Modelling of Pyrolysis Product Yields by Artificial Neural Networks

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Abstract- Artificial neural network (ANN) needs to be applied to the complex, multivariate, and highly variable biomass and pyrolysis data to define optimum input variables and develop effective models. In this study, two different ANN methods, the feed-forward network (FFN) and the cascade-forward network (CFN), were applied to model pyrolysis product yields (biochar-BC, bio-oil-BO, and gas mixture-G) from 11 biomass and pyrolysis variables through hierarchical modeling approach. Both methods were supplied with two subsets of data, with two-thirds being used for training and one-third for testing the performances of the methods, after normalizing all data (72 samples). The performances of both ANN methods were evaluated by using three statistical parameters. In general, FFN and CFN methods had very similar performances in training and testing. Both methods had mean R^2 of 0.91, 0.96, and 0.95 for training BC, BO, and G, respectively. For testing of all FFN and CFN models, the R^2 values of BC and G were less than 0.50, but the R^2 values of BO were over 0.50 (up to 0.81) for only the last 5 models of FFN and CFN. Both types of ANNs are promising tools in predicting pyrolysis product yields.

Keywords Biomass, pyrolysis, modelling, feed-forward network, cascade-forward network.

1. Introduction

Nowadays, a significant part of energy is obtained from the fossil energy sources (coal, petroleum, and natural gas). However, the depletion of fossil energy sources and the emissions of harmful and greenhouse gases when they are combusted cause global environmental problems such as acid rains and global warming or climate change. Therefore, nowadays, different studies have been focusing on producing bioenergy/biofuels from biomass by using modern technologies. Biomass is a plentiful, a renewable, and an environmental-friendly energy source. Biomass can be defined as all organic materials originated from plant and animal sources [1]. Elemental composition of biomass (as dry wt.%) is carbon-C (51%), oxygen-O (42%), hydrogen-H (5%), nitrogen-N (0.9%), and chloride-Cl (0.01-2%) [2]. Several other properties of biomass, such as moisture (M), volatile organic carbon (V), fixed carbon (F), ash (A), and higher heating value (HHV), are used in modeling studies. Since the direct use of biomass has some disadvantages [3], biomass should be converted to more usable materials.

Biomass can be converted to 3 main products (power/heat, biofuel, useful chemicals) by two main methods: a) thermal/thermochemical (combustion, pyrolysis, gasification, liquefaction) and b) biological/biochemical (anaerobic digestion, fermentation) [4]. Pyrolysis is the thermal decomposition of biomass in the absence of oxygen to produce solid biochar (BC), liquid bio-oil (BO), and gas mixture (G) products [5]. While BO and G products are generally used as biofuel, BC is used in the water treatment and agricultural applications. The portion of the pyrolysis product yields depend on the pyrolysis process parameters such as pyrolysis temperature (T), heating rate (HR), residence time, carrier gas type and flow rate, catalyst type and amount, and reactor type [6].

Biomass pyrolysis is affected by many parameters of biomass and pyrolysis process as explained above. Modeling of biomass pyrolysis product yields is a great degree of complexity due to the multivariable parameters, nonlinearity of the processes involved, and the lack of data. Numerical models have recently been employed to simulate pyrolysis product yields due to the fast development of computing technology. Artificial neural network (ANN) has some advantages over statistically based models, where they have capability to model complex and multivariable data, and nonlinear processes without requiring a priori relationship between input and output variables [7]. These advantages of ANN suggest that they can be utilized in the prediction of the pyrolysis product yields from biomass and pyrolysis process parameters.

Numerous experimental studies ([8-20, 58-65]) have been conducted to optimize the pyrolysis product yields by using biomass and pyrolysis process parameters. The optimization of the pyrolysis product yields through the experiments may be difficult due to the large variations in multivariable biomass and pyrolysis process parameters. On the other hand, the application of a model like ANN to especially complex data set is relatively easy and cheap, and offers the trial of many alternatives at shorter time in the optimization of the parameters compared to an experimental study. ANN models like the feed-forward network (FFN) and the cascade-forward network (CFN) can be applied to find the relationships among complex, multivariable, and nonlinear biomass and pyrolysis data. However, modeling studies with ANN ([21-24]) are limited in the literature. The most commonly used ANN among many types is the multilayer FFN trained by the back-propagation algorithm as in these studies. However, the application of the multilayer CFN is absent or limited (if available). In addition, the comparison of these two methods for evaluation of their performances in the prediction of the pyrolysis product yields (BC, BO, and G) is not observed in the literature. Such a comparison may offer to apply better technique in the modeling of pyrolysis product yields. Besides, the limited number of parameters are used in these modeling studies without hierarchical model development approach. Developing hierarchical models through alternative ANN methods by using significant number of biomass and pyrolysis parameters may allow to better define the individual effects of each input parameter on pyrolysis product yields, resulting in improving the predictive capacities of the models. In addition, the determination of significant input variables in the modeling of the pyrolysis product yields by hierarchical modeling approach may prevent unnecessary parameter measurements if further addition of a variable does not improve the model performance.

