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Multi-Layer Perceptron based forecasting model of biomass and coal gasification

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Highlights

- Multi-layer perceptron-based method for biomass gasification is developed.
- CO_2, CO, H_2 and CH_4 percentage in output gas composition is forecasted.
- Effect of some input variables on the gas yield is assessed.
- A good agreement of modeling and empirical data is obtained.

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Abstract

In the present work, the multi-layer perceptron neural network is applied to model biomass gasification in the fixed-bed downdraft gasifier. Therefore, the multi-layer perceptron neural network is implemented to analyze and predict the gas composition in the outlet flow of the gasifier concerning theCH_4,CO_2, H_2 and CO concentrations. On the other hand, the input data for the prediction includes biomass element content ($C, H,$ and O), the value of the ash and moisture contents, and the temperature of the reduction zone. Extensive values which are derived from the experimental data are used to train the Multi-Layer Perceptron Neural Network. The obtained results from the model prediction show a satisfying agreement with the empirical data. The result of statistical analysis in the case of R^2 values for CH_4 and CO is higher than 0.99, and for the CO_2 and H_2 is higher than 0.98, which shows a good agreement between the experimental and predicted data. Also, a comparative study between MLP and other well-known methods demonstrates the superiority of MLP for gasification yield prediction. Hence, this model can be a useful tool for the analysis and performance evaluation of the gasifier modules.

1. Introduction

Environmental issues like air contamination and ecology destruction due to the utilization of fossil fuels have urged many nations toward using green and renewable energy resources [1,2]. In This regard, biomass, an accessible renewable energy source, is regarded as a sustainable framework for energy extraction. Biomass is one of the most significant sources of green, renewable, and sustainable energy which is sufficiently accessible [3]. There have been recognized a wide range of biomass resources, including wood and agricultural products (wood, logs, bark, and sawdust), solid wastes (municipal solid waste, garbage, industrial residues), etc. The major contents of any biomass comprise cellulose, lignin, and hemicellulose [4]. Gasification of the biomass includes the partial oxidation changeover in a closed chamber to the gaseous product which is burned to release energy or utilized to value-added components generation [5]. Balat et al. [6], as well as Hosseini et al. [7], studied the biomass conversion into the hydrogen as a clean energy supply through different methods. Hydrogen has known as an environmental-friend, pollution-free and promising supply for providing demanded energy in various applications [8]. Hydrogen provides a variety of application in many sectors such as utilization in vehicles, feeding as fuel to many power generation systems such as fuel cells (FCs), heating and

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cooling aims, etc. [9]. The biomass conversion can be done for different aims such as hydrogen production, gas production, a mix of gaseous including, CH_4, H_2, CO, CO_2 within gasification process [10]. Investigating the gasification procedure function to enhance the gas production and component evaluation has been done in a wide range of literature. The gas composition in the product flow relies on the feedstock properties, the geometry of the gasification chamber, the content of the moisture in biomass, gasification medium, and the operational circumstances [11–15]. Amongst various gasification agents (steam, air, oxygen, etc.), air is regarded as the gasification media in the present work. Since the gasification process is an auto-thermal reforming procedure, it is possible to exploit the released heat from the exothermic reaction to supply the heat required for the endothermic reaction to continue the gasification process. The lower heating value (LHV) provided from the air gasification process is a value around 4-7 MJ/Nm^3 [16]. The gasification process can be split into four steps including, drying process, pyrolysis stage, combustion (oxidation) step, and char gasification (reduction) [17].

Many researchers have also been formulated the gasification process in different domains, including thermodynamic equilibrium modeling, kinetic modeling, computational fluid dynamic modeling, and using artificial neural networks [18–20] to assess the gasification performance criteria concerning the output gas composition, gas yield, and the produced gas values and qualities. Mahishi et al. [21] utilized the thermodynamic equilibrium formulation to forecast the output gas composition for the biomass gasification aims. They studied the effect of some important parameters, including the ratio of steam to biomass and the equivalence ratio of the hydrogen production rate. Karmakar et al. [22] used the kinetic modeling for the evaluation of the gasification process of the rice husk in the fluidized bed gasifier in the presence of the steam as the gasification agent. Xue et al. [23] present the computational fluid dynamic (CFD) model for the simulation of biomass gasification in the fluidized bed gasifier. The solid phase component equation was coupled with gaseous phase equations. Their modeling is applied for the gasification of the wood in the presence of the air. Mikulandrić et al. [24] applied neural network methodology to identify the gasification process parameters in two different types of gasifiers. Artificial neural networks depend on a great quantity of experimental data and utilize mathematical regression to make a correlation between the entering and exiting values [19].

