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Artificial neural network integrated with thermodynamic equilibrium modeling of downdraft biomass gasification-power production plant

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Abstract

This study is a novel attempt in developing of an Artificial neural network (ANN) model integrated with a thermodynamic equilibrium approach for downdraft biomass gasification integrated power generation unit. The objective of the study is to predict the net output power from the systems derived from various kinds of biomass feedstocks under atmospheric pressure and various operating conditions. The input parameters used in the models are elemental analysis compositions (C, O, H, N and S), proximate analysis compositions (moisture, ash, volatile material and fixed carbon) and operating parameters (gasifier temperature and air to fuel ratio). The architecture of the model consisted of one input, one hidden and one output layer. 1032 simulated data from 86 different types of biomasses in various operating conditions were used to train the ANN. The developed ANN shows agreement with simulated data with absolute fraction of variance (R^2) higher than 0.999 in the case of product power. Moreover, the relative influence of biomass characteristics and some specific operating parameters on output power are determined. Finally, to have a more detailed assessment, the variations of all input variables with respect to carbon content are compared and analyzed together. The suggested integrated ANN based model can be applied as a very useful tool for optimization and control of the process through the downdraft biomass gasification integrated with power generation unit.

Keywords: Biomass gasification, Artificial neural network, Power production, Downdraft, Simulation

1. Introduction

Growing concerns about energy security and environmental impacts have encouraged/ compelled the decision makers in the energy sector to consider renewable and sustainable energy alternatives to meet the increasing energy demands [1-5]. Biomass, as a naturally available and abundant renewable energy sources, is considered for energy extraction in the sustainable energy supply [6, 7]. Biomass is the only renewable energy source that can be the best substitution for fossil fuels since it is widely available and allows continuous power production and synthesis of various products as transportation fuels or chemicals [8-13].

In order to extract energy from biomass, gasification as a highly efficient and clean conversion technology is applied to converts various biomass feedstocks to a wide variety of products for various applications [8]. Biomass gasification systems produce much lower levels of air pollutants. The by-products of gasification are also non-hazardous and readily marketable. Much important, biomass gasification plants can be integrated with power production units and then it can be implemented as a more reliable energy supply technology for regions that are far from the central energy networks and need to have a district heat and power system [14, 15].

Biomass gasification is a thermochemical conversion in which through a high-temperature partial oxidation, a solid carbon based feedstock by using gasifying agents (like air, pure oxygen, steam, carbon dioxide, nitrogen or their mixtures) is converted to syngas (a gasses mixture including H_2, CO, CO_2, CH_4, light hydrocarbons, tar, char, ash and minor contaminates). H_2 and CO contain only around 50% of the energy in the gas while the remained energy is related to CH_4 and higher (aromatic) hydrocarbons [16].

The gasification process consists of the five stages: drying, pyrolysis, oxidation (combustion), reduction (char gasification), and cracking (Fig. 1) [17, 18].

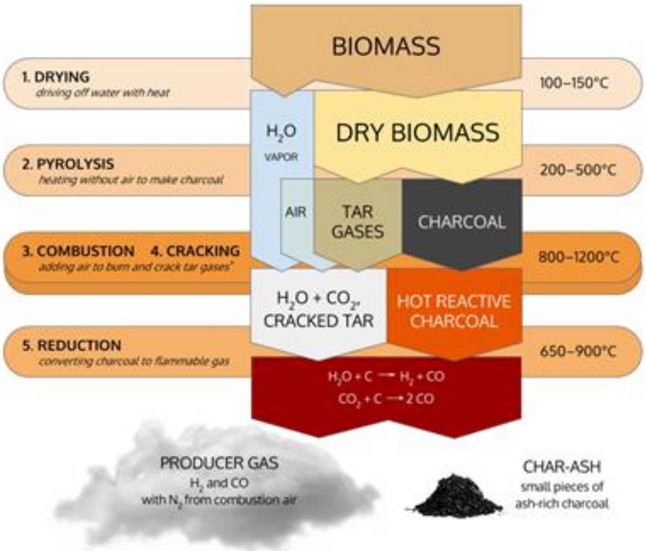

Fig. 1. Gasification process stages (Reprinted from www.allpowerlabs.com, Copyright 2018 All Power Labs, with permission from All Power Labs)

All the processes are temperature dependent; generally, the moisture content in the biomass ranges from 5–35% that through the drying step, it is reduced to under 5%. In the pyrolysis stage, the biomass is heated from 200 up to 700 °C with limited oxygen or air. Under these conditions the volatile components in the biomass are vaporized. The volatile vapor is a mixture of H_2, CO, CO_2, CH_4, tar (heavier hydrocarbon) gases, and water vapor. Moreover, char as a solid residue mainly containing carbon is produced from pyrolysis. The oxygen supplied to the gasifier reacts with the combustible substances, producing CO_2 and H_2O. Some of this CO_2 and H_2O subsequently are reduced to CO and H_2 upon contact with the char produced during pyrolysis. Hydrogen in the biomass can be also oxidized, generating water. The reduction reactions occurring inside the gasifier are endothermic, and the energy required for these reactions is provided by the combustion of char and volatiles. Reduction of the biomass yields combustible gases such as hydrogen, carbon monoxide, and methane through a series of reactions [18].

