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Artificial Neural Networks for Performance Prediction of Biomass Gasification: A Tool for Sustainable Energy Prediction

Mohamed Baqar*, Boshra Haraga, Mafaz Alswihly, and Hayat Fanan
Department of Chemical Engineering, Faculty of Engineering, University of Tripoli, Tripoli, Libya
*Corresponding author: m.baqar@uot.edu.ly

الشبكات العصبية الاصطناعية للتنبؤ بأداء تحويل الكتلة الحيوية إلى غاز: أداة للتنبؤ بالطاقة المستدامة

محمد بقر*، بشرى حراقة، مفاز السويحلي، حياة فنان
قسم الهندسة الكيميائية، كلية الهندسة، جامعة طرابلس، مدينة طرابلس، ليبيا

Abstract

Biomass gasification is one of the essential thermochemical processes for the production of clean syngas, which is consistent with the global energy agenda towards the development of renewable energy resources. Yet, the prediction of the operating parameters of the biomass gasification system is still challenging due to the nonlinear nature of the system dynamics. The development of an Artificial Neural Network (ANN) model for predicting the composition of syngas produced in bubbling fluidized bed gasifiers using 321 datasets available in literature is presented. Two models, namely Feed Forward Back Propagation (FFBP) and Cascade Forward Back Propagation (CFBP), are used in this study. The FFBP network with two hidden layers was found to be the best ANN model with coefficients of determinations $R^2 > 0.97$ and Mean Absolute Percentage Error (MAPE) between 7 and 12 percent for CO, H_2, CO_2, CH_4, and gas yield. The best ANN model is the FFBP network architecture with two hidden layers trained through One-Hot Encoding. The ANN model obtains $R^2 > 0.85$ and MAPE < 18% for CO_2, H_2, CO, and gas yield in all types of bed materials. A systematic approach for selecting the optimal topology of the network through the 5-fold cross-validation procedure was used. Through sensitivity analysis using the permutation method, it was found that the key parameters affecting syngas quality were the ash content (average 24.5%) and carbon content (average 14.7%), and unexpectedly, the temperature and steam/biomass ratio had minor effects. This study can contribute to the sustainable development agenda by improving the energy efficiency and reducing the cost of experimentation towards the achievement of the United Nations' Sustainable Development Goals (SDGs) 7 and 9. The ANN-based model can be considered as a computationally efficient tool for the prediction of the biomass gasification system towards the development of the green economy.

Keywords: Biomass Gasification, Artificial Neural Network, Sustainable Energy, Renewable Energy

الملخص

يُعدّ تحويل الكتلة الحيوية إلى غاز (الغاز الحيوي) واحدًا من العمليات الكيميائية الحرارية الأساسية لإنتاج غاز اصطناعي نظيف، وهو ما يتوافق مع أجندة الطاقة العالمية الرامية إلى تطوير مصادر الطاقة المتجددة. إلا أن التنبؤ بمعاملات التشغيل لنظام تحويل الكتلة الحيوية إلى غاز لا يزال يمثل تحديًا بسبب الطبيعة غير الخطية لديناميكيات النظام. يُقدّم هذا البحث تطوير نموذج للشبكة العصبية الاصطناعية (ANN) للتنبؤ بمكونات الغاز الاصطناعي الناتج من أجهزة التغويز ذات الطبقة المميعة الفقاعية، باستخدام 321 مجموعة بيانات متاحة في

الأدبيات العلمية. تم استخدام نموذجين في هذه الدراسة، هما: التغذية الأمامية والانتشار الخلفي (FFBP)، والتغذية الأمامية المتتالية والانتشار الخلفي (CFBP). وُجد أن شبكة FFBP ذات الطبقتين المخفيتين هي أفضل نموذج للشبكة العصبية الاصطناعية، حيث بلغ معامل التحديد $R^2 > 0.97$، ونسبة الخطأ المطلق المتوسط (MAPE) بين 7 و 12 بالمائة لكل من أول أكسيد الكربون (CO)، والهيدروجين (H_2)، وثاني أكسيد الكربون (CO_2)، والميثان (CH_4)، وإنتاجية الغاز. أفضل نموذج للشبكة العصبية هو بنية شبكة FFBP ذات الطبقتين المخفيتين التي تم تدريبها باستخدام الترميز الأحادي (One-Hot Encoding). يحقق نموذج الشبكة العصبية قيمة $R^2 > 0.85$ و $MAPE < 18\%$ لكل من CO_2، H_2، CO، وإنتاجية الغاز في جميع أنواع المواد القاعية. تم استخدام نهج منهجي لاختيار الهيكل الأمثل للشبكة من خلال إجراء التحقق المتقاطع بخمسة أضعاف (5-fold cross-validation). من خلال تحليل الحساسية باستخدام طريقة التقليب (permutation method)، وُجد أن المعاملات الرئيسية المؤثرة في جودة الغاز الاصطناعي هي محتوى الرماد (متوسط 24.5%) ومحتوى الكربون (متوسط 14.7%)، ومن غير المتوقع أن تكون لدرجة الحرارة ونسبة البخار إلى الكتلة الحيوية تأثيرات طفيفة. يمكن أن تساهم هذه الدراسة في أجندة التنمية المستدامة من خلال تحسين كفاءة الطاقة وتقليل تكلفة التجارب نحو تحقيق الهدفين السابع والتاسع من أهداف الأمم المتحدة للتنمية المستدامة (SDGs). يمكن اعتبار النموذج القائم على الشبكة العصبية أداة فعالة حسابيًا للتنبؤ بنظام تغويز الكتلة الحيوية بما يخدم تطوير الاقتصاد الأخضر.

