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Producer Gas Composition Prediction using Artificial Neural Network Algorithm

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ABSTRACT

Nowadays, methods to increase efficiency in producer gas have become major issues in biomass gasification research. Producer gas is a renewable energy source that does not take as much time to obtain as fossil fuels. It is typically a mixture of combustible gases like carbon monoxide, hydrogen and methane, and non-combustible gases like carbon dioxide and nitrogen. A high percentage volume of combustible composition in the producer gas output will have a high calorific value or heat of combustion. These combustible gases are determined by the design of the gasifier. In today's era of Industrial Revolution 4.0 and Society 5.0, the use of simulation is highly prioritised in all aspects of engineering, especially in gasification applications. Simulation is a useful tool for learning about the governing principles and optimal operating points of the gasification process. Artificial intelligence (AI), is a major focus of Industry Revolution 4.0. In this project, the producer gas composition prediction is studied by computer simulation. The goals are to predict the output producer gas using an algorithm and to compare the trained prediction result with actual experiment data for rice husk gasification. This simulation was created with MATLAB software's artificial neural network (ANN). Three parameters (the height of the gasifier, the diameter of the gasifier, and the weight of the rice husk) are set as input data, and six types of the composition of producer gas (carbon dioxide, carbon monoxide, methane, oxygen, hydrogen, and nitrogen) are set as output data. The algorithm is trained, tested, and verified with the experiment data. It is then used to predict the output gas composition from the parameters of a gasification experiment that has been used before in UiTM's laboratory. The simulation results of producer gas composition between prediction and actual values revealed a relative error of 1.159 %, 0.370 %, and 0.330 %. These results were less than 9% and were found to give a very good fit to the neural network algorithm.

Keywords: *artificial neural network, algorithm, producer gas, biomass gasifier, rice husk.*

1. INTRODUCTION

Energy from biomass can be converted to a gaseous or liquid fuel through gasification. The gases that are produced from biomass gasification are called producer gas. Producer gas is a renewable energy source that does not take as much time to obtain as fossil fuels. It is typically a mixture of combustible gases like CO, H_2, and CH_4 and non-combustible gases like CO_2 and N_2 [1]. Rice husk is one of the biomass raw materials that can be utilised to generate electricity and small power plants. In Malaysia, there is also a lot of paddy plantation and rice produced.

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Rice is an agricultural product that is still used to provide food and nourishment in Malaysia. There is a vast land area in Malaysia that is cultivated for paddy plantation, where there are 204,297 hectares of granary areas and 284,145 hectares outside the granary areas providing 86 % of the rice supply [2].

As mentioned before, rice husks will go through the gasification process. The gasification process has been widely studied by previous researchers using various gasifier designs [3-7]. Gasification design is one of the main factors in the production of the producer gas output. The difference in design size will also affect the weight of the filled rice husk. A high percentage volume of combustible composition in the producer gas output will have a high calorific value or heat of combustion. These combustible gases are determined by the design of the gasifier [8]. To produce producer gas effectively, the composition of producer gas data is important. Nowadays, methods to increase efficiency in producer gas have become major issues in biomass gasification research [9]. A lot of research has been done on predicting in certain fields such as biomass, but not enough research has been done in finding the best downdraft gasifier design, especially using rice husk.

In today's era of Industrial Revolution 4.0 and Society 5.0, the use of simulation is highly prioritised in all aspects of engineering, especially in gasification applications. Experimental methods to determine the best conditions for a particular gasifier require the allocation of more money and time. A simulation is a useful tool for learning about the governing principles and optimal operating points of the gasification process. Artificial intelligence (AI), is a major focus of Industry Revolution 4.0. Product gas composition of biomass gasification was predicted using the MS-Excel Solver tool with the method of minimisation of Gibbs free energy, which studies only the effect of temperature on equilibrium reaction conditions.[10] The gas composition and calorific values were also predicted using a thermodynamic equilibrium model, depending upon the impact of gasification temperature, Oxygen to biomass proportion, and Steam to biomass proportion. The developed model was solved by commercial MATLAB software using the 'Fsolve' function. The study was carried out in the state of Punjab in India, using four agricultural biomasses [11]. Other predictions were done by the equilibrium model. It estimated the syngas species, the char and tar yield and the elemental energy balances based on the water-gas shift reaction (WGS) and methanation reaction of the gasification process. The equilibrium model was used to examine two biomasses with various moisture content and various gasification conditions and the predicted values were compared with experimental data. [12]. A mathematical stoichiometric thermodynamic equilibrium model developed was used to estimate the exhibition of biomass gasification measures about the syngas yield and composition. The thermodynamic balance models are exact and helpful instruments for the assessment and comparison of the gasification process. The performance of the gasification process was estimated and it was approved for steam gasification and air-steam gasification. [13].

