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Development of twig dryness sensor for internet of things-based peatland fire early detection system

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ABSTRACT

Peatland fires are a severe threat to the global environment. Existing peatland fire early detection systems commonly detect parameters such as air temperature, humidity, gas, smoke, and fire. This paper proposes a new peatland fire early detection method using the twig moisture content parameter. This method utilizes the most significant parameter approach for fire vulnerability compared to current peatland fire early detection systems. In particular, we developed an internet of things (IoT)-based twig dryness sensor to realize a field-applicable system. We propose a twig dryness sensor using the resistive sensing method, which employs a needle electrode to measure twig moisture content. Using the twig dryness sensor, three classifications of flammability were obtained, namely very difficult (moisture above 30%), difficult (moisture between 5%-30%) and easy (moisture less than 5%). This device utilizes readily available compact and portable materials. This instrumentation is digitally controlled with a low-power consumption microcontroller and long range (LoRa) transmitter, providing a long-life battery and long-range data transmission. Sensor data visualization is presented as twig dryness values and categorized according to fire vulnerability levels. The proposed system provides real-time and sustainable measurement.

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1. INTRODUCTION

The world's peatland ecosystem is estimated to extend across approximately 398 million hectares [1]. Peatland plays an essential role in the balance of the environment [2]. Peatlands are organic lands prone to fire [3], [4]. Peatland fire produce carbon dioxide (CO_2) emissions, health problems, air pollution [5], causing ecological damage [6], water scarcity, and land erosion [7]. The main causes of peatland fires originate from land clearing through slash and burn methods for agriculture, negligence in land preparation, and peatland drainage [8]. Natural conditions such as extreme dry seasons can increase the risk of fires [9]. Early detection system plays a central role in minimizing the impact of fires by enabling a rapid response [10].

Carta *et al.* [11] have analyzed the various methods of forest fire early detection systems available today including satellite, ground sensor (wireless sensor network/WSN) and aerial sensor (unmanned aerial vehicle/UAV) technologies. Some of these are Yu *et al.* [12] propose a WSN paradigm for real-time forest fire detection. Sensor nodes collect measured data (*e.g.*, temperature, relative humidity) and send to their respective cluster nodes. Cui [13] present an internet of things (IoT)-based network where various types of sensors serve as monitoring devices, measuring variables such as temperature, atmospheric pressure, humidity, and the presence of pollutants such as CO and CO_2. Varela *et al.* [14] proposes a method for detecting forest fires, using a network of wireless sensors to detect a fire event using only the information from two sensors: temperature and humidity. A methodology using UAV-light detection and ranging (LiDAR) was proposed by Fernández-Álvarez *et al.* [15] to characterize forest fuels within a wildland-urban interface (WUI). Video-based fire detection uses the visible and infrared spectrum to exploit the characteristic properties of the flames, smoke, and thermal radiation emitted by fires. ForestWatch is a semi-automatic fire detection system based on an optical camera sensor system. A camera mounted on a tower scans the area for smoke during the day and for fire glow during the night. It can detect smoke within 16 to 20 km [16]. Image analysis is a standard process using satellite images. This research distinguishes smoke from fires, clouds and the earth's surface using a neural network and NOAA-14 satellite imagery [17]. Schroeder *et al.* [18] used images from the Landsat-8 satellite, which carries the infrared thermal sensor (TIRS). Satellite images alone cannot always detect fires in real-time. Even though sun-synchronous satellites are close to Earth, there is still a long delay in detecting fires. Detection speed is essential, even though it is more precise than other ground-based instruments.

Understanding the physical properties of the material involved in the fire and the mechanisms that occur during the burning process is fundamental [19]. Critical points in the physics analysis include the composition of peatland consisting of organic material such as litter, leaves, twigs, and roots which accumulate and decompose over years [20]. This organic material has a high carbon content and significant moisture levels [21]. High moisture in peatland makes it resistant to direct burning, but when the land dries, the flammability increases [22], [23]. Dimitrakopoulos *et al.* [24] found a correlation between the parameter of twig dryness and the level of forest and land fire susceptibility. In order to develop a relative flammability classification and to determine the extinction moisture of these fuels, the study carried out tests on fuel moisture. The study found that fuel flammability can be used to assess wildfire risk. Research indicates that moisture content is the most influential factor in natural fuel flammability. Schunk *et al.* [25] tested the use of litter and fuel moisture measurements for fire hazard analysis in eight forest stands in southern Germany. The findings indicate a reasonable ranking of fire hazard indexes, with coniferous and broadleaved stands differing considerably in terms of low to medium fire hazard. The study suggests that the twig dryness parameter can be used to determine the level of vulnerability to ground fire.

