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Machine Learning Approach for Prediction Model on Biomass Characteristic Analysis

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Abstract. Machine learning was utilized in the study to construct prediction models for predicting Net Output Power based on various characteristics such as moisture content and other materials. The temperature of the gasifier and the air-to-fuel ratio are other crucial factors in the prediction model. According to the findings, a Neural Network could accurately forecast the Net Output Power Yield based on biomass properties. In addition, the relative contribution of various percentages of elements on biomass, such as carbon (23.3-55.8%) and volatile materials (47.8-86.3%), was shown in the form of diverse feedstocks. Structural information was more essential than element compositions for biomass characteristics to predict Net output power yield effectively. RapidMiner software was used to perform the machine learning prediction method in this study. For the performance evaluation of the prediction model, the RMSE (Root Mean Square Error) was used. For predicting net output power from different feedstocks of solid biomass fuels, these models are the best available. The current study brought fresh insights into biomass characteristic analysis, which improved output power. This research indicates that machine-learning approaches can be implemented to predict the net outputs power successfully.

Keywords: Biomass, Gasification, Machine Learning, Net Output Power, Prediction Model

INTRODUCTION

Decision-makers in the energy business are motivated/compelled by environmental and energy security concerns to find out renewable - energy sources to meet the rising demand for these types of energy. The sustainable energy supply considers biomass as a naturally available and abundant renewable energy source for energy extraction (1,2). Only biomass can serve as a viable replacement for fossil fuels because to its abundant supply and the ability to continuously produce electricity and synthesize a variety of different products, such as transportation fuels or chemicals (2–4).

Gasification is a remarkably efficient and environmentally friendly conversion method for transforming a variety of biomass resources into a variety of useful end products. Biomass gasification is environmentally friendly because it produces fewer pollutants. Gasification's waste products, on the other hand, are non-toxic and can be easily repurposed. Biomass gasification plants can be linked with power production units and used as a more sustainable power supply technology in places far from major energy networks and demanding a district energy system(5).

To put it another way, biomass gasification is a thermochemical conversion in which a solid carbon-based feedstock is converted to syngas (a gasses mixture including H_2, CO, tar, light hydrocarbons, char, ash, and minor

contaminants) by using gasifying agents (such as pure oxygen, air, carbon dioxide, and steam). A little over half (50%) of the gas's energy is found in H_2 and CO, with the rest being found in CH_4 and other more highly volatile hydrocarbons. Drying, pyrolysis, oxidation (combustion), reduction (char gasification), and cracking are the five steps of the gasification process(5). This step was shown in figure 1. The biomass is vaporized to release the volatile compounds when exposed to these circumstances. Hydrocarbon gases (tars) and water vapor combine to form a volatile vapor. In addition, pyrolysis yields char, a carbon-rich solid residue. The combustible materials react with the oxygen in the gasifier to produce CO_2 and H_2O. Carbon monoxide and methane are produced during the reduction of biomass into combustible gases(6,7).

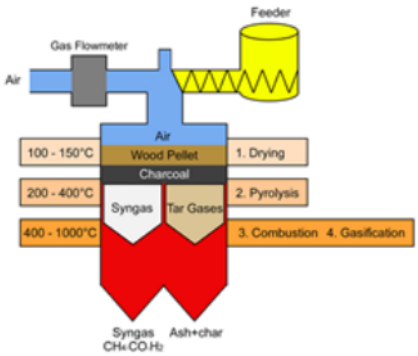

FIGURE 1. The Steps of Gasification Process

Among the carbon-based energy options, biomass is widely regarded as the only viable long-term option. Biomass is difficult to use as a fuel because of the wide variety of its physical and chemical properties. Energy biomass conversion processes are sensitive to wide variations in the feedstock material properties, so we require a non-destructive method for measuring biomass in real-time (5). Many studies have examined how biomass gasification systems perform using machine learning application(1,5,7–9). Thermo-chemical events have also been observed inside the gasifier, according to the research. This means that trials can give us information on the best conditions and feedstock for a reactor, but they are more time-consuming and costly than modeling(4,10).

Biomass gasification systems have used various models, including thermodynamic equilibrium, kinetic, CFD, and an Machine Learning model(5,9–12). Biomass gasification systems have been inspected using various models, including machine learning applications. This research reported the application of machine learning to predict net power output on biomass characteristic analysis. RapidMiner software had been applied for modeling with a thermodynamic equilibrium to predict the amount of power generated from 86 different biomass feedstocks under various operating conditions. Finally, all input variables' variations in carbon content are compared and analyzed together for a more thorough evaluation. The results are shown as Root Mean Squared Error, which is derived from the machine learning model's evaluation performance. To find the best model, we tested some different algorithms and models.