Among the various mathematical models, the application of neural networks is regarded in the present work. Neural network-based models do not need the mathematical formulation of the system's phenomenon. Hence, neural networks become suitable for the parameter identification and prediction of the nonlinear formulation, especially in the case of the biomass gasification process [25]. Besides, neural network methodologies can provide a highly efficient forecast with the same input parameters or even fewer parameters compared to the different modeling approaches.

Neural network methodologies were widely applied in different fields such as signal processing, recognizing the patterns, simulation of the procedures, and nonlinear function evaluation [26]. Kalogirou [27] offered the artificial neural networks (ANN) methods as a promising scheme for predicting the key parameters in the energy systems. In the case of hydrogen yield, many researchers have been related to forecasting and optimizing the artificial neural network in hydrogen yields [28–31]. Besides, the utilization of ANN in the pyrolysis of the biomass and gasification procedure fields has been narrated in the different works [32–40]. Gue et al.proposed a hybrid modeling scheme comprising the multi-layer artificial neural network to forecast the output products and composition of each gas in the exit stream in the fluidized bed gasifier in the presence of the steam in atmospheric conditions. Xiao et al. [32] used ANN for the parameter's prognostication of the municipal waste biomass gasification process. Souza et al. [33] developed an ANN-based method for gasification modeling using a fluidized bed gasifier and various biomass contents in different circumstances. In another work, Sreejith et al. [34] described the capability of the ANN models in the gasification modeling. Puig et al.applied ANN for forecasting the composition of the gas in product flow in the circular bubbling fluidized bed gasifier. The hydrogen yield from the pyrolysis of the waste contents was evaluated using the ANN model by Karaci et al. [35]. Sun et al. [36] developed an ANN model for the prediction of gas composition in the gaseous product of industrial waste gasification. Pandey et al. [37] predicted the lower calorific value of gaseous components in the waste pyrolysis by applying the ANN-based method. Moreover, Aydinli et al. [38] applied the ANN method for the prediction of the gasification procedure and energy potentiality of the biomass. Sunphorka et al. [39] stated the application of the ANN to predict the kinetic values of biomass from its components. Baruah et al. [40] used ANN modeling for the prediction of the gas yield in a fixed bed downdraft gasifier. Besides the reported literature review, for coal gasification,

ANN modeling is used in various papers [41–43]. Li et al. [44] used PSO-optimized back propagation neural network (BPNN) to assess the gas components in the gaseous flow of coal gasification in a fluidized bed gasification plant.

From the literature review, there are a few cases of MLP-based models that have been used for the modeling and identification of biomass gasification in fixed bed downdraft gasifiers. In the present work, the multi-layer perceptron neural network is applied for the modeling of the biomass gasification in the fixed-bed downdraft types of gasifiers since there is a relatively small number of neural network applications in the field of biomass gasification, especially in the case of the fixed-bed downdraft gasifiers. The downdraft gasifiers are the most-used type of gasifiers that are generally utilized in small-scale applications.

2. Biomass gasification process

Gasification is a process that includes a series of chemical phenomena, including drying, pyrolysis or thermal decomposition, oxidation, and reduction. The drying process is the step in which the biomass moisture content decreases. The process occurs in a medium with a temperature in the range of [100, 200 ℃], and the moisture content reduces to lower than 5%. The next step is the pyrolysis or decomposition process, in which the breakdown of the raw materials occurs in the absence of air or oxygen. The output composition of this step includes CO, H_2, CO_2, hydrocarbon gases, and solid charcoal. The hydrocarbon gases then condense to the liquid tar. Then, the released gases from the previous steps pass the oxidation stage based on the gasification type. Solid forms of carbonized biomass oxidize to carbon dioxide, and the hydrogen also burns into water. The oxidation reaction is an exothermic reaction that provides the heat for three other steps in the gasification process. The next zone in the gasification is reduction reactions that occur in a temperature range of 800,1000℃ and is an endothermic process [45]. The most important reactions occur in the reaction zone comprising the following reactions:

Water-gas reaction	$C + H_2O \rightarrow CO + H_2\ \Delta H = 131.4\ kJ/mol$
Boudouard reaction	$C + CO_2 \rightarrow 2CO\ \Delta H = 172.6\ kJ/mol$
Shift reaction	$CO_2 + H_2 \rightarrow CO + H_2O\ \Delta H = 42\ kJ/mol$
Methane formation reaction	$C + 2H_2 \rightarrow CH_4\ \Delta H = 75\ kJ/mol$

There are various types of gasifiers, including fixed-bed, fluidized-bed, and entrained suspension gasifiers [46]. The fixed-bed gasifiers are also comprising some models such as updraft, downdraft, and cross-flow gasifiers [47]. In this study, a fixed-bed downdraft gasifier is employed for detailed analysis. Fig. 1 illustrates a schematic of a fixed-bed downdraft gasifier.

Fig. 1. Schematic of fixed-bed downdraft gasifier.

3. Prediction methodology

Simulation and modeling provide an excellent opportunity to determine the key parameters' effect on system performance. In this regard, intelligent methods provide lower computational costs and higher accuracy. Artificial neural networks can model complex nonlinear models. A Multi-Layer Perceptron Neural Network (MLPNN) is proposed for a fixed-bed downdraft gasifier to investigate the gasifier gas composition.

3.1. Multi-Layer Perceptron Neural Network methodology

Multi-Layer Perceptron Neural Network (MLPNN) is one of the robust neural networks applied for highly nonlinear systems. Also, the MLP neural network is a feed-forward network capable of nonlinear fittings with higher precision [48–52].

For the formulation of the MLP, the number of input neurons is considered n, the number of hidden layer neurons is regarded as h, and the number for the output layers node is given m. The weighted summation of the input layer is presented as follows:

$$s_j = \sum_{i=1}^{n} (w_{ij} x_i) - \theta_j, \qquad j = 1, 2, \dots, h \tag{1}$$

Herein, $w_{ij}$is the connection weight of i^{th} node in the input layer and the j^{th} node of the hidden layer, The θ_j denotes the j^{th} node's bias in the hidden layer, and x_i stands for the i^{th}input.

The following equation defines the output of a node in the hidden layer.

$$S_j = sigmoid(s_j) = \frac{1}{1 + e^{-s_j}}, \qquad j = 1, 2, \dots, m \tag{2}$$

Following the calculation of the hidden layer output, the final output values are determined as the latter relation.

$$o_k = \sum_{j=1}^{h} w_{jk} S_j - \theta'_k, \qquad k = 1, 2, \dots, m \tag{3}$$

$$O_k = sigmoid(o_k) = \frac{1}{1 + e^{-o_k}}, \qquad k = 1, 2, \dots, m \tag{4}$$

Therein, $w_{ijk}$is the connection weight of j^{th} node in the hidden layer and the k^{th} node of the output layer and The θ'_k denotes the k^{th} node's bias in the output layer. The weight function and bias of the layers are the key parts of the MLP.

Training a neural network is an essential process to find the optimal values of weights and bias matrices. The most appropriate training method for the feed-forward neural network is the back-propagation algorithm. The nodes in the back-propagation network are organized in layers and each layer's output creates the input of the succeeding layer [49]. Three layers of MLP (input, hidden, and output) are linked within the network parameters, including weights and biases. Different training algorithms are selected for the training of the MLP. The algorithms used for the training aims in the present work comprise Conjugate Gradient, Gradient Descent, and Bayesian Adjustment for Confounding, and Levenberg-Marquardt algorithms [50].