Several techniques exist for the measurement of twig moisture content. The techniques used to determine a twig's moisture content (MC) can be classified into two main categories: direct and indirect [26]. The most commonly employed direct measuring procedures entail drying the material in a drying chamber. Indirect techniques employ electrical moisture sensors and systems that measure moisture content through electrical detection [27]. Barański *et al.* [28] obtained results of the electrical resistance comparison showed a dependence of wood resistance on the moisture content. The electrical resistance method is a common way to monitor moisture in many commercial systems [29]. Forsthuber *et al.* [30] have developed printed moisture sensors for wood. These sensors can monitor moisture in construction elements during use. The sensors use an interdigitated electrode design to monitor large areas. Saban *et al.* [31] have developed an IoT system based on wireless Bluetooth low energy (BLE) connectivity to monitor the moisture content of wood. This research using a compact device that relies on a resistance measurement for an ultra-wide range of resistance values. The printed moisture sensors, that can be integrated directly into wooden construction elements has been developed These sensors would allow in-situ monitoring of the moisture dynamics within construction elements during use. The printed sensors allow extensive area moisture monitoring, using an interdigitated electrode design [32].

As in the previous description, this paper addresses the issue of early detection methods for peatland fires. The existing early detection system method uses a general parameter approach such as temperature sensing, humidity sensing, gas sensing, smoke sensing, and fire sensing. The current work proposes a new peatland fire early detection method using the twig dryness parameter. This method is the most representative approach as single significantly influences peatland fire susceptibility. This method is expected to be a solution for overcoming the weaknesses of the old method when applied in the field. Therefore, the objective of this research is to create a sensor for detecting dryness in twigs as part of an IoT-based system for early detection of peatland fires. The system will involve wireless data transmission, data storage, data visualization, and a user interface. This sensor detects the voltage of the resistors to measure the dryness of the twig. This platform utilizes inexpensive, low-power materials and operates independently with a solar panel for power supply. The gateway collects data from long range (LoRa) sensor nodes and transmits it to a server via Wi-Fi. A web-based application was created to visualize the sensor data and display fire vulnerability alerts. Further work, this device can be used as an AI tool to predict twig moisture levels in real time.

2. METHOD

The methodology started with the design a twig dryness sensor, characterization of the twig dryness sensor, flammability categorization, and design of IoT devices. In this section, the necessary materials, both hardware and software, have been mentioned. The following is a description of the work steps:

2.1. Design of resistive sensing-based twig dryness sensor

The design of twig dryness sensor follows Figure 1. It was formed of two main parts: analog part containing the probe, voltage divider circuit, and signal conditioning unit, providing resistance measurement; and a digital part that process and transmits sensor data via LoRa. In this work we designed a probe with a size 12 cm long (P), 0.2 cm wide (L) and 5 cm apart probes (r). The probes are sharp to make it easier to insert into the twig. The other end is soldered on the cable and sealed with a plastic box. Each sensor probe cable is connected to a voltage divider circuit. The output voltage of the voltage divider circuit is connected to the signal conditioning unit and then to the microcontroller. The materials to build the twig dryness sensor described in Table 1.

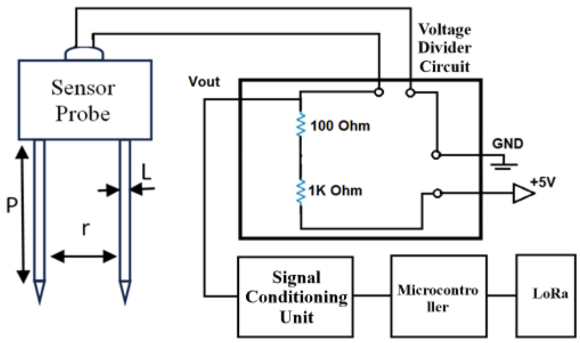


Figure 1. Design of twig dryness sensor

Table 1. Materials required

Materials	Specification
Nickel needle	(12×0.2) cm
Resistor	100 Ω, 1 kΩ
Cable	1 meter
PCB	(3×3) cm
Signal conditioning module	Vin: DC 5V
	Output: analog ADC (support all microcontroller and Arduino)
Transmitter	LoRaWAN Node STM32L052C8T6/SX1276
Receiver	ESP32 LoRa gateway
Server	Single board minicomputer Raspberry Pi 4 Model B

