results indicate that the conventional fire mitigation system is ready for use in environmental monitoring.

Table 2. Blackbox Testing for LoRa AI Mitigation Device

No	Test Scenario	Expected Output	Status
1	AI temperature data analysis	Data sent if temperature is above 40 degrees	Yes
2	AI humidity data analysis	Data sent if humidity is below 30%	Yes
3	AI smoke data analysis	Data sent if smoke is above 500	Yes
4	Buzzer activates when data is sent to the application	Buzzer sounds	Yes
5	Data sent to Gateway with LoRa	Data displayed on the Gateway LCD	Yes
6	Gateway sends data to the Application	Data displayed on the Dashboard	Yes
7	Device sleeps	Device in sleep mode if conditions are not met	Yes
8	Active device reads data	Device reads data every 5 seconds if conditions are met	Yes

This blackbox test table shows the results of evaluating a forest fire mitigation system equipped with LorA transmission technology and artificial intelligence (AI) IoT for real-time data analysis. This system uses AI to analyze data from various sensors, including temperature sensors with a threshold of 40 degrees, humidity sensors with a minimum threshold of 30%, and smoke sensors with a threshold of 500. In addition, the system is equipped with a buzzer that sounds every time data is successfully sent from the sensor, a LoRa gateway for wireless data transmission, a , and a sleep mode device that optimizes energy consumption. Each component is tested to ensure that it functions according to the specified parameters.

The test results show that all eight scenarios were successfully executed, marked with a "Yes" status for each test. The AI system is capable of accurately analyzing sensor data and providing appropriate responses when sensor values exceed the specified limits. The gateway successfully transmitted data to the dashboard application, while the sleep mode feature was only activated when conditions were not met. The device is also capable of reading data every 5 seconds when active, indicating that this monitoring system is well integrated and ready for use in automatic and continuous environmental monitoring.

3.4. Device Transmission Range Testing

In this study, testing the LoRa transmission range required a map of the Jompie Botanical Garden location to see the area coverage. The following is a map of the Jompie Botanical Garden:

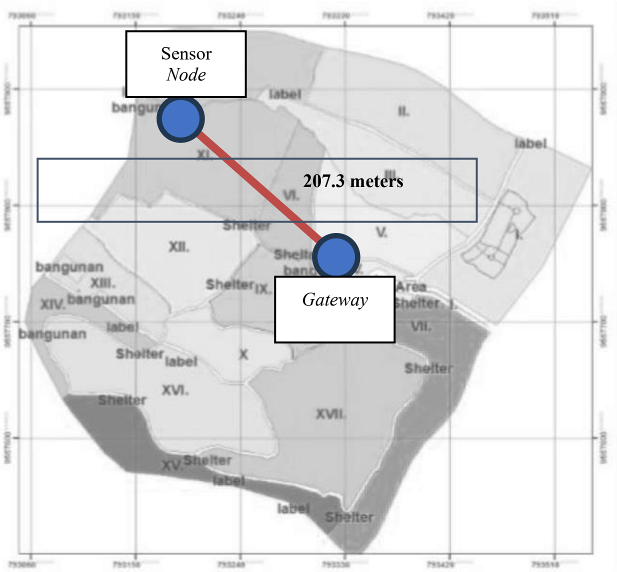

Figure 7. Map of The Jompie Botanical Garden

In testing the device coverage area with LoRa transmission, an analysis was conducted of the distance from the center of Jompie Botanical Garden to the edge of Jompie Botanical Garden. The area of Jompie Botanical Garden is 13.5 hectares, calculated using a circle formula. m^2The area of Jompie Botanical Garden is 13.5 hectares, which is equivalent to 135,000 square meters, where 1 hectare = 10,000 square meters . Using the circle area formula$A = \pi r^2$, then finding the radius length that becomes the center point to the edge of Jompie Botanical Garden.

