Renewable Energy 132 (2019) 243–254

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

# Artificial neural network approach for the steam gasification of palm oil waste using bottom ash and CaO

Muhammad Shahbaz [a, b, c, *], Syed A. Taqvi [b, d], Adrian Chun Minh Loy [a], Abrar Inayat [e], Fahim Uddin [b, d], Awais Bokhari [f], Salman Raza Naqvi [g]

[a] Biomass Processing Lab, Centre of Biofuel and Biochemical Research, Department of Chemical Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610, Perak, Malaysia
[b] Department of Chemical Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610, Perak, Malaysia
[c] Department of Chemical Engineering, University of Gujrat, Gujrat Pakistan
[d] Department of Chemical Engineering, NED University of Engineering & Technology, 75270, Karachi, Pakistan
[e] Department of Sustainable and Renewable Energy Engineering, University of Sharjah, 27272 Sharjah, United Arab Emirates
[f] Department of Chemical Engineering, COMSATS University Islamabad, Lahore Campus, Defense Road Lahore, Pakistan
[g] Department of Chemical Engineering, School of Chemical and Materials Engineering National University of Sciences and Technology Islamabad Pakistan

ARTICLE INFO

*Article history:*
Received 15 March 2018
Received in revised form
25 July 2018
Accepted 30 July 2018
Available online 3 August 2018

*Keywords:*
Artificial neural network
Biomass gasification
Syngas
Layer
Palm kernel shell
Temperature
Coal bottom ash

ABSTRACT

The Artificial Neural Network (ANN) modelling is presented for the steam gasification of palm kernel shell using CaO adsorbent and coal bottom ash as a catalyst. The effect of the parameters such as; temperature, CaO/biomass ratio and Coal bottom ash wt.% at fixed steam/biomass ratio and steam/biomass ratio at the fixed temperature on product gas composition of $H_2$, CO, $CO_2$, and $CH_4$ are modelled using ANN. The effect of parameters is used as an input, while the gas compositions, syngas yield, $LHV_{gas}$ and $HHV_{gas}$ of gas as the output of the network. Back propagation algorithm has been used for the training with 7 neurons in the hidden layer. Hence, the selected ANN architecture was (2-7-1). The gas composition predicted by the ANN model are compared with experimental results obtained from pilot scale gasification system that has been reported in our previous study. The ANN predicted results show high agreement with the published experimental values with the coefficient of determination $R^2 = 0.998$ for almost all the cases, i.e., the effect of parameters. RMSE, MAD, and AARE have been reported to be very insignificant for the predicted and experimental values.



## 1. Introduction

The transition of the world into a modern world has been taking place due to the introduction of fossil fuel that supplies the required demand of energy for modernization. The continuing modernization of the world is required the huge demand for energy and the sole dependence on fossil fuel is unable to meet this requirement due to the finite resources [1]. In addition, the use of fossil fuel has become the cause of many environmental concerns like greenhouse gas emission, global warming, disturbance of weather cycles due to the melting of ice at north poles, smog in cities, and skin deformation diseases [2]. From last two decades, extensive research has been made to find new and alternative sources of energy through renewable sources to accomplish the growing demand for energy and sustainable development of world [3,4]. In this regard, biomass enterprises itself to be the best energy source among all other renewable energy sources as advocated by the advantages such as abundant availability around 200–700 EJ/annum, sustainability, and green due to mitigation of $CO_2$ emission [5,6]. Biomass can be converted into liquid, gaseous and solid fuels through biological and thermochemical conversion [7,8]. Biomass gasification is fund to be the best source among thermochemical conversion for the production of gaseous fuel [9].

In biomass gasification process, the carbon-based biomass is thermally treated at the higher temperature in the presence of gasification agents (steam, oxygen, air) in a reactor known as the gasifier [10]. The gasification process produced a mixture of gases ($H_2$, CO, $CO_2$, $CH_4$, $CH_n$) known as product gas [11]. Hydrogen and syngas can be used directly as a fuel but also can be converted into

* Corresponding author. Biomass Processing Lab, Centre of Biofuel and Biochemical Research, Department of Chemical Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 32610, Perak, Malaysia.
*E-mail address:* muhammad_shahbaz@uog.edu.pk (M. Shahbaz).

https://doi.org/10.1016/j.renene.2018.07.142
0960-1481/

much conventional fuel and chemical such as methanol, ethanol, diesel, ammonia, and urea [12]. Cleaner production of hydrogen and syngas from biomass not only full fill the growing energy demand but also economically viable to utilized same current infrastructure without any major modification to replace the fossil fuel [6]. The performance of gasification and composition of product gas depend on the gasifier type, gasification agent, particle size, types of catalyst. The fluidized bed gasifier is found to be the best gasifier due to better heat and mass transfer in the temperature range of 600–900 °C. Steam is the preferable gasification agent for hydrogen-rich syngas production with no problem of nitrogen as in case of air, and economical as compared to oxygen [3].

The use of catalyst has many advantages in gasification such as to attain the augment quantity of desired product. It may also enhance the economic process by reducing gasification temperature and conversion of tar into gases [13]. Basically, three types of catalyst were used in the gasification process (e.g. transition metal Ni, dolomite bases catalyst, and alkaline earth metal) [14]. In order to make process economical, a catalyst is not only cheap but also has the ability to enhance the gasification process with minor problem of regeneration and sintering. Coal bottom ash is the waste residue of coal thermal power plant. It has normally used in construction industry, and cement industry [15]. It has many toxic elements so its handling and disposal not only costly as well as contaminated the soil, underground water and air [16]. The current research shows that coal bottom ash contained alkaline metals such as Al, Fe, K, and Ca in a reasonable quantity [17]. The catalytic effect of alkaline metal and CaO are well established and documented [18]. In our previous study potential of coal bottom ash used as a catalyst in gasification was studied [14]. However, Coal bottom ash as a catalyst in gasification is not be tested. Although, the use of biomass ashes is in gasification for some catalytic effect is reported. Husserman et al., 1994 [19] found the reactivity had increased a factor of 4 by using the wood ash in wood gasification. Meanwhile, Umike et al. [20] have reported the biomass ash can maintain the catalytic activity during gasification process. In the case of coal bottom ash, Xiong et al. [17] has reported the use of coal bottom ash as a bed material in coal gasification and found good for tar reduction. A conclusion can be made that, coal bottom ash has not been investigated as the catalyst in literature except our previous study.

Palm oil is the major crop of Malaysia and Indonesia which accommodate more than 86% of world palm oil production [7]. This large-scale production produced a huge amount of palm oil residue about 54.1 Mt/yr. The utilization of palm oil waste had increased a lot in the last for energy production. Yang et al. [21] used the palm oil waste such as EFB, PKS, and POF in pyrolysis process. In case of gasification, the air gasification is more focused on utilizing the EFB in air gasification using fluidized bed reported by Ref. [22]. CaO is used as an absorbent for $CO_2$ in the gasification process. Khan et al. used the PKS for steam gasification using CaO and Ni catalyst, and attained high $H_2$ yield of 82 vol% [23].

The advances in soft computing and computer science elaborate the interest in the development of prediction models for time-consuming and costly experiments. For the design of a new product using a series of experiment, researchers are facing difficulties to obtain the real data due to high cost and time-consuming experiments for different operating conditions [24]. To overcome these concerns, Artificial Neural Network (ANN) is a reliable tool for the prediction of experimental data. It has the capability to employ its computational power from parallel structure along with the ability of learning and generalization [25]. It is widely used for the solutions of non-linear problems. The prediction performance and generalization depend on the training of network. The generalization relates to the performance of the ANN for the inputs which were not used during the training of the network. In recent years, among the various methods of machine learning, ANN has been extensively used to predict the nonlinear system data due to its accuracy, precision, time and low cost. It is a nonlinear modelling tool which can be used in the application of different types of engineering problems with limited experimental data. The motivation behind the ANN is a human brain [26]. It utilizes parallel processing networks which are used to control the complex relationships between the input and output variables. According to our best knowledge, very few studies have been reported the use of ANN approach for gasification of biomass. The first study was developed by Robret et al. for biomass gasification system by using ANN on the basis of reported data for the gasification of the fixed bed [27]. Later, Dipal et al. [26] developed the ANN-based model for the biomass gasification using fixed bed down-draft gasifier and predicted the composition of gases $H_2$. CO, $CO_2$, and $CH_4$ by using input parameters such as C, H, O, ash, moisture content, and reduction zone temperature. Both studies are based on the fixed bed gasification. There is no study based on steam biomass gasification using the fluidized bed.