We have developed an integrated electronic board for the node sensor, which combines the twig dryness sensor, microcontroller and LoRa communication in a compact design, improving efficiency and reducing size. The board is organized into four distinct blocks, each serving a specific function essential for efficient operation:

a. Sensing unit: Dedicated to the twig dryness sensor, ensuring accurate readings and reliability. Contains a new voltage divider circuit to measure moisture content in twigs. The voltage divider circuit has three resistors: two fixed resistors (R1=1 kΩ and R2=100 Ω) and a sensor probe including the twig (R3). An input voltage (V_{in}) comes from a constant voltage source. The output voltage (V_{out}) is taken at between R3 and R2. The output voltage generated by the voltage divider is:

$$V_{out} = \frac{R3}{R1+R2+R3} \times V_{in} \quad (1)$$

b. Processing unit: This unit includes a signal conditioning module and a programmable microcontroller with firmware designed for sensing and LoRa transmission. The firmware also incorporates power management features to optimize energy consumption.

c. Communication unit: connects the sensor node to the LoRa gateway. It uses the LoRa communication protocol to send and receive data. This allows for reliable data transfer over long distances, making it useful for remote monitoring and IoT networks. This unit is key for keeping connections active and supporting real-time data sharing. This LoRa module has a programmable STM32L052C8T6 microcontroller (MCU) optimized for battery-driven applications.
d. Power unit: The board will be powered using two 18650 batteries. Each battery has a capacity of 3,500 mAh and a voltage of 2.85 to 4.2 V to supply the processing and communication units. It is supplied by the solar panel as 350×255×17 mm, providing 10 W of power supply.

2.2. Characterization of the twig dryness sensor

The next stage after the design and fabrication of the twig drought sensor is sensor testing. The assessment is carried out to determine the characteristics of the sensor, such as sensitivity, linearity, accuracy, and stability. The relationships between the output signal and the input stimulus will be known at this stage. The objective is to identify the relationship between moisture content and voltage. This will be achieved by determining the relationship between water content and vulnerability level. The relationship between vulnerability level and output voltage will also be determined. Finally, the effect of room temperature and humidity on the output voltage of the sensor will be evaluated. The assessment scenario was conducted by sticking the needle of the twig dryness sensor into the twig and then measuring the output voltage of the sensor with a voltmeter, at the same time, the moisture content of the twig was measured using a commercial wood moisture meter. Figure 2 illustrates the sensor testing scenario. The probe of the twig dryness sensor is connected to the twig, the voltmeter probe is connected to the output voltage of the twig dryness sensor, and the wood moisture meter probe is connected to the twig. Sensor sensitivity was calculated using (2):

$$Sensitivity\ (\%) = \left(\frac{V_{max}-V_{min}}{\%MC_{max}-\%MC_{min}}\right) \times 100 \quad (2)$$

Where V_{max} is the maximum value of output voltage obtained from measurement. V_{min} is the minimum value output voltage obtained from measurement. $\%MC_{max}$ is the maximum value of moisture content obtained from measurement. $\%MC_{min}$ is the minimum value of moisture content obtained from measurement.

Figure 2. Twig dryness sensor test set up

2.3. Categorization of flammability

The material used during the experiments was wood twigs. The categorization aims to obtain a classification of the flammability of the twig. This stage is carried out with experiments to determine the relationship between the moisture of the twigs and their flammability. Figure 3 shows the working sequence of the experiment. Before the experiment, the twigs were prepared as 30 to 50 cm long and a of 1 to 3 cm in diameter in Figure 4(a). The twigs were divided into three groups of 10 twigs each. Each group of twigs was soaked in water for 60 minutes. The moisture of the first group was measured using a commercial wood moisture meter in Figure 4(b). The second group was heated for 30 minutes, then the moisture was measured. The third group was heated for 15 minutes, then the moisture was measured. Each group then burned in Figure 4(c) with same conditions at 27 °C and a relative humidity of 75%. The burning time was recorded. Then categories were obtained based on the time required for the twigs to burn.

