Identification of Bioethanol Quality for Motorcycle Fuel

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ABSTRACT

The availability of crude oil as a raw material for vehicle fuel is dwindling and limited in nature. One of the renewable energies worth developing is bioethanol, which is one of the alternative fuels that can be used as a biofuel and can be processed from plants containing starch and glucose. In this research, the entire bioethanol identification system in a sugar cane drip distillation apparatus was examined. The distillation process using MQ3 and MQ135 sensors resulted in an alcohol percentage of 42% and 46%. The maximum temperature measured by a thermocouple during distillation was 88°C, while the minimum temperature recorded was 87°C. This study utilized a backpropagation artificial neural network method to identify the detected bioethanol. The architecture of the artificial neural network included 2 input nodes, 4 neuron nodes, and 2 output nodes. The training and testing results showed that the formed backpropagation was able to identify and differentiate the detection of bioethanol according to the given inputs with a success rate of 88.86% for detected bioethanol and 94.86% for undetected bioethanol.

1. Introduction

Lately, the automotive industry has been experiencing rapid development, and transportation has become a fundamental necessity for society today. [1]. It's also important to balance this with emissions from the energy supply in the future. [2]. Crude oil, which plays a crucial role as a raw material for fuel production, is becoming scarcer. There is a need for bioethanol with the aim of replacing crude oil as an environmentally-friendly fuel. Bioethanol can be produced from plants containing starch and glucose. [3].

The most common renewable fuel today is ethanol, which is derived from corn (starch) and sugarcane (sucrose) [4]. Ethanol or ethyl alcohol is an organic compound that is colourless and has a distinctive Odor. Ethanol has other characteristics, including being highly flammable, biodegradable, soluble in water, and non-carcinogenic. [5]. Bagasse or molasses is a solid waste left behind after processing sugarcane to extract sugarcane juice, which is used to produce sugar. [6]. The waste cannot be crystallized again because it contains glucose and fructose. [7]. Indonesia is among the top ten sugarcane producers in the world, with a production figure of up to 29 million tons of sugarcane in 2012 [8]. Bioethanol is also known as a biofuel made from vegetable oils, and it shares properties similar to premium gasoline [9]. It is considered environmentally friendly because it is clean and free from pollutant emissions. [10], A broader flammability range, higher ignition speed, increased vaporization heat, It also has a higher octane rating compared to fossil fuel-based fuels [11]. Compared to fossil fuels, bioethanol has lower toxicity and is more easily biodegradable. Bioethanol, as an alternative fuel, is expected to meet the increasing demand for fuel that grows every year. [12]. Some of the significant advantages of bioethanol are that it can enhance the performance of vehicle engines. This can be observed when using bio gasoline with a fuel blend ratio of 90:10 (gasoline to bioethanol), which results in higher torque and power values and lower specific fuel consumption compared to using pure gasoline, especially at high engine speeds. Bioethanol is also utilized as an additive that can boost the octane rating (octane booster), which has a positive impact on engine power, especially for high-compression ratio engines, and it helps prevent detonation (the improper timing of combustion in the engine) during the combustion process. [13]. The purpose of this research is to create a device for identifying the quality of Bioethanol for motorcycle fuel using Artificial Neural Network (ANN) method.

2. Research Methodology

Sugarcane bagasse is an abundant agricultural waste worldwide, capable of producing 540 million tons of biomass per year [14]. One of the important components in molasses is TSAI (Total Sugar as Invert), which is a combination of sucrose and reducing sugars. Molasses typically contains STAI levels ranging from 50% to 65% [15]. Molasses contains a significant amount of sugar, amino acids, and minerals. The sucrose content in molasses can vary between 25% to 40%, and its reducing sugar content ranges from 12% to 35% [16]

A thermocouple is an active temperature transducer composed of two different metals with the reading point at the junction of the two metals and the other point serving as its output. Thermocouples are one of the most commonly used sensors for temperature measurement because they are relatively inexpensive yet accurate. They can operate over a wide range of temperatures, both hot and cold. [17].

Sensor MQ3 is a gas sensor suitable for directly detecting alcohol. The MQ3 sensor element consists of a SnO_2 layer with low conductivity in clean air. The sensor's resistance changes as it detects the presence of ethanol gas. The MQ3 alcohol gas sensor is more affordable compared to other sensor types, with similar sensitivity. However, it does have a relatively high-power consumption compared to other gas sensors, at around 750 mW [18].