3.2. Performance evaluation and stopping metrics for MLP

Various performance criteria can be used for the determination of the MLP neural networks. Evaluation of errors and analyzing the difference between experimental and modeling data are the most conventional indicators for stopping. In the present work, the statistical parameters include the correlation coefficient (R^2), Root Mean Squared Error ($RMSE$), and Average Absolute Relative Error ($AARE$) are adopted to evaluate the MLP performance [51].

The correlation factor is defined as the following equation:

$$R = \frac{1}{N-1} \sum_{i=1}^{N} \left(\frac{Y_i^{Exp} - \bar{Y}}{St^{Exp}}\right) \left(\frac{Y_i^{MLP} - \bar{Y}}{St^{MLP}}\right) \tag{5}$$

The squared correlation coefficient is defined as follows:

$$R^2 = \frac{\sum_{i=1}^{N} \left(Y_i^{Exp} - \bar{Y}\right)^2 - \sum_{i=1}^{N} \left(Y_i^{Exp} - Y_i^{MLP}\right)^2}{\sum_{i=1}^{N} \left(Y_i^{Exp} - \bar{Y}\right)^2} \tag{6}$$

Herein, Y_i^{Exp} stands for the experimental values, $\bar{Y}$ represents the average of the empirical value, Y_i^{MLP} is the values calculated from the MLP neural network, and N is the number of samples.

The Root Mean Squared Error is given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(Y_i^{Exp} - Y_i^{MLP}\right)^2}{N}} \tag{7}$$

Also, for better analysis of the MLP effect on the forecasting process, the normalized RMSE metric is presented as follows:

$$NRMSE = \frac{\sqrt{\frac{\sum_{i=1}^{N} \left(Y_i^{Exp} - Y_i^{MLP}\right)^2}{N}}}{Y_{max} - Y_{min}} \tag{8}$$

According to the stopping criteria, the lowest values of $NRSME$ and $RSME$ are the most desirable, while the highest values of R^2 is acceptable. The highest value of the R^2 is one, so the values adjacent to one show the higher performance of the network.

3.3. Multi-layer perceptron flowchart

In this subsection, the MLP neural network is presented. Fig. 2 illustrates the MLP flowchart. Hidden layers' numbers and neurons number in the hidden layers are the key parameters in the multi-layer perceptron neural network. These numbers must be selected so that the over-fitting and under-fitting are avoided. Hence, the neural network structure should be designed with the lowest number of neurons.