Performance analysis of biomass gasification systems has been studied in many researches [2, 10, 14, 15, 19-25]. The biomass characteristics, the reactor design and the operating parameters are the effective variables in the gasification process which influence the gasifier performance, syngas composition and system overal efficiency [26]. The influencing feedstock characteristics are moisture content (MC), volatile matter (VM), ash content, fixed carbon (FC), thermal conductivity, organic constituents and inorganic constituents. It has been also reported that there are very complex thermo-chemical phenomena occuring inside the gasifier. As a result, experiments can practically provide information regarding the optimum conditions and appropriate feedstock for a reactor, but these lessons can be more time-consuming and expensive compared with modelling [18, 26].

Different kinds of models have been employed for biomass gasification systems, including thermodynamic equilibrium, kinetic, computational fluid dynamic (CFD) and artificial neural network (ANN). Thermodynamic equilibrium calculations are simple compared with kinetic models and independent of the gasifier design, and in the simplest, most ideal case, general thermodynamic properties can be used for equilibrium modelling, while a larger set of hard-to-come-by and accurate kinetic parameters is needed for kinetic modelling. These points grants equilibrium approach the more convenient method with which to study the general relations between fuel and process parameters as well as syngas composition and yield. In CFD models, a set of simultaneous equations are solved to conserve energy, momentum, mass, and species over a distinct region of the gasifier and then predict the distribution of various parameters such as temperature and concentration. Artificial neural networks (ANN) is based on a wide number of experimental data and utilize a series of mathematical regression to correlate between input and output streams [6, 18, 27].

Modeling derived from ANN approach can approximate nonlinear functions and does not need mathematical description of phenomena regarding to the system. Hence, ANNs become handy in the case of outcome prediction when significant interactions of complex nonlinearities exist in a data set, like in biomass gasification [8, 26]. However, there are very few studies reported about modeling of biomass gasification relied on ANN method in general and even fewer in the field of fixed bed downdraft gasifiers.

It is worth to mention that in all of the reported studies carried on ANN modeling of biomass gasification, the neural network learns by itself from sample experimental data that are described for that as inputs. However, the models will be able to predict the gasification process parameters precisely when adequate amount of experimental data in wide range of various biomasses and different operating conditions are defined for that. Although, data inadequacy results in poor prediction, large scale experiments for these purposes could often be expensive or problematic in terms of safety.

Combination of ANN method with thermodynamic equilibrium approach could solve this problem that authors are not aware of any published study on this matter. By using mathematical models or simulation models based on thermodynamic equilibrium, it would be possible to analysis large variety of biomass feedstocks and then extract different kinds of outputs like syngas yield, concentrations, power production and etc. At the next step, biomass characteristics and operating parameters as features matrix and thermodynamic equilibrium model`s outputs as output matrix could be defined as inputs for ANN model.

In fact, the purpose of using ANN when the process can be modelled using thermodynamic relations are as follows:

- Firstly, due to huge variety of feedstocks and operating conditions; Although, we tried to gather so many and different kinds of biomasses from various groups to have a rich database, there are still a wide number of biomasses with different elemental and proximate analysis. Apart of various types of feedstocks, biomass properties are mostly dependent on geographical location and other constraints. For example, many types of perennial grasses, such as sugarcane and cereals like wheat and maize, have widely different yields, depending on the growing conditions or have different moisture depending on the climatic conditions.
- Secondly, operating conditions applied to the system could be varied in different ranges. We studied some different temperature and air mass flow rates (in term of air flow ratio (AFR)) however, the operating conditions applied to the biomass gasification system could be varied. Hence, instead of the running again and again a simulation model for each case that is time consuming and needs separate models/runs for each one, we can have an ANN model to conclude the final results for all considered cases in a single run.
- Thirdly, due to specific requirements inputs in simulation model; if we want to use thermodynamic equilibrium simulation model for a specific case in biomass gasification system integrated with power production plant (BG-PPP), firstly before running the model, we need to extract and enter proximate and elemental analysis of biomass and then calculate diffident yields of components for pyrolysis part and mass flow rate of air entering to the gasifier (more in Section 2.1).
- Fourthly, we have to calculate how much air is required for combustion operation in power production part that is depending on syngas compositions coming from gasifier output. In fact, to obtain the output power from the BG-PPP, we have to run the simulation model two times. Firstly, we need to run the model without considering power plant to get gasifier outputs. Then the required amount of air for combustion is calculated based on syngas composition and finally the model is run to reach the output power from overall system.
- More important is that for each biomass, these running and calculations need to be done specifically that to have correct and feasible results. However, by having a

verified ANN model, all these steps are eliminated. It is just required to enter basically inputs (biomass compositions and two operating conditions) and it is not required to have knowledge of relations and different parts in BG-PPP.

Another matter that has not explicitly addressed by prior published works on ANN based modeling of biomass gasification is that they all focused on single gasifier with objective to predict the end gas composition but no one has worked on power production from gasification integrated with power generation unit. Hence, the primary objective of this research is development of a simulation model based on thermodynamic equilibrium for biomass gasification integrated power production unit by using ASPEN Plus. Then, an attempt is made to develop an ANN model for downdraft biomass gasification based on features matrix and output matrix that come from the simulation model. The objective of the study is to develop ANN model integrated with a thermodynamic equilibrium for prediction of power production for 86 biomass feedstocks in various operating conditions. Further, it is attempted to determine the relative influence of biomass characteristics and some specific operating parameters on output power. Finally, to have a more detailed assessment, the variations of all input variables with respect to carbon content are compared and analyzed together.