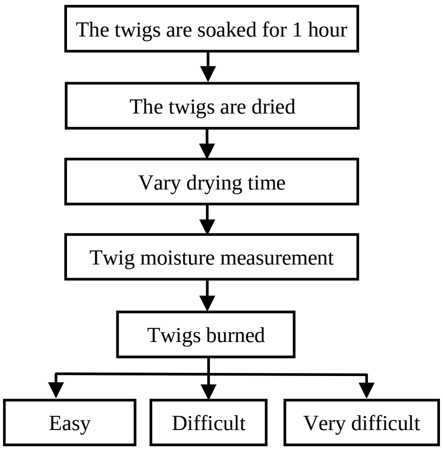


Figure 3. Process flow diagram of categorization of twig flammability levels

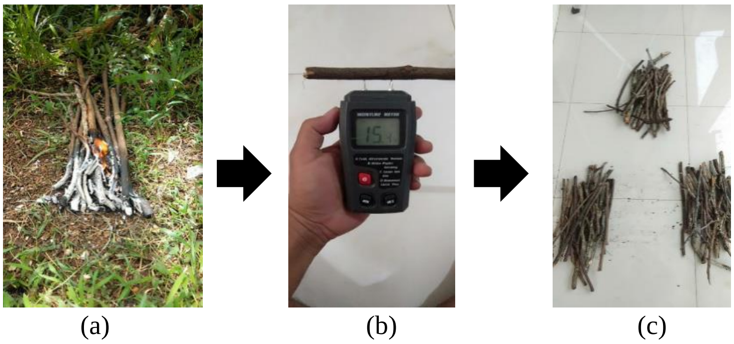


Figure 4. Experimental procedure, (a) twigs after soaking and drying, (b) moisture of twigs measured by wood moisture meter, and (c) twig burning process

2.4. Design of IoT devices

We designed the IoT device following Figure 5. This instrumentation has several parts, including a probe (twig dryness sensor), signal conditioning unit, microcontroller, transmitter, receiver (gateway), server and user interface (web service). The twig dryness sensor is the part of the early detection system that reads moisture content parameters. The signal conditioner then processes the sensor voltage. The microcontroller sends the sensor data wirelessly to a distant place using the Lora network on the transmitter unit. The receiver gets the sensor data from the transmitter remotely via Lora. Then, the data is sent to a server, which stores it. The admin can access the sensor data on the server and visualize the sensor data on the dashboard of a website page. The website page displays twig dryness data and shows peatland fire vulnerability in real time. Users can access the web page online via the internet network in real-time using a computer or smartphone.

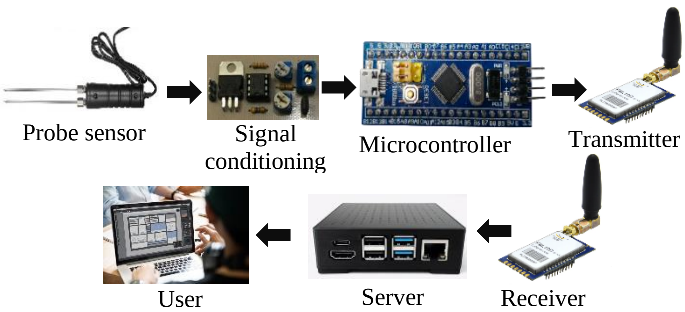


Figure 5. Block diagram of IoT-based peatland fire early detection system

This research uses LoRa and microcontroller modules as gateways. The gateway links the sensor to the server and receives sensor data. This research uses a Wi-Fi module to send sensor data to the server. The server uses a Raspberry Pi, Node-RED, InfluxDB as a database, and Grafana as the user interface. Node-RED processes and manages the data in real time, while Grafana shows how drought affects peatlands. Figure 6 shows the algorithm for the peatland fire early detection system. It starts with a request for data in the InfluxDB database. It then checks and decides on the twig dryness value. The data is categorized into "DRY" if the twig moisture is less than 5% MC. If the twig moisture is between 5% MC and 30% MC, it is "MOIST". If the twig moisture is more than 30% MC, the peatland is "WET". The level of peatland dryness is shown in numbers, graphs and colors. Green for wet, yellow for moist, red for dry. The early detection system also shows a map of the peatland where the sensors are placed.