Step 1. Area of a Circle

$$A = 135.000\ m^2 \qquad (1)$$

Step 2. Calculate the Radius

$$r = \sqrt{\frac{A}{\pi}} \qquad (2)$$

The distance from the center point to the edge of Jompie Botanical Garden is approximately 207.3 meters. After testing the LoRa transmission range between the Node device and the Gateway device, the maximum distance at which the devices can communicate to send sensor data is 3.1 kilometers. Therefore, devices with LoRa communication can cover 100% of the entire area of Jompie Botanical Garden.

3.5. Device Runtime Testing

In this study, artificial intelligence algorithms were applied in data-based decision making from sensors. Two approaches were used in this system: Threshold Adaptive Sampling (TAS) and Reinforcement Learning (RL), more specifically using the Q-learning algorithm. Threshold Adaptive Sampling (TAS) is a method for efficient data collection by varying sampling rates according to the environment, saving energy by collecting data when certain levels of thresholds (such as temperature or smoke) are satisfied. Reinforcement Learning (RL) including Q-learning is a model-free learning algorithm, in which an agent learns to act by making actions and getting reward or punishment. The Q-learning algorithm updates Q-values (the values corresponding to the quality of taking some action in given state), aiming to find optimal actions maximising the long-term return. When TAS and Q-learning are integrated, an IoT system can self-configure its data sampling frequency and make energy utilization in favour of maximizing battery lifetime by accurately detecting the event detection (e.g., forest fire monitoring) as in [38], where it is learning to balance between sampling frequency versus energy efficiency based on environmental information. These two algorithms enable the system to adapt to a dynamic environment based on data collected from sensors. The following is the sequence of application of the two algorithms in the LoRA AI-based fire mitigation system:

a. Implementation of Threshold Adaptive Sampling

Threshold Adaptive Sampling (TAS) is used to set the sampling interval based on certain conditions of environmental parameters, such as temperature, humidity, and gas. When certain conditions meet the specified threshold, the system will take samples and send data. This method aims to maximize resource utilization by only taking samples when the conditions are relevant, reducing workload and extending device life.

For example:

- T is temperature,
- H is humidity,
- G is the gas sensor value.

The thresholds for temperature, humidity, and gas are set as follows $T_{threshold}$, $H_{threshold}$, and $G_{threshold}$. The sampling conditions can be expressed by the following formula:

$$SendData = \{1 \ if \ T \geq T_{threshold \ or} \ H \leq H_{threshold \ or} \ G > G_{threshold} \ 0 \ etc \quad (5)$$

b. Implementation of Reinforcement Q Learning

Next, the reinforcement algorithm, specifically Q-learning, is implemented. This method provides the system with experience to make decisions based on previous data. In this implementation, the agent chooses between two actions (sending data or not) based on the Q value, which is updated using the following formula:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(R + \gamma \max_{a'} Q(s',a') - Q(s,a)\right) \quad (3)$$

Where:

- $Q(s,a)$ is the Q-value for the state s and action a ,
- α is the learning rate,
- R is the reward received after performing action a ,

- γ is the discount factor,
- $\max_{a'} Q(s', a')$ is the maximum value of all Q values for the next state s' .

In this case, the state (s) is defined by whether data should be sent or not based on a predetermined threshold condition. In this method, the reward system will be applied with the following conditions:

For example:

- C is the condition (boolean: 1 if the threshold is met, 0 if the threshold is not met).
- D is data transmission decision (boolean: 1 if data is transmitted, 0 if data is not transmitted).
- R is reward gifted.

Therefore:

$$R \{10 \ if \ C = 1 \ and \ D = 1 \ 5 \ if \ C = 0 \ and \ D = 0 \ -5 \ if \ (C = 1 \ and \ D = 0) \ or \ (C = 0 \ and \ D = 1) \quad (4)$$

c. Threshold in the sampling interval

The sampling interval (sampleInterval) is adjusted based on the decision made by the Q-learning algorithm. If data is sent, the sampling interval will be shortened, while if it is not sent, the interval will be extended.