From the above discussion, a conclusion can be drawn that palm oil waste gasification has not been reported using ANN approach. Moreover, coal bottom ash has not been used as a catalyst in the steam gasification process. The objective of this study is to develop an ANN model for the prediction of gas composition and validate with published [28] experimental data. In addition, the effect of four parameters which are temperature, steam/biomass ratio, CaO/biomass ratio and wt% of coal bottom was studied. The selected ranges for each of the parameters are: 650–750 °C temperature, 0.5–2 ratio of CaO/biomass, 0.02–0.10 ash wt% of coal bottom and 0.5–1.5 ratio of steam/biomass.

## 2. Methodology

### 2.1. Material

The biomass (palm oil waste) is employed for the gasification was collected from Kilang Sawit Felcra Nasarudin Sdn. Bhd. Malaysia. The biomass was dried using sun and oven drying. The biomass has grinned in the particle range of 0.5–1 mm. The palm oil waste (PKS) is selected for syngas production through gasification for its higher heating value of 18.46 MJ/kg [29]. The elemental and component compositions were determined experimentally as shown in Table 1. Coal bottom ash used as catalyst obtained from TNB Janamanjung Sdn Bhd power plant Selangor Malaysia. Dolomite is used for CaO source to adsorbed the $CO_2$ is obtained from Kinetic Chemical Sdn. Bhd. The coal bottom ash consist of Fe, Ca, Mg, and Al are shown its catalytic potential in gasification the chemical composition of coal bottom ash is given in Table 2 [28].

**Table 1**
Proximate and ultimate analysis of PKS [3,28].

| | |
|---|---|
| Moisture | 9.70 |
| Proximate analysis (dry mass fraction basis) | |
| Volatile matter (%) | 80.81 |
| Fixed carbon (%) | 14.25 |
| Ash content (%) | 4.94 |
| | |
| Ultimate Analysis (dry mass fraction basis) | |
| C (%) | 48.78 |
| H (%) | 5.70 |
| N (%) | 1.01 |
| S (%) | 0.21 |
| O (%) (by difference) | 44.3 |
| HHV(MJ/kg) | 18.82 |

**Table 2**
Chemical composition of CBA using XRF.

| Chemical composition by XRF | |
|---|---|
| SiO | 44.1 |
| $Fe_2O_3$ | 24.3 |
| CaO | 13 |
| $Al_2O_3$ | 9.21 |
| MgO | 1.88 |
| $K_2O_3$ | 1.25 |

CaO and CBA both were grounded in the size of 0.250 mm.

### 2.2. Procedure

The experimental setup used for the steam gasification of palm oil waste is shown in Fig. 1. The detail of setup has been given in our previous publication [28], and the current ANN model is used to validate the experimental results obtained at this setup and published in Ref. [28]. The gasification system comprises of fluidized and fixed bed reactor, biomass feeder, and boiler for steam generation, cyclone separators for cleaning, water supply, and treatment system. Scrubber and online gas analyser. Palm oil waste along with coal bottom ash is supplied into gasifier through feeding system. The boiler is used for steam generation, and it is further superheated at the temperature of 350 °C and supplied to the gasification system. Silica sand and dolomite is used as a bed material fluidized bed and fixed bed reactor for fluidisation and adsorption. The produced gases pass through the cyclone separator for the removal of tiny solid particles. The temperature is reduced up to 40 °C using water scrubbing system. The cool gases are measured through the online gas analysing system.

### 2.3. ANN network approach

ANN is a computation technique developed by imitating the learning skills of the human brain and biological cells. It is a significant and reliable tool that has gained attraction in the field of predictive modelling as it has the capacity to learn nonlinear and complex processes. The network comprises of simple elements which are functioning in parallel. These are stimulated by the biological nervous system. These networks are organized in form of connecting layers which are connected to each other by connection called nodes. The network comprises of three types of layers; the input layer, hidden layer, and the output layer. The selection of the number of hidden layers and the number of neurons in each layer is very crucial part in the development of neural network as it improves the capacity and ability of network. The networks are trained and adjusted in order to lead the input to the particular target output. Fig. 2 depicts the situation of adjusting the weights until there is an optimal deviation between the output and the targets.

Several neural networks are available for the modelling of experimental data such as Feed-Forward Neural Network (FFNN) [24,30], Radial Basis Function Neural Network (RBFNN), Kohonen Self-Organizing Neural Network (KSONN), General Regression Neural Networks (GRNN), Probabilistic Neural Networks (PNN), and Recurrent Network (RN) [31]. Among all, the FFNNs are widely used in the chemical engineering application. FFNN comprises of single layers and multi-layers' perceptron. In this type of networks, the information moves in one direction only. The signal generated from the input layer are transmitted to the hidden layer in which the activation function approximates the biases and weights of the network by applying learning algorithm. Finally, the output is known as predicted result. Back Propagation (BP) methods are widely used for the modelling of the neural network. It is a