2. Material and methods

2.1. Simulation model and input selection

An equilibrium simulation model is developed for downdraft biomass gasification integrated with power production unit by using ASPEN Plus. Penge Robinson equation of state with Boston-Mathias alpha function (PR-BM) is applied to calculate physical properties of the conventional components in the gasification process. HCOALGEN and DCOALIGT models are also employed for enthalpy and density of biomass and ash which are non-conventional components. MCINCPSD stream comprising three substreams of MIXED, CIPSD and NCPSD class, is also considered to define the biomass structure and ash streams which are not available in Aspen Plus component database [10, 14].

The flow chart of the system simulated by using ASPEN Plus is shown in Fig. 2. The BIOMSS stream was defined as a nonconventional stream and it was created by specifying the elemental and gross compositions of feedstock obtained from proximate and elemental analyses. In this work to have a comprehensive study we consider 86 different types of biomasses from different groups (e.g. wood and woody biomasses, herbaceous and agricultural biomasses, animal biomasses, mixed biomasses and contaminated biomasses) [28], as feedstock for gasifier. The proximate and elemental analysis of these biomasses are listed in Table 1 [28-56]. Drying occurs at 150 °C to achieve the moisture reduction to 5 wt.% of the original sample. This step is directed by the stoichiometric reactor RSTOIC in the Aspen Plus. This particular module is used to perform chemical reactions of known stoichiometry [21]. After drying, RYIELD, the yield reactor is brought to simulate the feed pyrolysis. In this step, the feedstock is converted to volatile materials (VM) and char. VM contains carbon, hydrogen, oxygen and nitrogen; Char is also converted into ash and carbon, by specifying the product distribution based on the proximate and ultimate analysis of the feedstock [10]. Then RGibbs is used to simulate the biomass gasification. The reactor calculates the syngas composition by minimizing the Gibbs free energy and assumes complete chemical equilibrium. The decomposed feed and air enter to the RGibbs reactor where partial oxidation and gasification reactions occur. Another RGibbs reactor is also simulated for combustion section with minimum air mixing. Principally, this process is also based on minimization of Gibbs free energy. The combustion chamber is followed by a gas turbine [57, 58]. The thermal content of the gas, obtained as the combustion heat is recovered to preheat the entering air to the combustion chamber and also to meet the heat required in dryer. The recovered heat can be also consumed to convert water to high pressure steam though a HEATER and then the generated steam drives a steam turbine and produces additional power [59, 60]. However, we did not consider this part in our study. The solid lines in the Fig. 2 stand for the mass streams whereas the dashed lines are for the heat streams. The system is assumed to be auto-thermal so that a part of the biomass is combusted inside the gasifier in order to provide the heat required in situ. Heat is also provided by the hot product gas as well as the combustion chamber and utilized wherever needed.

Table 1: Characteristics of input and output variables in the ANN model for downdraft gasifiers integrated with power unit

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

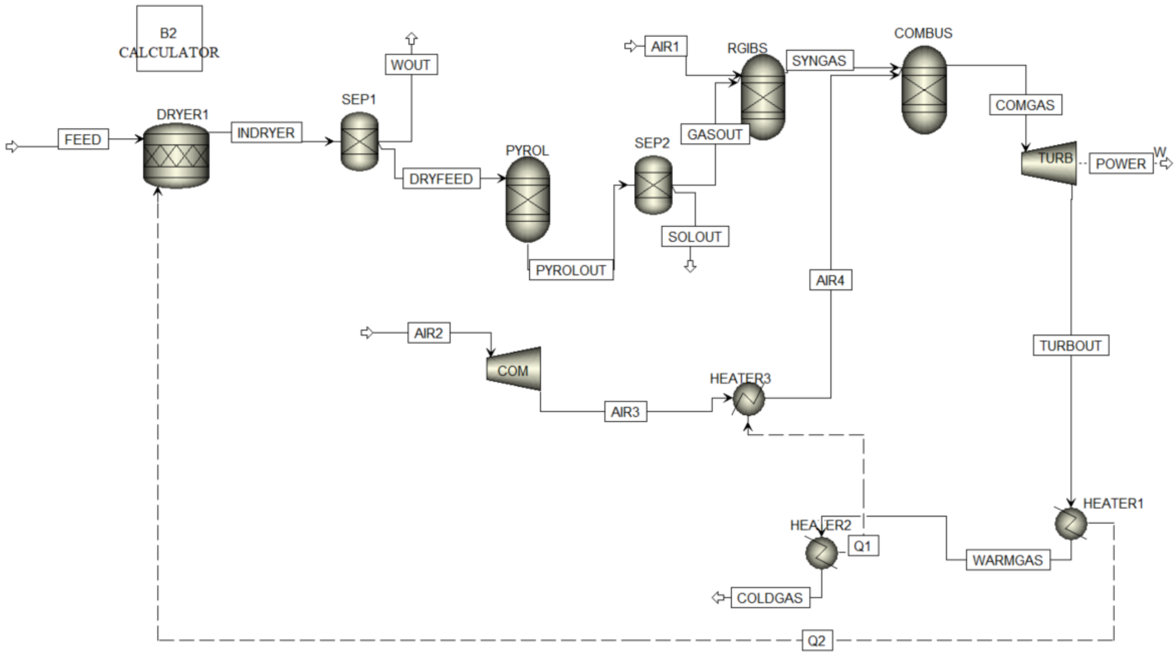

Fig. 2. Flow chart of gasification simulation in Aspen Plus

As it mentioned above, 86 different types of biomasses from different groups of wood and woody biomasses, herbaceous and agricultural biomasses, animal biomasses, mixed biomasses and contaminated biomasses were considered to be gasified in a downdraft gasifier. It is important to say that all analysis is directed based on a functional unit of 1 ton for each input feedstock under atmospheric pressure and different operating conditions. (i) Proximate analysis of feedstocks: moisture content (M), volatile materials (VM), fixed carbon (FC) and ash (A), (ii) elemental analysis of feedstocks: carbon (C), oxygen (O), hydrogen (H), nitrogen (N), sulphur (S) along with (iii) operating parameters: gasifier temperature (T) and air to fuel ratio (AFR) were took in account to be the input variables in the formulation of the ANN model. Table 1 lists the characteristics of the inputs and net output power ($W_{net} = W_{gas\ turbine} - W_{compressor}$) obtained from the simulation model results. The detailed input and output variables were brought in Data in Brief [61].