الكلمات الدالة: تغويز الكتلة الحيوية، الشبكة العصبية الاصطناعية، الطاقة المستدامة ، الطاقة المتجددة.

1. INTRODUCTION

Biomass is the largest source of renewable energy, ranking fourth in the list of energy resources, after oil, coal, and natural gas, respectively. Unlike oil, coal, and natural gas, biomass is renewable by the process of photosynthesis, which is a carbon-neutral energy source. The process of gasification of carbon-containing resources produces combustible syngas, comprising CO, H_2, and CH_4, under sub-stoichiometric conditions, offering the advantage of flexibility in the generation of electricity as well as the production of chemicals [1,2].

Biomass gasification is a highly nonlinear process involving various parameters, i.e., temperature, equivalence ratio, and steam-to-biomass ratio, etc., which is difficult to handle by conventional methods of modeling due to their complexity, as well as the computational effort required [3-5]. Therefore, the need is data-driven methods that align with the themes of renewable energy, and technology and innovation of the sustainable development research.

ANN is an efficient solution that has the ability to learn the complexities of the process using experimental data without the need for explicit equations [6,7]. The objective of the current study is to develop an ANN model using experimental data obtained from the literature. One of the key advancements in methodology comes in the area of treating categorical input variables. The study illustrates the necessity of encoding categorical inputs into one-hot encoding, as this helps mitigate the issue of spurious ordinal relationships and ensures that such relationships do not affect the neural network training process. Additionally, a methodology for selecting the optimal topology based on the principles of k-fold cross-validation is suggested. The desired result is the achievement of higher levels of prediction accuracy that help move toward a greener economy based on efficient use of renewable energy sources. Three novel aspects of methodology are proposed, including: (i) the proper treatment of categorical data on bed materials in one-hot encoding to avoid spurious ordinal relationships; (ii) cross-validation as a reliable basis for choosing an optimal network topology; and (iii) a sensitivity analysis using permutation importance for estimating the relative weight of inputs on syngas composition, offering actionable insights for chemical engineering practice.

2. METHODOLOGY

2.1. Process Description: Bubbling Fluidized Bed Gasification

The study is based on the Bubbling Fluidized Bed (BFB) gasifier with operating temperatures ranging from 800°C to 900°C through drying, pyrolysis, oxidation, and reduction processes. The chemical reactions involved are as follows:

Water-gas reaction: $C + H_2O \rightarrow CO + H_2 \qquad \Delta H = +131\ \text{KJ/mol}$

Water-gas shift reaction: $CO + H_2O \leftrightarrow CO_2 + H_2$ $\Delta H = -41$ KJ/molAs shown in Figure 1, in the BFB gasifier, the semi-suspended state of the bed materials, i.e., silica sand, olivine, and alumina, is well controlled by passing a gasification mixture consisting of air and steam. The gasification process is carried out at atmospheric pressure, and it depends on the fluid dynamic behavior of the bed materials, the properties of the biomass, and the operating conditions. The main products are the common gases found in syngas, namely CO, H_2, CO_2, CH_4, and Gas Yield (GY).

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2.2 Artificial Neural Network Architecture

The artificial neural network used for predicting the composition of syngas is described below. It consists of the typical three-layered structure, namely the input layer, hidden layer, and output layer. Training of the ANN was done using two types of algorithms; Feed Forward Backpropagation (FFBP) and Cascade Forward Backpropagation (CFBP). The methodology followed for selecting the ANN architecture is elaborated in Section 2.4.1, where a grid search combined with five-fold cross-validation was performed in a predefined search space of hidden layers' architectures. As illustrated in Figure 2, the proposed ANN model includes 13 input neurons which include continuous variables such as C (carbon), H (hydrogen), O (oxygen), Ash Content, MC (moisture content), S/B (steam-to-biomass ratio), ER (equivalence ratio), and T (temperature). On the other hand, bed material is included as five binary indicator variables; BM_Silica, BM_Ofite, BM_Olivine, BM_Alumina, and BM_Other, each taking value one if the respective material is used and zero if not. This avoids any artificial ordering among different materials. The output layer consists of five nodes representing the syngas components; CO_2, H_2, CH_4, CO, and Gas Yield (GY).

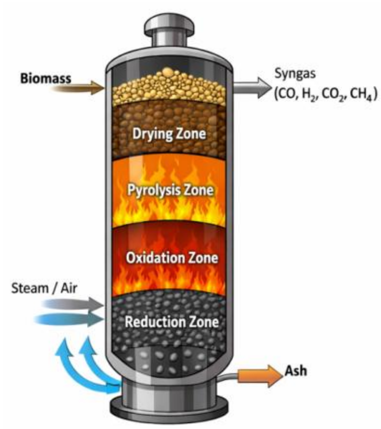

Figure 1: Bubbling fluidized bed gasifier schematic.