The formula is as follows:

$$sampleInterval = \{5000 \ \ if \ data \ send \ \ 20000 \ \ if \ data \ dont \ send \quad (5)$$

d. The system enters Sleep Mode for non-compliance

If the conditions do not meet the threshold, the system will enter sleep mode for a certain period, which is determined by the following formula:

$$sleep\ time = \begin{cases} 60\ seconds & if\ conditions\ fails\ to\ meet\ the\ threshold\ within\ 120\ seconds \\ Tcheck & if\ condition\ meets\ the\ threshold\ within\ 120\ seconds \end{cases}$$

This condition checks whether the threshold is met within 120 seconds, and triggers a 60 second timeout if it's not.

In device runtime testing, a battery with a capacity of 10000mAh is used to observe energy consumption on each device. Below are the results of device runtime testing with 10 test cycles.

Table 3. Runtime Testing

Cycle	Conventional Mitigation					LoRA AI Mitigation				
	Battery 100%		Battery 0%		Runtime	Battery 100%		Battery 0%		Runtime
	Date	Time	Date	Time		Date	Time	Date	Time	
1	8/12/25	12:44	8/13/2025	7:01	18 hours	8/12/2025	12:44	8/13/2025	9:00	20 hours
2	8/13/25	1:00	8/14/2025	6:00	18 hours	8/13/2025	1:00	8/14/2025	6:00	17 hours

		PM					PM			
3	8/14/25	3:00	8/15/2025	9:00	18 hours	8/14/2025	3:00 PM	8/15/2025	9:00	18 hours
4	8/16/25	5:00	8/16/2025	10:49	18 hours	8/16/2025	5:00	8/17/2025	6:10	25 hours
5	8/17/25	1:00	8/18/2025	6:33	18 hours	8/17/2025	1:00 PM	8/18/2025	10:02	21 hours
6	8/20/25	8:52 p.m.	8/21/2025	2:30 PM	18 hours	8/20/2025	8:52 PM	8/21/2025	9:40 PM	25 hours
7	8/22/25	4:50 PM	8/22/2025	10:30	18 hours	8/22/2025	4:50 PM	8/25/2025	12:30	56 hours
8	8/26/25	10:30	8/26/2025	11:00	18 hours	8/26/2025	10:30	8/28/2025	8:30 PM	58 hours
9	8/29/25	8:24	8/30/2025	1:00	18 hours	8/29/2025	8:24	8/31/2025	11:00 PM	63 hours
10	9/1/25	5:03 PM	8/2/2025	11:00	18 hours	9/1/2025	5:03 PM	9/4/2025	11:00	66 hours

In the table. Testing was conducted to compare energy consumption through battery life between conventional fire mitigation systems and mitigation using LoRa AI. This test used battery usage time to measure and record the energy consumption of the Conventional Mitigation and LoRa AI Mitigation systems. Each cycle began with a fully charged battery at 100% and ended with the battery completely depleted at 0%, and the date and time for each cycle were recorded. After conducting the tests, the results showed that the Conventional Mitigation system had stable battery usage time, with a recorded range of nearly 18 hours for each cycle. This stable battery usage time indicates that the conventional system operates using a constant energy schedule without any increase in energy efficiency. On the other hand, LoRa AI Mitigation had variable and significantly increased battery usage time. The first cycle recorded 20 hours and varied throughout the cycle, before reaching 66 hours in the 10th cycle. The above differences prove that the application of LoRa AI in the system is capable of optimizing battery usage. For this reason, we can calculate the percentage difference and how many times the battery consumption results are compared based on runtime.

Percentage calculation:

$$different\ percentage = \frac{Total\ Runtime\ \ LoRa\ AI - Total\ Runtime\ Conventional}{Total\ Runtime\ Conventional}\ x\ 100 \qquad (6)$$

From the equation above, the test results indicate that LoRa AI technology increases battery life to 105% or 2.05 times longer than the standard conventional mitigation cycle. Therefore, the application of this technology in fire extinguishing systems is not only suitable for improving energy efficiency but also for supporting the sustainability of the system over a longer period of time. The comparison results can also be seen in the graph.