Figure 6. IoT-based peatland fire early detection system algorithm

3. RESULTS AND DISCUSSION

The experiment examined burning times as a function of twig moisture content. Seven samples of twigs were tested. Figure 7 shows the result of the categorization of the flammability of the twig. The moisture content (MC) of a twig is a measure of the weight of water in the wood itself and is expressed as a percentage or unit. Three flammability levels were obtained from the experiments. The results imply that the burn time increases significantly if the twig moisture content is more than 5% MC. This research obtained a flammability category based on the difference in twig moisture content. The first category is VERY DIFFICULT as wet twigs, with 30% MC to 80% MC moisture content. The twigs burned for an average of 100 seconds. The second group is DIFFICULT, with moist twigs with moisture content between 5% MC and 30% MC. These groups burned for 40 to 80 seconds. The third category is EASY, as dry twigs have less than 5% MC moisture content. These twigs burned in 10 seconds on average. Experimental results show that twigs are flammable if the moisture content is below 5% MC.

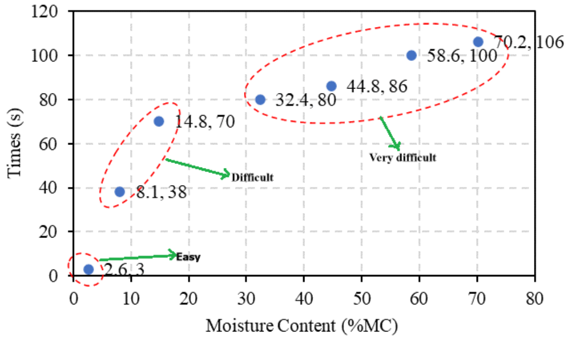
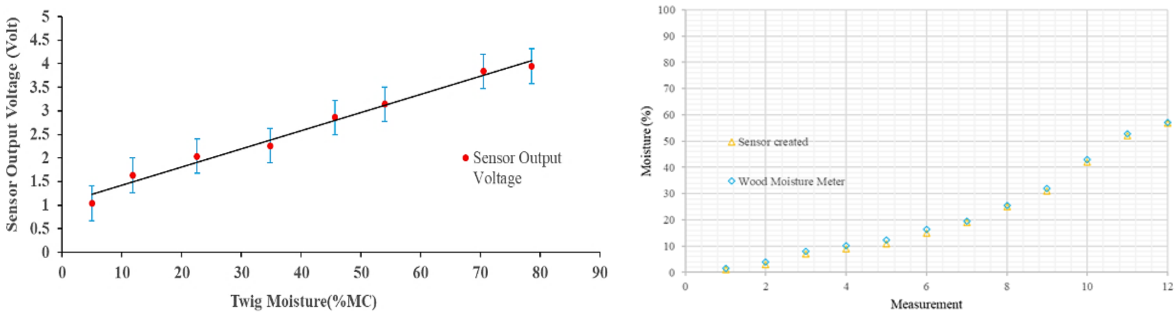


Figure 7. Categorization of flammability of twigs based on moisture content and time

The results of this study align with previous research [24], [25]. This study showed that the dryness of fuel affects flammability. Low moisture content makes twigs easier to burn, while high moisture content makes combustion more difficult. This discovery is important for understanding the risk of fire. This study found that twigs with a moisture content of 5% MC or less are prone to burn. This finding will help develop and characterize the sensor in the next stage. This research is one step further than previous research [33] in which the classification of fire vulnerability levels has been added. While previous research only measured wood moisture, there was no classification of fire vulnerability levels.

