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Identification of Bioethanol Destilator of Sugarcane Drops Kerosene Substitute Using Artificial Neural Network

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A B S T R A C T

The decreasing availability of crude oil as an energy source has driven efforts to develop alternative technologies, such as bioethanol distillators, to replace kerosene. This research focuses on creating an automatic bioethanol distillator equipped with artificial neural network (ANN) technology to assess the quality of bioethanol derived from sugarcane molasses. The system incorporates an electronic nose (e-nose) sensor and a temperature sensor to detect ethanol levels during the distillation process, operating at a maximum temperature of 80°C. The collected data on bioethanol quality is processed using an artificial neural network with a backpropagation algorithm, designed with two input variables, six neurons in the hidden layer, and one output variable. Experimental results reveal that the tool achieves a 79.21% success rate in identifying bioethanol quality through MATLAB simulations. This innovation demonstrates the potential to enhance bioethanol production by ensuring quality control and promoting energy independence. The developed system is intended to serve as an efficient and practical engineering solution that benefits both societal and industrial applications, contributing to a sustainable energy future

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INTRODUCTION

The increasing number of population growth in Indonesia greatly affects the amount of fuel energy use. In 2019, based on the inter-census population survey (SUPAS), Indonesia's population is projected to reach 266.91 million. The utilization of bioethanol as an additional fuel can reduce emissions of hydrocarbon organic compounds, carcinogenic benzene, butadiene, and particulate emissions resulting from petroleum combustion (Data, 2019). ioethanol is a liquid resulting from the fermentation process of sugar from carbohydrate sources (starch) using the help of microorganisms. Bioethanol production from plants containing starch or carbohydrates is done through the process of converting carbohydrates into sugar (glucose) (Rochani et al., 2015). In enzymatic hydrolysis, two methods are known, namely SHF and SSF. The SSF method is very important to develop because it can shorten the process of making bioethanol (Purba & Saragi, 2021; Balat et al., 2008; Aditiya et al., 2016). Bioethanol produced from sugarcane molasses fermentation contains ethanol as the main component (Rasmey et al., 2018).

The fermentation process by the microorganism Saccharomyces cerevisiae can produce ethanol concentrations of up to 9.56% under optimal conditions. This shows that bioethanol is an alcohol-rich fuel that can be an environmentally friendly alternative to fossil fuels (Raharja et al., 2019; Jayus et al., 2016). Bioethanol is also known as a biofuel made from vegetable oils and has similar properties to premium gasoline (Adriantono et al., 2020). Some significant advantages of bioethanol are that it improves vehicle engine performance. This can be seen when using biofuel with a fuel mixture ratio of 90:10 (gasoline to bioethanol), which results in higher torque and power values and lower specific fuel consumption than using pure gasoline, especially at high engine speeds (Yang, 2017). Bioethanol is also utilized as an additive to increase the octane number (octane booster) which has a positive impact on engine power, especially in engines with high compression ratios, and helps prevent detonation (improper combustion timing in the engine) during the combustion process (Wiratmaja & Elisa, 2020).

The fermentation process by Saccharomyces cerevisiae can produce ethanol concentrations of up to 9.56% under optimal conditions, making bioethanol an environmentally friendly alternative to fossil fuels (Raharja et al., 2019; Jayus et al., 2016). Bioethanol, made from vegetable oils, has similar properties to premium gasoline and improves vehicle engine performance. Using a 90:10 gasoline to bioethanol ratio results in higher torque and power values, and lower specific fuel consumption than pure gasoline, especially at high engine speeds (Yang, 2017). Additionally, bioethanol increases the octane number (octane booster), positively impacting engine power and preventing improper combustion timing, especially in high compression ratio engines (Wiratmaja & Elisa, 2020).The sensor is capable of sending a digital signal in binary form (1 or 0) as well as an analog signal in the range of 0 to 1023, which indicates the amount of alcohol in the air. With its high sensitivity and resistance to other interferences, such as smoke and fuel, the MQ-3 sensor is ideal for use in portable alcohol detection devices or breathalyzers (Hariharan et al., 2024; Nuissier et al., 2008).

The MQ-135 sensor is designed to detect a variety of gases, including alcohol, specifically ethanol. It uses lead dioxide ($SnO2$) as a sensitive layer that has low conductivity in clean air.