Therefore, in this study, 3 pyrolysis products (BC, BO, and G) yields are simulated by 2 ANN methods (FFN and CFN) using 9 biomass parameters (M, V, F, A, C, H, O, N, and HHV) and 2 pyrolysis process parameters (T and HR) as input variables to models. Systematic or hierarchical models of ANN methods are developed in order to investigate the significant input variables and their contribution order. After preprocessing of the data set (72 samples) by applying normalization, the networks were then trained and tested by using the two-thirds and the one-thirds of the data set, respectively. Finally, the performances of both ANN methods were evaluated visually by plotting and quantitatively by using 3 statistical parameters; coefficient of determination (R^2), root mean square error (RMSE), and mean error (ME).

2. Materials and Methods

2.1. Biomass and Pyrolysis Data

All biomass pyrolysis studies conducted in Turkey between the years 2001 and 2015 and published in the literature (Table 1) were used to gather the data for this modeling study. The database originally had several biomass and pyrolysis process variables such as biomass particle size, cellulose, hemicellulose, lignin, extractives, biomass sample weight, residence time, condenser temperature, carrier gas flow rate in addition to the variables used in this study. After removing the variables with the missing data a total of 14 input and output biomass and pyrolysis process variables (M, V, F, A, C, H, O, N, HHV, HR, T, BC, BO, and G) with a number of 72 samples were used in this study.

2.2. ANN Model Development

A typical ANN consists of many interconnected elements called neurons, nodes, or units which are organized based on a particular architecture. A neuron produces a single output from multiple inputs. The most commonly used connection pattern in ANN is the three-layer or multilayer neural network with input, hidden, and output layers. The data flow starts from the input layer, proceeds through the hidden layer, and ends with the output layer, therefore, the network is called feedforward, where it does not have any feedbacks or parallel connections within a layer of neurons (Haykin, 1994).

The network must be trained or learned first before the application of it to any case to investigate the relationships between input and output data sets. The least squares regression can be used to train output weights by means of error backpropagation method in multilayered neural network architectures. Two different ANN methods (FFN and CFN) were used to train the network in this study.

The general form of the selected FFN architecture and the input and output variables are illustrated in Figure 1.

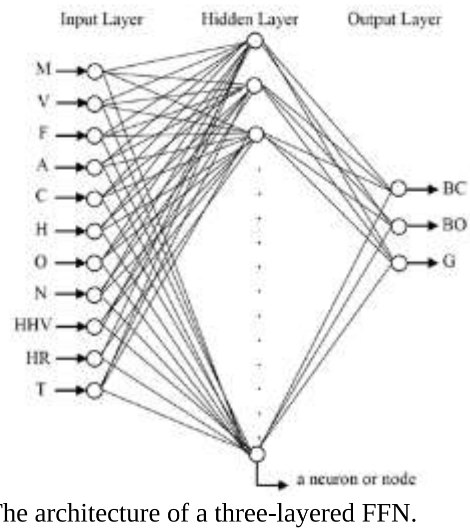

Fig. 1. The architecture of a three-layered FFN.

The total number of neurons in the input and output layers corresponds to the number of input and output variables, respectively. The number of hidden layers and the number of neurons in each hidden layer are usually determined by trial and error procedure until a satisfactory architecture is achieved [56] and MSE (mean square error) values are minimized. Each input neuron of FFN receives one or more inputs, calculates a weighted sum of inputs, and then applies a sigmoid transfer function to produce a unique output [56]. A hidden layer neuron sums up the weighted input received from each input neuron and then passes the result through a nonlinear transfer function. The output layer neurons have the same operation as that of the hidden neurons, resulting in output values predicted by the network. Each input is weighted and combined to produce a unique neuron value, p as:

Table 1. Literature of the data collected from.