2.2. ANN modeling concept

An ANN based model for downdraft gasifiers integrated with power production unit is developed to study system behavior in term of net output power. An ANN is an architecture consisting of a large number of neurons organized in different layers and the neurons of one layer are connected to those of another layer by means of weights and it can be trained to perform a particular task by making proper adjustment of its connecting weights, bias and architecture [62]. In this work, ANN model were developed in the MATLAB® environment using the Neural Network Toolbox (nntool). Fig. 3 represents the architecture of the ANN model developed for output (net output power (kW)). Each ANN has one input layer with 11 variables, M (wt%), VM (wt% dry basis), FC (wt% dry basis), ash (wt% dry basis), C (wt% dry basis), O (wt% dry basis), H (wt% dry basis), N (wt% dry basis), S (wt% dry basis), gasifier temperature, T (°C) and air to fuel ratio ($kg_{air}/kg_{drybiomass}$) with one hidden layer and one output. Indeed, there no clear rule to determine totally optimal structure for ANN and most of researchers in this field have been developed ANN models only with one hidden layer [6, 8, 26, 63-65]. Hence, we considered also one hidden layer but with various number of nodes to find the optimal structure by minimizing the Root Mean Square Error (RMSE) due to its capability to compare different ANN structure [66]. This comparison was brought in Table 2. As it is shown, the ANN model with one hidden layer with 40 neurons in the case of output power corresponding to the minimum value of RMSE. It is also found that RMSE value increases by applying more than 40 neurons in hidden layer that is due to over-fitting problems caused by using too many neurons in hidden layer.

Table 2. Performance of ANN with differnet number of hidden neoruns

Number of neurons	**RMSE**
7	4
11	2.44
18	1.24
22	0.8
28	0.87
33	0.74
40	0.496
50	0.61
60	0.69
100	0.69

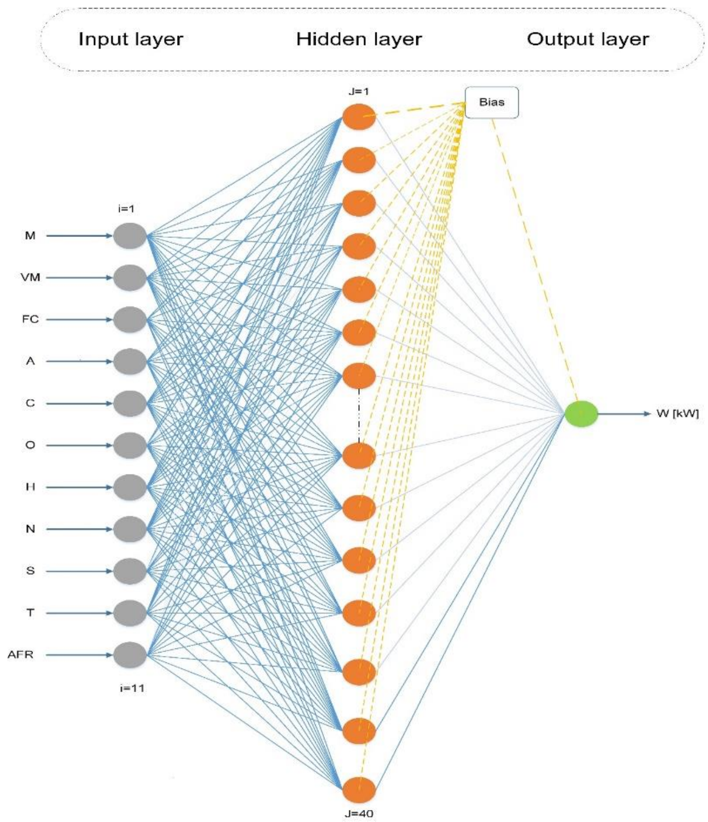

Fig. 3. ANN architecture to predict the net output power for downdraft gasifiers integrated power production unit

2.3. Training and validation of ANN model

In order to validate and check the prediction ability of the models, the database obtained from the simulation model (in Section 2.1) was divided into two parts as training (70%) and testing (30%) sub-sets. The simulation model used in this work has been developed, verified based on other experimental and modeling results from other researchers and it has been also employed for different assessments in our pervious works [2, 10, 14, 15, 19, 20]. So, it confirms the accuracy of both training and testing the ANN model with simulated data.

The training function used in the models were based on the TRAINLM function which updates the weight and bias values according to Bayesian Regularization optimization. This function is often the fastest backpropagation algorithm. Moreover, the Gradient descent with momentum weight and bias learning function (LEARNGDM) was used to minimize the errors. This function calculates the weight change for a given neuron from the neuron's input and error, the weight (or bias), learning rate, and momentum constant, according to gradient descent with momentum backpropagation. Training and test subsets were randomly selected from the available database. In addition, for activation function, a hyperbolic tangent sigmoid and liner functions were applied in hidden and output layer, respectively. These functions have also performed accurately in previous works [6, 8, 26, 63-68].