The sensor system used in this study will form patterns that are visually and quantitatively similar. Bioethanol detection uses an electronic sensor e-nose to obtain ethanol concentration values, and temperature control analysis uses the backpropagation type of artificial neural network method. Artificial Neural Networks (ANN) can be used to control the mixing process of chayote chips dough automatically, ensuring consistency and quality in the final product (Susanti et al., 2022). ANN have also been employed for detecting different types of coffee, specifically distinguishing between Arabica and Robusta varieties, based on their unique characteristics (Susanti et al., 2018). In addition to these applications, ANNs are utilized in various aspects of agricultural product processing. For instance, they help in identifying the aroma and quality of coffee products, especially focusing on Arabica and Robusta coffee (Susanti et al., 2023).

LITERATUR RIVIEW

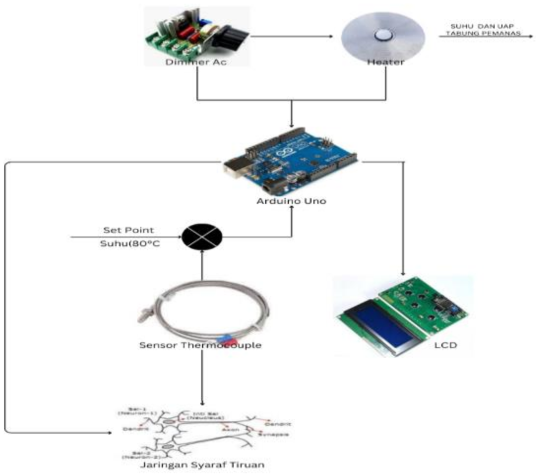
Bioethanol is a liquid produced through the fermentation of sugars from carbohydrate sources (cellulose) using the help of microbes (Arlianti, 2018).The production of bioethanol from plants containing cellulose is done through the conversion of lignocellulose into cellulose using several methods, including physical, chemical, and biological hydrolysis (No et al., 2021). Bioethanol is an alternative fuel that has the advantage of being able to reduce $CO2$ emissions by up to 18%.

Molasses, also known as sugarcane molasses, is a byproduct of sugarcane processing that still contains sugar and organic acids (Rakita et al., 2021). The electronic nose, abbreviated as e-nose, is an artificial olfactory system designed to analyze, recognize, and detect simple and complex odors as well as volatile compounds. The electronic nose (E-Nose) is an instrument capable of recognizing complex characteristic information (Xu et al., 2018). The E-Nose responds to various sensors with partial specificity and aroma reactions from different volatile compounds, functioning similarly to the human nose (Röck et al., 2008)(Mizanur Rahman et al., 2016). The working mechanism of animal or human noses involves gases emitting volatile organic compounds (VOCs) into the air, which are then recognized based on previously stored aromas in the brain (Firestein, 2001).The E-Nose detects gas mixtures in a manner similar to the human nose (Wongchoosuk et al., 2010)(Wongchoosuk et al., 2009).

METHODOLOGY

Research Method

The system design includes block diagram design, hardware, and software development. Before the system is developed, block diagram planning and flowcharts are created as guidelines to ensure the system aligns with the intended objectives. To illustrate each component in the designed system, a detailed explanation is presented through block diagrams that visualize the functions and workflows of each part.

