POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

Modeling of bio-oil production by pyrolysis of woody biomass: artificial neural network approach

Odunsu biyokütlenin pirolizi ile biyoyağ üretiminin modellenmesi: yapay sinir ağları yaklaşımı

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Bu makaleye şu şekilde atıfta bulunabilirsiniz (To cite to this article): Özbay G and Kokten E. S., "Modeling of bio-oil production by pyrolysis of woody biomass: artificial neural network approach", ***Politeknik Dergisi***, 23(4): 1255-1264, (2020).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: **10.2339/politeknik.659136**

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Highlights

- *This paper is dedicated to developing an ANN model in order to model the pyrolysis liquid product*
- *Artificial neural networks (ANNs) have been widely used in the field of process simulation as a result of its ability to solve complex and multivariable problems.*
- *Pyrolysis is a thermal decomposition process converting biomass into char (solid), bio-oil (liquid), and gas products*

Graphical Abstract

This study is dedicated to developing a reliable artificial neural network (ANN) model to model the pyrolysis liquid product (bio-oil).

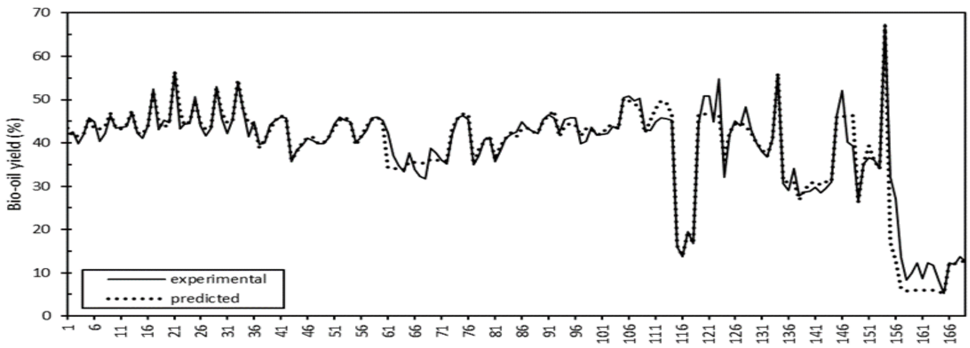

Figure. Comparison of the experimental data with the predicted results

Aim

In this study, it is aimed to model the pyrolysis liquid product using the ANN method. Due to the different characteristics of different biomass types and pyrolysis methods, only slow and intermediate pyrolysis data from woody biomass were considered in order to attain more homogeneous features

Design & Methodology

ANN model development procedures, materials, and bio-oil production conditions are described in Section 3. Developed ANN model.

Originality

Artificial neural networks (ANNs) have been widely used in the field of process simulation as a result of its ability to solve complex and multivariable problems. By using the ANN method, it is possible to optimize the input parameters in order to increase the production of bio-oil.

Findings

The relative impact results revealed that the most important parameter that affects the bio-oil yield was catalyst type (11.4%).

Conclusion

It can be concluded that it is possible to reduce the number of the required pyrolysis experiments by the developed ANN model.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Modeling of Bio-Oil Production by Pyrolysis of Woody Biomass: Artificial Neural Network Approach

Research Article / Araştırma Makalesi

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(Geliş/Received : 13.12.2019 ; Kabul/Accepted : 23.12.2019)

ABSTRACT

This study is dedicated to developing a reliable artificial neural network (ANN) model to model the pyrolysis liquid product (bio-oil). Some related parameters with the bio-oil yield such as the pyrolysis temperature, duration, catalyst type, catalyst ratio, particle size, proximate, and ultimate analysis of the biomass were tested. Due to the different characteristics of different biomass types and pyrolysis methods, only slow and intermediate pyrolysis data from woody biomass were used in modeling. The correlation coefficients (R) were 0.992, 0.933, and 0.951 for training, validation, and testing, respectively. In order to evaluate the predictability of the ANN model, the predicted results were compared with the experimental results that were not introduced before. The simulated data were in good agreement with the experimental results indicating the reliability of the developed model. The relative impact results revealed that the most important parameter that affects the bio-oil yield was catalyst type (11.4%).

Keywords: Artificial neural network, bio-oil, catalyst, modeling, pyrolysis.