Biomass	Biomass Particle Size (mm)	Biomass Sample (g)	Reference
Safflower seed (*Carthamus tinctorius* L.)	0.425-1.25	20	[25]
Sunflower-oil cake	0.425-0.85	5	[8]
Sunflower-pressed bagasse	0.224-0.425	5	[9]
Linseed (*L. Usitatissimum* L.) seed	0.6-1.8	2	[10]
Sesame stalk	0.425-0.85		[26]
Rapeseed (*Brassica napus* L.)	0.425-0.85	10	[27]
Cotton stalk	1.2	40	[28]
Olive residue	1.29	10	[29]
Cottonseed cake		3	[30]
Cottonseed cake		10	[11]
Olive bagasse (*Olea europea* L.)	0.425-0.6		[31]
Soybean cake	0.425-0.85	3	[32]
Safflower seed (*Carthamus tinctorius* L.)	0.85-1.25	3	[12]
Pistacia khinjuk seed (*Carthamus tinctorius* L.)	0.6-0.85	5	[13]
Pistachio shell	1.75	10	[33]
Tobacco residues	0.425-0.85		[34]
Wheat straw	0.5	10	[14]
Apricot pulp	0.85-1.25	10	[35]
Safflower seed press cake	1.8	20	[36]
Rapeseed (*Brassica napus* L.) oil cake	2	116	[37]
Corncob	0.65	10	[38]
Pomegranate (*Punica granatum* L.) seeds	3.2	125	[39]
Corn stalks	0.85-1.25	5	[40]
Laurel (*Laurus nobilis* L.) extraction residues	0.42-0.85	50	[41]
Cotton seed		5	[15]
Tea waste		5	[42]
Tobacco residues		25	[43]
Grape bagasse	0.425-0.600	15	[44]
Cherry seed shell	< 2	100	[16]
Onopordum acanthium L.	0.6-0.85	30	[45]
Walnut shell	1-2	20	[46]
Potato skin	0.8	10	[47]
Black cumin seed cake	> 0.85	10	[48]
Pistachio nut shell		10	[49]
Corncob (*Zea mays* L.)	0.425-0.600	10	[50]
Pine bark (*P. nigra*)	< 2	100	[17]
Pistacia terebinthus L.	0.5-4	10	[51]
Melamine coated chipboard		50	[18]
Pine sawdust	0.752	3	[52]
Apricot kernel shell	0.425-0.600	20	[19]
Cottonseed	0.92	5	[53]
Grape Seeds	< 0.45	25	[54]
Hornbeam shell (*Carpinus betulus* L.)	0.5-1.0	15	[20]
Paulownia wood	0.425-1.0	20	[55]

$$p = \sum_{i=1}^{n} w_i x_i + b \tag{1}$$

where n is the number of inputs, the x_i denotes the input values, and w_i and b refer to the weights and the bias associated with the neuron. The weighted input p is then used to calculate the output value of a neuron, y, in a sigmoidal transfer function, f as:

$$y = f(p) = \frac{1}{1 + e^{-p}} \tag{2}$$

The architecture of a three-layered CFN with an input, output, and hidden layers is displayed in Figure 2. Squares and x's indicate frozen and trained connections, respectively, between the input and output layers. When a new hidden neuron is added to the network, its weights in the input side are frozen.

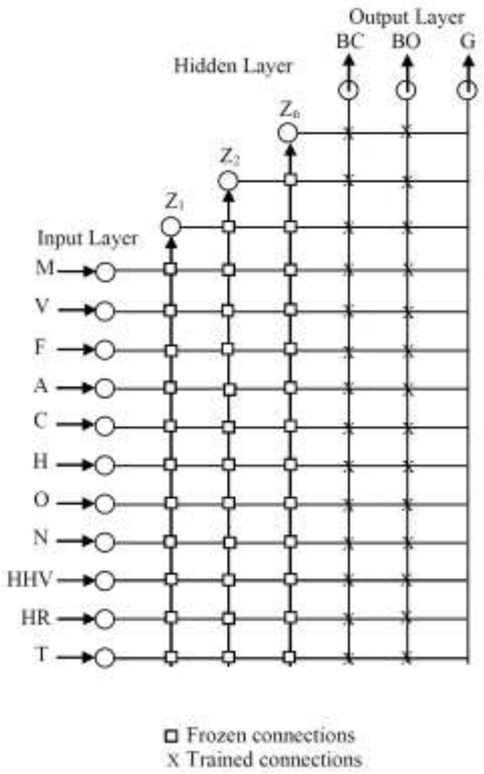

Fig. 2. The architecture of a three-layered CFN.

A new neuron is added and connected to every output and all previous hidden neurons after the output neurons are trained to minimize the total output error. New hidden neurons are continuously added until the maximum correlation between the hidden neurons and error is obtained [57]. CFN has some advantages over FFN: i) CFN begins with only the input and output layer neurons with no hidden layer neuron, then automatically trains and adds new hidden neurons one by one until the optimum network results are obtained in the CFN, whereas FFN has a fixed topology, ii) CFN has a very fast training time, making CFN suitable for large training sets, iii) CFN has less neurons than a dozen in the hidden layer, iv) CFN training produces good results with little or no parameter adjustments, v) The neurons of each subsequent layer have inputs from not only the previous layers but also input layer, leading to more interconnections than FFN [57].