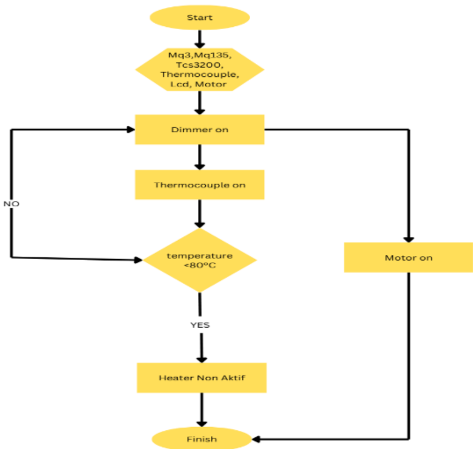


Picture 1. Sugarcane Drip Destiation Design

Picture 1 above shows a block diagram of a temperature control system consisting of several main components, namely Arduino Uno, AC dimmer, heater, thermocouple, LCD, and artificial neural network. The AC dimmer controls the power flowing to the heater, allowing the heat intensity to be adjusted as needed. The heater is responsible for increasing the temperature in the heating tube and maintaining the temperature around a predetermined set point of 80°C. The Arduino Uno acts as a control center that receives temperature data from the thermocouple sensor, then adjusts the AC dimmer to adjust the heater power to keep the temperature stable. The Arduino also sends temperature data to the LCD to be displayed in real-time, making it easier for users to monitor system conditions. The thermocouple sensor measures the temperature inside the heating tube and sends the data to the Arduino to determine whether the temperature needs to be increased or decreased. The LCD is used to display temperature information and system status directly. Meanwhile, an artificial neural network (ANN) is used for further analysis or modeling of the temperature data, allowing the system to make predictions or automatic adjustments based on learned patterns.

Picture 2. Distillation Apparatus

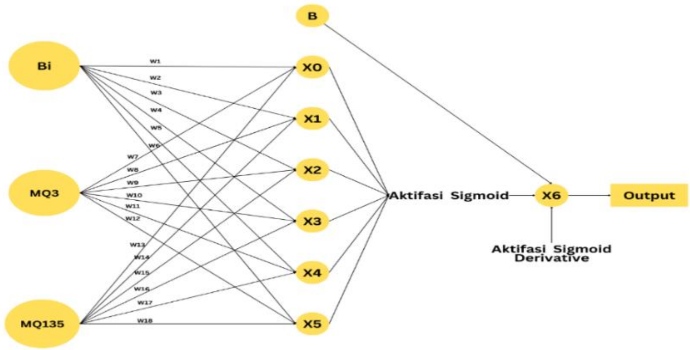
In Picture 2, there is a distillation device, which has the following main components: Number 1 is a molasses heating vessel for boiling molasses liquid with a heater underneath. Number 2 is a cooling container filled with ice or water to drain the heated molasses vapor. Number 3 is the MQ3 and MQ135 sensor readings to detect alcohol content, and the TCS3200 sensor to detect the color of bioethanol(Princewill, Charles, & Ekene, 2023). Number 4 is the container for distillation results. Finally, the system box stores the whole set of tools, with dimensions of 60 cm long, 40 cm wide, and 56 cm high.



Picture 3. System Flowchart

In Picture 3, the system flowchart shows the workflow of the automatic control system starting with setting up devices such as MQ3, MQ135, TCS3200, thermocouple, LCD, and motor sensors. The process begins with initialization which signifies the beginning of the overall operation. Once the system is activated, all components are initialized: MQ3 detects alcohol, MQ135 detects air quality, TCS3200 detects color, thermocouple measures temperature, LCD displays information, and the motor serves as an actuator that moves according to certain conditions. When all components are ready, the dimmer is activated to control the heater power, enabling gradual and precise temperature regulation to keep the temperature within the desired limits(Hamouda et al., 2015). After that, thermocouples monitor the temperature directly as a basis for determining the next step. The system checks whether the temperature is already below or equal to 80°C; if it is, the heater is turned off to prevent further temperature rise, and the process proceeds to the final stage. However, if the temperature is not below 80°C, the system repeats the previous step by reactivating the dimmer and thermocouple until the desired temperature is reached. Once the temperature is suitable or the temperature setting is complete, motors are activated to drive certain parts of the system, such as stirring or performing other final tasks. This process ends at the “Done” stage, which signifies that the automatic temperature control system has completed all the necessary procedures.

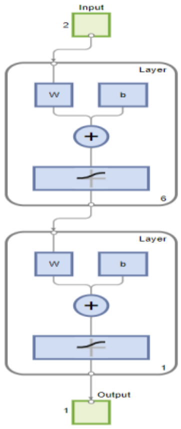
This molasses heating system uses a heater. When the heater is active, the thermocouple reads the temperature on the heating tube and displays it on the LCD. The dimmer regulates the voltage entering the heater to reach the temperature according to the set point. Sugarcane water vapor is then sucked by a DC motor and flowed into a container to be read by the MQ-3 gas sensor, MQ-135, and TCS3200 color sensor. The JST program then identifies the bioethanol and displays the results on the LCD.