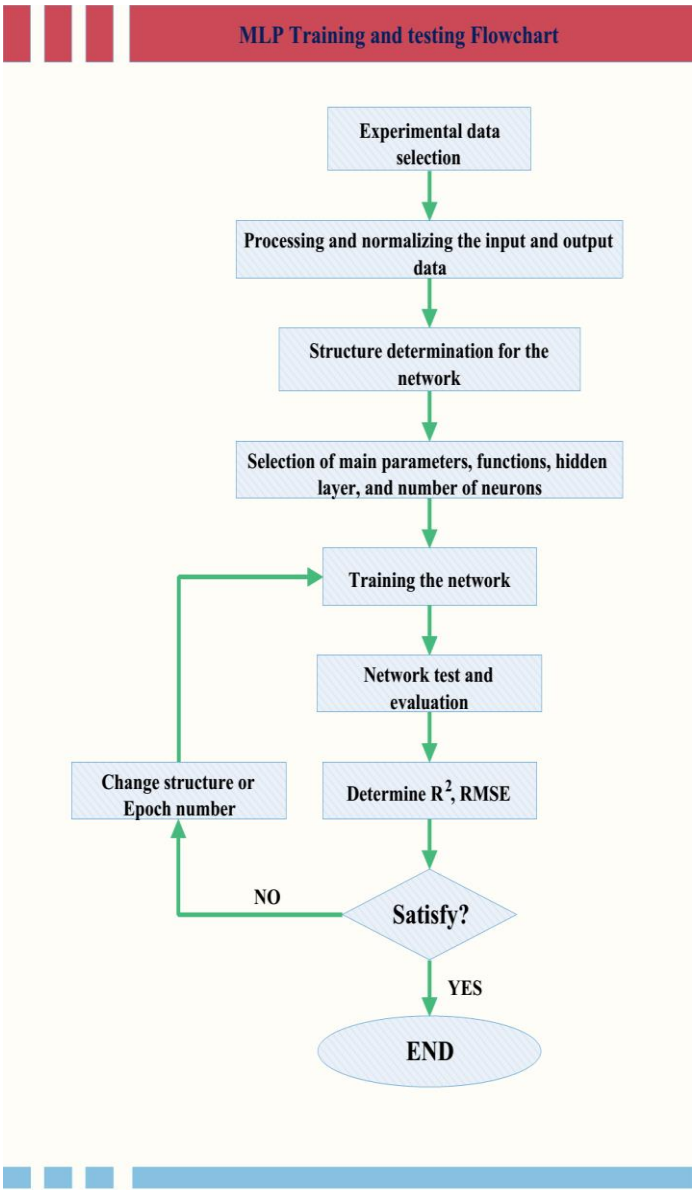


Fig. 2. Training, testing, and validation flowchart of MLP neural network.

3.4. Data acquisition for simulation

The data used for the simulation of the downdraft fixed-bed gasifier parameters comprises a dataset from various empirical execution of wood gasification. The variables are used as the input values for the formulation of MLP are Moisture content (MC), ash content, Carbon content, Hydrogen content, and Oxygen content, as well as the temperature of the reduction phase (T_R) [19- 35]. Table 1 presents the input and output parameters in the MLP-based model.

Table 1. Input and output variable bounds.

variable	range
Input	
C (wt % , dry basis)	[43.83, 53.40]
H (wt % , dry basis)	[5.42, 7.18]
O (wt % , dry basis)	[37.24, 45.83]
Ash (wt % , dry basis)	[4.20, 14.70]
MC (wt % , dry basis)	[43.83, 53.40]
T_R (℃)	[600, 1206]
Output	
CO (%)	[10.83, 24.00]
CH_4 (%)	[2.00, 6.91]
CO_2 (%)	[9.30 19.00]
H_2 (%)	[10.02, 23.93]

3.5. Network training, validation, and testing

Using the Multi-Layer Perceptron neural network model, the experimental datasets were applied to model the output gas composition. The data collections were randomly segmented into three parts. The first part of the dataset comprising 70 % was applied for training the network, the second part, including 15%, was used for validation, and the third part of datasets containing 15%was adopted for testing. Algorithms like Conjugate Gradient, Gradient Descent, Bayesian Adjustment for Confounding, and Levenberg-Marquardt were used to train the Multi-Layer Perceptron neural network model. Fig. 3 illustrates the application of the various algorithm to the MLP neural network. Based on Fig. 3, the optimum optimizing algorithm is the Levenberg-Marquardt method that is running based on the TRAINLM function. Various structures for the MLP can be defined by the aim of the assessment factors. However, the best case for the MLP structure is selected. The best structure for the MLP Model consists of an input layer with six different parameters, including C, O, H, MC, ash, and TR and a hidden layer with five neurons and an output layer with four different variables comprising CH_4, CO, CO_2, and H_2 percent. Fig.4 shows the MLP neural network architecture.