Both ANN methods (FFN and CFN) are multilayer and feed-forward and use the Levenberg-Marquardt (LM) back-propagation (BP) algorithm for learning or training. In both ANN methods, hierarchical modeling approach was utilized by adding variables one by one to the model to determine how variance in the dependent or output variable can be explained by adding one or more independent or input variables. The number of neurons in the input and output layers of both methods corresponds to the number of input and output variables, respectively, whereas the number of hidden layers and the number of neurons in each layer were determined by trial and error. Initially, the input and output data was normalized as a preprocessing procedure with the mean of zero and the standard deviation of 1 before being evaluated by ANN methods. Then the two-third and the one-third of the samples were used in training and testing of both ANN methods, respectively. The training data was formed by the MATLAB program by skipping every third sample of the data. Neural network toolbox of the MATLAB^{TM} package (version 7.10, MathWorks, Inc., USA) were used in training and testing of all ANN models.

2.3. Evaluation of ANN Model Performance

The performances of ANN models in predicting pyrolysis product yields from different biomass and pyrolysis process parameters were evaluated using the following statistical parameters: coefficient of determination (R^2), the root mean square error (RMSE), and mean error (ME), where each of these statistical parameters uses the differences between the measured and predicted values, and defined as:

$$R^2 = 1 - \frac{\sum_{1}^{N} (M_i - P_i)^2}{\sum_{1}^{N} \left(M_i - \overline{M}_i\right)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{1}^{N} (M_i - P_i)^2}{N}} \tag{4}$$

$$ME = \frac{\sum_{1}^{N} (M_i - P_i)}{N} \tag{5}$$

where M_i indicates the measured value, P_i refers to the predicted value, i = 1, 2, 3,….., N, $\overline{M}$ represents the average of the measured values, and N is the total number of observations. The values of R^2 change between 0 and 1 with the ideal value of 1, whereas the range of RMSE values is 0-(+∞) with the ideal value of 0, corresponding to a perfect matching between the measured and predicted data. Under- and over-prediction of a model for a given parameter are represented by negative and positive values of ME, respectively. The prediction results of two methods (FFN and CFN) were also visually analyzed by plotting sample number versus measured and predicted, and measured versus predicted values of BC, BO, and G.

3. Results and Discussion

Biomass characteristics of the experimental studies conducted in the literature, where the data used in this study are collected from, are presented in Table 1. A wide range of biomass types from herbaceous to lignocellulosic are used in these studies. Biomass particle size also has wide range between 0.224 and 4 mm. Biomass sample weight changes between 2 and 125 g, but 19 of 41 samples are either 5 or 10 g. All experimental studies are conducted in a fixed-bed reactor except the two which are conducted in a free-fall reactor (not shown in Table 1).

The descriptive statistics of biomass and pyrolysis process and product data used in the training and testing of two ANN methods are tabulated in Table 2. Input data have relatively large variations in especially the variables of T (400-800ºC), HR (5-800 ºC min^{-1}), HHV (14.18-41.55 MJ kg^{-1}), O (10.49-52.26%), C (41.78-79.77%), and F (0.10-70.11%). Pyrolysis products data (BC, BO, and G) have also wide ranges; 8-52%, 10-55%, and 4.10-47%, respectively (Table 2). The large variations in biomass type, biomass particle size, and biomass sample weight, or experimental system configuration used for pyrolysis experiments in Turkey (Table 1) may cause these large variations in the biomass features, pyrolysis process parameters, and product distributions.

Table 2. Descriptive statistics of the biomass and pyrolysis data used in the training and testing of the FFN and CFN methods.

Input variables	Acronym	Unit	Minimum	Maximum	Mean	SD*
Moisture	M	%	2.28	10.74	6.84	1.849
Volatile Organic Carbon	V	%	9.69	85.55	74.81	9.355
Fixed Carbon	F	%	0.10	70.11	13.79	7.953
Ash	A	%	0.38	19.90	4.81	3.706
Carbon	C	%	41.78	79.77	52.68	6.402
Hydrogen	H	%	4.95	10.15	6.80	1.377
Oxygen	O	%	10.49	52.26	37.96	8.198
Nitrogen	N	%	0.15	9.29	2.51	2.028
Higher Heating Value	HHV	MJ kg^{-1}	14.18	41.55	21.30	4.859
Heating Rate	HR	ºC min^{-1}	5	800	111	181
Temperature	T	ºC	400	800	5230	86
Output variables						
Biochar	BC	%	8.00	52.00	27.20	7.892
Bio-oil	BO	%	10.00	55.00	32.24	11.654
Gases	G	%	4.10	47.00	26.79	8.280

*SD: Standard deviation.