Picture 4. Artificial Neural Network Architecture

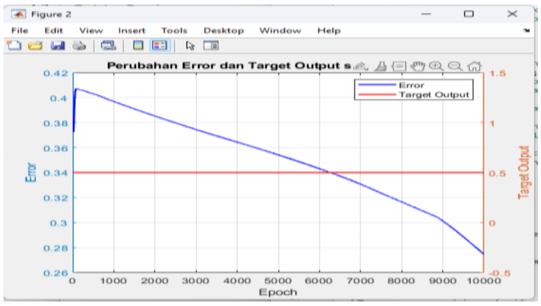
Picture 4 shows the architecture of an artificial neural network (ANN) with the backpropagation method processing input data from sensors. The input consists of bias, MQ3, and MQ135 nodes that represent initial data, such as alcohol or gas data. This data is passed to the hidden layer with nodes X0 to X5, which are connected via weights W1 to W19. The sigmoid activation function in the hidden layer converts the input into a value between 0 and 1, to enable classification. The output of this hidden layer is forwarded to node X6 in the output layer to generate the network's prediction. During training, the weights between nodes are adjusted to minimize error, so that the network is able to predict or classify data more accurately.

Testing and analysis in MATLAB was conducted in two stages: training and identification. The training sample data was taken from the measurement results of alcohol after distillation using MQ3 and MQ135 sensors. A total of 100 data were recorded for each sensor, then divided into five groups to obtain the average value. This training data was entered into the MATLAB workspace for the training process.



Picture 5. Backpropagation Artificial Neural Network Architecture

Picture 5 shows the structure of an artificial neural network with two hidden layers that receive inputs from two neurons. In each hidden layer, there are weights (W) and biases (b) that are used to determine the strength of the relationship between the neurons. The input at each layer is summed with the bias, and then processed through an activation function to capture non-linear patterns in the data. The first layer consists of six neurons after passing through the activation function, which then passes its output to the second layer. In the second layer, a similar process is performed, and the end result is an output with one neuron residing in the output layer. This output is the result of the entire artificial neural network process, both for prediction and classification purposes.



Picture 6. Neural Network Regression Graph

In Picture 6, there is a graph of changes in error and target output in the process of training the neural network model. The X-axis represents the number of epochs, which is the number of times the model goes through the dataset to learn, ranging from 0 to 10,000. On the left Y-axis is the error value represented by the blue line, indicating the error rate of the model. At the beginning of training, the error is around 0.42 and steadily decreases to near zero, indicating that the model gets better at predicting the output as the epochs increase. Meanwhile, the right Y-axis shows the constant output target value at 0.5, represented by the horizontal red line. The gradual decrease in error shows that the neural network model successfully achieves prediction results that are close to the desired target value.

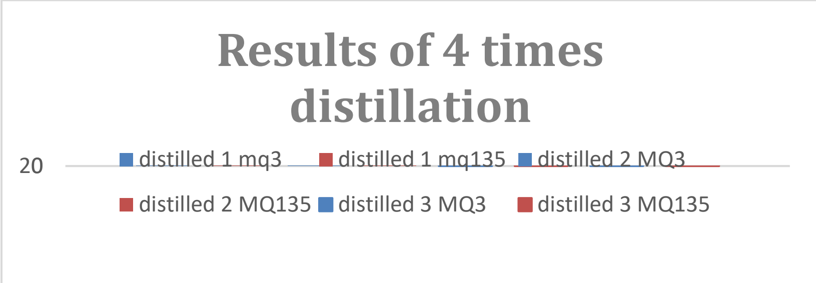
RESULTS AND DISCUSSION

Picture 7. Results of Four Distillations

Picture 7 shows the results of bioethanol after distillation at 0-80°C, which was done four times. Initially, the bioethanol came from 2 liters of sugarcane molasses that had been fermented for 1 month. After the first distillation, the molasses turned into bioethanol with a greenish color, and the amount decreased to 1.1 liters. The second distillation produced 520 ml of bioethanol, the third distillation 300 ml, and the fourth distillation 200 ml with 10% alcohol content using an alcohol meter.

Picture 8. Bioethanol Combustion Test Results

Picture 8 shows the results of the bioethanol combustion test, where only bioethanol can be ignited. Several factors influence this result, such as the duration of molasses fermentation, the amount of fermented molasses, and the remaining water content in the bioethanol, which makes it difficult to ignite. MQ-135 and MQ-3 sensors are used to detect different types of gas. The MQ-135 sensor has high sensitivity to toxic gases, such as ammonia, carbon dioxide, and carbon monoxide, so it is often used in air quality monitoring and pollution detection to identify polluted air in both closed and open environments. Meanwhile, the MQ-3 sensor is highly sensitive to alcohol, making it suitable for use in applications such as alcohol detectors or breathalyzers. In addition to alcohol, the MQ-3 can also detect other gases, such as benzene, methane (CH4), hexane, LPG, and carbon monoxide, making it a good choice for various applications that require gas detection.