In this project, the producer gas composition prediction is studied by computer simulation. The goals are to predict the output producer gas using an algorithm and to compare the trained prediction result with actual experiment data for rice husk gasification. This simulation was created with MATLAB software's artificial neural network (ANN). Three parameters (height of gasifier, diameter of the gasifier, and weight of rice husk) are set as input data, and six types of the composition of producer gas (carbon dioxide, carbon monoxide, methane, oxygen, hydrogen, and nitrogen) are set as output data. The MATLAB programme processed the data

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and produced a neural network algorithm that simulated the producer's gas output through prediction. The algorithm is trained, tested, and verified with the experiment data. The algorithm will be tested with other data to check the precision of the prediction. It is then used to predict the output gas composition from the parameters of a gasification experiment that has been used before in UiTM's laboratory.

2. METHODS AND MATERIALS

2.1 Input and Output Data

Twenty sets of data from an experiment using a downdraft gasifier and rice husk as the fuel are collected from other research [3, 5, 14-17]. The data collected are the height of the gasifier, the diameter of the gasifier, the weight of the rice husk, and six types of the composition of the producer gas, which are carbon dioxide CO_2, carbon monoxide CO, methane CH_4, oxygen O_2, hydrogen H_2, and nitrogen N_2. These data were used to train, test and verify the algorithm (Table 1).

Table 1: Data from other researcher's works used as train data in MATLAB

Authors	High (m)	Diameter (m)	Rice Husk Weight (Kg)	CO (%)	H_2 (%)	CH_4 (%)	N_2 (%)	CO_2 (%)	O_2 (%)
14	1	0.22	4	13.7	9.28	1.49	61.02	8.91	5.23
3	1.50	0.30	5.0	18.48	14.00	0.16	53.71	10.44	2.24
15	1.8	0.275	3	12.07	9.6	2.21	50.77	13.31	3.21
	1.8	0.275	3	11.09	26.53	2.06	45.29	14.52	2.3
	1.8	0.275	3	8.77	14.39	1.91	60.47	60.47	1.97
	1.8	0.275	3	8.76	9.48	1.63	52.88	52.88	4.09
	1.8	0.275	3	8.55	7.31	1.61	52.78	52.78	2.85
16	2.04	0.9	15	22	13	1.7	40.1	8	1.5
17	1.8	0.35	5	14.5	9.8	1.7	55.4	15.5	3.1
	1.8	0.35	5	15.6	11.1	2	55.4	15	1.9
	1.8	0.35	5	17	11.8	2.8	53.7	13.8	0.9
	1.8	0.35	5	15.3	10.3	1.8	54.4	16	2.2
	1.8	0.35	5	13.4	9.4	1.4	54	17.2	4.6
5	1.70	0.50	8.4	15.80	10.60	2.00	52.00	18.00	1.60
	1.70	0.50	8.4	17.50	12.40	2.30	49.10	17.20	1.50
	1.70	0.50	8.4	18.60	13.50	1.80	48.60	16.00	1.50
	1.70	0.50	8.4	19.20	12.80	1.90	49.40	15.40	1.30
	1.70	0.50	8.4	18.80	11.90	1.80	50.00	16.20	1.30
	1.70	0.50	8.4	17.70	9.60	1.50	53.20	16.80	1.20
	1.70	0.50	8.4	16.00	9.20	1.10	55.10	17.50	1.10

The parameters investigated in this research affect the composition of producer gas, according to these researchers [5,18-19]. To achieve the best gasification performance, the structural parameters of the gasifier such as the diameter and height of the gasifier were optimised. The height and diameter of the gasifier influence the output and can be optimised to produce more combustible producer gas. This is because the parameters are related to the air stage and air-to-fuel (AFR) value. The addition of an air stage can affect the air-to-fuel ratio (AFR) value, which significantly correlates with the temperature distribution inside the gasifier. The drying, pyrolysis, oxidation, and gasification zone temperatures are greatly affected by this AFR value. The parameters are related to the AFR value because the height, diameter, and weight of the rice husk determine the space inside the gasifier and affect the air-to-fuel ratio value. The AFR