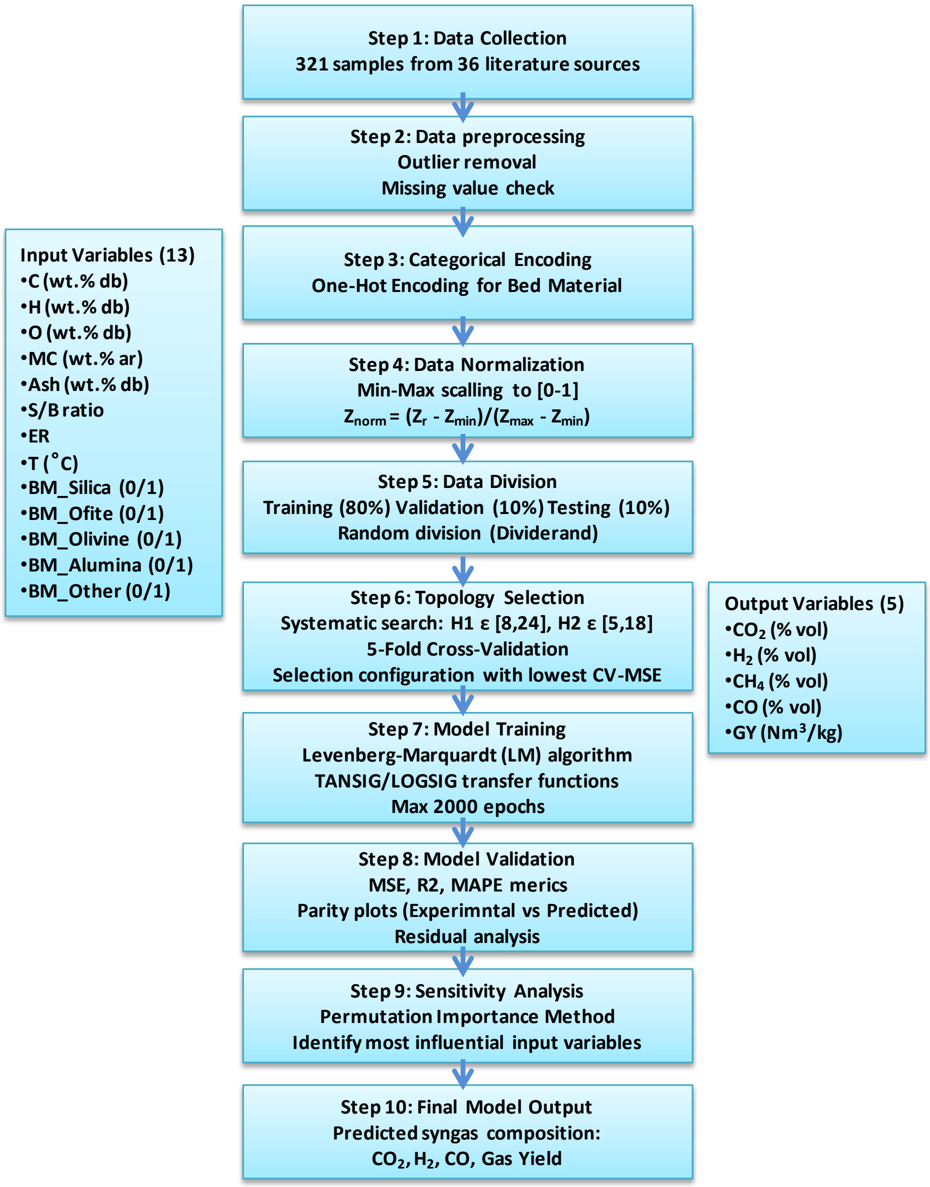

Figure 2: Proposed ANN Methodology Flowchart for Biomass Gasification Prediction

2.3. Data Collection and Normalization

The data set was collected from 321 samples, as reported in 36 studies in the literature [8-43]. It was then divided into training, validation, and testing sets 80%, 10%, and 10%, respectively. Table 1 shows the range of the data.

Table 1: Characteristics of input and output variables in the ANN based model

Output variables	Range	Input variables	Type	Range/Values
CO_2 [% vol]	0.1 - 62.97	C [%wt db]	Continuous	27.3 - 85.99
H_2 [% vol]	0.09 - 62.7	H [%wt db]	Continuous	0.74 - 14.04
CH_4 [% vol]	0 - 14.5	O [%wt db]	Continuous	0 - 59.42
CO [% vol]	0.08 - 47.29	Moisture [%wt ar]	Continuous	0 - 46.34

GY [Nm³/kg daf]	0 - 80.4	Ash [%wt db]	Continuous	0 - 44.00
		ER [–]	Continuous	0 - 0.47
		T [°C]	Continuous	25 - 1100
		BM_Silica	Binary	0 or 1
		BM_Ofite	Binary	0 or 1
		BM_Olivine	Binary	0 or 1
		BM_Alumina	Binary	0 or 1
		BM_Other	Binary	0 or 1
		S/B [–]	Continuous	0 - 4.04

Data normalization was performed using Equation (1) to scale values between 0 and 1:

$$Z_{norm} = \frac{Z_r - Z_{min}}{Z_{max} - Z_{min}} \qquad (1)$$

Where Z_r is the raw measured value, and Z_{min} , Z_{max} are the minimum and maximum values in the dataset.