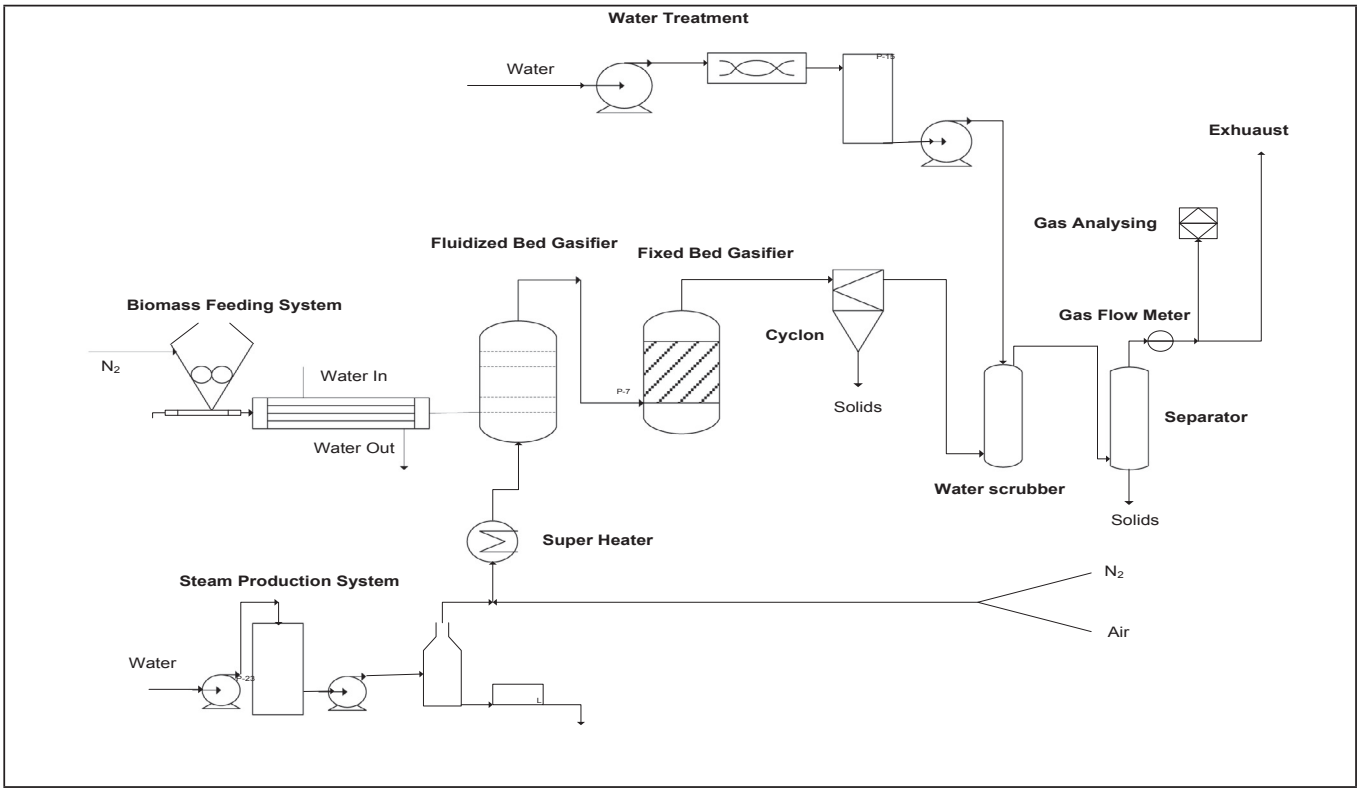


**Fig. 1.** Experimental gasification set up for the steam gasification of palm oil waste.

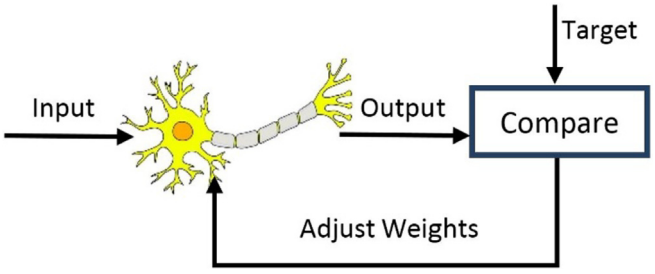


**Fig. 2.** Neural network operation.

supervised learning technique used for the approximation of nonlinear mapping. It utilized the gradient search techniques to reduce the error by changing the weights via activation function and improves the performance of the network. From different learning algorithms, Levenberg-Marquardt (LM) has been used for the modelling of syngas derived products for its better performance [24,31–33]. LM is known as the fastest algorithm for the training of neural network since it has a feature of memory reduction in case of a large dataset. The network error is calculated by comparing the output and the target. At the start, the calculated error shows the large deviation between the actual and predicted output. The network minimizes the error by adjusting weights and biases till obtaining the minimum error. It is noted that the over fitting is a crucial problem in the training of neural networks. It associated with the situation when system predicts the accurate result but fails to perform better in case of a new dataset. The ANN performance is measured by mean square error (MSE) [34] given below;

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{ANN} - Y_{Exp}\right)^2$$

where $Y_{ANN}$ is the predicted output from ANN and $Y_{Exp}$ is the experimental data and N is the number of samples.

The input parameter used for the training of neural networks are steam-biomass ratio, temperature, Coal bottom ash %, and CaO/Biomass, for the prediction of output parameter which are $H_2$, $CO_2$, CO and $CH_4$ (vol%) in the product gas, Syngas yield, $LHV_{gas}$ and $HHV_{gas}$. All the data (i.e., inputs and outputs) are normalized between 0 and 1 to enhance the performance of the network. Due to the fact that the higher values of the inputs may lead to minimizing the effect of smaller values in case of a network is being trained without normalization. Moreover, the rescaling of an input/output vector make the training faster and it also gives the equal values to all inputs. This process can guarantee the convergence process stable for weights and biases.

In this study, the dataset was divided into three different sets, out of which 80% for the training, 20% for the testing, and 20% were used for the validation of the network. The optimal structure of the neural network was selected by means of trial and error method. For the current study, the number of the neuron is the hidden layer was found by the iterating the network for minimum mean square value (MSE). The selection of the number of the neuron is also a vital step in the development of the neural network. Less number of neurons may not help the network in obtaining anticipated error while the high number of neurons may cause over-fitting of the network. Training and validation-test data were randomly selected from the available sample. The details of ANN model parameters are presented in Table 3.

## 3. Results and discussion

Four neural networks were developed for the prediction of gas composition in the product gas. The developed multi-input and single-output neural network for the prediction of gas composition in the product is comprises two inputs layers namely (steam/biomass ratio and temperature), (Steam/biomass ratio and Coal bottom ash %), (Steam/biomass ratio CaO/Biomass) and (Temperature and Steam/Biomass ratio) and single output ($H_2$, CO, $CO_2$, and $CH_4$), with one hidden layer. This scheme was found to be effective for the development of prediction model for gas composition as shown in Fig. 3. The layers are interconnected by processing element called neurons. Before training of the network, the hidden neurons were selected and tested for the ANN model. The number of neurons in the hidden layer was selected on the basis of minimum Mean Square Error (MSE). The error minimization within the network requires appropriate selection of the number of neurons in the hidden layer.

To obtain the minimum MSE for the training network, the number of hidden neurons was tested for the corresponding MSE starting for the smallest value. This process will give the optimized neurons at the lower value of MSE. In this study, the ANN model was trained and tested from 1 to 20 number of neurons. The trained

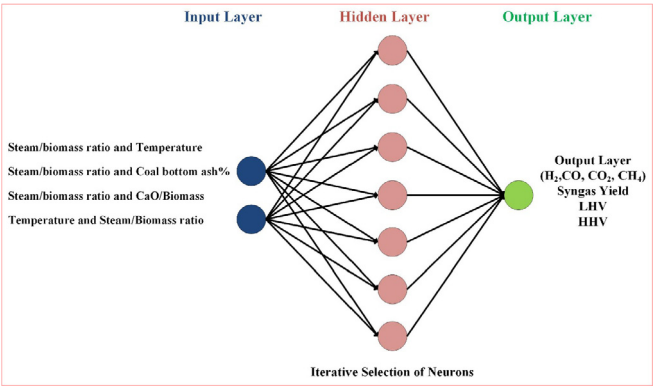


**Fig. 3.** ANN Model Structure for the prediction of syngas composition.

**Table 3**
ANN model parameters.

| S.No. | Particulars | Specifications |
|---|---|---|
| 1 | Type of Network | Feed Forward Neural Network |
| 2 | Training Algorithm | Levenberg-Marquardt backpropagation |
| 3 | Performance Function | Mean Square Error (MSE) |
| 4 | Data Division | Random |
| 5 | Number of Input Layer | 2 |
| 6 | Number of Hidden Layer | 1 |
| 7 | Number of Output Layer | 1 |
| 8 | Number of Hidden Neurons | Iterative |
| 9 | Learning Cycle (Number of Epochs) | 1000 |

network with 7 hidden neurons was found to have minimum MSE value. It can be seen that the experimental and simulated values have very minor difference which can be determined by the errors. The values of these errors show that the predicted values are in good agreement with experimental values. The minimum is the error, the maximum is $R^2$ value for the experimental and simulated case studies. Besides, the use of coefficient of determination, the performance of developed ANNs for $H_2$, CO, $CO_2$, and $CH_4$ was statistically measured by different types of errors i.e. Root Means Square Error (RMSE), Mean Absolute Deviation (MAD) and Absolute Average Relative Error (AARE) which were calculated on the basis of experimental and simulated values as mentioned in Table 4.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Y_{ANN} - Y_{Exp})^2}{n}}$$

$$MAD = \frac{1}{n} \sum_{i=1}^{n} |Y_{ANN} - Y_{Exp}|$$

$$AARE = \frac{\sum_{i=1}^{n} \left| \frac{Y_{ANN} - Y_{Exp}}{Y_{ANN}} \right|}{n} * 100$$