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value will influence the temperatures in the drying, pyrolysis, oxidation, and gasification zones, as well as the composition of the syngas produced afterwards. The interactions between oxygen and char are to blame for the increase in carbon monoxide content with increased airflow rates. It has a major impact on the gasifier's output. The height and diameter of the gasifier are proportional to its volume, which is influenced by the weight of the rice husk employed to control the airflow rate inside the gasifier during burning. As a result, the parameters studied in this study have a considerable impact on producer gas.

2.2 Neural Network Algorithm

As shown in Figure 1, an artificial neural network works by accepting input into a set of input nodes, processing the data through neural connections, and then outputting a collection of outputs as output nodes. The output is obtained by using a transfer function called the activation function to process the weighted sum of the inputs. The ultimate output is determined by the number and strength of weighted connections between input and output nodes. Because the weights of the connections between nodes cannot be predetermined on a large scale, an artificial neural network's learning ability is necessary to change the weight during the learning process, which entails continuously giving all of the examples to the artificial neural network. After it has been trained, the artificial neural network can be used to obtain the answer to an input pattern [20].

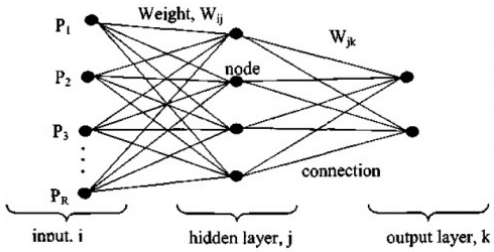

Figure 1: Basic Structure of an Artificial Neural Network

The software used in this research is the MATLAB R2021a version. A feedforward network with a single hidden layer was used. A backpropagation training algorithm was utilised. It's termed "feedforward" because, unlike recurrent networks, the connections in this neural network topology are "feed forward." Backpropagation, on the other hand, is a supervised learning method used primarily by multi-layer perceptrons to modify the weights attached to the net's hidden neuron layer(s). It comprises three input nodes, fifteen hidden nodes, six output layers, and six output nodes. Three inputs are the height, diameter, and weight of the rice husks. Fifteen hidden nodes are the number of neurons used to process the data, relate the connection between parameters and output, and create the algorithm. Six output layers and six output nodes are required to generate the six producer gas compositions.

Table 1 categorises the data into two groups: First, all three parameters for each set of data were copied and pasted in the form of a table inside the workspace in a new folder named "Input" as shown in Figure 2. The parameters were set as input data patterns. Second, the compositions of producer gas data were copied and pasted in the form of a table in the workspace and named targets. This set of data is the target data pattern. The file was then exported to the data manager as input data and target data.

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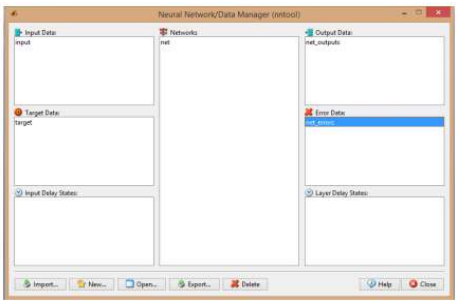