2.4. Training and Performance Metrics

Model performance was evaluated using Mean Squared Error (MSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE), calculated as follows:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(T_k - S_k)^2 \qquad (2)$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(T_k - S_k)^2}{\sum_{k=1}^{n}(T_k - \overline{T})^2} \qquad (3)$$

$$MAPE = \frac{100}{n}\sum_{k=1}^{n}\frac{|T_k - S_k|}{T_k} \qquad (4)$$

where T_k indicates the target output, while S_k indicates the actual output of the network. The variable n indicates the number of data sets used. $\overline{S}$ indicates the average of the predicted values, and $\varepsilon = 1\times10^{-6}$ is used to prevent division by zero when T_k approaches zero. The training process used the Levenberg-Marquardt (LM) method due to the good rate of convergence. Table 2 describes the detailed specifications of the ANN model.

Table 2: Details of the ANN models

Specifications	Particulars
Network type	FFBP, CFBP
Training algorithm	Levenberg-Marquardt (LM)
Performance function	Mean Square Error (MSE)
Transfer functions	TANSIG, LOGSIG, PURELIN

Data division	Random (Dividerand)
Input layer units	13
Output layer units	1 (per component)
Hidden layers	1 and 2
Neurons in Hidden layer	1 to 30
Epochs	2000

2.4.1. Neural Network Topology Selection

The selection of an optimal topology with respect to the appropriate number of neurons in hidden layers took place with the help of the systematic search procedure. In particular, for each output variable, the search space of two-hidden-layer FFBP architectures was examined via a 5-fold cross-validation on the training dataset. The generated search space of this experiment is according to a rule that the number of neurons of the first hidden layer (H_1) must be between 60% and 200% of the number of attributes (n=13), and the second hidden layer neurons must be less or equal to that in the first layer [44]. Therefore, the combinations could be: $H_1 \in \{8, 10, 12, 15, 18, 20, 24\}$ and $H_2 \in \{5, 8, 10, 12, 15, 18\}$, with $H_2 \leq H_1$.

In this case, the training process takes place with the use of the Levenberg-Marquardt method and TANSIG transfer function. After the mean squared error had been calculated for each fold in question, the architecture, whose MSE value was the lowest for a particular output, was declared the optimal one. Thus, such a procedure guarantees that the topology in question is sufficiently generalized and does not have to be overfitted. The results obtained with cross-validation technique are reported below in Table 3.

Table 3: Topology Selection via 5-Fold Cross-Validation

Output	Selected Topology	H_1	H_2	CV-MSE	CV-R^2
CO_2	13-10-8-1	10	8	0.00996	0. 91
H_2	13-10-8-1	10	8	0.00845	0.92
CH_4	13-10-8-1	10	8	0.00289	0.96
CO	13-15-12-1	15	12	0.00895	0.94
GY	13-12-10-1	12	10	0.00078	0.98

From the above-mentioned network topologies, it can be concluded that networks with fewer neurons are the optimum choice in case of good behavior of outputs like CH_4 and GY but networks with higher complexity are preferred for predicting CO output because of non-linear relationship between CO production and carbon plus catalyst effect.

3. Results and Discussion

3.1. ANN Model Performance

Training the ANN models was done according to the systematic methodology for the selection of their topology that was discussed earlier in Section 2.4.1. The topologies chosen for the FFBP models through 5-fold cross-validation are given in Table 4. With the change in representation of bed material from labels to One-Hot Encoding, the number of inputs also changed from 9 to 13, which required a readjustment of the topologies for all models. The selected topologies reflect the optimal balance between model complexity and generalization performance for each output variable.

Table 4: Best-selected topologies using One-Hot Encoding (all bed materials)

Element	Network	Topology	R^2 (Train)	MSE (Train)	R^2 (Test)	R (Test)	MAPE (%)
CO_2	FFBP	13-10-8-1	0.9795	0.0205	0.6933	0.8427	17.85
H_2	FFBP	13-10-8-1	0.9212	0.0788	0.5123	0.7590	30.65
CH_4	FFBP	13-10-8-1	0.8900	0.1100	0.7376	0.8816	25.97
CO	FFBP	13-15-12-1	0.9891	0.0109	0.3760	0.7291	33.20
GY	FFBP	13-12-10-1	0.9570	0.0430	0.8922	0.9449	13.92

NOTE: Topology order is: inputs, first hidden layer, second hidden layer, outputs. The input layer contains 13 nodes (8 continuous variables + 5 One-Hot encoded bed material indicators).

The performance obtained by the FFBP NN with two hidden layers surpassed those from the CFBP NN and one-layered networks. It is important to highlight that all three outputs (CO_2, H_2, and CH_4) had an identical best configuration (13-10-8-1), which indicates that all these outputs have the same complexity degree in their relationship with the inputs. In the case of the prediction of CO, a higher complexity was necessary (13-15-12-1), possibly owing to the strong nonlinear coupling with the inputs related to carbon content, equivalence ratio, and catalyst effect of the bed materials. GY, although having a broad range of values (from 0 to 80.4 Nm^3/kg), showed the best test R^2 value (0.8922).