In the sensor characterization stage, three different analyses were carried out. In the first analysis, the sensor was characterized a calibration process at a stable temperature of 28 °C. We tested the sensor for linearity, sensitivity, and accuracy. We used a HELES UX-838TR digital voltmeter to measure the sensor voltage. The test results indicate that the sensor works according to the working principle of the sensor, as stated in (1). The sensor output voltage increases when the resistance decreases. This can be interpreted as a reduction in the level of dryness of the twigs. In other words, the output voltage increases if the moisture content of the twig rises. Figure 8 displays the sensor characterization curve. Figure 8(a) shows the test results for the linearity and sensitivity of the twig dryness sensor. Figure 8(b) shows the results of measuring the dryness of the twigs using the twig dryness sensor and a more accurate commercial moisture meter. Through this calibration process, we can determine the accuracy of the resistance measurement. The curve of correlation between the sensor voltage and the moisture content is given. The test results indicate that the sensor voltage changes linearly with twig moisture content. The sensitivity is 0.0395 volts/% MC with average relative error of 2.83%. Equation (2) is used to calculate the sensor's sensitivity. Sensor fabrication in our research is easier than in previous research [30] because it requires special high-viscosity inks. Whereas, our research uses easily available materials.

The characterization of the sensor shows an interval of output voltage against the category of twig dryness. The characteristic curve shows that the flammable twig produces a sensor output voltage of less than 1.5 volts. The difficult-to-burn of twigs produces a voltage between 1.5 to 2 volts. While it is the very difficult to burn of twig produces a voltage of more than 2 volts. This finding is important for the next step, which is to design the algorithm for decisions in fire vulnerability ranking.



(a) (b)

Figure 8. The sensor characterization curve, (a) the linearity, sensitivity and absolute error of the twig dryness sensor and (b) the accuracy of twig dryness sensor

Figure 9 shows the result of twig dryness sensor testing on environmental temperature changes. The sensor output voltage demonstrated remarkable stability despite fluctuations in environmental temperature. Tests were conducted spanning a range of temperatures from the minimum to the maximum, around 22 °C to 34 °C. The curve shows that the performance of the twig dryness sensor is stable. The sensor was also tested in different humidity to obtain a comprehensive understanding of the sensor's performance. The experiment was done from morning to night in open field which varied from 70% to 90% of humidity. The results are shown in Figure 10, the output voltage of the sensor tends to be stable even though the humidity of the surrounding air changes.

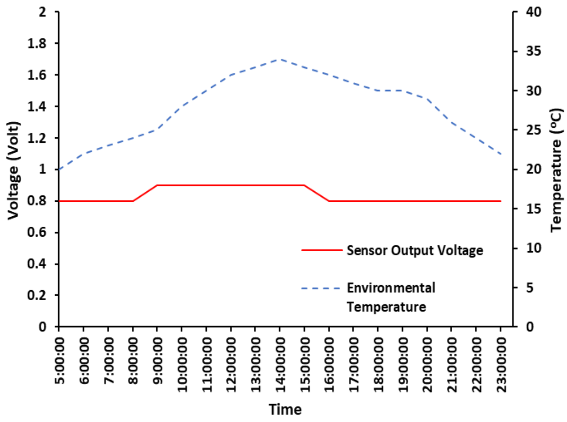


Figure 9. Sensor performance at different temperatures

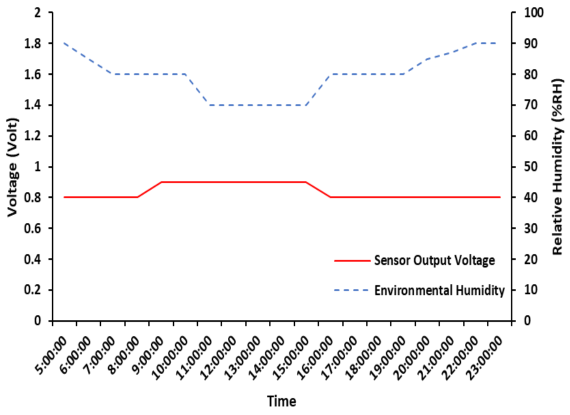
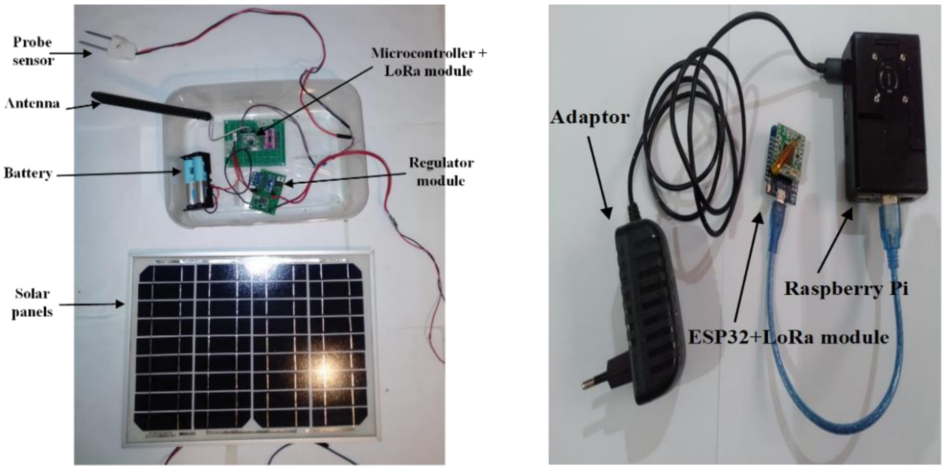


