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ANN-Based modeling and performance analysis of pyrolytic oil production system

Pirolitik yağ üretim sisteminin YSA-Tabanlı modellenmesi ve performans analizi

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Abstract

In this study, the modeling of the Pyrolytic oil production system using Artificial Neural Networks (ANNs) has been conducted with oak acorn, which can be considered as non-wood forest product. The parameters used in the pyrolytic oil production system have been determined as reactor temperature, nitrogen gas flow rate, biomass particle size, and heating rate. In experimental studies, the highest pyrolytic oil production has been achieved at 500 °C temperature, 1.5 L/min nitrogen gas flow rate, 5 °C/min heating rate, and 0-2 mm biomass particle size, with a product yield of 17.83%. 164 different Multi-Layer Feed Forward (MLFF) ANN-based network architectures have been trained for 20,000 iterations using the data obtained from the pyrolytic oil production system. In the training process, various network architectures including activation functions such as TanSig, LogSig, and RadBas with one or two hidden layers have been utilized. According to the results obtained from the studies, the Multi-Layer Feed Forward ANN-based Pyrolytic Oil Production System structure, which has a single hidden layer and contains 16 LogSig activation function neurons, has been the network structure with the best performance with the value of 1.08E-15.

Keywords: Acorn, Activation functions, Artificial neural networks, Pyrolytic oil production.

Öz

Bu çalışmada, odun dışı orman ürünü olarak değerlendirilebilecek meşe palamudu ile Yapay Sinir Ağları (YSA-Artificial Neural Network) kullanılarak Pirolitik yağ üretim sisteminin modellenmesi gerçekleştirilmiştir. Pirolitik yağ üretim sisteminde kullanılan parametreler; reaktör sıcaklığı, azot gazı akış hızı, biyokütle parçacık boyutu ve ısıtma hızı olarak belirlenmiştir. Deneysel çalışmalarda, 500 °C sıcaklıkta, 1.5 L/dk. azot gazı akış oranı, 5 °C/dk. ısıtma oranı ve 0-2 mm biyokütle tanecik boyutunda en yüksek pirolitik yağ üretimi gerçekleştirilmiş olup ürün verimi %17.83 elde edilmiştir. Pirolitik yağ üretim sisteminden elde edilen veriler kullanılarak 164 farklı Çok Katmanlı İleri Beslemeli (MLFF) ANN-tabanlı ağ mimarisi 20.000 iterasyon için eğitilmiştir. Eğitim sürecinde, bir veya iki gizli katmana sahip TanSig, LogSig ve RadBas transfer fonksiyonları içeren farklı ağ yapıları kullanılmıştır. Çalışmalardan elde edilen sonuçlara göre, tek gizli katmanlı olan ve 16 LogSig aktivasyon fonksiyonlu nöron içeren Çok Katmanlı İleri Beslemeli YSA-tabanlı Pirolitik Yağ Üretim Sistemi yapısı 1.08E-15 değeri ile en iyi performans elde edilen ağ yapısı olmuştur.

Anahtar kelimeler: Meşe palamudu, Aktivasyon fonksiyonları, Yapay sinir ağları, Pirolitik yağ üretimi.

1 Introduction

The need for fossil fuels has been increasing significantly with the developing technology day by day. The limited use of fossil fuels in energy production has increased the interest in alternative energy sources [1]-[4]. Pyrolysis, one of the alternative energy production methods, is a thermochemical decomposition process that takes place under high temperature conditions in the absence of oxygen; pyrolytic oil, gas and char are obtained because of this process. A multitude of production parameters exists for the production of pyrolytic oil. Examples of such parameters include the type and size of the biomass, the temperature at which the reaction occurs, pressure, heating rate, among others. Variations in reaction conditions and biomass selection can significantly impact the production of pyrolytic oil [5]-[7]. The parameters used in the study for the pyrolytic oil production system include reactor temperature, nitrogen gas flow rate, biomass particle size and heating rate. In this respect, optimization of the parameters that affect the generation of the system is of great importance for the efficient extraction of energy produced from alternative energy sources. In this study, Artificial Neural Networks (ANNs) were preferred for the modeling the pyrolytic oil production system.