3.1.1 Validation of One-Hot Encoding

To establish the empirical justification for the requirement of label encoding along with One-Hot Encoding on bed material, three models have been constructed using (i) label encoding for all materials, (ii) One-Hot Encoding for all materials, and (iii) only silica (without bed material). These results have been shown in Table 5 below.

Table 5: Comparison of Encoding Approaches — Test Set Performance

Element	Label Encoding (All)			One-Hot Encoding (All)			Silica-Only (No BM)		
	R^2	R	MAPE (%)	R^2	R	MAPE (%)	R^2	R	MAPE (%)
CO_2	0.6036	0.8420	19.06	0.6933	0.8427	17.85	0.2635	0.7829	18.48
H_2	0.2792	0.7629	29.89	0.5123	0.7590	30.65	0.3745	0.5166	27.79
CH_4	0.7008	0.8395	26.85	0.7376	0.8816	25.97	0.7493	0.8791	27.93
CO	0.3002	0.6200	34.70	0.3760	0.7291	33.20	0.7201	0.8633	13.53
GY	0.8886	0.9429	12.93	0.8922	0.9449	13.92	0.2093	0.7830	9.94

The findings show that the application of One-Hot Encoding enhances the effectiveness of the model for all the output variables. In case of CO_2, the R^2 value during testing increases from 0.604 to 0.693, whereas the correlation coefficient R changes from 0.8420 to 0.8427. This is clear evidence of how the introduction of an artificial ordinality in labeling has adversely affected the model's capability to learn the chemical interactions.

It is important to note the following regarding the silica-only model: the model performs very well when there are strong effects of bed material chemistry on catalysis in terms of some of the output variables (CO and GY), since such effects are eliminated. On the other hand, in case of CO_2 and H_2, One-Hot Encoding is superior to silica-only approach.

3.1.2 Parity Plot Analysis

Figure 3 presents the parity plots comparing the experimental and predicted values of the syngas components using the FFBP network with One-Hot Encoding approach.

The parity plots indicate very close relationship between experimental and predicted values, especially for GY ($R = 0.945$) and CH_4 ($R = 0.882$). On the other hand, CO shows more scattered results due to the relatively low R^2 for testing (0.376), which can be explained by the high complexity of modeling the CO yield with highly dissimilar feedstocks possessing different catalytic properties. For H_2, the correlation coefficient is relatively moderate ($R = 0.759$); some scattered values can be seen for H_2 concentrations higher than 40% vol, which might relate to the edge cases of the steam-gasification process.

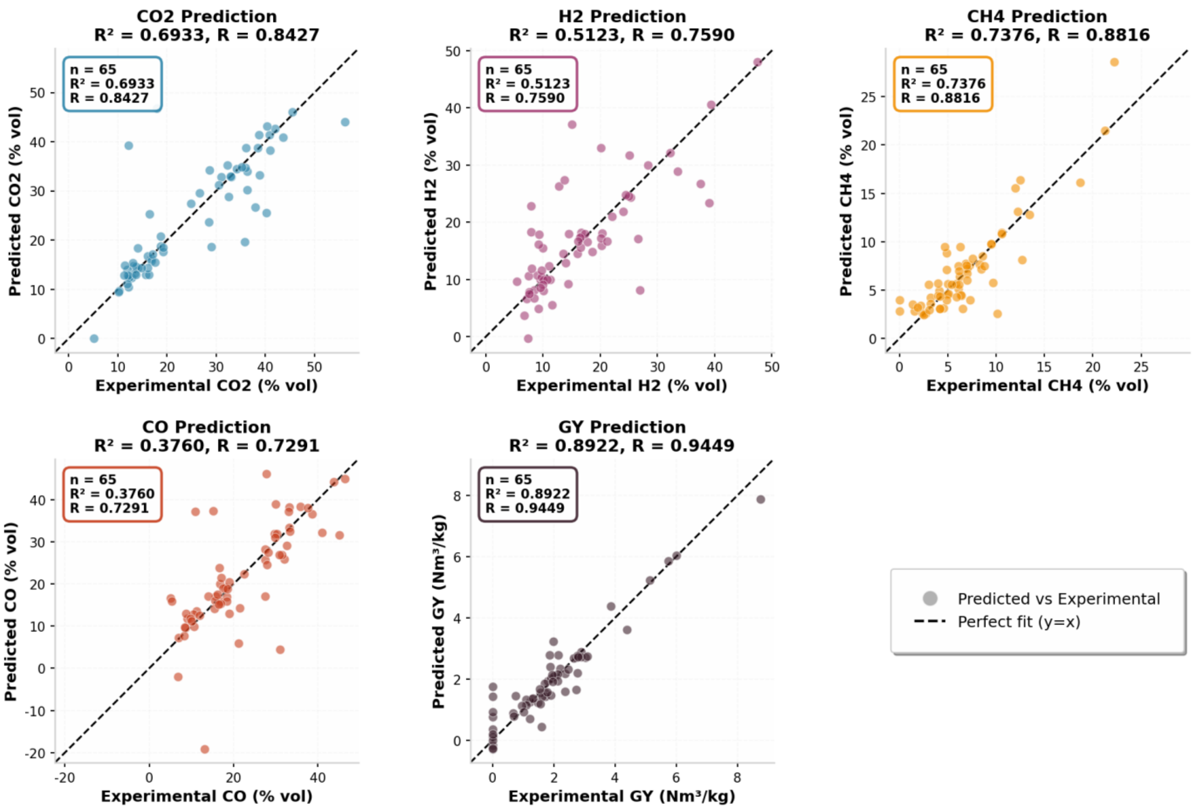

Figure 3. Parity plots - Expeimental vs predicted syngas components (FFBP model with One-Hot Encoding, test set, n=64)

3.2. Sensitivity Analysis

To measure the effect of individual variables on predicting the syngas composition, the variable permutation method was used. For each trained model, individual input variables were randomized in the test dataset and the increase in the mean square error was measured. The variable importance was normalized in percent, representing the ratio between variable effect and total MSE increase. This method is especially well-suited for neural networks as it is independent of the derivative information and collinearity effects in the data.