MATERIALS AND METHODS

Many conditions and terms were applied to the modeling process based on biomass characteristic analysis. With such a wide range of input materials and operating conditions, even though we tried to collect as much data as possible from various groups to build an extensive database, there are still many biomass with varying elemental and proximate analyses. Biomass properties are largely determined by geographical location and other restrictions, in addition to the various feedstocks. We experimented with a range of air mass flow rates and temperatures. This means that instead of running a simulation model time and time again for each case, we can use a machine learning model to arrive at the results for all the cases considered in a single run. We must first extract and enter the proximate and elemental analysis of biomass before running the model. The amount of air required for combustion in the power production part must be calculated based on the syngas compositions produced by gasifier output. All these steps can be omitted if a machine learning model is used. Figure 2 depicts the simulated system's flow chart. Data in Brief included all of the input and output variables in detail(13).

FIGURE 2. Flow Chart of Prediction Model on Biomass Characteristics Analysis

As previously stated, a downdraft gasifier was capable of gasifying 86 different types of biomass. For each input feedstock under atmospheric pressure and different operating conditions, all analysis is conducted using a 1-ton functional unit. Table 1 shows the input and net output power characteristics.

TABLE 1. Characteristic of Input and Output Variables in The Prediction Model for Downdraft Gasifiers

Input variables to the ANN	**Range**	**Unit**
C	23.3-55.8	(%)
H	2.9-9.7	(%)
O	11.18-46.9	(%)
S	0-1.29	(%)
N	0.096-9.3	(%)
Ash	0.1-46.3	(%)
Fixed Carbon	0.5-37.9	(%)
Volatile Materials	47.8-86.3	(%)
Air to Fuel Ratio	1.8-2.3	(kg/kg)
Moisture Content	2.5-62.9	(%)
Gasifier Temperature	600-1500	(°C)
Output variable for the ANN	**Range**	**Unit**
Net Output Power	0-436.8	(kW)

Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) model is used to examine the behavior of a downdraft gasifier integrated with a power production unit in terms of net output power. An ANN can be trained to perform a specific task by modifying its connecting weights, bias, and architecture. ANN is a system composed of many neurons organized into layers, with the neurons in each layer being linked together via weights. For this project, an ANN model was built with RapidMiner. The ANN model's output architecture (the net output power (kW)) is shown in Figure 3. There are 11 variables in the output of each ANN, which has one input layer with a hidden layer. Most researchers in this field have only developed ANN models with one hidden layer because there is no set rule for determining the optimal ANN structure. The best structure was found by minimizing the Root Mean Square Error using a hidden layer with various nodes (RMSE). We used a Neural Network model with a single hidden layer and 40 neurons to get the best RMSE.

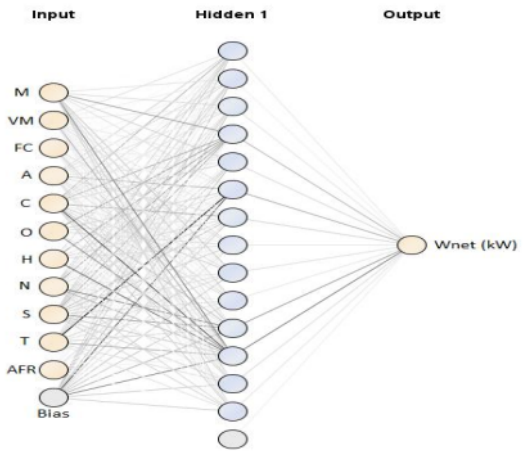

FIGURE 3. Neural Network Model

Support Vector Machine (SVM)

To classify, predict, and detect anomalies in large, nonlinear datasets, machine learning techniques such as Support Vector Machine (SVM) can be used. High-dimensional SVM-modeled datasets contain many columns and many observations (many rows, samples, also referred to as big data). The absolute value of each variable was estimated using Radial Base Function (RBF) kernel SVM models with weights (Lagrange multipliers). It was necessary to use dummy code for discrete variables in order to use support vector machines (SVMs)(14).