Odunsu Biyokütlenin Pirolizi ile Biyoyağ Üretiminin Modellenmesi: Yapay Sinir Ağları Yaklaşımı

ÖZ

Bu çalışma, piroliz sıvı ürününü (biyoyağ) modellemek için güvenilir bir yapay sinir ağı (YSA) modeli oluşturmak amacıyla yapılmıştır. Bu maksatla piroliz sıcaklığı, piroliz süresi, katalizör türü, katalizör oranı, biyokütle parçacık boyutu ve biyokütle kısmi ve kesin analizi gibi biyoyağ verimliliği ile ilgili parametreler test edilmiştir. Modellemede, farklı biyokütle tiplerinin ve piroliz yöntemlerinin neden olduğu farklı karakteristiklerden dolayı, yalnızca odunsu biyokütleden yavaş ve orta piroliz yöntemleri ile elde edilen sıvı ürün verimlilikleri dikkate alınmıştır. Sonuç olarak, korelasyon derecesini gösteren R değerleri eğitim, doğrulama ve test adımları için sırasıyla 0.992, 0.933 ve 0.951 bulunmuştur. YSA modelinin güvenilirliğini değerlendirmek amacıyla tahminlenen değerler, daha önce modele tanıtılmamış yeni deneysel veriler ile kıyaslanmıştır. Buna göre, simülasyon sonuçlarının deneysel sonuçlar ile uyum içerisinde bulunduğu ve oluşturulan modelin güvenilir olduğu tespit edilmiştir. Ayrıca, girdi parametrelerinin çıktı üzerine etkileri incelendiğinde, biyoyağ verimliliğini etkileyen en önemli parametrenin katalizör türü (%11.4) olduğu belirlenmiştir.

Anahtar kelimeler: Yapay sinir ağları, biyoyağ, katalizör, modelleme, piroliz.

1. INTRODUCTION

Every year, large quantities of wood waste are generated by wood-products industries. Recently, the conversion of biomass residues to value-added products has received considerable interest [1-3]. Pyrolysis is a thermal decomposition process converting biomass into char (solid), bio-oil (liquid), and gas products [4, 5]. The bio-oil produced from biomass pyrolysis can be used to produce fuels and chemical products [6-8]. The yield of bio-oil is affected by various factors, including pyrolysis conditions, properties of biomass, the addition of catalyst and pyrolysis method [9, 10]. The pyrolysis of biomass is a very complex process due to the multivariable factors that affect the yield of bio-oil. It is essential to simulate the pyrolysis process considering the high cost of large-scale experimental tests and time consuming of these experiments. Artificial neural networks (ANNs) have been widely used in the field of process simulation as a result of its ability to solve complex and multivariable problems. By using the ANN method, it is possible to optimize the input parameters in order to increase the production of bio-oil which have the potential to produce fuels and chemicals.

This paper is dedicated to developing an ANN model in order to model the pyrolysis liquid product. The rest of this paper is organized as follows: A literature review and contribution to literature in the field is given in Section 2. Biomass and pyrolysis data selection from previous studies of literature, ANN model development procedures, materials, and bio-oil production conditions are described in Section 3. Developed ANN model, the relative impact of each input parameter, and accuracy testing of ANN with new pyrolysis runs are discussed in Section 4. Finally, the conclusions are shown in Section 5.

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2. LITERATURE REVIEW

In this section, the studies on modeling of processes such as pyrolysis and gasification were reviewed in the recent literature. The main objectives of these type of researches vary in increasing or estimating the product (liquid, gas, and char) yields, determine the effects of input parameters, prediction of outputs such as heating value, hydrogen-rich gas, kinetic parameters, and thermal behaviors. In the literature, there are studies on process modeling using the ANN [11-13], support vector machine (SVM) [14, 15], response surface methodology (RSM) [16-18], and regression analysis [19] methods.

Recently, the ANN has received attention in the modeling of production methods mentioned above. In this way, it is possible to reduce the number of required experiments. The ANN method is also widely used to solve non-linear and complex problems [20, 21]. Puig-Arnavat and co-workers [22] used the ANN for modeling the biomass gasification process. They found that the proposed ANN presented good performance to predict the process parameters.

In literature summary, we reviewed studies on modeling of different outputs (liquid, gas, and char yields, hydrogen-rich gas, heating value etc.) obtained from various feedstocks (wood and animal waste, agricultural residues, scrap tyres, plastic etc.). Table 1a and Table 1b present the literature contributions in this field. The use of wood waste [15, 23-26] and agricultural residues [16, 17, 27, 28] as feedstock are common in the literature due to its low market value and availability [29, 30].