The parameters used in both FFN and CFN methods and their values are given in Table 3.

Table 3. The parameters of FFN and CFN methods.

Parameters	Value
Network type	FFN and CFN
Number of input layer neurons	1 to 11
Number of hidden layer	2
Number of hidden layer neurons	10, 10
Number of output layer neuron	3
Transfer function	TANSIG
Training function	TRAINLM
Performance function	MSE
Learning cycle	1000 Epochs
Goal	0.000001
Max_fail	15
Mu_inc	10
Mu_dec	0.1
Mu	0.1

*FFN: Feed-Forward Network, CFN: Cascade-Forward Network, TANSIG: Tangent Sigmoid, TRAINLM: Training Levenberg-Marquardt, MSE: Mean Square Error.

The number of neurons in the input layers varied from 1 to 11 as the number of input variables (M, V, F, A, C, H, O, N, HHV, HR, and T) changed in hierarchical modeling, whereas the output layers had 3 neurons corresponding to the output variables BC, BO, and G. The number of hidden layers and the number of neurons in each hidden layer were determined by trial and error procedure in order to minimize the MSE values, resulting in 2 layers and 10 neurons in each layer of both methods. The overfitting problem during the training of both methods was controlled by using optimum number of hidden layers and neurons in the hidden layers. Tangent sigmoid (TANSIG) was used as the transfer function, whereas the training Levenberg-Marquardt (TRAINLM) was selected as the training function. MSE was used as the performance function and its goal value was set as 0.000001. Learning cycle was set 1000 epochs.

The values of model performance evaluation for the training and testing of the FFN and CFN methods are displayed in Table 4. For the training of FFN, in general, the models 1 through 9 simulated BO the best, BC the worst, and G between the two, with almost constant R^2 of 0.96, 0.91, and 0.95, respectively. However, the models 10 and 11 had perfect training performances with the R^2 of 1.00. The ME values of all models were zero, indicating a perfect model performance. For testing of FFN, in general, the models were the best, the worst, and between the two, in the simulation of BO, G, and BC, respectively, with the mean R^2 of 0.49, 0.31, and 0.42, respectively. The RMSE and ME values of all models increased significantly compared to that of training, indicating the worse model performance. In addition, almost all models under-predicted BC and over-predicted BO and G, where ME values were negative and positive, respectively (Table 4).

For the training of CFN, the same performances as the FFN training were observed in the simulation of BO, BC, and G with the same R^2 of 0.96, 0.91, and 0.95, respectively (Table 4). The training performances of the models 10 and 11 were perfect with the R^2 of 1.00. All models except the last one had zero values of ME, indicating a perfect model performance. For testing of CFN, in general, the models were the best, the worst, and between the two, in the simulation of BO, G, and BC, respectively, with the mean R^2 of 0.51, 0.32, and 0.37, respectively. The RMSE and ME values of all models increased significantly compared to that of training, indicating the worse model performance. In addition, similar to FFN, almost all models under-predicted BC and over-predicted BO and G (Table 4).

In general, both FFN and CFN models had very similar performances in training and testing for the simulation of BC, BO, and G as seen in Table 4. For testing, even though the addition of the input variables to the models improved the performances of the FFN and CFN models for BO simulation, no clear trend was observed in both methods for the simulation of BC and G. The R^2 values of BC and G for testing of the all FFN and CFN models were less than 0.50, but the R^2 values of BO were over 0.50 for only the last five models of FFN and CFN. Overall, the models 11 and 8 were the best in the training and testing of FFN and CFN, respectively, indicating that the addition of the last 3 input variables (HHV, HR, and T), in general, did not improve the performances of CFN models for the simulation of BC, BO, and G. Overall, the best FFN model was slightly better than the best CFN model in the simulations of BC, BO, and G (Table 4). In general, the FFN and CFN methods simulated BO acceptably well-enough, but they had some problems in the simulations of BC and G.

Measured and predicted values of pyrolysis products versus sample number for the best models of FFN (model 11) and CFN (model 8) are presented in Figure 3.