Figure 10. Sensor performance environment at different humidity

The realization of the IoT device that has been built is illustrated in Figure 11. In this research, the twig dryness sensor is connected to the STM32L052C8T6 microcontroller module and LoRa SX1276 module on the printed circuit board (PCB) as transmitter as shown in Figure 11(a). The voltage source used is a direct current (DC) voltage source from a regulated 18650 battery. The battery is charged with electricity generated by the solar panel. The hardware for the receiver (gateway) uses the STM32L052C8T6 microcontroller module, and the ESP32 LoRa gateway module is shown in Figure 11(b). For the server we use Raspberry Pi 4 model B. In this research, message queue telemetry protocol (MQTT) is used as a communication protocol between the server and the gateway, while communication between the gateway and sensor nodes uses LoRa communication. This enables communication in areas lacking internet connectivity, such as forests. While research [34] employs Wi-Fi, it is difficult to implement in the forest. Bluetooth and IEEE 802.11 (Wi-Fi) are two communication protocol standards within a short range (from a few meters up to 100 m) [34]. Our research uses the MQTT and LoRa protocol as a communication protocol. The LoRa technology is available for long-range and low-power communication [35]. MQTT is one of the protocols that can be used to communicate on computer systems. The MQTT work system uses publish and subscribe data. The device will connect to a broker (server) and have a certain topic. The broker in MQTT functions to manage, publish, and subscribe data from various devices. Node-RED is a browser-based tool for creating IoT applications with a visual programming environment. In this research, Node-RED is used to access the system through the website. InfluxDB is an open-source database service that provides a time series platform for measuring, studying, and automating systems. In this IoT device, InfluxDB is used to store sensor data in the peatland fire monitoring system. Grafana is an open-source software designed to read metric data and convert the data into a graph, panel, or written data.

This research uses LoRa technologies, the same as the research [31]. However, our research can achieve a transmission distance of 764.55 m. Previous research only can transmit data up to 430 m [31] and 71 m [32]. Our research used the LoRa SX1276 module, while the previous research used the WiMOD iM881-XL module [31] and CYBLE-012012-1-BLE module [32] of the communication units. Our research utilizes a frequency of 915 MHz, which falls within the industrial, scientific, and medical (ISM) frequency band designated for industrial, scientific, and medical applications. The bandwidth used is 125 kHz (default value), with a spreading factor value of 12, the output power is 10dBm (default value), and coding rate is 4/5 (default value). The spreading factor value was adjusted due to the positive correlation between distance and the spreading factor. Based on the experiments conducted, the maximum range for LoRa devices in tree-lined areas is 764.55 meters. At this range, the received signal strength indicator (RSSI) value is -134.25 dBm, and the signal to noise ratio (SNR) value is -17.25 dB. This range is considered less reliable for communication between sensor nodes because the lowest typical RSSI value is around -126 dB. In contrast, at a distance of 712.55 meters, the RSSI value is -123.25 dBm, and the SNR value is -9.35 dB. This range offers more reliable communication without experiencing timeouts. During testing of LoRa under open land conditions, or line of sight (LOS), a maximum range of up to 2 kilometers was achieved.