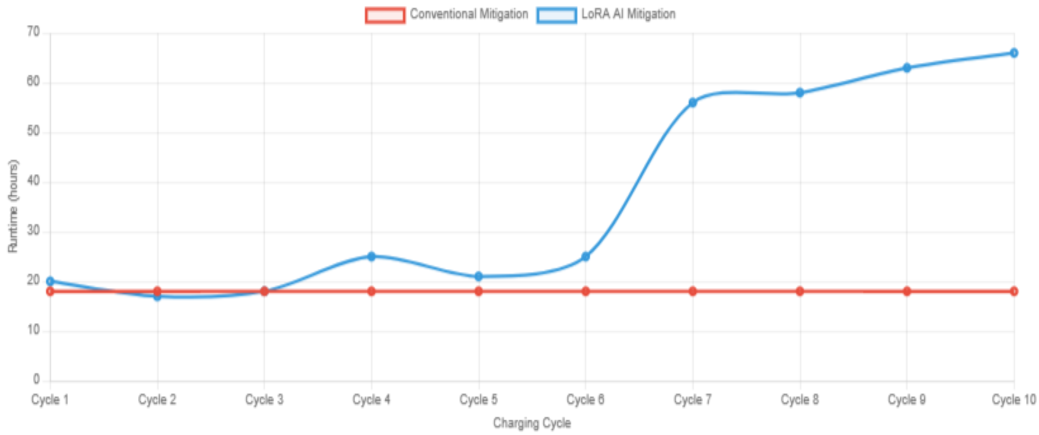

Figure 8. Graph Result Runtime Testing

4. CONCLUSION

This study began with the design of a forest fire mitigation device using an esp32 microcontroller, a dht22 sensor, and an MQ2 sensor. Two devices were designed: a conventional forest fire mitigation device and a forest fire mitigation device with LoRA and AI. Next, a cloud-based application was designed to display data from the sensors using the thinkspeak platform. The LoRa and AI-based mitigation device applied the Adaptive Sampling and Reinforcement Q Learning algorithms to adjust environmental data collection. The results of the test with a 10000mAh battery and conducted for 10 cycles showed that the application of LoRaWAN and AI technology in forest fire mitigation devices can overcome network infrastructure problems and optimize energy consumption. LoRa technology enables data transmission over a distance of 3 kilometers to a wide area, such as the Jompie Botanical Garden, without the need for an internet connection. In addition, it has been proven that the use of AI with reinforcement learning and adaptive sampling methods improves energy efficiency. Compared to conventional mitigation devices, this system has the ability to increase device life by up to 105%. Furthermore, test results show that devices using LoRaWAN and AI technology can last longer with less energy consumption, indicating that this technology is more energy-efficient. Overall, this LoRaWAN and AI-based forest fire mitigation system can improve early fire detection efficiency and offer sustainable energy solutions for IoT devices in remote locations.

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References

Aan Ariska Febriansyah. (2023). *Kebun Raya Jompie, Hutan Alami di Tengah Kota Parepare*. Www.Rro.Cp.Id. https://www.rri.co.id/wisata/213399/kebun-raya-jompie-hutan-alami-di-tengah-kota-parepare#:~:text=Di Indonesia%2C hanya ada dua,spot alami menarik untuk berfoto.