**Table 4**
Artificial neural network input and output parameters for gas composition.

| Input Neurons | | Output Neuron | Errors | | |
|---|---|---|---|---|---|
| Effect of Temperature at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Temperature | Gas component | RMSE | MAD | AARE % |
| 1.5 | 650 | $H_2$ | 0.427470364 | 0.29896357 | 0.38580605 |
| | 660 | CO | 0.153582174 | 0.110281776 | 1.691586518 |
| | 671 | $CO_2$ | 0.132041546 | 0.092825682 | 1.346120185 |
| | 681 | $CH_4$ | 0.153047992 | 0.109447442 | 1.056688367 |
| | 692 | | | | |
| | 702 | | | | |
| | 713 | | | | |
| | 723 | | | | |
| | 733 | | | | |
| | 743 | | | | |
| | 750 | | | | |
| Effect of Coal Bottom Ash% at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Coal bottom ash % | Gas Component | RMSE | MAD | AARE % |
| 1.5 | 0.02 | $H_2$ | 0.328020462 | 0.180290148 | 0.366935135 |
| | 0.028 | CO | 0.101699527 | 0.080034897 | 1.097372153 |
| | 0.036 | $CO_2$ | 0.10102947 | 0.075693623 | 1.113068401 |
| | 0.044 | $CH_4$ | 0.129789927 | 0.098766874 | 1.025030944 |
| | 0.052 | | | | |
| | 0.06 | | | | |
| | 0.07 | | | | |
| | 0.076 | | | | |
| | 0.084 | | | | |
| | 0.092 | | | | |
| | 0.1 | | | | |
| Effect of CaO/Biomass at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | CaO/Biomass ratio | Gas Component | RMSE | MAD | AARE % |
| 1.5 | 0.5 | $H_2$ | 0.540243239 | 0.283842135 | 0.918124565 |
| | 0.65 | CO | 0.132364159 | 0.10852901 | 1.585205279 |
| | 0.8 | $CO_2$ | 0.09075913 | 0.073443094 | 1.168669858 |
| | 0.95 | $CH_4$ | 0.135505285 | 0.100531738 | 0.94395947 |
| | 1.1 | | | | |
| | 1.25 | | | | |
| | 1.42 | | | | |
| | 1.55 | | | | |
| | 1.7 | | | | |
| | 1.85 | | | | |
| | 2 | | | | |
| Effect of Steam/Biomass Ratio at fixed Temperature | | | | | |
| Temperature | Steam/Biomass ratio | Gas Component | RMSE | MAD | AARE % |
| 692 | 0.5 | $H_2$ | 0.533662772 | 0.30703862 | 1.146252703 |
| | 0.6 | CO | 0.164190386 | 0.108456366 | 1.033690945 |
| | 0.7 | $CO_2$ | 0.221884974 | 0.14696826 | 1.421572416 |
| | 0.8 | $CH_4$ | 0.140558585 | 0.101300707 | 0.761568496 |
| | 0.9 | | | | |
| | 1 | | | | |
| | 1.1 | | | | |
| | 1.2 | | | | |
| | 1.3 | | | | |
| | 1.4 | | | | |
| | 1.5 | | | | |

It can be observed that all the errors show very small values for the predicted models. The higher the value of $R^2$, with smaller error values. It signifies the good fitting between experimental and predicted values. Hence, it shows that the developed ANN model is suitable to represent syngas product composition.

### 3.1. Effect of temperature

The effect of parameter i.e., temperature, CaO/biomass ratio, coal bottom ash wt.% at fixed steam/biomass ratio and seam/biomass ratio at fixed temperature predicted by the model is also compared with the experimental data obtained at pilot scale gasification plant reported in Ref. [28]. The impact of varying temperature on gas composition can be seen in Fig. 4. $H_2$ composition is varied from 66 vol% to 79 vol% by varying the temperature from 650 to 750 °C. The maximum $H_2$ production is observed at 692 °C. The CO decreased from 13.92 vol% to 5.93 by increasing the temperature from 650 to 692 °C. The increase in $H_2$ production is due to the activeness of water gas shift reaction and steam reforming reaction as reported by many researchers [29,35]. The $CO_2$ production is observed very low and varied from 8.39 vol% to 5.93 vol% in the temperature range of 650–750 °C. The lower production of $CO_2$ is due to the presence of CaO that captured the $CO_2$ through carbonation reaction [36]. Methane composition is predicted by the model is maximum 14.93 vol% at 650 °C and minimum at 692 °C and is also good agreement with the experimental results as shown by Fig. 4. The dropped in methane yield is due to the enhancement of tar cracking of steam methane reforming reaction, that enhanced at the higher temperature with higher steam/biomass ratio of 1.5 [37]. The ANN modelling results for the effect of temperature has been mentioned in Table 4. It can be seen that the RMSE, MAD and AARE errors have very small values. It can be observed that there is a good agreement between ANN model prediction and experimental values as depicted in Fig. 4. It can be observed that ANN model predict all the experimental value for product compositions for $H_2$, CO, $CO_2$ and $CH_4$ significantly. This model gives better results at 7 number of neurons.

### 3.2. Effect of steam/biomass ratio

Fig. 5 depicted the comparison of gas composition predicted by the ANN model with the experimental result by increasing the steam/biomass ratio from 0.5 to 1.5. The predicted gas composition

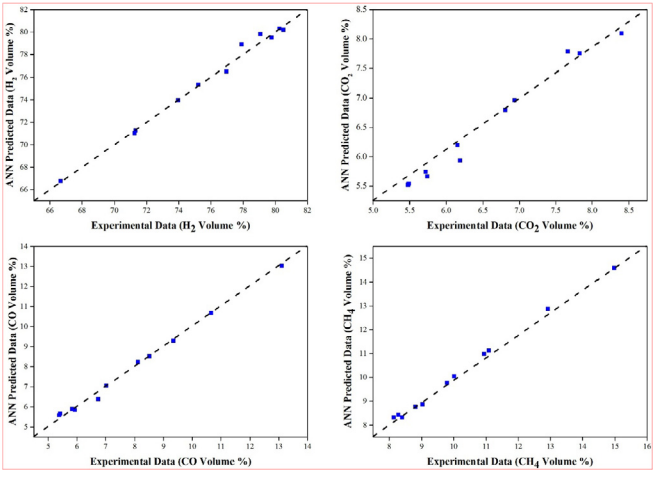


**Fig. 4.** Comparison of experimental results with ANN predicted for fluidized bed gasifier
at fixed steam/biomass ratio and varying temperature.

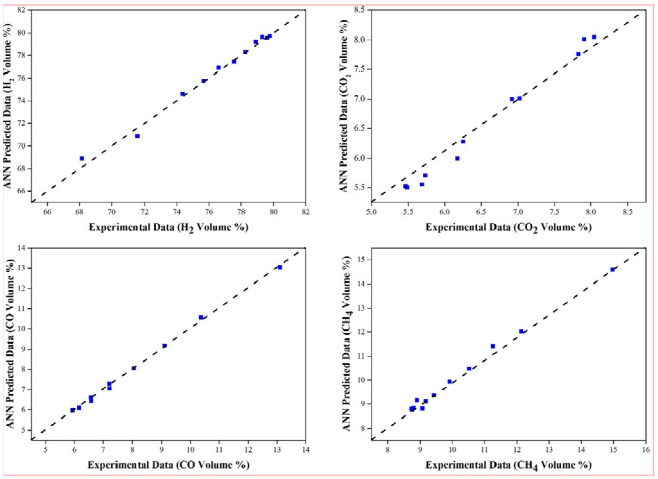


**Fig. 5.** Comparison of experimental results with ANN predicted for fluidized bed gasifier
at fixed steam/biomass ratio and varying coal bottom ash%.

have shown good agreement with experiment result as depicted by higher $R^2$. The $H_2$ content is increased from 35.75 vol% to 79.77 vol% by increasing the steam/biomass ratio from 0.5 to 1.5. On the other hand, the CO content reduced from 25.55 vol5 to 5.93 vol%. The same trend is observed for $CO_2$ and $CH_4$ with the addition of steam. The enrichment of $H_2$ content in product gas is the activation of endothermic reaction such as water gas shift reaction, tar cracking and steam methane reforming. The acceleration of this reaction with the introduction of steam in palm oil waste gasification is also observed by many other researchers [35,38]. The lower composition of methane and $CO_2$ is due to the functioning of steam methane reforming reaction and carbonation reaction respectively that is active due to the presence of steam and CaO [4]. It can be seen in Table 4 that AARE error is not more than 2% for all the product gases. Moreover, the RMSE and MAD error are also small in range. Hence the smaller values of errors show the higher value for the coefficient of determination which is $R^2$ value close to 0.999.