The root mean square error (RMSE) and absolute fraction of variance (R2) were applied to evaluate the prediction ability of the ANN model. RMSE and R^2 are calculated with the simulation results values and networks predictions by using equations (1) and (2), respectively [26].

$$RMSE = \left((\frac{1}{p}) \sum_j \left| T_j - O_j \right|^2 \right)^{\frac{1}{2}} \tag{1}$$

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

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

2.4. Relative influence of input variables on model output

Relative influence is one of the most important indicators to assess the effects of input variables on output. In this work, the influence of the input variables on the outputs was evaluated by applying the Garson equation which is based on neural net weight matrix [62]. In this equation, the sums of absolute weights products for each input are defined as the numerator and the sum of all weights feeding into hidden unit are defined as the denominator, taking the absolute values. The Garson equation, adapted to the present ANN topology is given in equation (3).

$$I_i = \frac{\sum_{j=1}^{j=40}\left(\left(\frac{\left|IW_{j,i}\right|}{\sum_{i=1}^{i=11}\left|IW_{j,i}\right|}\right).\left|LW_{j,i}\right|\right)}{\sum_{i=1}^{i=11}\left\{\sum_{j=1}^{j=40}\left(\left(\frac{\left|IW_{j,i}\right|}{\sum_{i=1}^{i=11}\left|IW_{j,i}\right|}\right).\left|LW_{j,i}\right|\right)\right\}} \qquad (3)$$

Where, i is the input variables, j is the hidden layer neurons, I_i is the relative influence of the i^{th} input variable on the output variable, $IW_{j,i}$ is the weight to j^{th} neuron of hidden layer from i^{th} input variable, $LW_{j,i}$ is the weight to output layer from j^{th} neuron of hidden layer and n is the number of neurons (40 for output power). After calculation of the relative influence of the input variables on the output, the input variables are ranked in descending order of magnitude and then they are compared together.

3. Results and discussions

A neural network with 11 inputs, 40 neurons for net output power in the hidden layer and one output, were found to be efficient in predicting product power. The parameters ($IW_{j,i}$, $LW_{1,j}$, b_{1j}, b_2) of the best fit for 40 neurons in the hidden layer for the ANN developed in the downdraft biomass gasification model are shown in Table 3 and 4.

Table 3. Weights of the ANN model for predicting the output power

neuron	M	VM	FC	A	C	O	H	N	S	T	ARF
1	0.01	-0.13	-0.29	0.00	0.23	-0.08	0.16	-0.23	-0.20	0.61	0.08
2	0.36	0.16	-0.46	0.06	0.66	-0.63	0.13	-0.29	-0.35	-0.52	0.02
3	-0.58	-0.38	0.42	-0.13	0.37	-0.18	-0.30	0.25	-0.44	0.39	0.01
4	1.46	0.50	-0.49	0.16	-0.74	0.25	0.46	0.32	0.07	0.18	0.11
5	-0.22	0.13	-0.77	-0.23	0.12	0.18	-0.02	0.57	0.66	-0.28	-0.36
6	0.46	-0.52	-0.39	0.02	0.58	-0.57	0.21	-0.04	0.33	0.46	-0.04
7	-0.09	0.00	0.05	0.16	-0.20	-0.14	0.22	0.03	0.17	0.06	0.39
8	1.22	-0.01	0.38	-0.27	-0.74	0.48	0.88	0.18	-0.13	0.02	-0.05
9	1.22	-0.10	-0.23	0.25	-0.07	0.12	-0.03	-1.06	-0.39	-0.12	0.03
10	-0.39	0.41	-0.45	-0.49	0.71	-0.21	0.37	-0.22	0.48	1.03	-0.02
11	0.31	0.03	0.36	-0.05	0.20	-0.20	0.07	-0.07	-0.59	-0.15	-0.16
12	-0.96	-0.08	0.53	-0.13	0.45	-0.14	-0.22	0.25	0.17	0.20	-0.03
13	0.00	1.04	0.73	0.53	-0.11	-0.49	0.05	-0.24	0.06	-1.49	-0.03
14	-0.24	0.34	0.44	0.28	-0.31	0.12	-0.35	-0.20	0.27	-0.06	0.29
15	0.18	-0.12	0.07	-0.02	-0.03	0.04	-0.15	0.06	0.05	0.01	0.17
16	-0.19	-0.42	-0.68	-0.38	0.42	0.32	-0.21	-0.01	0.11	-0.58	-0.74
17	-0.96	-0.40	0.30	0.29	1.04	-0.58	-0.65	-1.46	-0.42	0.03	-0.02
18	0.20	-0.54	0.00	-0.18	-0.49	0.48	0.17	0.25	0.03	0.55	-0.16
19	0.19	-0.44	0.00	-0.01	-0.04	-0.10	0.25	0.23	-0.38	0.36	0.21
20	-0.38	-0.46	0.46	0.22	-1.06	1.13	-1.53	0.23	0.70	-1.04	0.17
21	-0.01	0.44	-0.15	0.13	-0.25	-0.33	-0.35	1.49	-0.84	0.02	-0.02
22	-0.09	-0.94	0.85	0.10	0.40	0.55	0.48	-4.42	1.65	0.00	0.00
23	-0.54	-0.12	0.07	-0.11	0.66	-0.05	-0.15	-0.14	-1.15	-0.47	0.06
24	0.22	-0.26	0.44	-0.25	0.26	-0.07	0.10	1.08	-0.22	-0.18	0.03
25	0.49	-0.18	0.04	-0.13	-0.33	0.46	0.48	-0.29	-0.06	-0.14	-0.25
26	-0.05	0.00	0.03	0.09	-0.07	0.17	-0.48	-0.11	-0.13	-0.19	0.28
27	-0.09	0.10	0.33	-1.00	-0.08	0.30	0.44	2.30	0.32	0.04	-0.01