One of the subfields of Artificial Intelligence, ANNs are widely used in various fields today [8]-[10]. These areas include

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control [11], chaotic oscillator design [12], prediction [13], diagnosis [14], modeling of the energy generation systems [15]-[16], pseudo-random [17] and true random number generator design [18], and bio-oil production systems [19]. ANN-based pyrolytic oil production systems are extensively utilized in the literature. For instance, studies using different biomasses such as biochar from cattle dung pyrolysis [20], pine sawdust from industrial biomass waste [21], lignocellulosic materials obtained from agricultural waste materials [22], biochar production from banana peels via pyrolysis [23], lignocellulosic forest residue and olive oil residue as biomass raw materials [24], algal mat (lablab) biomass, including microalgae, macroalgae and cyanobacteria [25], cotton boll shells, fabricated tea waste, olive shells, and hazelnut shells from biomass waste [26] are exemplified.

The importance of pyrolytic oil cannot be denied when examining the search for alternative energy sources to prevent dependence on fossil fuels. Acorns, which are abundant in forest areas in Türkiye, are biomass with high cellulose and lignin content and can be used in pyrolytic oil production by utilizing them as non-wood forest products. In this study, the production, modeling, and analysis of pyrolytic oil from acorns were investigated and it was demonstrated that the production system can be modeled with ANN and applied safely. The study aims to fill the gaps in the literature while providing opportunities in terms of sustainable biofuel production, environmental pollution reduction, and renewable energy. In future studies, the potential use of this oil as a fuel in internal combustion engines and the possibilities of modeling with different machine learning methods will be examined. In the second part of the study, general information about pyrolytic oil production and ANNs is given. In the third section, the pyrolytic oil production system is introduced. In the fourth section, ANN-based pyrolytic oil production system is demonstrated. In the last section, the results obtained from the studies are interpreted.

2 Material and methods

2.1 Raw material

Acorns were collected from Bursa's Uludağ forests. Then, the acorns were properly dried, ground, and sieved. After sieving, 0-2 mm, 2-4 mm, and 4-6 mm sized pieces were obtained and prepared as pyrolytic oil production material.

2.2 Experimental setup and result

The pyrolytic oil production was performed by the pyrolysis method in the fixed bed reactor shown in Figure 1. The design of the experimental studies was determined by using the central composite face-centered (CCF) method. Since the experiments are carried out in laboratory environments, it is possible to encounter incorrect and abnormal results. However, to minimize the variations in the error tolerance values of the experiments, the experiments were carried out at three different times under the same conditions and parameters, and the average values were noted. The temperature plays an important role in obtaining the optimum oil yield in pyrolytic oil production. It is observed that temperatures in the reaction and cooling zones should be between 400-500 °C to ensure optimum yield [27]-[29]. In this context, experimental designs were prepared with specific parameters such as temperature (400 °C, 450 °C, and 500 °C), nitrogen gas flow rates (0.5, 1, and 1.5 L/min), heating rates (5, 10, and 15 °C/min) and biomass particle sizes (0-2 mm, 2-4 mm, and 4-6 mm). Subsequently, a total of 30 distinct experimental investigations were concunted employing various configurations. A total of 30 different experimental investigations were then carried out using various configurations. This design of the experimental study and the results obtained are shown in Table 1.