The MQ135 sensor is a chemical sensor type that is sensitive to compounds such as NH_3, NO_x, alcohol, benzene, smoke (CO), CO_2, and others. This sensor operates by detecting changes in resistance (analogue value) when exposed to gases. The sensitivity adjustment of the sensor is determined by the resistance value of the MQ135, which varies for different gas concentrations. Therefore, when using this component, sensitivity adjustment is essential. [19].

Backpropagation, or error propagation, is a common method for training artificial neural networks to perform a given task [20] [21]. It is a supervised learning process and is an implementation of the delta rule [22]. Backpropagation provides an efficient computational method for adjusting the weights in a feedforward neural network with differentiable activation functions to learn a set of input-output patterns. [23]. In its training, backpropagation in artificial neural networks requires a target. It's called backpropagation because during the training process, the errors produced are propagated back to the units below [24] [25]. The training process of Artificial Neural Networks (JST) uses MATLAB software, which provides specialized functions for solving Artificial Neural Network (ANN) models. [26].

Describe the preparation methods and characterization techniques used. Explain briefly, but still accurately such as size, volume, replication and workmanship techniques. The new method must be explained in detail so that other researchers can reproduce the experiment. While established methods can be explained by picking out references.

The parameters used for this research include the activation function, which calculates the output value based on the input values and weights on the neuron [27]. This function falls under the category of hidden layers connecting to the output/target [28]. If the error is minimized, the model's architecture design during training can be tested on validation data, and the best training results are applied to the testing data using prepared test data. The best weights are stored for the testing process to achieve good test results as well [29][30]. The characteristics that activation functions in a backpropagation neural network should possess include being continuous, differentiable, and monotonically non-decreasing. Furthermore, for computational efficiency, the derivative of the function should be readily obtainable, and the derivative's value can be expressed using the activation function itself. The analysed activation functions are binary sigmoid and bipolar sigmoid [31][32].

2.1. How The System Works

In this research, the MQ3 and MQ135 sensors are used to detect alcohol levels, and a thermal Thermocouple sensor is used to measure the temperature of molasses. The measurements will be sent to an Arduino, and a dimmer circuit is used as a heater controller.

Based on the block diagram, the operation of the sugarcane molasses distillation device using a microcontroller is as follows:

1. The system uses a heater as the heating element for the molasses. When the heater is activated, a thermocouple measures the temperature in the heating tube and displays the temperature data on an LCD.
2. A dimmer is used to regulate the voltage supplied to the heater to achieve the desired temperature setting.
3. The resulting vapor from the sugarcane juice is sucked by a DC motor and directed into a prepared container.
4. The gas from this process is then analyzed by gas sensors MQ-3 and MQ-135.
5. Subsequently, a JST (Artificial Neural Network) program identifies the bioethanol content and displays the identification results on the LCD for observation.

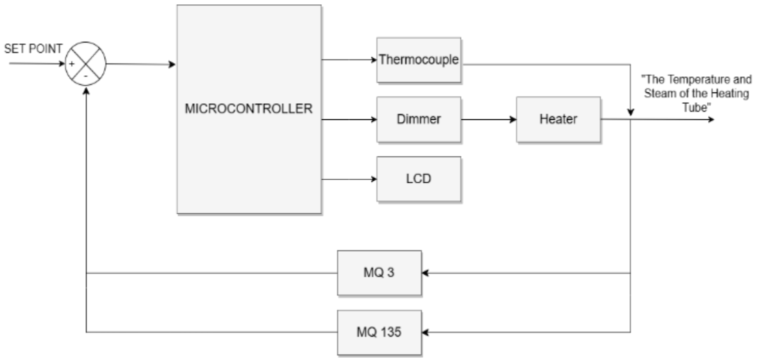

Figure 2. Diagram Block

2.2 Manuscript Organization

A flowchart is a diagram with specific symbols that illustrate the detailed sequence of processes and the relationships between one process (instruction) and other processes within a program.In the flowchart diagram Figure 2., there are inputs from the MQ3 sensor, MQ135 sensor, and thermocouple sensor to read bioethanol and molasses temperature. The setpoint will be configured in the software that controls the dimmer, producing PWM voltage for the heater load. Next, the thermocouple sensor will become active and read the temperature. If the temperature exceeds the setpoint, which is 100°C, the voltage and PWM will be reduced to the setpoint. After the vaporization occurs, a DC motor will suction the vapor, which will eventually become liquid bioethanol.