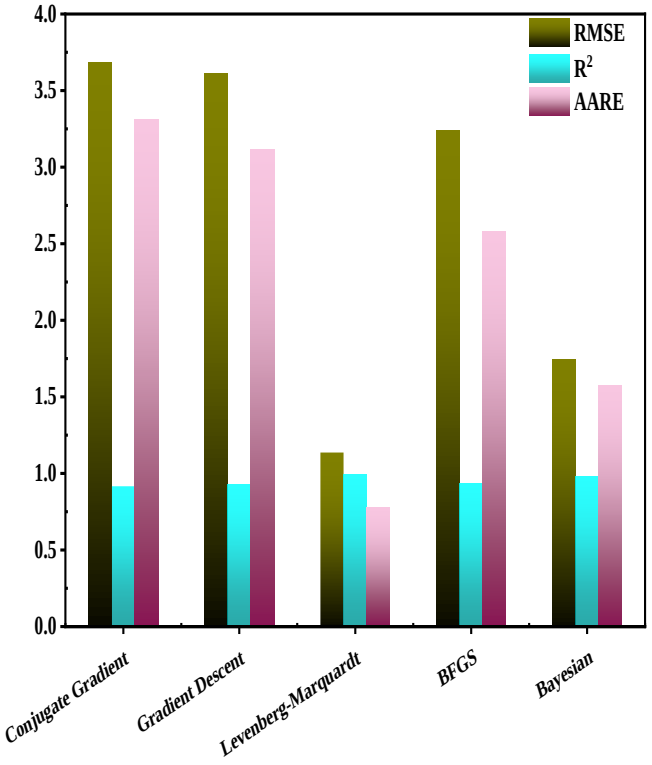


Fig. 3. Evaluation metrics for the different algorithms.

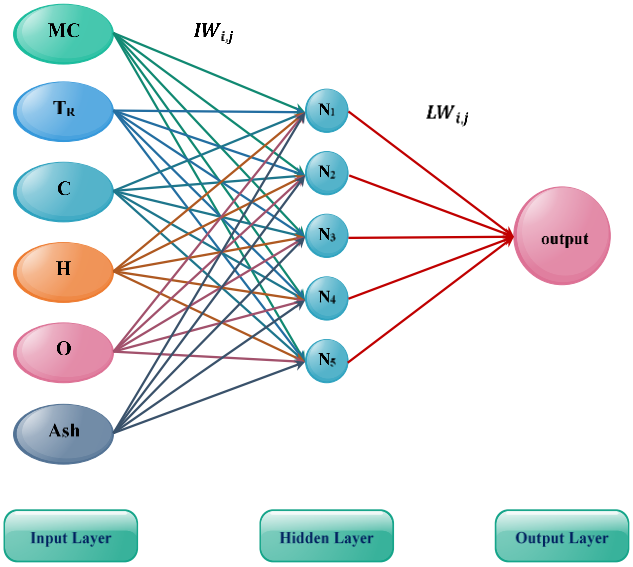
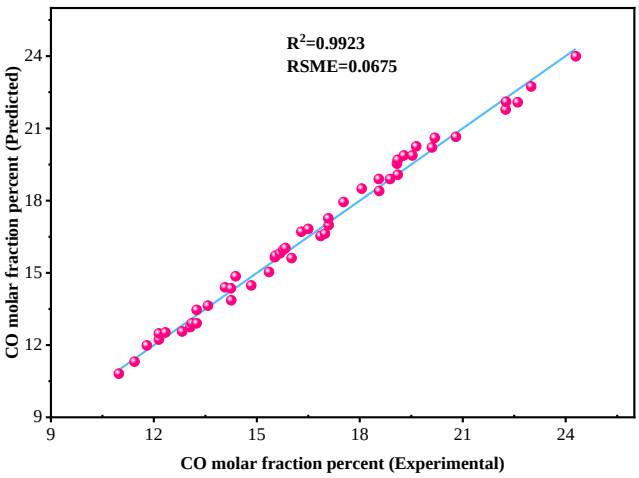


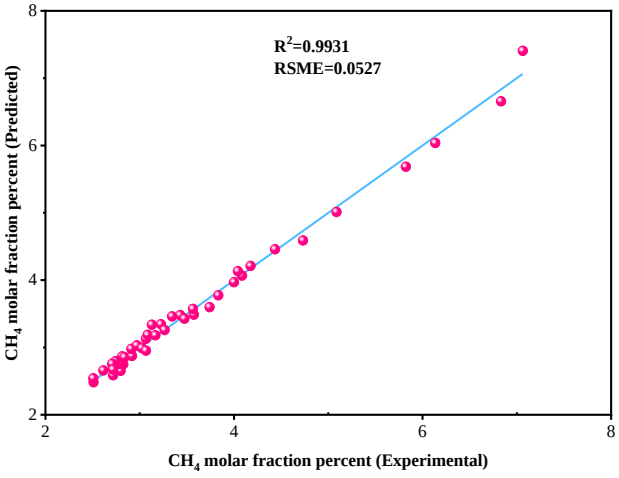
Fig. 4. MLP configuration for forecasting the output composition.