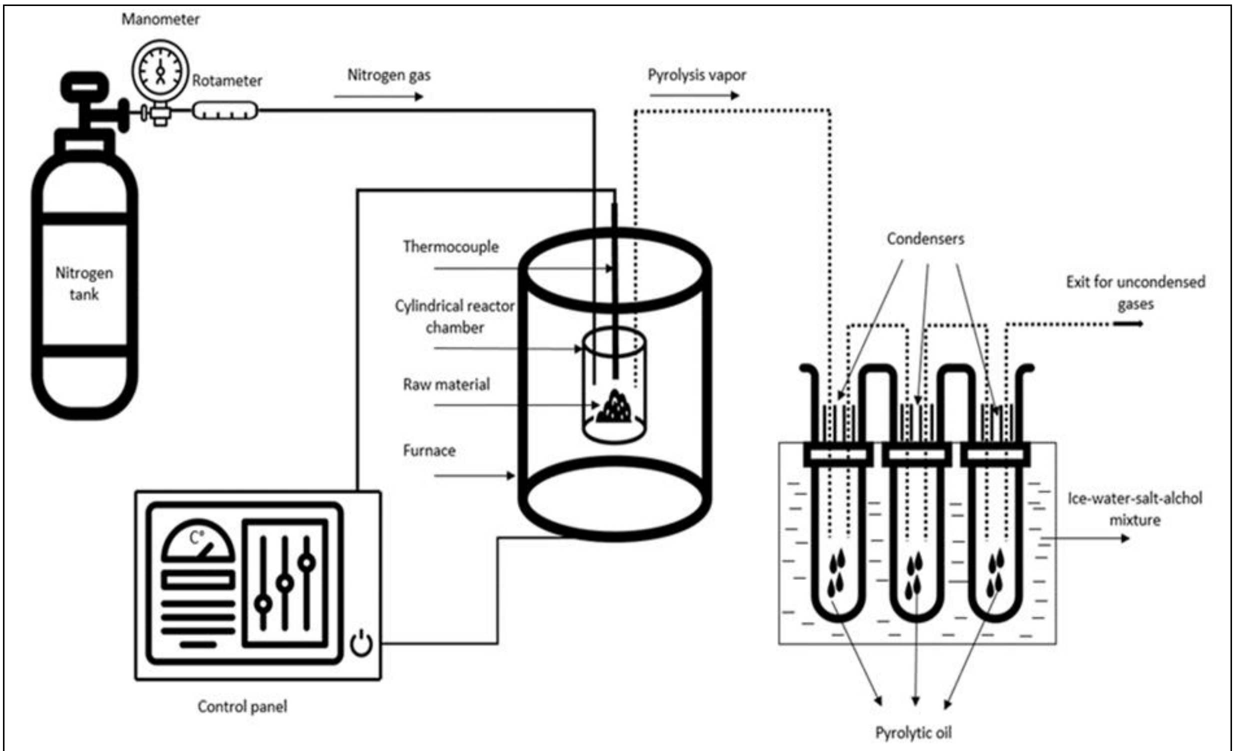

Figure 1. A schematic diagram of a fixed bed reactor system.

Table 1. Experimental set variable input and output parameters.

Inputs				Outputs			
Temperature (°C)	Gas flow rate (L/min)	Heating rate (°C/min)	Particle size (mm)	Pyrolytic oil (g)	Water (g)	Char (g)	Vapor (g)
400	0.5	15.0	2.0	09.91	32.52	26.09	31.48
400	0.5	05.0	2.0	13.45	18.68	27.75	40.12
400	1.5	15.0	6.0	09.26	34.43	27.75	28.56
400	1.5	15.0	2.0	11.73	22.69	29.45	36.13
400	1.0	10.0	4.0	11.56	21.60	31.70	35.14
400	1.5	05.0	6.0	13.09	31.58	28.75	26.58
400	0.5	05.0	6.0	12.70	33.72	27.85	25.73
400	1.5	05.0	2.0	13.26	30.88	27.75	28.11
400	5.0	15.0	6.0	09.24	31.22	27.97	31.57
450	1.0	15.0	4.0	09.51	32.25	27.13	31.11
450	1.5	10.0	4.0	11.32	27.90	27.44	33.34
450	1.0	05.0	4.0	13.79	29.53	29.93	26.75
450	1.0	10.0	2.0	15.46	34.68	27.78	22.08
450	1.0	10.0	4.0	13.95	34.33	27.72	24.00
450	1.0	10.0	4.0	13.68	35.32	27.68	23.32
450	1.0	10.0	6.0	13.46	32.10	29.22	25.22
450	1.0	10.0	4.0	13.36	32.33	28.45	25.86
450	0.5	10.0	4.0	14.93	31.10	29.32	24.65
450	1.0	10.0	4.0	14.00	31.20	27.00	27.80
450	1.0	10.0	4.0	14.33	33.10	29.33	23.24
450	1.0	10.0	4.0	13.12	35.48	29.25	22.15
500	1.5	15.0	2.0	11.23	29.77	27.03	31.97
500	1.5	15.0	6.0	10.18	34.53	27.09	28.20
500	0.5	15.0	6.0	15.04	33.98	27.75	23.23
500	0.5	05.0	2.0	17.42	33.20	28.77	20.61
500	0.5	05.0	6.0	15.91	30.03	28.01	26.05
500	1.5	05.0	2.0	17.83	26.12	26.60	29.45
500	0.5	15.0	2.0	15.07	34.80	28.30	21.83
500	1.5	05.0	6.0	14.37	32.12	29.13	24.38
500	1.0	10.0	4.0	17.12	34.12	29.22	19.54

2.3 Artificial neural networks

An ANN is constituted by a group of neurons working parallelly and connected by weight and threshold links simulating synapses of brain [30]-[31]. The most common structure of ANN is in the form of a multilayer perceptron (MLP), also called a multilayer feed-forward neural network (MLFNN) [32]-[34] as shown in Figure 2. This figure also demonstrates the basic network structure used in this study.