### 3.3. Effect of CaO/biomass ratio

The use of CaO in biomass steam gasification has numerous advantages. It is not only captured the $CO_2$ through adsorption but also has the catalytic effect and enhance the gasification process [39]. Fig. 6 depicted the effect of CaO/biomass ratio at steam/biomass ratio of 1.5 on product gas composition predicted by the model and compared with experiment result. Experimental and ANN simulation model values for $H_2$, CO, $CO_2$, and $CH_4$ were compared as shown in Fig. 6. It can be observed that model has shown good performance as having the value of $R^2$ is 0.998 with AARE less than 1% for all gas compositions. The concentration of $H_2$ in produced gas is highly influenced with CaO/biomass ratio as it increased from 66.66 vol % to 79.77 vol% with the increased from 0.5 to 1.42 and then little dropped at higher CaO/biomass ratio. The $CO_2$ production is very low in product gas as CaO is used for the adsorption of $CO_2$ in produced during gasification process. The enrichment of $H_2$ content in product gas is due to catalytic effect of CaO as it enhance the tar cracking, steam methane reforming reaction, and water gas shift reaction as it a proven catalyst in biomass gasification [40]. Secondly, at higher temperature, CaO produced due to calcination of $CaCO_3$ and captured $CO_2$ through carbonation reaction [41]. The reduction of $CO_2$ content enhances the $H_2$ content in product array. The lower production of methane

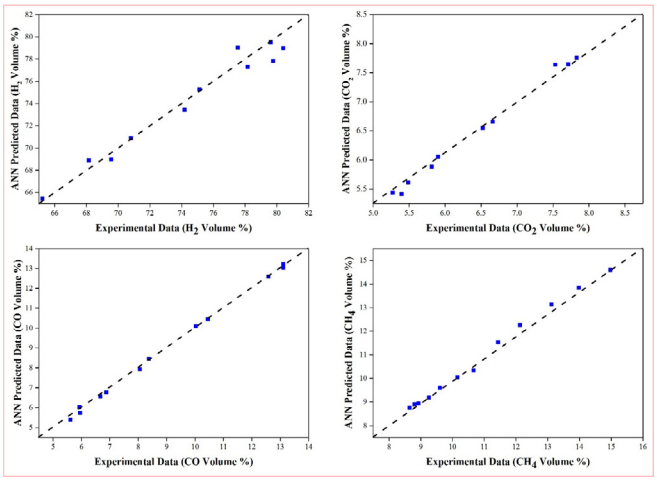


**Fig. 6.** Comparison of experimental results with ANN predicted for fluidized bed gasifier
at fixed steam/biomass ratio and varying CaO/Biomass.

with the addition of CaO/biomass ratio is due to steam methane reforming reaction. This catalytic and $CO_2$ adsorption effect in biomass (palm oil waste) steam gasification is noticed by many researchers [4,42].

### 3.4. Effect of coal bottom ash wt.%

Fig. 7 represented the effect of varying coal bottom ash wt. % on product gas composition $H_2$, CO, $CO_2$, and $CH_4$ predicted by the model. The gas compositions have the close agreement with experimental value as advocated by the errors presented in Table 4. The AARE for the all the gas compositions is relatively very small as compared to other cases. The RMSE and MAD for this case show smaller values of errors. The coefficient of determination $R^2$ was found to be 0.999. The neural network prediction model gives good results for the effect of coal bottom ash %. Catalyst has a capital role in gasification process to enhance the tar cracking, product gas composition and specific yield of product. It can be observed that $H_2$ content enhance remarkably from 65 to 79.99 vol% by increasing the cola bottom ash wt.%. The other constituents of product gas CO, $CO_2$, and $CH_4$ are decreased with the increase of coal bottom ash

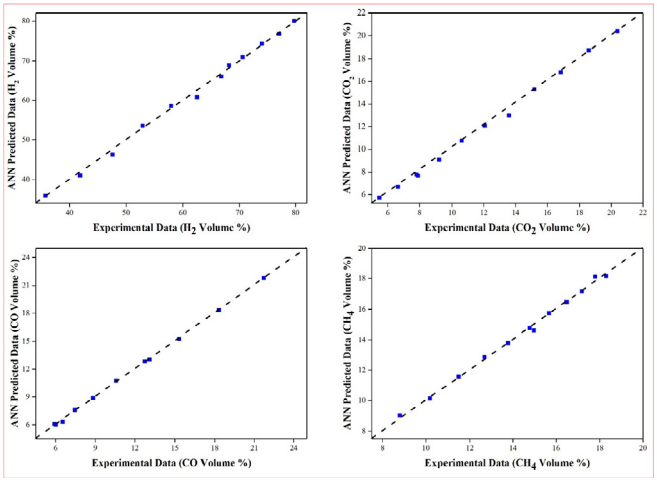


**Fig. 7.** Comparison of experimental results with ANN predicted for fluidized bed gasifier at fixed temperature and varying steam/biomass ratio.

from 0.02 to 0.07. This show the catalytic effect of coal bottom ash in biomass gasification process. Catalyst effect the gasification reactivity and enhance tar cracking and convert the solid into gaseous products The catalytic effect of coal bottom ash is due to presence of Al, Ca, Mg, Fe content present in coal bottom ash as described in our previous publication [28]. The effect of these metal content in gasification process is well documented [43]. The alkaline metal enhances the biomass conversion and reactivity in biomass gasification [7]. The Fe based catalyst used in palm oil waste gasification and enhancement in $H_2$ content is noticed [44].

The yield of syngas is very important to measure the performance of gasification system. It was observed that the syngas yield is high as 284, 287 and 284.20 g/kg of biomass at fixed steam/biomass ratio of 1.5 by varying the temperature, CaO/biomass ratio and coal bottom wt %. The heating value of product gas are evaluated to measure the performance of gasification system. It was observed that LHV and HHV of gases obtained from 12.48 to 12.89 and 14.32–14.69 MJ/$Nm^3$ by varying the temperature from 650 to 750 °C at fixed steam/biomass ratio of 1.5. Similarly, the LHV varies from 12.50 to 13.02 and 12. 47 to 13.58 MJ/$Nm^3$ by varying coal bottom ash wt% and CaO/biomass ratio. The HHV of gases 14.32 to 14.64, 14.23 to 14.84 and 14.42–15.42 MJ/$Nm^3$ by varying the temperature, cola bottom ash wt% and CaO/biomass ratio at fixed steam/biomass ratio 1.5. The effect of various parameters on syngas yield, $LHV_{gas}$ and $HHV_{gas}$ is also modelled using neural network. It was observed that ANN model predicts the significant results for the prediction of syngas yield, LHV and HHV (gas) with effect of temperature, CaO/biomass ratio and Coal bottom ash wt.% at fixed steam/biomass ratio and steam/biomass ratio at the fixed temperature. (See Figure A-1 – Figure A-3 in Appendix). Furthermore, the developed ANN model gives accurate results for all the practical gasification process with $R^2 > 0.98$ with smaller value of RMSE, MSE and AARE for the syngas yield, LHV and HHV of gas. (See Table A-1–Table A-3 in Appendix). Hence, ANN model is able to map the accurate experimental value which shows the significance of the model for the experimental data prediction of biomass gasification.

## 4. Conclusion

The ANN modelling for the experimental results on temperature, CaO/biomass ratio, coal bottom ash wt.% at fixed steam/biomass ratio and steam/biomass ratio at fixed temperature has been investigated. Feed-forward back propagation neural network has been used for the development of model. Levenberg-Marquardt (LM) has been used for the modelling of syngas derived products for its better performance. Four neural networks were developed for the prediction of gas composition in the product gas. The developed multi-input and single-output neural network for the prediction of gas composition in the product comprises of two input layers (steam/biomass ratio and temperature), (Steam/biomass ratio and Coal bottom ash %), (Steam/biomass ratio, CaO/Biomass ratio) and (Temperature and Steam/Biomass ratio) and single output ($H_2$, CO, $CO_2$, and $CH_4$), with one hidden layer. The results obtained by the ANNs show good agreement with published experimental results. The predicted values show small errors for RMSE, MAD, and AARE along with higher values for the coefficient of determination $R^2$ ($R^2 = 0.99$) in almost all the cases. This study shows a good approach and has a valuable potential for the predictive modelling of biomass gasification. These models can further be used for the optimization and dynamic control of biomass gasification process.