28	-0.53	0.29	0.65	-0.46	1.00	-0.04	-0.14	-0.12	1.11	0.02	-0.01
29	-0.40	-0.23	-0.12	0.04	-0.80	0.63	-0.50	0.12	0.37	-0.41	0.07
30	-0.02	0.03	0.45	-0.12	1.10	-0.70	-0.06	0.04	-1.15	-0.45	0.04
31	0.29	-0.14	-0.03	-0.12	0.24	-0.14	-0.15	0.31	-0.45	0.17	0.63
32	-0.96	0.06	0.10	0.02	0.06	-0.14	0.25	-0.26	0.20	-0.24	-0.10
33	-0.34	0.49	-0.02	-0.76	0.90	-0.29	0.42	0.21	0.76	0.99	-0.04
34	-0.23	0.61	0.27	0.20	0.10	-0.18	-0.37	-0.15	0.09	-0.62	-1.09
35	0.54	0.13	0.06	0.14	-0.31	0.24	-0.86	0.03	0.46	-0.04	0.05
36	0.00	0.81	0.14	0.21	-0.18	-0.27	-0.04	0.48	0.49	-0.27	-0.34
37	0.12	-0.13	0.07	0.15	-0.41	0.22	-0.24	-0.27	-0.36	0.44	0.00
38	0.05	-0.79	-0.97	-0.46	0.40	0.49	0.14	0.00	0.07	-1.41	-0.01
39	-0.20	-0.28	-0.29	0.26	0.17	-0.64	0.17	0.01	-0.49	0.47	0.03
40	0.45	-0.77	0.65	-0.20	-0.40	0.23	-0.03	0.39	-0.19	0.12	-0.03

Table 4. Weights of hidden to output layer and biases of the ANN model for predicting the output power

	neuron	Weights to output layer	bias
Hidden layer	1	-1.365400826	-0.208790169
	2	0.48	0.29246506
	3	-1.01	0.187257889
	4	0.68	-0.107065513
	5	0.66	-0.44
	6	0.66	0.109236253
	7	0.57	0.132557403
	8	-0.99	0.829973138
	9	1.26	-0.31261119
	10	-1.02	0.782156872
	11	1.11	0.418229656
	12	1.64	-0.265956467
	13	1.40	-0.195432414
	14	0.72	-0.395102066
	15	-0.35	0.06
	16	-1.13	-0.413681034
	17	1.57	-0.380586154
	18	0.62	0.165910912
	19	-0.59	0.17685421
	20	-0.25	-1.151836359
	21	-1.54	0.232946775
	22	-2.75	-0.046532151
	23	0.806408153	-0.729363678
	24	-1.063728305	-0.352199291
	25	0.474795076	-0.13245391
	26	-0.596876701	-0.35
	27	1.60323122	1.226945911
	28	-0.996344905	-0.451668773
	29	-0.937677285	0.02599315
	30	-0.661605924	0.092254468
	31	0.18663061	0.219096132
	32	0.862835425	0.252141573
	33	0.764702236	1.259868065
	34	0.664865911	-0.170177343
	35	0.980292534	-0.115372872
	36	-0.927908102	0.033664555
	37	0.963584311	0.100437998
	38	-1.559829217	-0.824027897
	39	0.735497373	0.502309867
	40	-0.53609804	0.87

Out put layer	1	-	-0.37674

The simulated and predicted values of each output power were compared satisfactorily through a linear regression model for training, testing and all targets as shown in Fig. 4. It is observed that R^2 value is more than 0.999 in the case of product power from downdraft biomass gasifier integrated power generation plant for all target cases. Moreover, to guarantee more, the predicted and target values of output power for some sample data were brought in Fig. 5. The comparison of the predicted and target values and very low error of production in Fig. 5 confirm that whole ANN model has a satisfactory level of confidence.

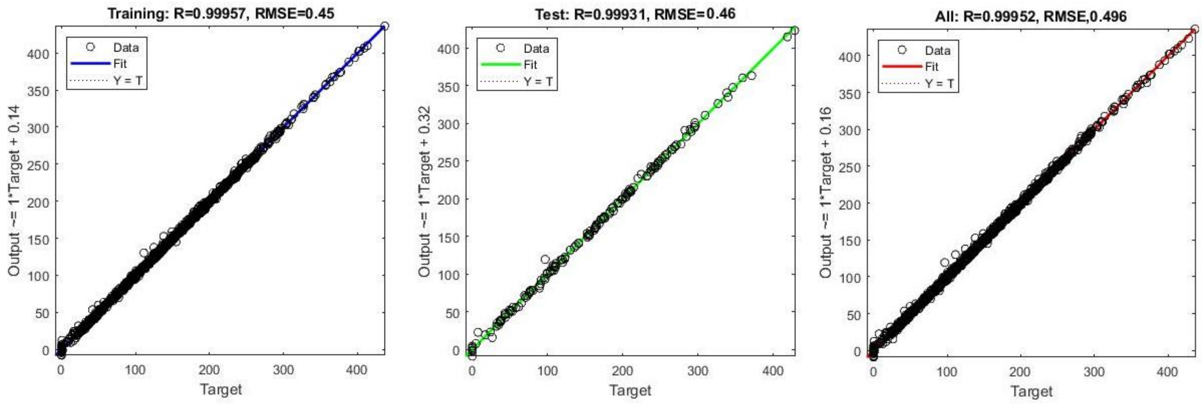

Fig. 4. Comparison between simulated data and predicted data by the ANN model for downdraft gasifier integrated with power generation plant