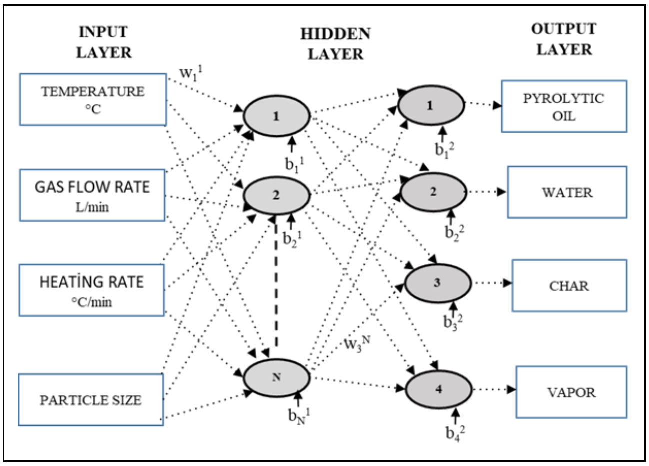

Figure 2. The basic sample of MLFNN structure used in this study.

The network has 4 different input parameters of the system as: Temperature (°C), gas flow rate (L/min), heating rate (°C/min), and particle size. Therefore, the number of inputs in the network is 4. Similarly, 4 different output parameters of the system, oil, water, char, and steam, were presented to the network. As a result, the number of outputs of the network is 4. As shown in the figure, a hidden layer and N neurons were used in this hidden layer. The neuron structure in the ANN layers is given in Figure 3.

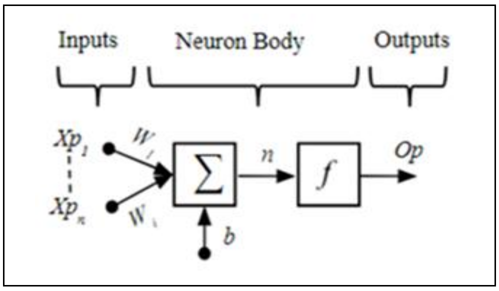

Figure 3. The structure of the basic neuron.

This structure includes inputs, multiplication and addition units, transfer functions, and outputs. The signals from the inputs are multiplied by the weights. Afterwards, all values are summed and the *n* value is obtained. Some neurons may have *b* (bias) values according to the system. In this case, this *b* value is added to the *n* value to obtain the *n* value. After this process, the *n* value is transmitted to the transfer function *f*. The *n* value passing through the transfer function is sent to the *Op* neuron output.

Activation functions (AF) or transfer functions (TF), which are one of the most basic structures in ANN structures, are generally separated into two parts as linear and nonlinear TF. Examples of linear activation functions are PosLin (Positive Linear), HardLim (Hard Limiting), HardLims (Symmetric Hard Limiting), SatLin (Saturating Linear), and PureLin (Pure Linear). RadBas (Radial Basis), LogSig (Logarithmic-Sigmoid), and TanSig (Hyperbolic Tangent-Sigmoid) AF are nonlinear transfer functions that are widely used in ANN applications [35]. Equation 1 shows the equations of RadBas, Equation 2 shows the equations of LogSig and Equation 3 shows the equations of TanSig TFs used in the hidden layer and output layer neuron structures in this study. Here, the variable *n* is the net input of the system.