The related variables with output can be used to reach more accurate results. Merdun and Sezgin [24] reported that the models in more homogeneous characteristics (single or a few biomass types) and more related inputs with output may result in better performances. Aydinli et al. [27] specified that in order to attain the more reliable models, the variables such as particle size and residence time as well as the ultimate analysis data can be considered as input parameters. The yields and

Table 1a. Literature summary: Characteristics of the studies on modeling of products from feedstock

Literature[a]	Feedstock (Data)				Process			Considered output			
	Wood waste	Agricultural residues	Animal waste	Other	Slow and intermediate pyrolysis	Fast pyrolysis	Other	Liquid	Gas	Char	Other
[16]		√			…	…		√			
[17]		√			…	…		√		√	
[27]		√			…	…		√	√	√	
[14]			√		√					√	
[15]	√	√				√		√	√	√	√[b]
[30]	√	√					√[c]		√[d]		
[11]	√	√	√				√[e]		√[f]		
[28]		√				√					√[g]
[23]	√	√			…	…		√			
[12]		√					√[h]	√	√	√	
[24]	√	√			√	√		√	√	√	
[19]		√					√[i]				√[b]
[18]	√			√[j]	…	…		√			
[22]	√						√[c]		√[d]		
[25]	√				…	…			√[k]		
[13]	√	√	√	√[l]	…	√					√[m]
[26]	√	√			√					√	
[20]				√[n]	…	…					√[o]
This study	√				√			√			

a: The symbol "√" refers to a defined characteristic. Triple dot "…" means the pyrolysis method is unspecified
b: Heating value
c: Gasification
d: Gas composition
e: Digestion
f: Specific biogas production
g: Hydrogen-rich gas
h: Flash pyrolysis
i: Proximate & ultimate analysis
j: Scrap tyres & recycled plastic
k: Gas products
l: Pure & mixed pure components
m: Kinetic parameters
n: Refuse-derived fuel
o: Temperature dependent weight loss

Table 1b. Literature summary: Modeling approaches of the studies

Literature[a]	Method				Inputs/Parameters													
	ANN	RSM	SVM	Other	Moisture	Ash content	Volatiles	Fixed carbon	Main components[b]	Elemental composition	Particle size	Catalyst type	Catalyst ratio	Heating rate	Temperature	Duration	Equivalence ratio	Other
[16]		√									√				√	√		√[c]
[17]	√	√												√	√			
[27]	√				√	√	√	√	√						√			
[14]	√		√		√									√	√	√		√[d]
[15]	√		√		√	√				√	√				√			√[e]
[30]	√				√	√				√					√		√	
[11]	√														√	√		√[f]
[28]	√											√	√		√			√[g]
[23]				√[h]	√	√	√	√		√								√[i]
[12]	√										√				√			√[c]
[24]	√				√	√	√[j]	√		√				√	√			√[i]
[19]				√[k]		√	√	√		√								
[18]		√													√	√		√[l]
[22]	√				√	√				√					√		√	√[m]
[25]	√										√				√			√[n]
[13]	√								√									
[26]				√[o]		√			√									√[p]
[20]	√													√	√			
This study	√				√	√	√	√		√	√	√	√		√	√		

a: The symbol "√" refers to a defined characteristic
b: Main components include cellulose, hemicellulose and lignin
c: Sweep gas flow rate
d: Sample mass
e: Fluidization number
f: Feedstock composition
g: Feedstock type
h: An approach to predict pyrolysis output based on the feedstock element characteristic
i: Heating value
j: Volatile organic carbon
k: Multiple regression analysis
l: Initial pressure
m: Steam to dry biomass ratio
n: Space velocity
o: A prediction model based on inputs
p: Extractives

composition of the products depend on the pyrolysis conditions, properties of biomass, and pyrolysis method. The parameters that affect the pyrolysis products are particle size, heating rate, pyrolysis temperature, holding time (duration), feedstock type, and the addition of catalyst [31-33]. The various types of catalysts are used in pyrolysis process to improve the quality of the pyrolysis liquid product [34-37]. Zhao and Li [38] examined the impact of catalyst (NaCl) additives on pyrolysis bio-oil. They reported that the quality of bio-oil was enhanced with the addition of the catalyst, because of its higher heating value and lower acidity.