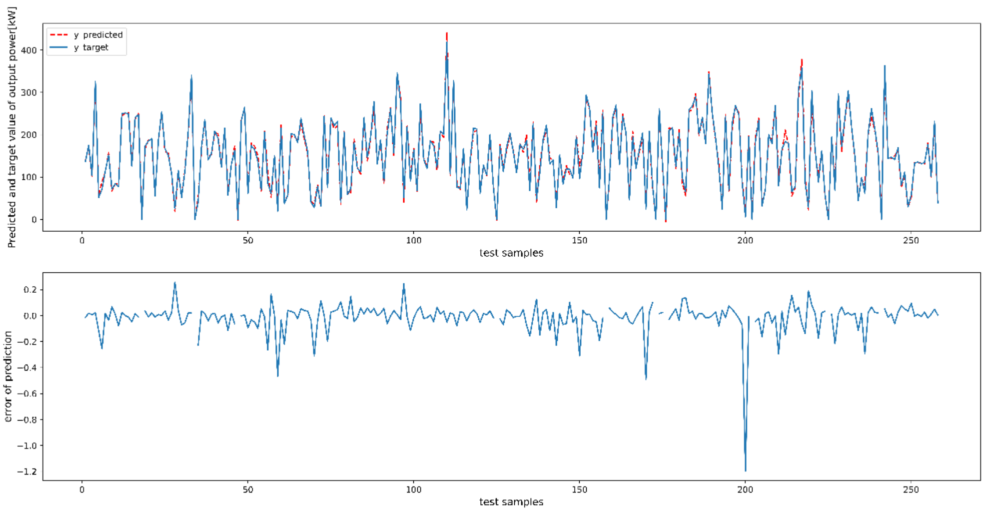

Fig. 5. Comparison of the predicted and target values and error of production for sample test data

The influences of the 11 input variables on the output prediction were calculated using the Garson's equation. Fig. 6 represents the relative influences of input variables on the net output power for the developed ANN. It can be seen that variables considered for biomass composition (C, H, O, S and N) represent between 8% to 12% and proximate analysis compositions (M, VM, FC and A) show between 7% to 11% of the influence on the output power. Further, gasifier temperature has the most important effect on output power prediction (with 13%).

Reduction zone temperature has the most effective variable in conformation to the fact that increase in temperature favors H_2 and CO production, leads to the improvement of heating value (LHV) of syngas. Then, improving LHV of syngas leads to enter gases with higher quality into the combustion chamber and following enter gasses at high temperature to the gas turbine. Finally, increasing the turbine inlet temperature enhances output power from the system. Carbon is also the second dominant variable influencing on the output power prediction, followed by moisture content, oxygen and sulphur occupying 11%. It may, however, be commented that each of the variables have a strong influence on the output.

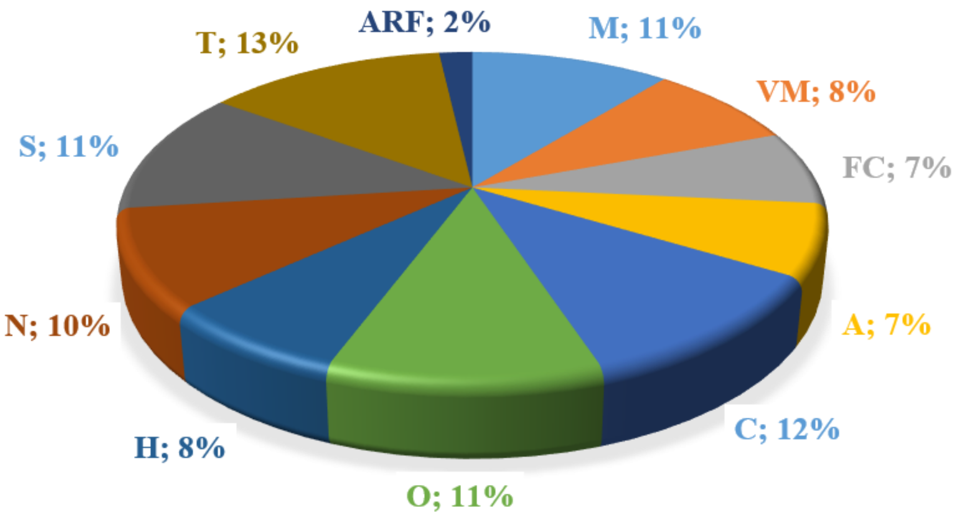

Fig. 6. Relative influence (%) of input variables on the net output power for the ANN model

In this work to have a high accuracy and minimum uncertainty, a rich database from various biomasses from different groups were considered. So, if a new biomass is described to the model, its components will be in the range of pervious properties. Moreover, the considered operating conditions for the model are the most applied operating conditions on the real gasification systems. In addition, the required data for training and testing of the model are selected randomly that this matter decreases uncertainty. Moreover,in continue a sensitivity analysis is directed to have a more comprehensive comparison. The variations of all input variables with respect to carbon content are depicted by 10 contour plots in Fig. 7. Obviously, by increasing carbon content and decreasing moisture content in biomass, the higher amount of power will be produced by the gasification system. However, other proximate analysis compositions show the influencing trend similar to the carbon on output. On the other hand, by increasing both variables, the generated power is also increased. From comparison of carbon and operating parameters can be found that for each amount of carbon content need to select the optimum ARF and gasifier temperature to have the maximum extractable power from the biomass. It is reported that if C/H ratio be in the range of 2.08 to 2.5 and C/O ratio in span of 5-7, the highest amount of power will be produced from the system.