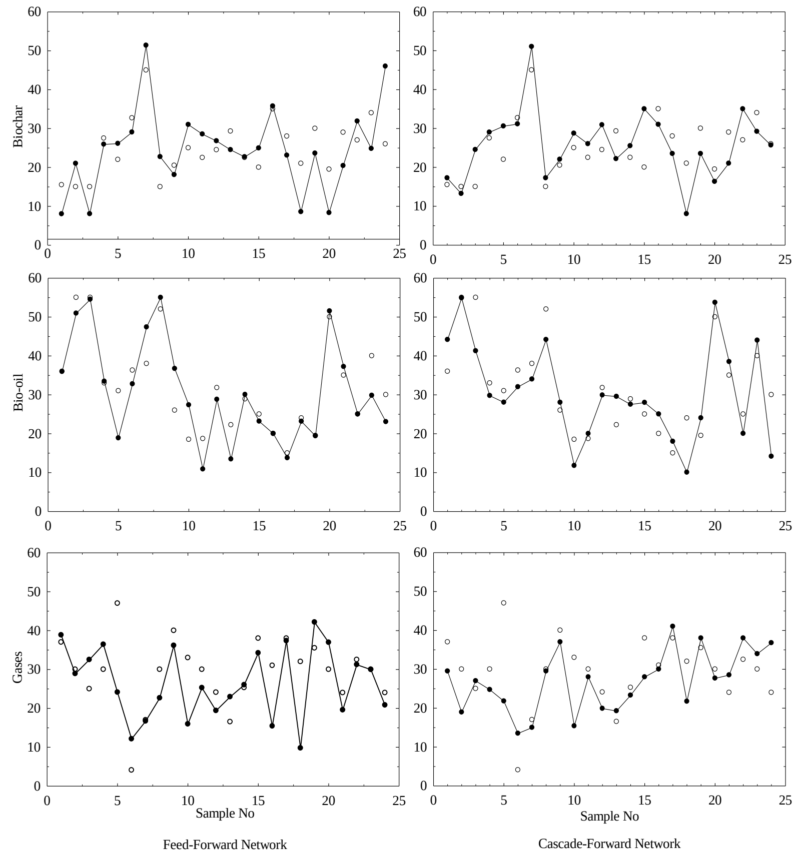

Fig 3. Measured (empty circle) and predicted (solid circle line) values of pyrolysis products versus sample number for the best models of FFN (model 11) and CFN (model 8).

The quantitative results (R^2 values) of BC, BO, and G for the FFN and CFN methods correspond to the visual results, where less scattering between the measured and predicted BO points are observed compared to that of BC and G points. Measured versus predicted values of pyrolysis products for the best FFN and CFN models are shown in Figure 4. Less scattering of the measured versus predicted BO points around a hypothetical line, which is crossing the origin to the right corner of the plots, indicates that the FFN and CFN methods are good at the predictions of BO compared to the predictions of BC and G.

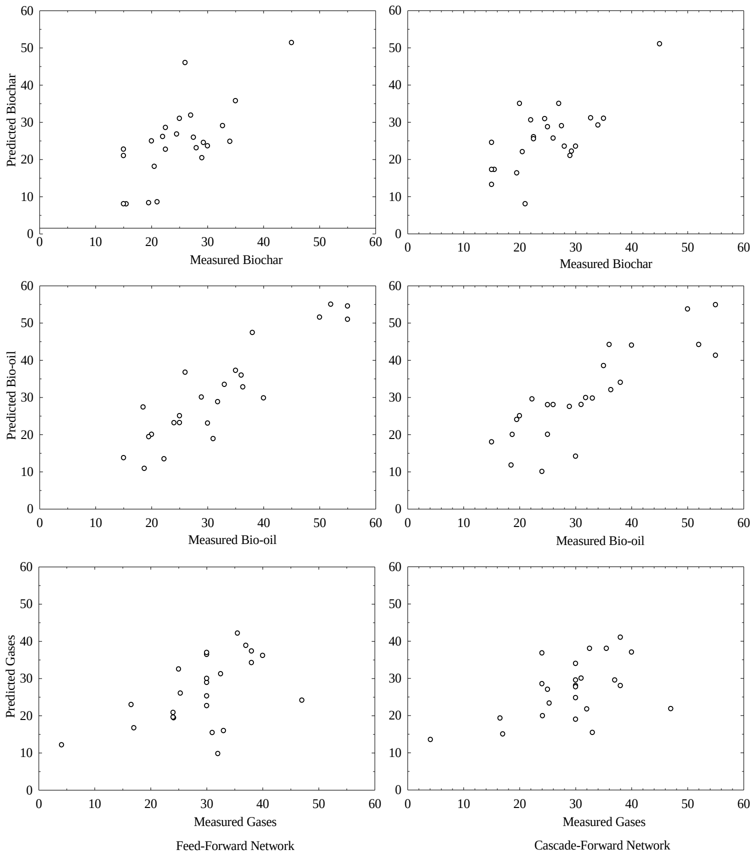

Fig. 4. Measured versus predicted values of pyrolysis products for the best models of FFN (model 11) and CFN (model 8).