There is still a need for research on process modeling using catalysts as an input parameter. In this study, it is aimed to model the pyrolysis liquid product using the ANN method. Due to the different characteristics of different biomass types and pyrolysis methods, only slow and intermediate pyrolysis data from woody biomass were considered in order to attain more homogeneous features. The pyrolysis temperature, duration, catalyst type, catalyst ratio, particle size, proximate and ultimate analysis of the biomass were used as the ANN model inputs, whilst the bio-oil yield was obtained as the output.

3. MATERIAL AND METHOD

Within the activity field of the present study, two related parts are included. In the first part, an ANN model was developed in order to predict the bio-oil yield. In this way, pyrolysis temperature, duration, catalyst type, catalyst ratio, particle size, proximate, and ultimate analysis of the biomass were considered as the model inputs, whilst the bio-oil yield was obtained as the output. In the second part, pyrolysis experiments that were not introduced before were carried out to create new data. Afterward, experimental results were compared with predicted values.

3.1. Biomass and Pyrolysis Data Selection

In the current study, the data that were utilized to create the ANN models were selected from previous studies of literature on biomass pyrolysis. Table A1 (see appendix) summarizes the biomass type, particle size, catalyst type, catalyst ratio, temperature, and duration of the selected data. The data were all selected from slow and intermediate pyrolysis of woody biomass in order to attain the more homogeneous features.

The biomass characteristics that were used to develop the ANN models in the present study were moisture content, ash content, volatiles, fixed carbon, carbon content, oxygen content, hydrogen content, and particle size. The operating conditions of the pyrolysis runs included the temperature, duration, catalyst type, and catalyst ratio.

3.2. ANN Development

Due to its ability to model complex linear and nonlinear input-output correlations, ANN method was used to predict the pyrolysis bio-oil yield [39]. As shown in Figure 1, the ANN architecture proposed in the current study is composed of one input layer, one hidden layer, and one output layer. Twelve input neurons represent twelve inputs including moisture content, ash content, volatiles, fixed carbon, carbon content, oxygen content, hydrogen content, particle size, catalyst type, catalyst ratio, temperature, and duration in the input layer of the network. One output neuron in the output layer reflects the bio-oil yield which is the dependent parameter of the model. The number of hidden neurons and transfer functions were determined by trying 4-20 neurons and tan-sigmoidal (*tansig*), log-sigmoidal (*logsig*) and linear (*purelin*) transfer functions in order to attain the best neural network model.

The feedforward backpropagation neural network which tries to minimize the error between the experimental and predicted values was applied in the current ANN modeling. In the neural network model Levenberg-Marquardt (*trainlm*) algorithm was used as learning algorithm. The ANN model was developed using the editor in MATLAB® R2018b software. All the data were separated using *dividerand* function for training, validation, and testing as 70% (total of 119), 15% (total of 25), and 15% (total of 25), respectively. The data collected from the literature were used for training, validation, and testing procedures. Another test was applied to check the accuracy of the developed model with data obtained from pyrolysis experiments. All the data (input and output) were normalized in the range of [0.1, 0.9] before the ANN model development. The normalized values were calculated according to Eq. (1);

$$v_n = 0.8 \times \left[\frac{v - v_{min}}{v_{max} - v_{min}} \right] + 0.1 \tag{1}$$

where v_n is the normalized value, v is the original value, v_{max} and v_{min} are the maximum and minimum values of v, respectively.

The errors of the ANN models during the training, testing, and validation periods is expressed as mean squared error Eq. (2) and mean absolute percentage error Eq. (3);

$$MSE = \frac{1}{n}\left[\sum_{i=1}^{n} \left(\alpha_i - \beta_i \right)^2 \right] \tag{2}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| \alpha_i - \beta_i \right|}{\alpha_i} \times 100 \tag{3}$$

where *MSE* is the mean squared error, *MAPE* is the mean absolute percentage error, α_i is the experimental values, and β_i is the predicted values.

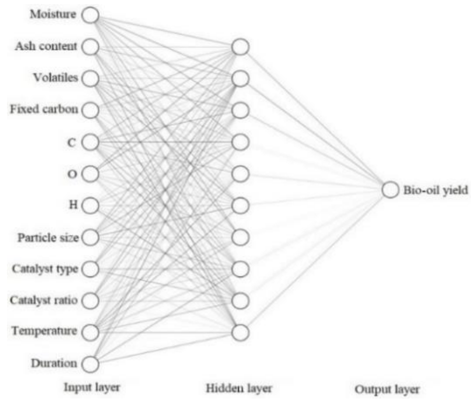

Figure 1. The developed ANN model to predict the pyrolysis bio-oil yield

3.3. Relative Impact of Each Input Parameter

The ANN weight matrix and Garson's equation were used in order to calculate the relative impact of the inputs on bio-oil yield [40]. The mentioned equation is shown in Eq. (4);