Figure 2: Neural Network/Data Manager

The "trainlm" function is a network training function that uses Levenberg-Marquardt optimisation to update weight and bias variables. It was incorporated into the creation of this neural network. Although it requires more memory than other algorithms, 'trainlm' is often the quickest backpropagation technique in the toolbox and is highly recommended as a first-choice supervised approach. The Levenberg-Marquardt approach is a least-squares problem that minimises the sum-of-squares function f(x). The Levenberg–Marquardt method's core principle is that it undertakes a combined training process: at areas with complex curvature, it changes to the steepest descent approach until the local curvature is proper to produce a quadratic approximation; then it approximates. The hidden layer in this neural network has 15 nodes. The 15 nodes are arranged in accordance with the number of neurons required to process the 20 sets of data (80 % training, 10 % testing, and 10 % verifying) and relate the inputs and outputs using an algorithm. Hidden layers allow a neural network's function to be broken down into specific data modifications. Each function in the hidden layer is tailored to generate a certain result. Hidden layers are critical to neural network performance, particularly in complicated tasks where accuracy and timing complexity are the primary limitations. Then, the simulation is started and trained using the data. In the simulation process of the trained network, the training process stopped when the maximum epoch was reached at 1000 epochs with six maximum failures. An epoch is a unit of time used to train a neural network for a single cycle with all of the training data. In an epoch, authors use all of the data exactly once. One pass is made up of a forward and a backward pass. An epoch consists of one or more batches in which the neural network is trained on a subset of the dataset. In this research, epochs are set to 1000 to make sure the network can be trained repeatedly and the outcomes from the trained network will be better. The time to run the process is set to infinity to ensure that there is no time limit and that the programme runs until it completes. The parameter "min grad" defines the minimal magnitude (scalar) of gradient descent (vector) for which the neural network training is complete. The neural network algorithm is said to be optimised when the gradient descent magnitude is less than "min grad," and hence, further training stops. In this network, the "min grad" is set to 1E-07, and the value is tending to zero. The optimisation algorithm should be able to locate the global minima of the loss function. At global minima, the gradient is very small and tends to be zero. Table 2 shows the setup training parameters.

Table 2: Training parameters setup

showWindow	true	mu	0.001
showCommandLine	false	Mu_dec	0,1
show	25	Mu_inc	10
epochs	1000	Mu_max	10000000000
time	Inf		
goal	0		

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After the network has been trained with input and target data, it will produce a trained neural network named the net. The "net" has a certain weight or bias to process any other input pattern and produce prediction data as the output. The net also comes out with "net_output" and "net_errors" data. The "net_output" data is a prediction based on the input pattern from the earlier sets of data. The network automatically produces this prediction after being trained. The "net_errors" are a set of data errors from the prediction data. The data errors are based on the calculation of target data minus prediction data.

The final step is to run the algorithm with the parameters data of the gasifier and setup used in the previous experiment. Table 3 shows the parameter values for the gasification experiment. The height of the gasifier, the diameter of the gasifier, and the weight of the rice husk are entered as experiment data in the workspace. Then the experiment file was uploaded to the data manager. A "Net" network was set up with experiment data as the input pattern and the results named "prediction."

Table 3: Input Parameters Value of Gasification Experiment in UiTM [18]

High (m)	Diameter (m)	Weight of Rice Husk (Kg)
0.9	0.404	1

3. DISCUSSION OF RESULTS

The neural network training progress is shown in Figure 3. During training, an iteration is a single gradient update (weights update for the model). The number of iterations required to accomplish one epoch is the same as the number of batches required to complete one epoch. So, for this network, a single epoch will take 6 iterations to complete.

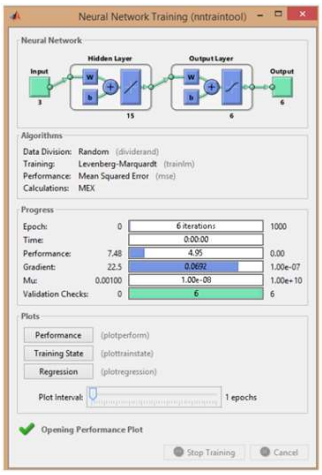

Figure 3: Neural network training progress

The comparison between computed and measured results of the training, testing, and validation for producer gas composition output which are carbon dioxide CO_2, carbon monoxide CO, methane CH_4, oxygen O_2, hydrogen H_2, and nitrogen N_2 were presented in Figure 4. The method of post-training analysis was used. The vertical axis represents the predicted amounts of producer gas produced by the computer, and the horizontal axis represents the actual values of producer gas from the collected data from other research (Table 1). The training process

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stopped when the maximum epoch was reached at 1000 epochs. The number of epochs was set as high as possible, and training was terminated based on the error rates. An epoch is one learning cycle where the network sees the whole training data set. Epoch is set high so that the network can learn and process the data completely until it reaches error rates. Table 4 shows the results of training, testing, validation, and the entire network in terms of the correlation coefficient R, the best linear regression model m, and the relative percentage error.