[21] predicted pyrolysis kinetic parameters (activation energy, pre-exponential factor, and reaction order) separately from biomass components (cellulose, hemicellulose, and lignin). A total of 150 thermogravimetric analysis (TGA) results obtained from different biomass components were used to develop and test the networks. The relationships between the biomass components and pyrolysis kinetic parameters were non-linear and predicted by the ANN models with $R^2 > 0.9$. The number of hidden layers was 20, 17, and 30 for log k_0, log E_a, and log n, respectively. [22] predicted biomass (cotton shell) pyrolysis products (bio-oil, biochar, and gas) yields from pyrolysis process parameters (biomass particle size, pyrolysis temperature, and carrier gas flow rate) by using ANN. After normalizing all the input and out data, 80 and 20% of the data were used for training and testing of the ANN models. The ANN model structure was 3-10-3 with input, hidden, and output neurons, respectively. The ANN models predicted the yields of bio-oil, biochar, gas with R2 of 0.9914, 0.9978, and 0.9969, respectively. [23] predicted pyrolysis gas yields such as H_2, CO, CH_4, and CO_2% from pyrolysis process parameters like biomass (pine sawdust) particle size, temperature, and space velocity by using ANN. The ANN model had the neurons of 3, 7, and 4 for input, hidden, and output layers, respectively. There was a good agreement between the measured and simulated results. [24] predicted biomass (cotton, tea, olive, and hazelnut) pyrolysis products yields (solid, liquid, and gas) from pyrolysis temperature and biomass characteristics (cellulose, hemicellulose, lignin, moisture, volatiles, fixed carbon, and ash) through ANN modeling. The ANN model had 8 input neurons/parameters, 9 hidden neurons, and 3 output neurons/parameters. The model had high accuracy in the predictions during training and testing with R values of 0.9999 and 0.9941, respectively. The performances of the ANN models in the literature mentioned previously in training were very similar to that of this study. However, in general, the models had relatively better performances in the predictions of the product yields during testing. Using larger experimental data set produced in the controlled experimental conditions, leading to more homogeneous data, may cause such a difference in the ANN performances in the favor of their studies. Specifically, the studies in the literature with single or a few biomass types and therefore their more homogeneous features in addition to the controlled pyrolysis process conditions may result in somewhat better performances of the ANN models compared to the study presented here. Besides, the input variables may be more related with the output variables in their studies. For instance, it is interesting that [22] produced better results even with the smaller data set, may be due the fact that more homogeneous data with more related input and output variables may give favor to that study.

Table 4. The values of evaluation parameters of the FFN and CFN methods.

Feed-forward network

Model	Inputs	Outputs	Training			Testing		
			R^2	RMSE	ME	R^2	RMSE	ME
1	M	BC, BO, G	0.90, 0.96, 0.93	2.50, 2.46, 2.08	0.00, 0.00, 0.00	0.41, 0.13, 0.28	8.36, 13.82, 8.87	-3.18, -1.80, 2.19
2	M, V	BC, BO, G	0.90, 0.96, 0.95	2.50, 2.46, 1.68	0.00, 0.00, 0.00	0.47, 0.42, 0.34	6.72, 9.89, 7.35	-1.66, 0.71, 1.51
3	M, V, F	BC, BO, G	0.90, 0.96, 0.95	2.50, 2.46, 1.68	0.00, 0.00, 0.00	0.35, 0.19, 0.34	8.53, 12.12, 7.65	-2.17, 0.29, 1.10
4	M, V, F, A	BC, BO, G	0.90, 0.96, 0.95	2.50, 2.46, 1.68	0.00, 0.00, 0.00	0.45, 0.25, 0.35	7.80, 11.53, 7.90	-3.77, 1.96, 3.10
5	M, V, F, A, C	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.34, 0.47, 0.23	8.36, 9.25, 9.12	-4.26, 0.21, 2.82
6	M, V, F, A, C, H	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.36, 0.49, 0.35	8.50, 8.78, 7.57	-3.74, 0.31, 2.28
7	M, V, F, A, C, H, O	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.44, 0.64, 0.32	6.27, 7.32, 7.73	-1.90, 1.63, 1.77
8	M, V, F, A, C, H, O, N	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.43, 0.80, 0.28	6.84, 5.38, 8.60	-2.83, 1.19, 3.12
9	M, V, F, A, C, H, O, N, HHV	BC, BO, G	0.92, 0.99, 0.97	2.30, 1.37, 1.33	0.00, 0.00, 0.00	0.45, 0.61, 0.46	7.37, 8.16, 7.38	-2.72, 1.72, 1.01
10	M, V, F, A, C, H, O, N, HHV, HR	BC, BO, G	1.00, 1.00, 1.00	0.12, 0.20, 0.10	0.00, 0.00, 0.00	0.41, 0.60, 0.25	9.14, 8.31, 9.67	-3.57, 1.20, 1.70
11	M, V, F, A, C, H, O, N, HHV, HR, T	BC, BO, G	1.00, 1.00, 1.00	0.03, 0.04, 0.03	0.00, 0.01, 0.00	0.49, 0.81, 0.26	7.44, 5.71, 9.16	0.43, 1.00, 2.87