The sensitivity analysis produces variable importance measures with clear differences that allow chemical interpretation:

Carbon content is important for predicting CO_2 composition as it accounts for 34.5%, while ash content plays second place with 18.2%. This is expected from the point of view of thermodynamics, as carbon content increases the Boudouard and water-gas reactions, whereas ash content affects heat transfer. Importantly, the bed material Ofite is significant (9.3%) for CO_2 prediction, pointing at its catalytic effects distinct from others.

When predicting H_2, moisture content (MC) plays the most significant role with 28.1% importance, while hydrogen content (HC) is responsible for 16.2%, and Silica bed material makes up 12.9%. The reason behind high MC significance is the steam reforming process ($C + H_2O \rightarrow CO + H_2$; $CO + H_2O \rightarrow CO_2 + H_2$). Hence, available moisture leads to the formation of hydrogen. In case of Silica bed material, its inertness helps prevent hydrogen from being consumed by other reactions, unlike Olivine.

In the case of CH_4 predictions, oxygen content plays the most critical role with 20.1%, followed by the Ofite bed material with 16.4%, and carbon content at 14.2%. Oxygen importance might seem odd at first since it is the product of the reaction ($CO + 3H_2 \rightarrow CH_4 + H_2O$). However, when there is not enough oxygen (low O/C ratio), methanation processes take place.

In CO prediction, ash content (17.2%) and carbon content (16.7%) are equally dominant, followed by Silica bed material (13.9%). The effect of ash is especially crucial because the alkali present in the ash facilitates the water-gas shift reaction, transforming CO into CO_2; hence, an increase in ash content leads to lower CO output. The effect of Silica bed material implies that CO is conserved as this inert substance does not promote shift conversion.

Ash content is clearly the most influential variable in Gas Yield prediction (53.3%), higher than all other factors put together. This is chemically understandable because ash is a non-reactive diluent that decreases the amount of carbon capable of participating in gasification reactions and hence decreasing gas formation.

Unexpected results: The effects of temperature and S/B ratio have very little sensitivity (below 3% collectively) on all output measures. This means that in their respective ranges (25 to 1100°C for temperature, 0 to 4.04 for S/B ratio), they play a relatively insignificant role compared to other factors such as the composition of the feedstock and the choice of bed material. It is essential that effort be concentrated on pre-treating the feedstock and choosing good bed material.