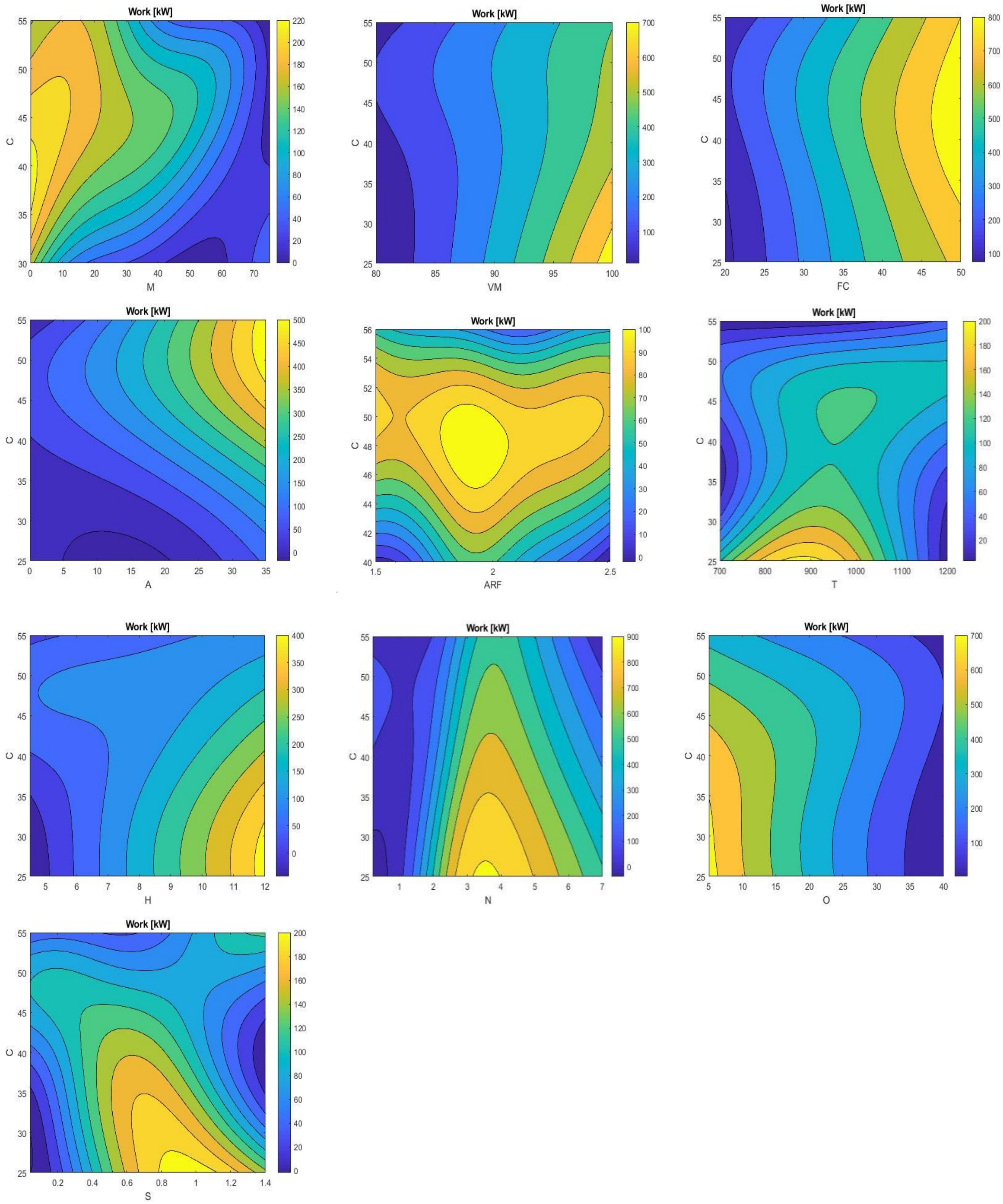

Fig. 7. Contour plots of sensitivity analysis results

4. Conclusions

Generally, there are very few reported studies about modeling of biomass gasification relied on ANN method and even fewer in the field of fixed bed downdraft gasifiers. Moreover, authors are not aware of any published work on ANN based modeling of biomass gasification integrated with power production plant. Hence in this work, an ANN model integrated with a thermodynamic equilibrium approach for downdraft biomass gasification integrated power generation unit is developed. In fact, the objective of the study is to predict the net output power from the systems derived from various kinds of biomass feedstocks under atmospheric pressure and various operating conditions.

The developed ANN shows agreement with target data with absolute fraction of variance (R^2) higher than 0.999 in the case of product power. All of the variables have a strong influence on the output power. Generally, elemental compositions considered for biomass (C, H, O, S and N) represent between 8% to 12% and proximate analysis compositions (M, VM, FC and A) show between 7% to 11% of the influence on the output power. Further, gasifier temperature has the most important effect on output power prediction (with 13%).

The results show how the generated power through the downdraft biomass gasification integrated with power production plant can be successfully predicted by applying a neural network with one hidden neurons in the hidden layer and using backpropagation algorithm. The model is applicable for a wide variety of feedstocks. The results also depict the relative importance of different compositions and operating parameters on the product power. The model has this potential to be used as a practical application in screening proper biomass feedstocks for energy extraction based on gasification technology integrated power unit.

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