$$I_i = \frac{\sum_{j=1}^{j=n} \left(\left(\frac{\left| IW_{j,i} \right|}{\sum_{i=1}^{i=12} \left| IW_{i,j} \right|} \right) \times \left| LW_{1,j} \right| \right)}{\sum_{i=1}^{i=12} \left(\sum_{j=1}^{j=n} \left(\left(\frac{\left| IW_{j,i} \right|}{\sum_{i=1}^{i=12} \left| IW_{j,i} \right|} \right) \times \left| LW_{1,j} \right| \right) \right)} \tag{4}$$

where I_i is the relative impact of the i^{th} input on the output, n is the number of hidden neurons, $IW_{j,i}$ is the weight of inputs to hidden layers, and the $LW_{1,j}$ is the weight of hidden neurons to the output layer.

3.4. Experimental Materials and Pyrolysis Process

In the present paper, scots pine (*Pinus sylvestris* L.) sawdust supplied from a commercial wood products company in Karabuk-Turkey was selected as a biomass feedstock. Biomass, having an average 1.22 mm particle size was air dried prior to pyrolysis process. Proximate and ultimate analysis of the biomass are shown in Table 2. The sodium hydroxide (NaOH) and potassium hydroxide (KOH) catalysts were selected in order to apply in catalytic pyrolysis experiments. The slow pyrolysis runs were carried out in a vacuum pyrolysis reactor, which had a stainless-steel cylinder. In an uncatalyzed pyrolysis experiment, the reactor was charged with the 2000 g of biomass. For NaOH and KOH catalytic runs, the reactor was charged with the 2000 g of biomass sample and 200 g (10 wt%) of catalyst. Then, the pyrolysis reactor was externally heated up to the final temperature of 500 °C. After the determined temperature was obtained, the system was maintained at this temperature for 60 min. The same procedure was applied in catalytic pyrolysis experiments. Finally, the pyrolysis reactor was cooled down to the room temperature. The bio-oil yield obtained from each pyrolysis run were determined based on Eq. (5);

$$bio\text{-}oil\_yield(\%)=\frac{bio\text{-}oil\_obtained(g)}{biomass\_feedstock(g)}\times 100 \quad (5)$$

4. RESULTS AND DISCUSSION

4.1. Artificial Neural Network Modeling

In the present study, the optimal number of hidden neurons and the transfer function were obtained by trying to minimize the MSE. As shown in Figure 2, the minimum MSE is 0.00058 with ten hidden neurons and *logsig* transfer function at the hidden layer.

The parameters of the developed ANN are shown in Table 3. The feedforward backpropagation neural network composed of one input layer, one hidden layer, and one output layer was applied in the ANN modeling. The *trainlm* algorithm with a *logsig* transfer function at the hidden layer and a *purelin* transfer function at the output layer was considered as learning algorithm. The number of neurons in the input, hidden, and output layers were 12, 10 and 1, respectively. The performance and the data division functions determined as MSE and *dividerand*. The data were divided as 70%, 15%, and 15% for training, testing, and validation procedures, respectively.

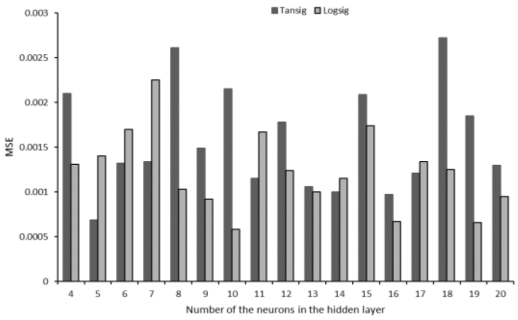

Figure 2. Plots of the MSE of ANN models for each transfer function in the hidden layer

The correlation coefficient (R), MSE, and MAPE were selected to evaluate network accuracy. The calculated performance evaluation parameters for training, validation, and testing are shown in Table 4. The R values that indicate the correlation degree are 0.992, 0.933, and 0.951 for training, validation, and testing, respectively. The R values close to one represent a strong relationship between the predicted and the intended outputs [44]. The MAPE values were also found to be 2.39%, 5.35%, and 3.70% for training, validation, and testing steps, respectively. The regression between the predicted results and the targets for training, validation, and testing procedures are presented in Figure 3. Figure 4 represents the experimental and predicted values of bio-oil yield. The evaluation parameters showed that the developed ANN model is satisfactory in order to predict the bio-oil yield, considering the inputs including pyrolysis temperature, duration, catalyst type, catalyst ratio, particle size, proximate, and ultimate analysis of the biomass. This result is supported by earlier work. Chen et al. [15] specified that the artificial intelligence models can accurately predict the bio-oil yield, considering the parameters including particle size, temperature, proximate, and ultimate analysis of the biomass.