(a) (b)

Figure 11. The realization of the IoT device, (a) sensor nodes (transmitter) and (b) gateway and server (receiver)

In this research, the solar panel is 350×255×17 mm and can produce 10 W in sunny weather. The solar panel has a voltage of 21.96 V and a current of 0.63 A and produces 20.20 volts. The power source has two 18,650 batteries. Each battery has a capacity of 3500 mAh and a voltage of 2.85 to 4.2 V. The TP5100 recharger module can charge at 2 A with 9 V. The solar panel can only charge the battery at about 1.05 A. The MOSFET U2 is the IRF9540, which has a minimum $V_{GS(th)}$ of -2 V. If it is sunny weather (or the buck converter circuit provides 9 V output), then V_{GS} is approximately 0.4 V. Since $V_{GS} > V_{GS(th)}$, no current flows from drain to source (battery not used). In dark conditions, the voltage across the IRF9540 parasitic diode is 0 V. The voltage across the battery is therefore -V. Since 2/3 of the battery is between 5.7 and 8.4 V, the voltage across the battery is less than the voltage across the power source. The current flows from drain to source, and the sensor node's power comes from the battery.

The results of this study have found that the power required by the microcontroller and LoRa components varies depending on their state, such as shutdown, standby, or transmit. Solar panels and batteries provide the power. Since the voltage of the solar panel and battery exceeds the maximum safe voltage of the sensor node components, the system is equipped with a linear regulator to provide an output voltage of 3.3 V. In this study, the maximum current and power required by the twig dryness sensor were determined to be 2.1 mA and 6.93 mW, respectively. This power requirement is much smaller than the power the solar panel generates. So, the power supply guarantees that the power requirements for the device will work continuously. Our research uses STM32L052C8T6 and LoRa SX1276 to produce a sensor data transmitter providing lower power consumption. Prior research [32] utilizing the ESP8266 Wi-Fi module and the CYBLE-012012-1-BLE module clearly demonstrates that the BLE device consumes approximately 13.36 mA, while the Wi-Fi device consumes around 77.71 mA. Notably, the proposed LoRa circuit effectively transmits data to the gateway, achieving 15.7% less power consumption than the BLE device and 2.7% less than the Wi-Fi circuit. This indicates a significant improvement in energy efficiency for the LoRa technology.

This peatland fire early detection system has a visualization as shown in Figure 12. The dashboard built using the Grafana application is able to visualize the location of the sensor and fire vulnerability of peatland. This feature produces a map with a higher resolution than the map from satellite imagery. The dashboard also displays the location of the sensor and a color indicating the category of peatland dryness level. The color can change according to the classification based on the twig dryness value. The mark will be red if the twig moisture is 0% to 5% MC, yellow if the twig moisture is 5% MC to 30% MC, and green if the twig moisture is 30% MC to 100% MC.

This research provides a new method of the early detection system using a single significant parameter of fire hazard ranking: the moisture content of the twigs. The implications of this new method include the potential for the arrival time of a fire at a particular place to be known through the fire spread rate equation [36]. In the fire spread rate equation, there is a value of fuel moisture content (M_f). This research shows that the resistive sensing technique can measure twig moisture content. This research shows that IoT technology is overcoming the weaknesses of older instrumentation that is not based on IoT. Future research could focus on developing an early detection system for peatland fires using artificial intelligence (AI) and machine learning models, which can monitor and predict twig moisture levels in real-time.

Figure 12. Screenshots from the user interface of monitoring and early detection of twig dryness

4. CONCLUSION

In this study, we discovered a relationship between the moisture content of twigs and the flammability of peatlands. When the moisture content is below 5% MC, the twigs are considered flammable. Conversely, when the moisture content exceeds 30% MC, the twigs become very difficult to ignite. In this study, we found that moisture content can be represented by voltage. The results show that flammable twigs produce a voltage of fewer than 1.5 volts. While twigs that are very difficult to burn produce an electrical voltage of more than 2 volts. Based on these results, we believe that the twig dryness parameter can be used as an approach to a new method of peatland fire early detection system. In addition, the integration of this sensor into an IoT-based system makes it possible to detect peatland dryness in real-time and continuously, thereby improving the efficiency and effectiveness of peatland fire prevention efforts. The device can also act as an artificial intelligence device to predict the moisture level of the twigs through real-time monitoring. Further research could also test adding more sensors and modelling to improve the system's ability to predict fires. Also, looking at how well different ways of stopping fires work could help policymakers and conservationists.

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