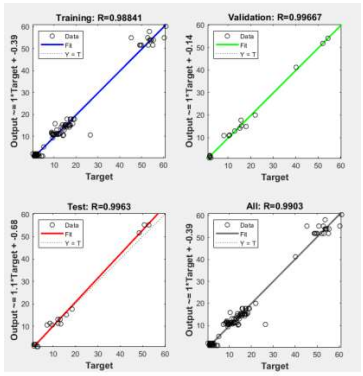

Figure 4: Neural Network Training Regression

Table 4: Computational analysis of train, test and validation

Network	R	m	Relative Error (%)
Train	0.98841	1.00000	1.159
Test	0.99630	1.00000	0.370
Verify	0.99667	1.00000	0.330

There are two reasons why a trained network is relatively good: First, the values of the slope of the best linear regression, m, and the correlation coefficient, R, must be close to one. The data in Table 4, shows that the values of R and m are very close to one. When the network was perfectly fit (predictions exactly equal to actual), the R and m values were equal to one [21]. It shows that the correlation between the prediction and the actual value of the composition of producer gas is a good fit. Second, the reason is the relative error between the prediction and actual value of producer gas composition. 1.159 % of relative error for train networks gives a very good fit. The testing and validation processes were used to determine whether or not the network had been successfully established and could predict events on its own. It is shown that the R and m values for testing and validation are also close to one. More accuracy is obtained because the algorithm has been trained and stores the necessary weight when the training is done. It proved that the algorithm neural network developed for prediction is a good fit. Although the value of relative error for testing networks was increased, it still had a good fit and was considered a success.

In Table 5 it can be seen that there is only a slight difference in most values between actual and predicted data. The range of difference in the percentage of composition of producer gas is only 0.00227 % to 16.07678 %. Figure 5 represents the simulation results of the composition of producer gas between the actual and predicted values in terms of a graph. It shows that the actual and predicted values are close. A relative error below 20 % has the capability to give a good prediction. It proved to be a very efficient model for predicting the composition of producer gas from a gasification process using a downdraft gasifier and rice husks as the fuel.

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Table 5: Training Prediction Error

No.	CO (%)	H_2 (%)	CH_4 (%)	N_2 (%)	CO_2 (%)	O_2 (%)
1	0.246765	-0.01676	0.015007	0.743442	-3.00257	0.153782
2	2.822326	3.792055	-1.70239	-4.26077	-5.39743	1.049709
3	0.727625	-0.85322	0.253833	-4.32271	0.298582	2.304775
4	-0.25238	16.07678	0.103833	-9.80271	1.508582	1.394775
5	-2.57238	3.936779	-0.04617	5.377295	-1.77142	1.064775
6	-2.58238	-0.97322	-0.32617	-2.21271	1.498582	3.184775
7	-2.79238	-3.14322	-0.34617	-2.31271	-0.75142	1.944775
8	2.137962	-0.02581	0.118162	-1.19806	-2.98442	0.514442
9	0.221745	-0.96536	-0.27811	1.40227	0.273231	2.190135
10	1.321745	0.334637	0.021886	0.40227	-0.22677	0.990135
11	2.721745	1.034637	0.821886	-0.29773	-1.42677	-0.00986
12	1.021745	-0.46536	-0.17811	0.40227	0.773231	1.290135
13	-0.87825	-1.36536	-0.57811	0.00227	1.973231	3.690135
14	-1.9264	-0.45882	0.189292	0.270189	2.975874	0.551991
15	-0.2264	1.341183	0.489292	-2.62981	2.175874	0.451991
16	0.873596	2.441183	-0.01071	-3.12981	0.975874	0.451991
17	1.473596	1.741183	0.089292	-2.32981	0.375874	0.251991
18	1.073596	0.841183	-0.01071	-1.72981	1.175874	0.251991
19	-0.0264	-1.45882	-0.31071	1.470189	1.775874	0.151991
20	-1.7264	-1.85882	-0.71071	3.370189	2.475874	0.051991