Table 2. Chemical characteristics of biomass feedstock

Characteristics	Method	Value (wt%)
Proximate analysis (as received basis)		
Moisture	ASTM D 4442-92 [41]	8.44
Volatiles	ASTM E 897-88 [42]	78.16
Ash	ASTM D 1102-84 [43]	0.44
Fixed carbon	Calculated by difference	12.96
Ultimate analysis (as received basis)		
C		46.12
O	Calculated by difference	47.8
H		6.08

Table 3. The parameters of the ANN model used for the simulation of bio-oil yield

Network	Feedforward backpropagation
Number of input layer neurons	12
Number of hidden layers	1
Number of hidden layer neurons	10
Number of output layer neurons	1
Learning algorithm	*trainlm*
Hidden layer transfer function	*logsig*
Output layer transfer function	*purelin*
Performance function	MSE
Learning cycle	1000 Epochs
Validation checks	15
Data division function	*dividerand*
Data division	70:15:15

Table 4. Performance values of the developed ANN model

ANN	R	MSE	MAPE (%)
Training	0.992	0.0003	2.39
Validation	0.933	0.0013	5.35
Testing	0.951	0.0010	3.70

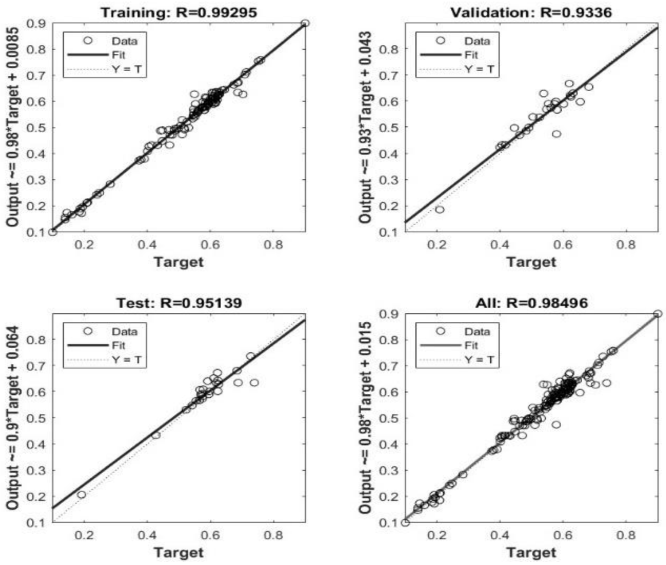

Figure 3. Comparison of the experimental data with the predicted results

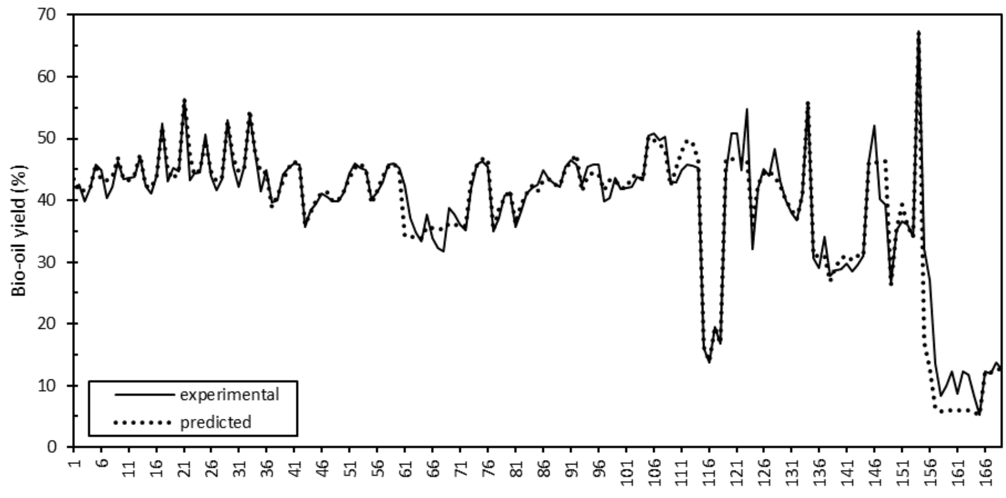

Figure 4. Plots of experimental data and ANN predicted data

4.2. Relative Impact

The relative impact of the twelve input parameters determined using Eq. (3) is presented in Figure 5. All the selected parameters have a significant effect on pyrolysis bio-oil yield. The most important parameter that affects the bio-oil yield was found to be catalyst type (11.4%). The effect of the catalysts on bio-oil yield is attributed to decomposition reactions accelerating with the chemical additives [35, 45]. The next parameters that affect the bio-oil yield were the biomass characteristics (C, H, O, moisture, volatiles, ash content, fixed carbon) and the catalyst ratio (7.2%-10.9%). The impact of particle size, temperature, and duration were 7.1%, 6.2%, and 6.2%, respectively. The effect of particle size is generally attributed to uniformly heating of smaller particles [46]. The temperature and duration impacts are mainly the results of the decomposition of biomass bonds at the higher temperatures and the gasification/thermal cracking of the products in longer reaction time, respectively [32, 47, 48].

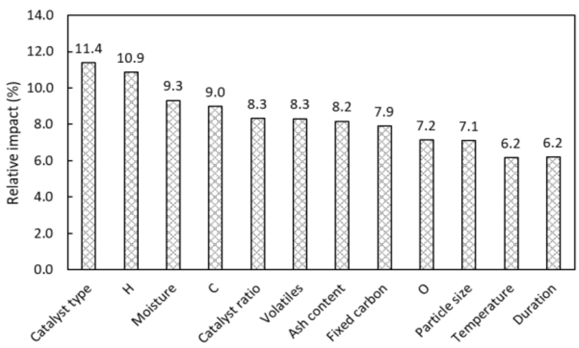

Figure 5. Relative impact (%) of each input parameters on bio-oil yield

4.3. Testing the Accuracy of the Developed ANN Model