Cascade-forward network

Model	Inputs	Outputs	Training			Testing		
			R^2	RMSE	ME	R^2	RMSE	ME
1	M	BC, BO, G	0.90, 0.95, 0.95	2.57, 2.47, 1.68	0.00, 0.00, 0.00	0.40, 0.17, 0.30	9.03, 13.98, 8.91	-3.60, -0.76, 1.77
2	M, V	BC, BO, G	0.90, 0.96, 0.95	2.50, 2.46, 1.68	0.00, 0.00, 0.00	0.45, 0.40, 0.30	7.19, 10.59, 7.82	-2.09, 0.65, 0.53
3	M, V, F	BC, BO, G	0.90, 0.96, 0.95	2.50, 2.46, 1.68	0.00, 0.00, 0.00	0.44, 0.30, 0.38	7.79, 10.71, 7.53	-4.22, 0.69, 2.24
4	M, V, F, A	BC, BO, G	0.90, 0.96, 0.95	2.50, 2.46, 1.68	0.00, 0.00, 0.00	0.42, 0.58, 0.44	7.72, 7.54, 6.93	-3.22, 0.84, 2.17
5	M, V, F, A, C	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.27, 0.44, 0.26	8.86, 9.57, 8.23	-4.05, 0.37, 1.96
6	M, V, F, A, C, H	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.44, 0.43, 0.35	7.20, 10.09, 7.37	-2.78, 0.20, 1.22
7	M, V, F, A, C, H, O	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.34, 0.60, 0.29	7.23, 7.86, 8.25	-1.77, 2.24, 0.66
8	M, V, F, A, C, H, O, N	BC, BO, G	0.91, 0.96, 0.95	2.41, 2.40, 1.67	0.00, 0.00, 0.00	0.46, 0.72, 0.27	6.38, 6.64, 8.53	-0.66, 1.49, 2.40
9	M, V, F, A, C, H, O, N, HHV	BC, BO, G	0.92, 0.99, 0.97	2.30, 1.37, 1.33	0.00, 0.00, 0.00	0.15, 0.54, 0.31	10.33, 9.22, 10.16	-2.43, 0.53, 4.58
10	M, V, F, A, C, H, O, N, HHV, HR	BC, BO, G	1.00, 1.00, 1.00	0.12, 0.20, 0.10	0.00, 0.00, 0.00	0.34, 0.76, 0.30	10.67, 6.92, 9.78	2.64, 2.02, 0.43
11	M, V, F, A, C, H, O, N, HHV, HR, T	BC, BO, G	1.00, 1.00, 1.00	0.05, 0.02, 0.01	-0.01, -0.01, 0.00	0.40, 0.70, 0.28	9.33, 6.73, 9.44	0.38, 0.21, 1.09

*M: Moisture (%), V: Volatile Organic Carbon (%), F: Fixed Carbon (%), A: Ash (%), C: Carbon (%), H: Hydrogen (%), O: Oxygen (%), N: Nitrogen (%), HHV: Higher Heating Value (MJ kg^{-1}), HR: Heating Rate (ºC min^{-1}), T: Temperature (ºC), BC: Biochar (%), BO: Bio-oil (%), G: Gases (%), R^2: Coefficient of Determination, RMSE: Root Mean Square Error, ME: Mean Error. Note: Statistical values for training and testing of both feed-forward and cascade-forward networks refer to BC, BO, and G,

4. Conclusions

This study presented the application of two ANN methods (FFN and CFN) in the modeling of pyrolysis product yields (BC, BO, and G) using 9 biomass and 2 pyrolysis process parameters as input variables to the models. In general, FFN and CFN methods had very similar performances in training and testing. Both methods were trained with good performances, but they were not good enough in testing of especially BC and G. Hierarchical modeling approach showed that there was no clear trend in the contribution order of the input variables to the models in testing of BC and G except BO, indicating that a few related variables may be used in the modeling of BC and G rather than using all of them.

The study results suggest that the ANN models are easy-to-use modeling tools for pyrolysis process modelers with no a priori knowledge of the relationships between input and output variables. In addition, they can easily be utilized compared to the other modeling techniques in the modeling of complex, nonlinear, and limited biomass and pyrolysis data. The potential of both ANN methods is worthy to be investigated further by applying to a larger data set produced from limited biomass types under the controlled pyrolysis process conditions. Such a study may help developing more case-specific models to use in pyrolysis modeling studies.

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Conflict of Interest

The author declares that there is no conflict of interest.

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