4. Results and discussion

The modeling and laboratory results are plotted in Fig. 5 and show a satisfactory agreement based on the regression criteria for output components, i.e., CO_2, H_2, CH_4, and CO. As can be seen, the correlation coefficient (R^2) for CH_4 and CO is greater than 0.99 while this value is greater than 0.98 for CO_2 and H_2. Moreover, the Root Mean Squared Error (RMSE) values for CO, CH_4, H_2, and CO_2 were found 0.0675, 0.0527, 0.0925, and 0.0885, respectively.



(a)



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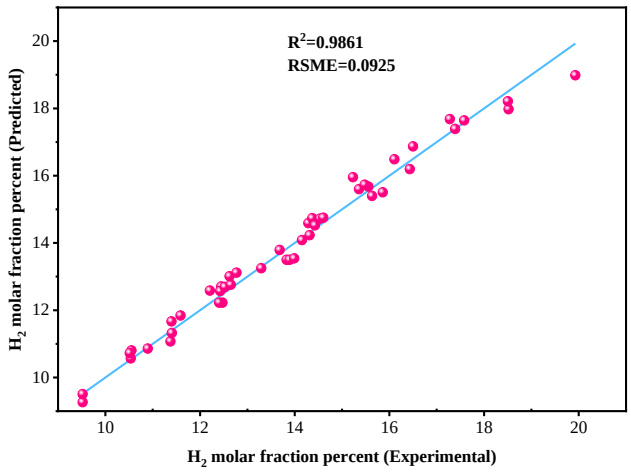
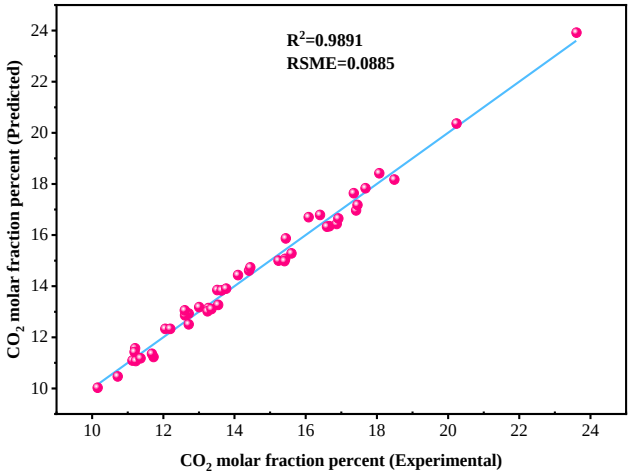


(c)



(d)

Fig. 5. Empirical data vs. predicted data by MLP model.

A comparison between modeling and experimental data is illustrated in Fig. 6, in which a good agreement between the empirical and modeling data is obvious. The average relative error between the experimental and modeling data is around 2.64 %. As can be seen, the best agreement with the lowest relative error belongs to the CO_2.

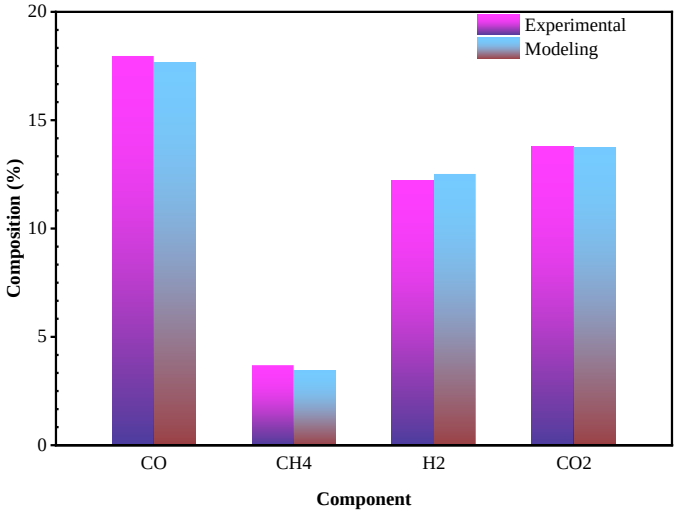


Fig. 6. Comparison between empirical and modeling data for major gas components.