To check the accuracy of the developed model, the final testing procedure is important. The results obtained from the pyrolysis runs were used for testing the ANN predictability. The bio-oil production conditions for temperature, duration, and biomass particle size were 500 ˚C, 60 min, and ~1.22 mm, respectively. Two different catalysts, NaOH and KOH, were also tested to evaluate the effects of catalysts on bio-oil yield. The pyrolysis experiments were performed in defined conditions to create new data. Afterward, the new experimental results were compared with the predicted results (Table 5).

The result showed that the developed model is able to accurately predict the pyrolysis bio-oil yield. The ANN model predicted the bio-oil yield of 50.47% in pyrolysis conditions of temperature 500 ˚C, duration 60 min, uncatalyzed, particle size 1.22 mm, and biomass type of scots pine. During the experimental run, the bio-oil yield of 52.19% was obtained in the same pyrolysis conditions. The bio-oil yields of 47.46% (NaOH) and 43.55% (KOH) were predicted in conditions of temperature 500 ˚C, duration 60 min, catalysts NaOH and KOH, catalyst ratio 10 wt%, particle size 1.22 mm, and biomass type of scots pine. During pyrolysis experiments, the bio-oil yields of 46.42% (NaOH) and 45.17% (KOH) were acquired in the same conditions. The simulated data are in good agreement with the experimental results (given in Table 5) indicating the reliability of the developed model in the prediction of the pyrolysis oil yield.

As shown in Table 5, catalysts led to a decrease in bio-oil yield. This result is supported by earlier works. Özbay [35] reported that the use of KOH as a catalyst caused a decrease in the liquid yield. Guedes et al. [32] stated that in spite of the lower oil yield, catalytic pyrolysis improves the quality of the final product.

5. CONCLUSIONS

This study is devoted to developing a reliable model which can be used for pyrolysis liquid product prediction. In this way, an ANN model was developed to predict the yield of bio-oil. The network architecture with ten hidden neurons and *logsig* transfer function at the hidden layer acquired the minimum MSE of 0.00058 and the highest R-value of 0.9849. The reliability of the model was tested with unseen data obtained from pyrolysis experiments. The results revealed that the prediction performance of the developed model for this unseen dataset was satisfactory. According to the relative impact results, the most important parameter that affects the bio-oil yield were catalyst type. The next parameters that affect the bio-oil yield were the biomass characteristics, catalyst ratio, particle size, temperature, and duration, respectively. It can be concluded that it is possible to reduce the number of the required pyrolysis experiments by the developed ANN model. And, the yield of bio-oil