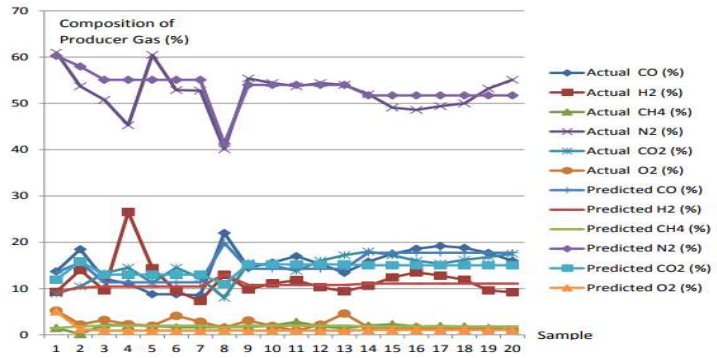

Figure 5: Actual vs. Predicted Value of Producer Gas Composition

Table 6 shows the composition of the producer gas prediction value. The prediction seems to be a good one. According to data gathered from other researchers, the predicted compositions of producer gases are within range. The neural network has been processed and refers to the sample data. This neural network algorithm can predict the output from the input pattern with good fit values. Therefore, it can be said that the prediction was made successfully.

Table 6: Prediction Value of the Composition of Producer Gas

CO (%)	H2 (%)	CH4 (%)	N2 (%)	CO2 (%)	O2 (%)
8.552	8.647	0.379	54.487	8	5.227

These prediction data were compared with the range of actual data (maximum and minimum values) collected from other researchers. The prediction for the CO percentage is 8.552 %, which is good because the data collected show that it is between 8.55 % and 22 %. The H_2 percentage is also satisfactory at 8.647 %. The percentage ranges from 7.31 % to 26.53 %,

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according to the actual data collected. The CH_4 percentage is 0.379 %, putting it between 0.166 % and 2.8 %. The percentage of N_2 is a good fit because it is in the range of 40.1 % to 61.02 % compared to the actual data range. The CO_2 percentage is also in the same ballpark, ranging from 8 % to 17.5 %. The final composition of producer gas, O_2, is 5.227 %, and the range of 0.9 % to 5.23 % refers to the actual value of collected data. Based on the analysis, the predictions for CO, H_2, CH_4, N_2, CO_2, and O_2 are well-fitted and in the normal range. The result is compared with the actual value from the collected data. This shows that the neural network algorithm can predict the compositions of producer gases successfully. The patterns of height, diameter, and weight of rice husks and the compositions of producer gases have influenced each other based on the results.

4. CONCLUSION

This research was carried out through a study and the use of MATLAB software to create a simulation. The parameters of the gasifier's height, diameter, and weight of the rice husk used are investigated. The relationship between parameters and producer gas compositions was demonstrated. The parameters have a significant influence on the composition of producer gas produced by a downdraft gasifier using rice husks. After producing the data, MATLAB (ANN) produces a clear and understandable output. The information is presented in the form of graphs.

The results have been used to compare the actual data from the experiment with the predicted data from the neural network. The validation network has the lowest relative error (0.33%) as compared to the train network (1.159 %), which has the highest correlation coefficient value. The correlation coefficient, R, for the train network is 0.98841, and for the validation network, it is 0.99667. The R-value for the validation network is closest to 1. Hence, the relative error for the test network is the lowest. The simulation results of producer gas composition between prediction and actual values revealed a relative error of 1.159 %, 0.370 %, and 0.330 %. These results were less than 9 % and were found to give a very good fit to the neural network algorithm. The graph in Figure 5 shows that the actual value and predicted value of the composition of producer gas have only a small difference for most of the values. Thus, the training prediction of the network is successful.

The algorithm has been used to predict the composition of producer gas by setting the parameter data as an input pattern. These parameters pertain to a downdraft gasifier experiment conducted in the UiTM laboratory using rice husks. All the values (CO, CH_4, H_2, N_2, CO_2, and O_2) predicted are acceptable and within the range of the data collected. The neural network algorithm predicts the outputs successfully. Hence, this is also proof that the pattern of input parameters (height, diameter of the gasifier, and weight of the rice husk) influenced the outputs (the compositions of the producer gas). When trained with data of inputs and output target values, the developed artificial neural network model from feedforward architecture with a backpropagation training algorithm using MATLAB (ANN) can be an accurate and efficient model to predict the output producer gas composition from the gasification process. There is no limit to how much ANN can be trained. The more data there is, the better for training. The 20 data sets used are enough to provide accurate answers for the trained algorithms. It is proven when the answer during the test and verification is obtained. The model laid the groundwork for gaining useful insights and a better understanding of designing rice husk gasification by utilising a downdraft gasifier with an artificial neural network.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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