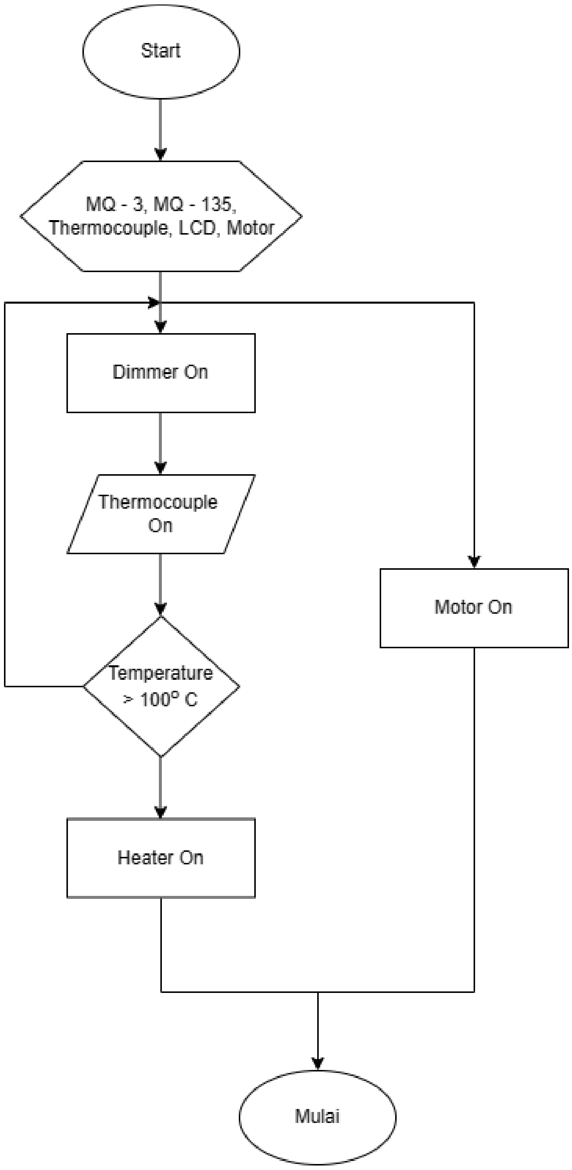

Figure 3. Flowchart

3. Results And Discussion

Testing was conducted by preparing bioethanol obtained from molasses distillation and comparing the alcohol content to that of Pertalite fuel. Subsequently, the MQ3 and MQ135 sensors would read the alcohol content in the bioethanol vapor, and the changes in the percentage of alcohol data would be observed on the serial monitor and the LCD display.

In this identification process, the weight and bias values obtained during the training process are used. The identification process occurs at the end of the distillation process when the bioethanol result is obtained. The bioethanol is detected by sensors MQ-3 and MQ-135, and sensor data is collected every second for 350 seconds using the JST algorithm implemented in the Arduino program. The results of this identification are then displayed on a 20x4 LCD screen.

The series of research results is based on a logical sequence / arrangement to form a story. The contents indicate facts / data and do not discuss the results. Can use Tables and Numbers but not repeatedly repeat the same data in figures, tables and text. To further clarify the description, you can use subtitles.
Discussion is the basic explanation, relationship and generalization shown by the results. The description answers the research question. If there are doubtful results then display it objectively.

3.1. Identification occurs when bioethanol is detected

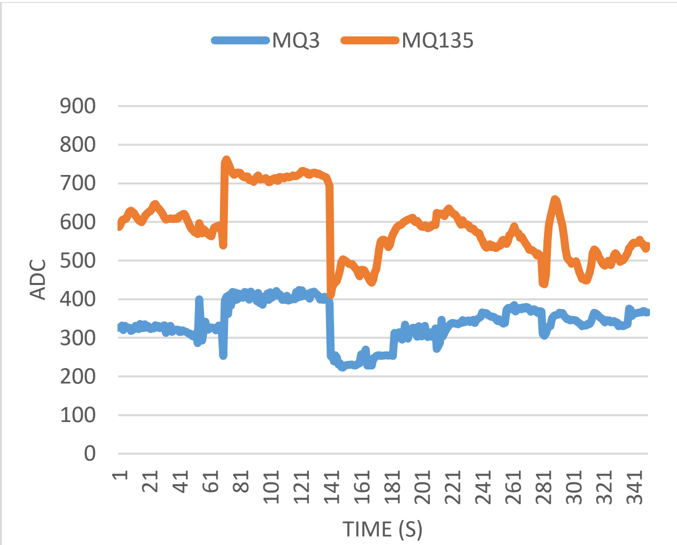

Figure 4. Response identification graph when bioethanol is detected

From the image fig.4, the identification result match the given inputs. Therefore, from all the identification data, the program's success rate is:

$$\frac{311}{350} \times 100\% = 88{,}86\%$$

The success rate of bioethanol identification is 94,86%.