## Acknowledgement

This research project is funded by the Ministry of Higher

Education Malaysia under the Long-term Research Grant Scheme (LRGS) and (KETHHA). The author would like to thank Universiti Teknologi PETRONAS for providing facilities to conduct this research work.

## Appendices A

**Table A-1**
Artificial neural network input and output parameters For Syngas Yield.

| Input Neurons | | Output Neuron | Errors | | |
|---|---|---|---|---|---|
| Effect of Temperature at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Temperature | Syngas Yield g/kg biomass | RMSE | MAD | AARE % |
| 1.5 | 650 | 230.05 | 1.516401161 | 0.953072582 | 0.78655457 |
| | 660 | 244.31 | | | |
| | 671 | 257.54 | | | |
| | 681 | 267.28 | | | |
| | 692 | 275.48 | | | |
| | 702 | 280.65 | | | |
| | 713 | 283.81 | | | |
| | 723 | 284.39 | | | |
| | 733 | 282.81 | | | |
| | 743 | 279.04 | | | |
| | 750 | 275.10 | | | |
| Effect of Coal Bottom Ash% at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Coal bottom ash % | Syngas Yield g/kg biomass | RMSE | MAD | AARE % |
| 1.5 | 0.02 | 261.54 | 1.769888058 | 0.952595973 | 0.634961842 |
| | 0.028 | 273.95 | | | |
| | 0.036 | 282.48 | | | |
| | 0.044 | 287.13 | | | |
| | 0.052 | 287.90 | | | |
| | 0.06 | 284.80 | | | |
| | 0.07 | 275.47 | | | |
| | 0.076 | 266.96 | | | |
| | 0.084 | 252.22 | | | |
| | 0.092 | 233.61 | | | |
| | 0.1 | 211.12 | | | |
| Effect of CaO/Biomass at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | CaO/Biomass ratio | Syngas Yield g/kg biomass | RMSE | MAD | AARE % |
| 1.5 | 0.5 | 165.33 | 1.646062425 | 0.931847397 | 1.019143918 |
| | 0.65 | 206.59 | | | |
| | 0.8 | 238.76 | | | |
| | 0.95 | 261.87 | | | |
| | 1.1 | 275.89 | | | |
| | 1.25 | 280.84 | | | |
| | 1.42 | 275.48 | | | |
| | 1.55 | 263.51 | | | |
| | 1.7 | 241.22 | | | |
| | 1.85 | 209.86 | | | |
| | 2 | 169.42 | | | |
| Effect of Steam/Biomass Ratio at fixed Temperature | | | | | |
| Temperature | Steam/Biomass ratio | Syngas Yield g/kg biomass | RMSE | MAD | AARE % |
| 692 | 0.5 | 201.18 | 0.730786044 | 0.374038128 | 0.391888908 |
| | 0.6 | 205.82 | | | |
| | 0.7 | 211.07 | | | |
| | 0.8 | 216.95 | | | |
| | 0.9 | 223.44 | | | |
| | 1 | 230.56 | | | |
| | 1.1 | 238.30 | | | |
| | 1.2 | 246.66 | | | |
| | 1.3 | 255.65 | | | |
| | 1.4 | 265.25 | | | |
| | 1.5 | 275.48 | | | |

**Table A-2**
Artificial neural network input and output parameters for LHV (gas).

| Input Neurons | | Output Neuron | Errors | | |
|---|---|---|---|---|---|
| Effect of Temperature at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Temperature | $LHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 1.5 | 650 | 12.89 | 0.029868605 | 0.024924329 | 0.196436555 |
| | 660 | 12.75 | | | |
| | 671 | 12.63 | | | |
| | 681 | 12.56 | | | |
| | 692 | 12.50 | | | |
| | 702 | 12.48 | | | |
| | 713 | 12.49 | | | |
| | 723 | 12.53 | | | |
| | 733 | 12.61 | | | |
| | 743 | 12.71 | | | |
| | 750 | 12.79 | | | |
| Effect of Coal Bottom Ash% at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Coal bottom ash % | $LHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 1.5 | 0.02 | 13.02 | 0.031810781 | 0.016641636 | 0.302231723 |
| | 0.028 | 12.90 | | | |
| | 0.036 | 12.81 | | | |
| | 0.044 | 12.72 | | | |
| | 0.052 | 12.64 | | | |
| | 0.06 | 12.57 | | | |
| | 0.07 | 12.50 | | | |
| | 0.076 | 12.46 | | | |
| | 0.084 | 12.42 | | | |
| | 0.092 | 12.39 | | | |
| | 0.1 | 12.37 | | | |
| Effect of CaO/Biomass at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | CaO/Biomass ratio | $LHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 1.5 | 0.5 | 13.58 | 0.097526921 | 0.051377295 | 0.587568741 |
| | 0.65 | 13.21 | | | |
| | 0.8 | 12.91 | | | |
| | 0.95 | 12.68 | | | |
| | 1.1 | 12.54 | | | |
| | 1.25 | 12.47 | | | |
| | 1.42 | 12.49 | | | |
| | 1.55 | 12.58 | | | |
| | 1.7 | 12.75 | | | |
| | 1.85 | 13.01 | | | |
| | 2 | 13.33 | | | |
| Effect of Steam/Biomass Ratio at fixed Temperature | | | | | |
| Temperature | Steam/Biomass ratio | $LHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 692 | 0.5 | 13.64 | 0.021827309 | 0.01143416 | 0.365441985 |
| | 0.6 | 13.63 | | | |
| | 0.7 | 13.61 | | | |
| | 0.8 | 13.55 | | | |
| | 0.9 | 13.48 | | | |
| | 1 | 13.37 | | | |
| | 1.1 | 13.25 | | | |
| | 1.2 | 13.10 | | | |
| | 1.3 | 12.92 | | | |
| | 1.4 | 12.72 | | | |
| | 1.5 | 12.5 | | | |

**Table A-3**
Artificial neural network input and output parameters for HHV (gas).

| Input Neurons | | Output Neuron | Errors | | |
|---|---|---|---|---|---|
| Effect of Temperature at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Temperature | $HHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 1.5 | 650 | 14.32 | 0.011044398 | 0.008101911 | 0.055999263 |
| | 660 | 14.34 | | | |
| | 671 | 14.37 | | | |
| | 681 | 14.40 | | | |
| | 692 | 14.44 | | | |
| | 702 | 14.47 | | | |
| | 713 | 14.50 | | | |
| | 723 | 14.54 | | | |
| | 733 | 14.57 | | | |
| | 743 | 14.61 | | | |
| | 750 | 14.64 | | | |
| Effect of Coal Bottom Ash% at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | Coal bottom ash % | $HHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 1.5 | 0.02 | 14.84 | 0.012492279 | 0.006665292 | 0.202202391 |
| | 0.028 | 14.77 | | | |
| | 0.036 | 14.70 | | | |
| | 0.044 | 14.63 | | | |
| | 0.052 | 14.57 | | | |
| | 0.06 | 14.51 | | | |
| | 0.07 | 14.44 | | | |
| | 0.076 | 14.39 | | | |
| | 0.084 | 14.34 | | | |
| | 0.092 | 14.28 | | | |
| | 0.1 | 14.23 | | | |
| Effect of CaO/Biomass at fixed Steam/Biomass Ratio | | | | | |
| Steam/biomass ratio | CaO/Biomass ratio | $HHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 1.5 | 0.5 | 15.40 | 0.035203817 | 0.019495822 | 0.342529727 |
| | 0.65 | 15.07 | | | |
| | 0.8 | 14.80 | | | |
| | 0.95 | 14.61 | | | |
| | 1.1 | 14.48 | | | |
| | 1.25 | 14.42 | | | |
| | 1.42 | 14.44 | | | |
| | 1.55 | 14.50 | | | |
| | 1.7 | 14.65 | | | |
| | 1.85 | 14.86 | | | |
| | 2 | 15.14 | | | |
| Effect of Steam/Biomass Ratio at fixed Temperature | | | | | |
| Temperature | Steam/Biomass ratio | $HHV_{gas}$ ($MJ/Nm^3$) | RMSE | MAD | AARE % |
| 692 | 0.5 | 15.07 | 0.040731088 | 0.019651841 | 0.276154492 |
| | 0.6 | 15.19 | | | |
| | 0.7 | 15.28 | | | |
| | 0.8 | 15.32 | | | |
| | 0.9 | 15.32 | | | |
| | 1 | 15.28 | | | |
| | 1.1 | 15.19 | | | |
| | 1.2 | 15.07 | | | |
| | 1.3 | 14.90 | | | |
| | 1.4 | 14.69 | | | |
| | 1.5 | 14.44 | | | |