Fig. 7 presents the effect of input parameters (C, O, H, MC, ash, and TR) on the outputs (CO_2, H_2, CH_4, and CO) composition. Based on Fig. 7, the reduction temperature (T_r) has the highest impact on the output yield of the CO and H_2 and ranked second in effect on the CH_4 and CO_2 prediction. Moisture Content (MC) was known to have the same effect on the CO, CH_4, and H_2 while it has a greater influence on the CO_2 yield. H content in the biomass (% wt) was found in the second rank in effect on the CO yield, in the third rank in effect on the H_2 yield, while ranked fourth in the case of CO_2 and CH_4. Ash content in the dry biomass has the highest impact on the CH_4 prediction, while in the case of the CO_2, the highest impact belongs to C. Greater ash content may result in some side effects, for instance: fouling, agglomeration, and gasifier corrosion.

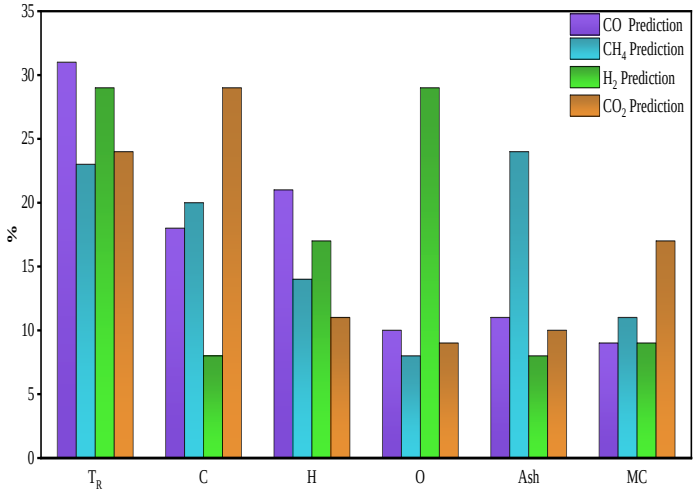


Fig. 7. Input variables effect on the gas yield.

In addition, the obtained results using the proposed MLP structure are compared with two other well-known neural networks to validate the efficiency of the proposed method for the case of gasification yield prediction. Table 2 lists the obtained results for all methods, which demonstrates the higher efficiency of the proposed MLP structure.

Table 2. Different criteria of various methods to evaluate the prediction precision

Method	Yield	R^2	*RMSE*	*NRMSE*
RBF neural network	CO	0.9747	0.0694	0.5269
	CH_4	0.9836	0.0603	1.2281
	CO_2	0.9584	0.0894	0.9216
	H_2	0.9894	0.0904	0.6499
Artificial neural network	CO	0.9865	0.0749	0.5687
	CH_4	0.9757	0.0583	1.1873
	CO_2	0.9902	0.0857	0.8835
	H_2	0.9684	0.0987	0.7096
Proposed MLP	CO	0.9923	0.0675	0.5125
	CH_4	0.9931	0.0527	1.0733
	CO_2	0.9891	0.0885	0.9123
	H_2	0.9861	0.0925	0.6650

5. Conclusion

There are a few studies of MLP neural network-based simulations of the biomass gasification process. An MLP model is proposed to evaluate the biomass properties and also operational circumstances according to the empirical datasets. The evaluation of the statistical criteria showed that the efficiency of the proposed model is satisfactory. The satisfactory efficiency of the developed model is also a metric that reveals the choice of parameters for the input layer was proper. Forecasting the gas yield in the gasifier exit with six different input variables in the input layer and with five neurons in the hidden layer by applying the back-propagation algorithm has been proposed. The proposed MLP neural network revealed a good agreement with a squared regression coefficient greater than 0.99 for the CH_4 and CO prediction while this value for the CO_2 and H_2 is obtained greater than 0.98. Based on the study, there are different parameters that influence the gas composition in the gasifier outlet. The reduction temperature (T_r) had the greatest effect on the output yield of the CO and H_2 and ranked second in effect on the CH_4 and CO_2 prediction. Forecasted values also trace the empirical trend based on the reduction temperature variation. The proposed MLP model with prosperous generalization abilities is a helpful method in mapping biomass gasification and evaluating the overall gasifier efficiency.

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