The bioethanol identification process uses a backpropagation artificial neural network with 2 input nodes, 4 hidden layer nodes, and 2 output nodes. The training process involves 140 data points, consisting of 70 data points with high bioethanol content and 70 data points without bioethanol. Each classification is given a different target value: 01 for detected bioethanol content and 10 for undetected bioethanol.

The training process is time-consuming due to the system design that needs to achieve the given targets. To stop the program, two conditions are used: the first condition limits the number of epochs, and the second condition regulates the Mean Square Error (MSE) value. In the training process, a binary sigmoid activation function is used to ensure the output values are within the range of 0 to 1. To expedite the training process, the TRAINGD algorithm is employed, which is one form of the backpropagation function and is a standard numerical optimization technique. The TRAINGD learning function is the fastest algorithm for training large-sized feed-forward neural networks (up to hundreds of weights).
After the training process is completed, weight values are obtained, which are then used for the identification process. The next test involves preparing bioethanol from molasses distillation and comparing the alcohol content with Pertalite fuel. Then, the MQ3 and MQ135 sensors will read the alcohol content in the bioethanol vapor by monitoring the percentage alcohol data changes on the serial monitor and LCD display.

Table 1. Testing of Bioethanol and Pertalite Alcohol Content

Sample	ADC MQ 3	ADC MQ 135	MQ3 (%)	MQ 135 (%)
Bioethanol 1	420.00	466.00	41.05	45.55
Bioethanol 2	427.00	472.00	41.73	46.13
Bioethanol 3	432.00	479.00	42.22	46.82
Bioethanol 4	436.00	465.00	42.61	45.45
Bioethanol 5	423.00	469.00	41.34	45.84
Pertalite 1	515.00	540.00	50.34	52.78
Pertalite 2	529.00	555.00	51.71	54.25

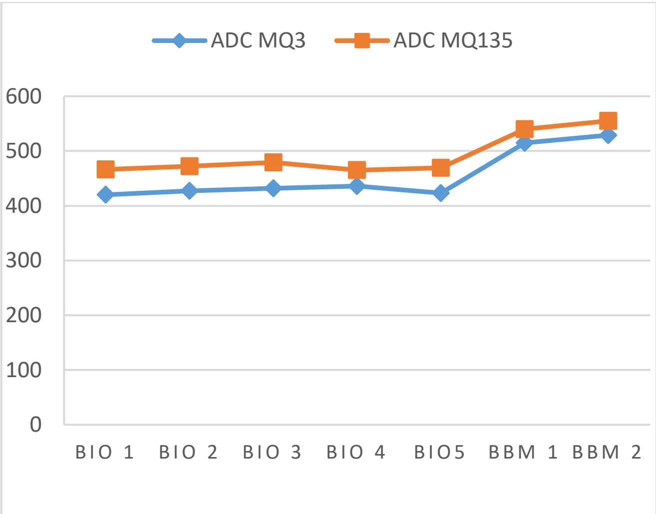

Figure 6. ADC Value

The ADC value represents the reading from the sensor. The equation for calculating the percentage using the ADC value from the outputs of the MQ3 and MQ135 sensors is as follows:

$$"Percentage"\ (\%) = \frac{ADC}{1023}\ x\ 100$$

With ADC being the output data from the sensor (A0), 1023 is the maximum value that can be read by the 10-bit Arduino ADC, and 100 is used to convert it to a percentage (%).

4. Conclusion

From the identification results regarding the bioethanol content, the average success rate for detecting bioethanol is 88.86%, and for undetected bioethanol, it is 94.86%.
From the conducted testing, it can be concluded that the detected bioethanol content reached a maximum of 42% for MQ3 and 46% for MQ135. However, these values are not yet sufficient to match the content of Pertalite fuel due to the relatively short fermentation period of 3 weeks. Therefore, it cannot be currently implemented for motorcycles. Additionally, the MQ3 and MQ135 sensors require a longer response time for stable readings during the molasses boiling process

In conclusion there must be no reference. The conclusion contains the facts obtained. State the possible applications, implications and speculations accordingly. If needed, give suggestions for further research.

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