$$RadBas(n) = e^{-n^2} \tag{1}$$

$$LogSig(n) = \frac{1}{1+e^{-n}} \tag{2}$$

$$TanSig(n) = \frac{2}{(1+e^{(-2)})} - 1 \tag{3}$$

3 Results and discussion

The results obtained show that among the parameters used in pyrolytic oil production, temperature is a factor that significantly increases the production yield compared to other parameters. Bhattacharjee and Biswas stated in their study that the optimum yield of lignin derived oligomers was reached in the temperature range of 450-500 °C [36]. In a study conducted by Santos et al., it was observed that the optimum yield was obtained at 500 °C as a result of production at 400 °C, 450 °C and 500 °C [37]. Kim et al. investigated the pyrolysis of pine wood at 500 °C, 525 °C and 550 °C and recorded an optimum yield of 59.8% at 500 °C. They also noted that pyrolytic oil production increases parabolically with temperature and that maximum production can be achieved at temperatures of 450-500 °C depending on the choice of biomass and reactor type [38]. As a result of the experimental studies, the maximum pyrolytic oil yield was obtained at a temperature of 500 C°, nitrogen gas flow rate of 1.5 L/min, heating rate of 5 °C/min, and biomass particle size of 0-2 mm, and the amount of pyrolytic oil produced was produced with a yield of 17.83% for 100 g of sample used in 0-2 mm size. When the studies conducted in the literature were examined, it was seen that similar results were obtained despite minor differences that could be ignored in our study [39]. Furthermore, it is estimated that pyrolytic oil production efficiency can be realized at higher levels if acorns, which are considered as non-wood forest products, are used by removing the stems and husks. The pyrolytic oil produced as a result of each experimental study was placed in a glass sample jar and stored in an environment away from sunlight. The total pyrolytic oil produced after all experimental procedures were completed is shown in Figure 4.

Figure 4. The total pyrolytic oil produced.

To determine the properties of pyrolytic oil produced from acorns, various analyses were conducted at Afyon Kocatepe University; Technology Application and Research Center (TUAM), and Standard Laboratories Management Inc. The properties of pyrolytic oil produced from acorns and its comparison with diesel fuel are presented in Table 2.

The network structures, neurons, and performance results obtained during the ANNs modeling of the pyrolytic oil production system from acorns are presented in Table 3. Each ANN shown in the table indicates a feed-forward multilayer network structure. The dataset has been randomly divided as 70% for training, 15% for validation, and 15% for testing. In this study, 164 different trainings were performed for different numbers of hidden layers, the number of neurons in the hidden layer or layers, and different transfer functions such as LogSig, TanSig, and RadBas used in these layers. Nevertheless, only the results for 50 training runs are presented in order not to take up too much space in the paper. Although parameters such as the number of neurons or the number of hidden layers are not very important in software-based ANN structures, they are very significant in terms of resource utilization in hardware-based applications. For this reason, the results not included in the table are the network structures where the performance results are low or the number of neurons in the hidden layer is high. The results of each ANN shown in the table are the values obtained for 20,000 iterations. The purelin transfer function was used in the output layer of each network structure given in the table. In this context, ANN-based models were created by training 164 ANN structures for 20,000 iterations based on different hidden layers and hidden neuron numbers. According to the results from the studies, the MLFNN structure with one hidden layer containing 16 LogSig nonlinear activation function neurons of the hidden layer is the most efficient network structure with a value of 1.08E-15.

Table 2. The properties of the pyrolytic oil and diesel fuel produced.

Analysis	Unit	Result of Analysis	Diesel Fuel	Analysis Method
Kinematic Viscosity (40 °C)	(mm^2/s)	9.20	1.5-4	TS 1451 EN SO 3104
Water	(mg/kg)	2.72	<200	TS 6147 EN ISO 12937
Density	(g/cm^3)	1.089	0.82-0.845	PN EN ISO 3675
Sulfur content	(ppm)	0.47	<0.01	TS 440 ISO 351

Table 3. ANN-based pyrolytic oil production system parameters and performance values with acorns.