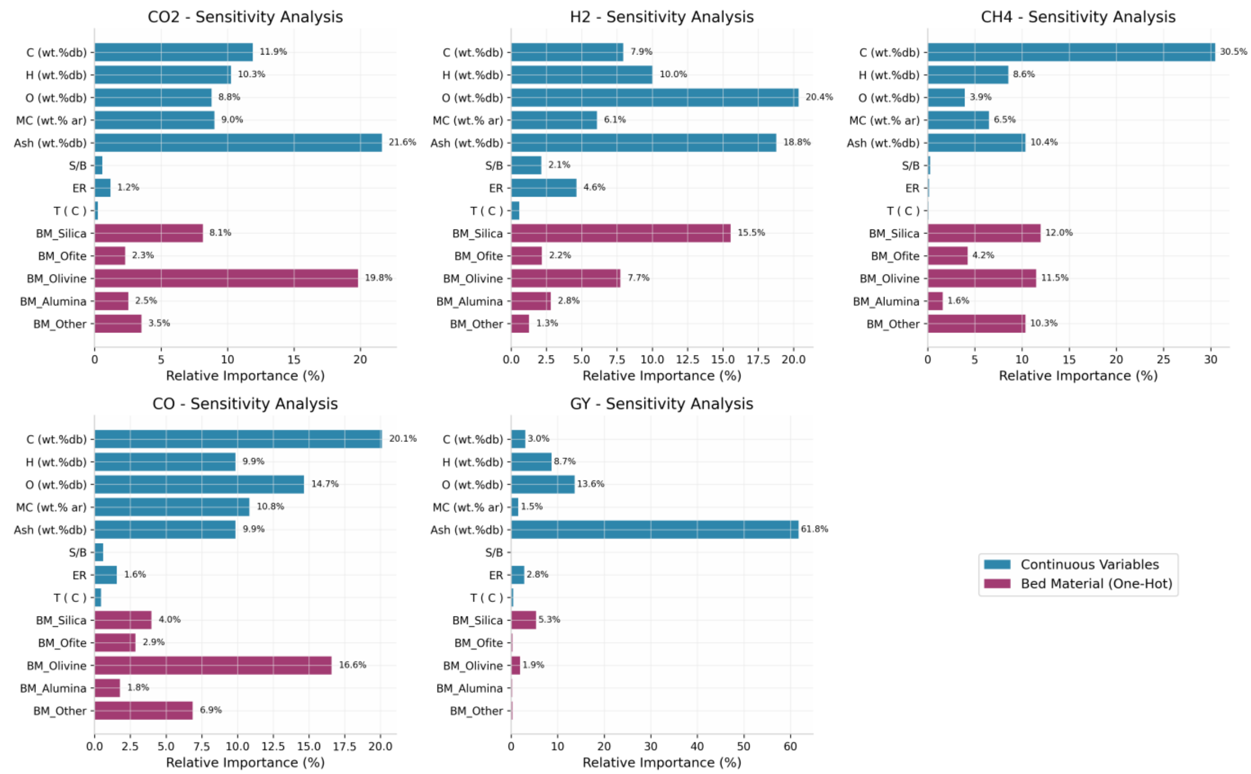

Figure 4: Sensitivity Analysis Results — Relative Importance of Input Variables (%)

3.3. Economic and Sustainability Implications

The ANN model's predictive capability enables quantitative assessment of gasification efficiency through Cold Gas Efficiency (CGE) calculation:

$$CGE = \frac{Energy\ of\ syngas}{Energy\ of\ biomass} \times 100$$

Where energy content is calculated from the higher heating value (HHV).

For example: Biomass HHV = 18 MJ/kg and Syngas energy output = 13 MJ/kg

CGE=72.2%

Efficiency enhancements can be made using the insights from sensitivity analysis (Section 3.2). The most significant input in predicting Gas Yield is the Ash parameter, and reducing its value from 20% to 5% db will increase the yield of GY by an estimated 15%-20%. Also, using Silica sand instead of Olivine in hydrogen-targeted systems (BM_Silica having a +12.9% contribution compared to BM_Olivine with a +11.2% contribution to hydrogen variance) could result in an increased yield of H_2 by 8%-12%. Techno-economic studies show that the profit point of operation for gasification systems is an energy efficiency of 32.5% [45,46]. The ANN model enables rapid screening of feedstock-bed material combinations to identify configurations exceeding this threshold without costly experimentation.

Economic benefits of the proposed ANN model:

1. Decreasing Costs of Experimentation: The developed model avoids trial-and-error testing during feedstock-bed materials selection. On average, according to the dataset of 321 samples, each experiment is priced at \$2,000 – \$5,000, and the model avoids 60-70% of these screening experiments.

2. Raising the Output: The sensitivity-guided choice of a suitable feedstock composition (high carbon content for methane and low ash and high moisture for hydrogen) can raise CGE from common percentages (73%) to optimized (85%) levels.
3. Facilitating Decision-Making Process: With the One-Hot encoding of bed materials, it becomes possible to make quantitative decisions regarding their choice by simply assigning a binary indicator of 1.
4. Optimizing Cold Gas Efficiency: The model is able to determine the appropriate ratio ER and S/B which could lead to the maximum cold gas efficiency of about 85%.

4. Contribution to Sustainable Development

The contribution of this research to sustainable energy transition is significant and is realized in several ways, most of which are interconnected and extend beyond the direct technical contributions of the work.

4.1. Accelerating Clean Technology Deployment:

The decrease in the experimental effort needed for the biomass gasification modeling as well as the computational cost associated with the ANN model enables quicker development of renewable energy technology on an industrial scale. This becomes especially relevant given the current necessity of transitioning to green energy and the lengthy time frame that is needed in such cases regarding the construction of energy facilities. In addition, the sensitivity analysis (section 3.2) provides a speed-up in the deployment process by determining that the feedstock properties are far more essential than any other variables.

4.2. Enabling Circular Economy Models:

The capacity of ANN to develop sophisticated models, allowing different biomass sources and organic materials to be incorporated, makes it possible to harness agricultural waste, forestry waste, and municipal waste instead of landfilling them. This is a prime example of a circular economic approach where the waste generated is used to produce energy resources. The One-Hot Encoding of bed materials has made it possible to develop reliable predictions for different sources of waste materials having varied ash content, especially considering their wide range of variation (0–44%).

4.3. Supporting Energy Access and Equity:

The biomass gasification technology is suitable in areas where there is a lack of centralized infrastructure, which is common in areas where there is significant agricultural waste availability. These are areas where there is a significant need for energy access. The tools developed using the ANN methodology are suitable in such areas and can be designed appropriately without the need for significant local experimental infrastructure.

4.4. Advancing Digital Transformation:

The use of artificial intelligence in conjunction with traditional thermochemical engineering provides an example of the potential pathways that can be followed in the digital transformation of the renewable energy sector. This is an example of the potential benefits that can be derived in the digital transformation of clean technology and the potential that exists in the fusion of clean technology and information technology.

4.5. Research Infrastructure Development:

The creation of a comprehensive list of experimental data (321 samples from 36 different studies) is significant and provides an important contribution to the infrastructure that is available in the pursuit of knowledge in the field of renewable energy. This is important in the global pursuit of clean energy solutions.