Linear Regression (LR)

To find the best linear regression parameters for predicting variables, the grid approach was used. However, the variable search was an optimization process in and of itself, as the model parameters were LR estimates. For each possible candidate. The best parameter, weight, and variable choices were made for each model based on maximizing predictive accuracy. There are several models in this study for which predictions were made using RapidMiner (see Figure 4). Based on root mean square error and absolute variance fraction, the machine learning-based prediction model's ability to predict was evaluated (R2). R2 is derived from simulation results and network predictions using Equations (1, 2) to calculate the RMSE and R2. Researchers use the RMSE to gauge a model's accuracy in predicting quantitative data. We should use the RMSE to determine the typical observed value's standard deviation from our model's prediction (9,11)

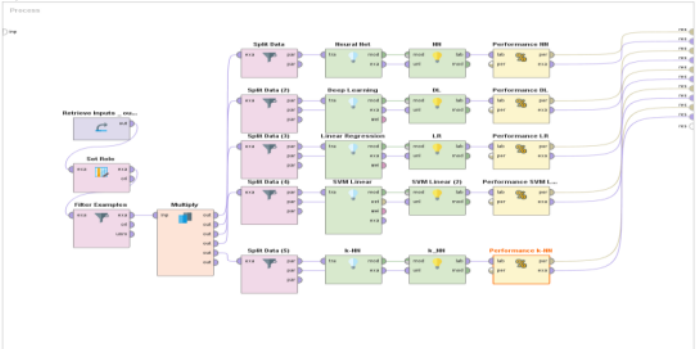

FIGURE 4. The Prediction Model on Net Power Output Using RapidMiner

$$\text{RMSE} = \left(\left(\frac{1}{p}\right)\Sigma_j|T_j - O_j|^2\right)^{\frac{1}{2}} \quad (1)$$

$$R^2 = 1 - \left(\frac{\Sigma_j(T_j - O_j)^2}{\Sigma_j(O_j)^2}\right) \quad (2)$$

Where, p is the number of samples, Tj is the target value and Oj is the output (predicted) value

RESULT AND DISCUSSION

Figure 5 shows that the simulated and predicted output power values for training, testing, and goals could be satisfactorily compared using an Artificial Neural Network (ANN) model. All target cases have an R^2 value greater than 0.999 when the power is generated by a downdraft biomass gasifier integrated power plant. Further assurance was provided in Table 2 by the predicted and target output power values for a few examples of data. Table 2 shows that the ANN model has a higher confidence level than SVM and Linear Regression for Prediction because of the comparison between predicted and target values and the low production error.

The results show that there are two lines in Figure 5, namely the blue line symbolizing the algorithm prediction and the green line representing the real data Power Net Output. In the figure, the predictions made by the model with NN are quite accurate, and it is just that in the end, there are some wrong predictions. These results were compared with the prediction results with the SVM model and the LR model. Moreover, the RMSE results show that the NN model has the smallest RMSE value compared to other models. A vast database of varied biomasses from distinct groups was studied in this work to have high accuracy and minimal uncertainty. As a result, if new biomass is described to the model, its constituents will fall inside the previous property range. Furthermore, the model has examined operating conditions that match the most used for natural gasification systems. Moreover, a sensitivity analysis is designed to have a more comprehensive comparison in the future. There is greater evidence to support this claim because of the model's examination of real-world settings. To further reduce uncertainty, all the data used to train and test the model is generated at random. To make future comparisons even more thorough, sensitivity analyses are created. A gasification system generates more electricity when biomass has a higher carbon content and lower moisture content. Comparing the amount of carbon produced by the system with operational parameters reveals that the best ARF (Air Fuel Ratio) and gasifier temperature must be selected for each amount of carbon content to get the most power out of the biomass.

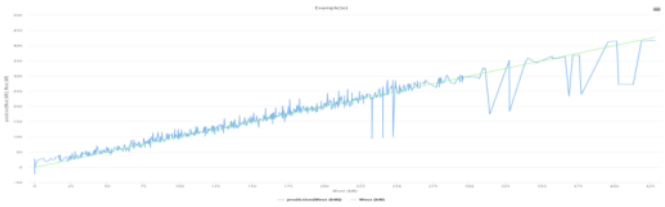

FIGURE 5. Simulated and Predicted Data for Downdraft Gasifier-Integrated Power Plant using the ANN Model

TABLE 2. The RMSE Value for Prediction Model

Prediction Model	RMSE Value
Artificial Neural Network (ANN)	18.214 +/- 0.000
Linear Regression (LR)	30.274 +/- 0.000
Support Vector Machine Linear (SVM Linear)	41.725 +/- 0.000

CONCLUSION

Product power or Net output power is a good example of a prediction model that has a high absolute variance fraction (R^2) and agrees with the target data. The output power is substantially influenced by each of the variables. Most of the output power is accounted for by biomass components (C, H, O, S and N), which range from 8 to 12 percent. As opposed to this, the influence of proximate analysis compositions (M, FC, A and VM) is 7 and 9 percent. The temperature of the gasifier also has a significant impact on predicted output power (with 13 percent). Research shows how downdraft biomass gasification power generation can be accurately forecasted using a ANN model instead of SVM or linear regression with RapidMiner software. In comparison to other models, the ANN prediction model's RMSE value was the lowest. The model can be used with a wide range of different feedstocks.

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