Arumingtyas, L. (2019, 16). Bank Dunia: Kerugian Indonesia Dampak Karhutla 2019 Capai Rp72,95 Triliun. *Mongabay.Co..Id*. https://www.mongabay.co.id/2019/12/16/bank-dunia-kerugian-indonesia-dampak-karhutla-2019-capai-rp7295-triliun/

Avila-Campos, P., Astudillo-Salinas, F., Vazquez-Rodas, A., & Araujo, A. (2019). Evaluation of lorawan transmission range for wireless sensor networks in riparian forests. *MSWiM 2019 - Proceedings of the 22nd International ACM Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems*, 199–206. https://doi.org/10.1145/3345768.3355934

Cai, Q., Cui, C., Xiong, Y., Wang, W., Xie, Z., & Zhang, M. (2023). A Survey on Deep Reinforcement Learning for Data Processing and Analytics. *IEEE Transactions on Knowledge and Data Engineering*, *35*(5), 4446–4465. https://doi.org/10.1109/TKDE.2022.3155196

Fathoni, A., & Oktiawati, U. (2021). Blackbox Testing terhadap Prototipe Sistem Monitoring Kualitas Air Berbasis IoT. *Jurnal Nasional Teknik Elektro Dan Teknologi Informasi*, *10*, 362–368. https://doi.org/10.22146/jnteti.v10i4.2095

Gaveau, D. L. A., Descals, A., Salim, M. A., Sheil, D., & Sloan, S. (2021). Refined burned-area mapping protocol using Sentinel-2 data increases estimate of 2019 Indonesian burning. *Earth System Science Data*, *13*(11), 5353–5368. https://doi.org/10.5194/essd-13-5353-2021

Grant, E., & Runkle, J. D. (2022). Long-term health effects of wildfire exposure: A scoping review. *The Journal of Climate Change and Health*, *6*, 100110. https://doi.org/https://doi.org/10.1016/j.joclim.2021.100110

Irfanianingrum, I., Rizal Chaidir, A., Sumardi, S., Aditya Rahardi, G., & Wahyu Herdiyanto, D. (2023). Sistem Pendeteksi Dini Kebakaran Hutan Berbasis Logika Fuzzy dengan Integrasi Telegram. *Emitor: Jurnal Teknik Elektro*, *22*(2), 120–127. https://doi.org/10.23917/emitor.v22i2.22019

Kavitha, S., Kanchana, K., & Venkatesan, G. (2023). Long Range (LoRa) and Alert Network System for Forest Fire Prediction. *Asian Journal of Water, Environment and Pollution*, *20*(6), 61–66. https://doi.org/https://doi.org/10.3233/AJW230080

Pambudi, S. A., Rahma, I. M., Artono, B., Prasetyo, Y., & Baidlowi, I. (2023). Sistem Monitoring Alat Pendeteksi Dan Pemadam Kebakaran Hutan Bertenaga Solar Cell Berbasis Internet of Things (IoT). *Journal of Electrical,Electronic,Control and Automotive Engineering*, *8*(1), 13–21.

Rajab, H., Al-Amaireh, H., Bouguera, T., & Cinkler, T. (2023). Evaluation of energy consumption of LPWAN technologies. *Eurasip Journal on Wireless Communications and Networking*, *2023*(1). https://doi.org/10.1186/s13638-023-02322-8

Rodriguez-Pabon, C., Riva, G., Zerbini, C., Ruiz-Rosero, J., Ramirez-Gonzalez, G., & Corrales, J. C. (2022). An Adaptive Sampling Period Approach for Management of IoT Energy Consumption: Case Study Approach. *Sensors*, *22*(4), 1–22. https://doi.org/10.3390/s22041472

Saputro, U. A., & Tuslam, A. (2022). Sistem Deteksi Kebakaran Berbasis Internet Of Things Dengan Pesan Peringatan Menggunakan NodeMCU ESP8266 Dan Platform ThingSpeak. *Jurnal Infomedia*, *7*(1), 24. https://doi.org/10.30811/jim.v7i1.2958

Waruwu, M. (2024). Metode Penelitian dan Pengembangan (R&D): Konsep, Jenis, Tahapan dan Kelebihan. *Jurnal Ilmiah Profesi Pendidikan*, *9*, 1220–1230. https://doi.org/10.29303/jipp.v9i2.2141