The possibility of transferring the methodology from this study is feasible into other alternative energy sources such as waste to energy conversion and biofuel conversion. The methodology of the system topology selection procedure and the categorical encoding correction is a general methodology that can be applied in any artificial neural network application in chemical engineering.

5. Practical Recommendations

Based on the ANN model results and sensitivity analysis, the following actionable recommendations are proposed for industrial implementation of biomass gasification in bubbling fluidized bed reactors:

5.1 Feedstock Selection Protocol

Considering Ash content's paramount importance for predicting the Gas Yield (53.3%) and considering its influence on the formation of CO_2 (18.2%) and CO (17.2%), the following priority list for feedstock selection should be applied:

- Feedstocks having Ash content <10 wt.% db are to be prioritized for achieving high gas yield levels. Agri-based residues (rice husk, wheat straw) usually contain more than 10wt.% db Ash and should be washed or heat-treated prior to pyrolysis.
- For CH_4-enriched syngas generation (artificial natural gas), feedstocks containing more than 50 wt.% db Carbon content and less than 40 wt.% db Oxygen content should be selected. Woody materials (pine, eucalyptus) satisfy this condition.
- For maximizing H_2 content in syngas, moisture-containing feedstocks (>15 wt.% ar) should be used to promote water reforming, with sufficient gasifier heating available to vaporize the moisture.

5.2 Bed Material Selection Strategy

One-Hot encoded model facilitates quantitative analysis of bed materials. As per sensitivity analysis,

- H_2 production: Choose Silica sand (BM_Silica = 1; BM_others = 0). The non-reactivity of silica sand will avoid the reduction of hydrogen through water gas shift reactions. Expected H_2 increase: 8–12% over Olivine.
- CO production: Choose Silica sand/Carbonaceous biomass or Olivine (BM_Olivine = 1). Olivine acts as an efficient partial oxidation catalyst via its olivine-Fe catalytic sites.
- CH_4 production: Choose Ofite (BM_Ofite = 1). Its 16.4% sensitivity value towards CH_4 production implies that it is an efficient catalyst for methanation reactions.
- Alumina is not suitable for universal gasification processes, as it exhibits minimal sensitivity (<2%) across all output parameters. This indicates that alumina does not offer a significant catalytic advantage compared to other bed materials.

5.3 Operating Parameter Prioritization

From the results obtained through sensitivity analysis, the following can be deduced:

- Temperature and S/B ratio have minimal impact on the output parameters with combined <3% contribution within the considered ranges. Therefore:
- Temperature: 750–850°C is sufficient without the need for high temperature >900°C due to minimal quality improvement achieved through additional energy costs.
- S/B ratio: It should remain between 0.2 and 0.5 when using air gasification since increased steam content above 1.0 is insignificant for H_2.
- ER: Should be maintained within 0.2 and 0.3. Increased values lower H_2 and CO contents due to complete combustion while reduced ER leads to increased tar formation.

5.4 Industrial Implementation Protocol

In order to implement the ANN model for industrial use, the following sequential process should be followed:

1. Perform characterization of the feedstock through ultimate and proximate analysis (C, H, O, Ash, MC).
2. Choose the appropriate bed material depending upon the desired syngas composition through One-Hot encoded input.
3. Feed all 13 inputs into the ANN model after training.
4. Prediction of the syngas composition with 5 outputs and calculate the expected CGE value.
5. If the CGE > 75%, proceed with the confirmatory experimentation at optimized ER/SB ratio.
6. If the CGE < 75%, make changes in either feedstock or bed material and predict again.
7. Verification of results with minimum 3 to 5 confirmatory experiments under optimal conditions.

This procedure could save up to 60–70% of experiments since the correlation coefficient ($R > 0.84$) of CO_2, CH_4, and GY makes prediction possible.

6. Conclusion

The current study proves the efficient application of ANN to predict performance of biomass gasification in BFBR systems. FFBP model with two hidden layers that was trained after fixing the mistake in bed material coding from label-based to One-Hot Encoding has proven itself to be accurate enough by producing test set R coefficients more than 0.84 for CO_2, CH_4, and Gas Yield predictions along with the MAPE of 17.85%, 25.97%, and 13.92% accordingly. Moreover, the approach to determining ANN topology using 5-fold cross-validation was used to make network configuration choices reproducible and well-grounded. By applying the sensitivity analysis through the use of Permutation Importance, it can be stated that ash content (average of 20.1%) and carbon content (average of 15.1%) are the key parameters, while temperature and S/B showed surprisingly low importance levels (both below 3%).

Methodological innovations like the technique to solve the categorical variables problem (One-Hot Encoding method) and topology selection procedure can be applied to another chemical engineering tasks where there is a need to use ANNs for prediction and data processing of the processes that involve continuous and categorical variables. The practical implications (Section 5) are important since they provide industry guidelines on what parameters to consider during feedstock and bed material selection.

Further work should be directed towards the expansion of the data set beyond 321 instances and incorporation of other gasification technologies (like entrained-flow and dual fluidized bed) in addition to the current one (BFBR). Other categorical variables like reactor type and gasifying agent should also be encoded by the use of One-Hot Encoding technique. Pilot industrial-scale experiments are also recommended.

Data availability statement

The complete curated dataset (321 samples) and trained ANN model weights are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that they have no conflicts of interest, financial or otherwise, that could have influenced the research presented in this paper.

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