Picture 9. Results of Four Distillations

Picture 9 shows the measurement results of the MQ3 and MQ135 sensors after four distillations of 2 liters of molasses. The first distillation yielded 1.1 liters of bioethanol, with the MQ3 sensor recording the highest alcohol content of 15.60% and MQ135 15.99% at 70-80°C. The alcohol meter showed an alcohol content of 3-8%. In the second distillation, 520 ml of bioethanol was produced, with the MQ3 sensor reading the highest alcohol content of 17.45% and MQ135 15.99% at 70-80°C. The third distillation yielded less than 300 ml, with MQ3 registering 18.10% and MQ135 18.00% at the same temperature. The fourth distillation yielded less than 200 ml, with the MQ3 sensor showing 15.60% and MQ135 15.66% at 60-70°C, and the alcohol meter registering 10% alcohol content. At 80°C, bioethanol vaporizes first as it has a lower boiling point than the other components.

Table 1. Confusion Matrix

	Prediction 0	**Prediction 1**
There is no bioethanol.	**35**	**4**
There is bioethanol	**6**	**28**

Based on the data, bioethanol detection results fall into several categories. True Positive (TP) recorded 28 cases where bioethanol was correctly detected as bioethanol. True Negative (TN) recorded 35 cases where bioethanol was not detected and the result was correct. False Positive (FP) recorded 4 cases where bioethanol was detected when it was not, while False Negative (FN) recorded 6 cases where bioethanol was not detected when it should have been.

$$\begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix} = \begin{bmatrix} 35 & 4 \\ 6 & 28 \end{bmatrix}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Accuracy = \frac{28 + 35}{28 + 35 + 4 + 6} = 100\% = 86.3\%$$

In Table 1 there is a confusion matrix that shows that this neural network model is able to detect bioethanol with a good accuracy of 86,3%, using 100 data. Each row represents a set of inputs and the predicted output of the model after training. The inputs are presented as pairs of values, while the prediction output is the value generated based on the inputs. If the prediction output value is above 0.5, the result indicates 'Bioethanol detected'. If it is below 0.5, the result indicates 'Bioethanol not detected'. For example, a target of '0' means that bioethanol is not expected to be detected, while a target of '1' means that bioethanol is expected to be detected.

CONCLUSION

MQ-3 and MQ-135 gas sensors have the ability to detect changes in bioethanol levels based on gases released during the molasses distillation process. In this study, the bioethanol produced reached a concentration of 35% which was detected using an alcohol meter. The highest alcohol content produced in this experiment is 35%, indicating that the distillation and fermentation process has run optimally under these conditions. In addition, the MQ-3 and MQ-135 sensors proved effective in detecting bioethanol produced from distillation with the help of artificial neural network method based on *backpropagation* algorithm. The test results show that the developed system has a success rate of 79.21% in identifying bioethanol in MATLAB. This success shows that the sensor system used is able to work with a fairly good accuracy. However, the quality and alcohol content of the bioethanol produced are greatly influenced by various factors, including the duration and conditions of the molasses fermentation process, which determine how well bioethanol can be produced and detected.

FURTHER STUDY

Further studies can focus on enhancing the accuracy of bioethanol detection systems by exploring advanced machine learning algorithms or integrating deep learning techniques. Optimizing fermentation and distillation conditions, such as temperature, pH, and fermentation duration, is essential to improve bioethanol yield and quality. Scaling up the system for industrial applications and evaluating its efficiency under varied operational conditions can provide valuable insights into its scalability. Additionally, investigating the sensitivity and reliability of MQ-3 and MQ-135 sensors under complex environments with multiple gas interferences is crucial. Future research could also explore alternative feedstocks for bioethanol production, such as lignocellulosic biomass or agricultural waste, while integrating Internet of Things (IoT) technology for real-time monitoring and control. Finally, comprehensive environmental impact analyses of the production process should be conducted to ensure sustainability and eco-friendliness across the entire production cycle.

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