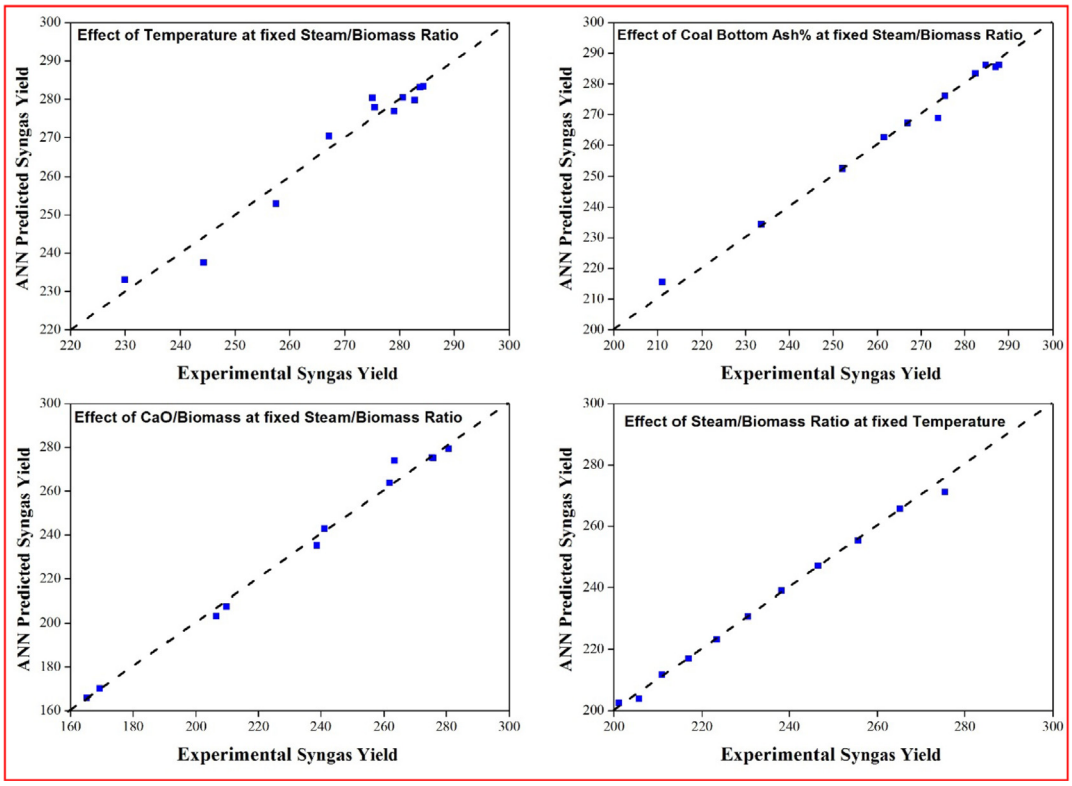


**Fig. A-1.** Comparison of experimental results with ANN predicted for syngas yield at various parameters effect.

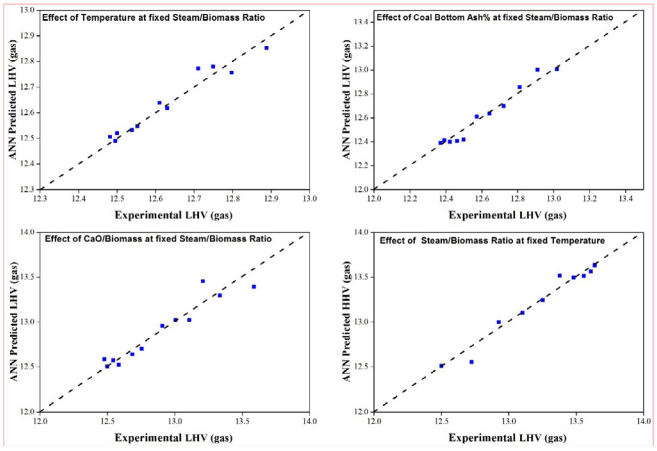


**Fig. A-2.** Comparison of experimental results with ANN predicted for LHV (gas) at various parameters effect.

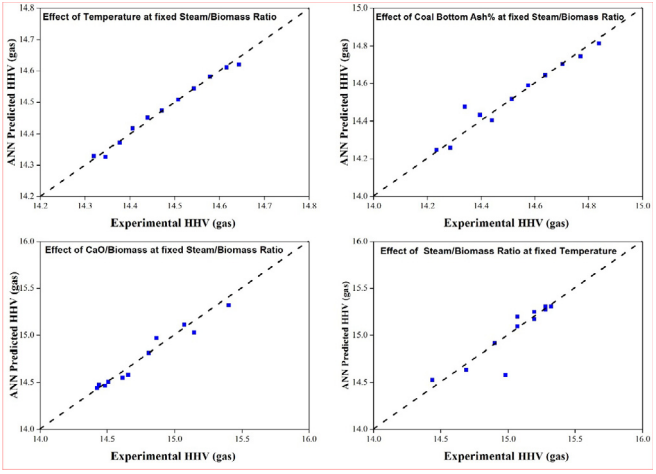


**Fig. A-3.** Comparison of experimental results with ANN predicted for HHV (gas) at various parameters effect.

## References

[1] D. Mallick, P. Mahanta, V.S. Moholkar, Co-gasification of coal and biomass blends: chemistry and engineering, Fuel 204 (2017) 106–128.
[2] W.-H. Chen, J. Peng, X.T. Bi, A state-of-the-art review of biomass torrefaction, densification and applications, Renew. Sustain. Energy Rev. 44 (2015) 847–866.
[3] M. Shahbaz, S. Yusup, A. Inayat, D.O. Patrick, A. Pratama, M. Ammar, Optimization of hydrogen and syngas production from PKS gasification by using coal bottom ash, Bioresour. Technol. 241 (2017) 284–295.