Table 5. Experimental (unseen) and predicted results at different operating parameters (Moisture: 8.44%; ash content: 0.44%; volatiles: 78.16%; fixed carbon: 12.96%; C: 46.12%; O: 47.8%; H: 6.08%)

Method	Biomass Feedstock	Temperature (˚C)	Duration (min)	Catalyst type	Catalyst ratio (wt%)	Particle size (mm)	Bio-oil yield (%)
ANN	Scots pine	500	60	None	-	1.22	50.47
Experimental	Scots pine	500	60	None	-	1.22	52.19
ANN	Scots pine	500	60	NaOH	10	1.22	47.46
Experimental	Scots pine	500	60	NaOH	10	1.22	46.42
ANN	Scots pine	500	60	KOH	10	1.22	43.55
Experimental	Scots pine	500	60	KOH	10	1.22	45.17

from the pyrolysis process can be predicted with minor deviation by a well-trained ANN model.

ACKNOWLEDGEMENT

The support from TUBITAK (The Scientific and Technological Research Council of Turkey) [Project grant number: 115O453] for this research are gratefully acknowledged. This study was made as a part of the Ph.D. thesis by Erkan Sami KÖKTEN in the Institute of Graduate Programs, Karabük University, [Adviser: Assoc. Prof. Dr. Günay ÖZBAY].

APPENDIX A

Table A1

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

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Table A1. The literature of the collected data about slow and intermediate pyrolysis of woody biomass

Biomass	Biomass particle size (mm)	Catalyst type	Catalyst ratio (wt%)	Temperature	Duration (min)	Reference
Masson pine *(Pinus massonia* L.*)*	0.149-0.841	Uncatalyzed	-	773 (K)	-	[64]
MCPB[a], Scots pine *(Pinus sylvestris* L.*) and* Oriental beech *(Fagus orientalis* L.*)*	0.85-1.6	Uncatalyzed $FeCl_3$ Na_2CO_3 K_2CO_3	10	400-600 (˚C)	60	[65]
Eucalyptus	0.85	Uncatalyzed	-	300-800 (˚C)	30	[49]
Oil palm (Trunk)	1-2	Uncatalyzed	-	500 (˚C)	60	[50]
Umbrella tree (*Maesopsis eminii* L.)	<1	Uncatalyzed	-	500 (˚C)	60	[51]
MCPB[a]	~1	Uncatalyzed $AlCl_3$ $TiCl_4$ $FeCl_3$ NaOH KOH Na_2CO_3 K_2CO_3	10	400-700 (˚C)	60	[3]
Chinese fir	200–40 (meshes)	Uncatalyzed	-	500 (˚C)	30	[52]
Moso bamboo (*Phyllostachys edulis* L.)	0.25-0.38	Uncatalyzed	-	300-700 (˚C)	10	[53]
Eucalyptus	<2	Uncatalyzed	-	350 (˚C)	70	[54]
Giant leucaena	0.075-0.150	Uncatalyzed $NiMo/Al_2O_3$	10-30	325-400 (˚C)	0-60	[55]
Untreated and heat-treated ash wood (*Fraxinus excelsior* L.)	<1	Uncatalyzed	-	350-600 (˚C)	30	[56]
Fir wood (*Abies bornmülleriana* Mattf.)	<1	Uncatalyzed	-	350-600 (˚C)	30	[57]
Turkish pine (*Pinus brutia* Ten.)	<1	Uncatalyzed KOH $ZnCL_2$ ZnO	5 10 15 20	350-600 (˚C)	30	[35]
Pine wood (pellet)	15-45	Uncatalyzed	-	350-550 (˚C)	15	[58]
Rubberwood and Malaysian wood pellets	~15 (Rubberwood) ~40 (Malaysianwood)	Uncatalyzed	-	500-800(˚C)	20	[59]
Hornbeam (*Carpinus betulus* L.)	<1	Uncatalyzed	-	400-600 (˚C)	30	[60]
Eucalyptus	<10	Uncatalyzed	-	750 (˚C)	30	[61]
Paulownia wood (*P. tomentose* L.)	0.224-1.8	Uncatalyzed	-	623-873 (K)	30	[62]
White pine	~5.5	Uncatalyzed	-	520 (˚C)	30	[63]

a: Melamine Coated Particleboard

Conflict of interest

The authors declare that they have no conflict interest.

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