[4] A. Inayat, M.M. Ahmad, M.I.A. Mutalib, S. Yusup, Process modeling for parametric study on oil palm empty fruit bunch steam gasification for hydrogen production, Fuel Process. Technol. 93 (1) (2012) 26–34.
[5] J.F. Pérez, A. Melgar, F.V. Tinaut, Modeling of fixed bed downdraft biomass gasification: application on lab-scale and industrial reactors, Int. J. Energy Res. 38 (3) (2014) 319–338.
[6] M. Shahbaz, S. Yusup, S. Inayat, D.O. Patrick, A. Partama, System Analysis of poly-generation of SNG, power and district heating from biomass gasification system, Chem. Eng. Transact. 52 (2016).
[7] M. Shahbaz, S. Yusup, A. Inayat, D.O. Patrick, A. Pratama, Application of response surface methodology to investigate the effect of different variables on conversion of palm kernel shell in steam gasification using coal bottom ash, Appl. Energy 184 (2016) 1306–1315.
[8] P. Kangas, I. Hannula, P. Koukkari, M. Hupa, Modelling super-equilibrium in biomass gasification with the constrained Gibbs energy method, Fuel 129 (2014) 86–94.
[9] J. Zeng, R. Xiao, H. Zhang, Y. Wang, D. Zeng, Z. Ma, Chemical looping pyrolysis-gasification of biomass for high H2/CO syngas production, Fuel Process. Technol. 168 (2017) 116–122.
[10] A. Abuadala, I. Dincer, A review on biomass-based hydrogen production and potential applications, Int. J. Energy Res. 36 (4) (2012) 415–455.
[11] H. Karatas, F. Akgun, Experimental results of gasification of walnut shell and pistachio shell in a bubbling fluidized bed gasifier under air and steam atmospheres, Fuel 214 (2018) 285–292.
[12] A. Molino, G. Braccio, Synthetic natural gas SNG production from biomass gasification—Thermodynamics and processing aspects, Fuel 139 (2015) 425–429.
[13] D. Sutton, B. Kelleher, J.R. Ross, Review of literature on catalysts for biomass gasification, Fuel Process. Technol. 73 (3) (2001) 155–173.
[14] M. Shahbaz, S. yusup, A. Inayat, D.O. Patrick, M. Ammar, The influence of catalysts in biomass steam gasification and catalytic potential of coal bottom ash in biomass steam gasification: a review, Renew. Sustain. Energy Rev. 73 (2017) 468–476.
[15] A.P. Herman, S. Yusup, M. Shahbaz, D.O. Patrick, Bottom ash characterization and its catalytic potential in biomass gasification, Proc. Eng. 148 (2016) 432–436.
[16] M. Shahbaz, S. Yusup, A. Pratama, A. Inayat, D.O. Patrick, M. Ammar, Parametric study and optimization of methane production in biomass gasification in the presence of coal bottom ash, Proc. Eng. 148 (2016) 409–416.
[17] R. Xiong, L. Dong, J. Yu, X. Zhang, L. Jin, G. Xu, Fundamentals of coal topping gasification: characterization of pyrolysis topping in a fluidized bed reactor, Fuel Process. Technol. 91 (8) (2010) 810–817.
[18] J. Long, H. Song, X. Jun, S. Sheng, S. Lun-shi, X. Kai, Y. Yao, Release characteristics of alkali and alkaline earth metallic species during biomass pyrolysis and steam gasification process, Bioresour. Technol. 116 (2012) 278–284.
[19] W.B. Hauserman, High-yield hydrogen production by catalytic gasification of coal or biomass, Int. J. Hydrogen Energy 19 (5) (1994) 413–419.
[20] K. Umeki, A. Moilanen, A. Gómez-Barea, J. Konttinen, A model of biomass char gasification describing the change in catalytic activity of ash, Chem. Eng. J. 207 (2012) 616–624.
[21] H. Yang, R. Yan, H. Chen, D.H. Lee, C. Zheng, Characteristics of hemicellulose, cellulose and lignin pyrolysis, Fuel 86 (12) (2007) 1781–1788.
[22] P. Lahijani, Z.A. Zainal, Gasification of palm empty fruit bunch in a bubbling fluidized bed: a performance and agglomeration study, Bioresour. Technol. 102 (2) (2011) 2068–2076.
[23] S. Yusup, Z. Khan, M.M. Ahmad, N.A. Rashidi, Optimization of hydrogen production in in-situ catalytic adsorption (ICA) steam gasification based on response surface methodology, Biomass Bioenergy 60 (0) (2014) 98–107.
[24] B.V. Ayodele, C.K. Cheng, Modelling and optimization of syngas production from methane dry reforming over ceria-supported cobalt catalyst using artificial neural networks and Box–Behnken design, J. Ind. Eng. Chem. 32 (2015) 246–258.
[25] M. Puig-Arnavat, J.A. Hernández, J.C. Bruno, A. Coronas, Artificial neural network models for biomass gasification in fluidized bed gasifiers, Biomass Bioenergy 49 (Supplement C) (2013) 279–289.
[26] D. Baruah, D. Baruah, M. Hazarika, Artificial neural network based modeling of biomass gasification in fixed bed downdraft gasifiers, Biomass Bioenergy 98 (2017) 264–271.
[27] R. Mikulandrić, D. Lončar, D. Böhning, R. Böhme, M. Beckmann, Artificial neural network modelling approach for a biomass gasification process in fixed bed gasifiers, Energy Convers. Manag. 87 (2014) 1210–1223.
[28] M. Shahbaz, S. Yusup, D.A. Inayat, D.O. Patrick, M. Ammar, A.P. Herman, Cleaner production of hydrogen and syngas from catalytic steam palm kernel shell gasification using CaO sorbent and coal bottom ash as a catalyst, Energy Fuel. 31 (12) (2017) 13824–13833.
[29] Z. Khan, S. Yusup, M.M. Ahmad, N.A. Rashidi, Integrated catalytic adsorption (ICA) steam gasification system for enhanced hydrogen production using palm kernel shell, Int. J. Hydrogen Energy 39 (7) (2014) 3286–3293.
[30] N.G. Turan, B. Mesci, O. Ozgonenel, The use of artificial neural networks (ANN) for modeling of adsorption of Cu (II) from industrial leachate by pumice, Chem. Eng. J. 171 (3) (2011) 1091–1097.
[31] S.A. Taqvi, L.D. Tufa, H. Zabiri, S. Mahadzir, A.S. Maulud, F. Uddin, Artificial neural network for anomalies detection in distillation column, in: Asian Simulation Conference, Springer, 2017, pp. 302–311.
[32] P. Benardos, G.-C. Vosniakos, Optimizing feedforward artificial neural network architecture, Eng. Appl. Artif. Intell. 20 (3) (2007) 365–382.
[33] D. Scott, P. Coveney, J. Kilner, J. Rossiny, N.M.N. Alford, Prediction of the functional properties of ceramic materials from composition using artificial neural networks, J. Eur. Ceram. Soc. 27 (16) (2007) 4425–4435.
[34] A. Zamaniyan, F. Joda, A. Behroozsarand, H. Ebrahimi, Application of artificial neural networks (ANN) for modeling of industrial hydrogen plant, Int. J. Hydrogen Energy 38 (15) (2013) 6289–6297.
[35] A. Inayat, M.M. Ahmad, M. Mutalib, S. Yusup, Process modeling for parametric study on oil palm empty fruit bunch steam gasification for hydrogen production, Fuel Process. Technol. 93 (1) (2012) 26–34.
[36] S. Koppatz, C. Pfeifer, R. Rauch, H. Hofbauer, T. Marquard-Moellenstedt, M. Specht, H 2 rich product gas by steam gasification of biomass with in situ CO 2 absorption in a dual fluidized bed system of 8 MW fuel input, Fuel Process. Technol. 90 (7) (2009) 914–921.
[37] X. Xiao, X. Meng, D.D. Le, T. Takarada, Two-stage steam gasification of waste biomass in fluidized bed at low temperature: parametric investigations and performance optimization, Bioresour. Technol. 102 (2) (2011) 1975–1981.
[38] M. Ammar, M.I.A. Mutalib, S. Yusup, A. Inayat, M. Shahbaz, B. Ali, Influence of effective parameters on product gas ratios in sorption enhanced gasification, Proc. Eng. 148 (2016) 735–741.
[39] M. Shahbaz, S. Yusup, A. Inayat, M. Ammar, D.O. Patrick, A. Pratama, S.R. Naqvi, Syngas production from steam gasification of Palm kernel shell with subsequent CO2 capture using CaO sorbent: An Aspen plus modeling, Energy Fuel. 31 (11) (2017) 12350–12357.
[40] B. Acharya, A. Dutta, P. Basu, An investigation into steam gasification of biomass for hydrogen enriched gas production in presence of CaO, Int. J. Hydrogen Energy 35 (4) (2010) 1582–1589.
[41] I. Narváez, A. Orío, M.P. Aznar, J. Corella, Biomass gasification with air in an atmospheric bubbling fluidized bed. Effect of six operational variables on the quality of the produced raw gas, Ind. Eng. Chem. Res. 35 (7) (1996) 2110–2120.
[42] Z. Khan, S. Yusup, M.M. Ahmad, B.L.F. Chin, Hydrogen production from palm kernel shell via integrated catalytic adsorption (ICA) steam gasification, Energy Convers. Manag. 87 (2014) 1224–1230.
[43] J. Li, Y. Yin, X. Zhang, J. Liu, R. Yan, Hydrogen-rich gas production by steam gasification of palm oil wastes over supported tri-metallic catalyst, Int. J. Hydrogen Energy 34 (22) (2009) 9108–9115.
[44] K. Zakir, Y. Suzana, A. Murni Melati, R. Anita, A. Mohammad Taufiq, A. Sharifah Shahidah, M. Mas Fatiha, Effect of steam and catalyst on palm oil wastes thermal decomposition for hydrogen production, Res. J. Chem. Environ. 15 (2) (2011) 466–472.