ANN Structure	1st Hidden Layer		2nd Hidden Layer		Performance
	The Number of Neurons	Transfer Function	The Number of Neurons	Transfer Function	
1	4	TanSig	-	-	6.93E-15
2	8	TanSig	-	-	7.37E-15
3	12	TanSig	-	-	2.08E-15
4	16	TanSig	-	-	4.76E-15
5	4	LogSig	-	-	5.23E-09
6	8	LogSig	-	-	2.58E-14
7	12	LogSig	-	-	3.73E-14
8	16	LogSig	-	-	1.08E-15
9	4	RadBas	-	-	5.18E-14
10	8	RadBas	-	-	4.70E-15
11	12	RadBas	-	-	2.24E-15
12	16	RadBas	-	-	2.74E-15
13	4	TanSig	4	TanSig	2.79E-14
14	4	TanSig	12	TanSig	5.43E-13
15	8	TanSig	4	TanSig	3.19E-14
16	8	TanSig	8	TanSig	7.00E-15
17	12	TanSig	4	TanSig	2.78E-14
18	4	TanSig	4	LogSig	6.87E-15
19	4	TanSig	8	LogSig	1.18E-14
20	8	TanSig	4	LogSig	4.59E-14
21	12	TanSig	4	LogSig	9.65E-15
22	4	LogSig	4	TanSig	1.47E-13
23	4	LogSig	8	TanSig	4.03E-15
24	8	LogSig	4	TanSig	1.67E-14
25	8	LogSig	8	TanSig	4.28E-15
26	12	LogSig	4	TanSig	3.39E-14
27	4	LogSig	4	LogSig	2.29E-13
28	4	LogSig	12	LogSig	1.76E-15
29	8	LogSig	4	LogSig	9.87E-15
30	4	TanSig	4	RadBas	1.71E-14
31	4	TanSig	8	RadBas	7.66E-15
32	4	TanSig	12	RadBas	9.62E-15
33	8	TanSig	4	RadBas	1.39E-14
34	12	TanSig	4	RadBas	1.68E-14
35	4	LogSig	4	RadBas	8.02E-14
36	4	LogSig	8	RadBas	5.00E-14
37	8	LogSig	4	RadBas	5.21E-14
38	12	LogSig	4	RadBas	2.44E-14
39	4	RadBas	4	TanSig	2.48E-15
40	8	RadBas	4	TanSig	5.42E-14
41	8	RadBas	8	TanSig	5.83E-15
42	4	RadBas	8	LogSig	7.07E-15
43	8	RadBas	4	LogSig	4.95E-14
44	12	RadBas	4	LogSig	2.32E-14
45	4	RadBas	4	RadBas	1.55E-13
46	4	RadBas	8	RadBas	7.61E-15
47	4	RadBas	12	RadBas	1.92E-15
48	8	RadBas	4	RadBas	2.12E-14
49	8	RadBas	8	RadBas	1.30E-14
50	12	RadBas	4	RadBas	1.66E-14

Figure 5 shows the performance graph showing the Mean Square Error (MSE) of the most efficient network structure using the Levenberg-Marquardt training algorithm according to the number of iterations. Since MSE is an accepted measure of performance index often used in MLFNN, MSE has been used.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \widehat{x_1})^2 \quad (4)$$

Here, x_i $and \widehat{x_i}$ are the observed data and modeling data respectively. N is the length of the observed data. As can be seen from the graph, the network converged to the target values with a sensitivity of 1.08E-15. The network was trained for 20,000 iterations, during which the performance change was very little by 8.44e-12. This value shows that the network model can accurately match the input-output relationship.

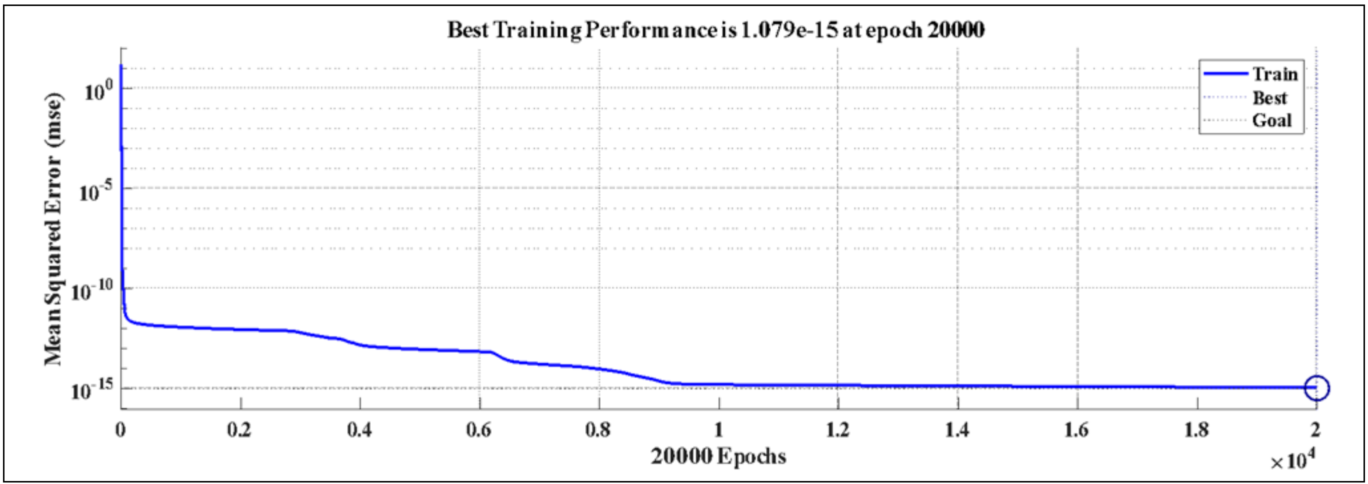

Figure 5. The network performance graph of the most efficient network structure.

An important tool to evaluate network performance is a scatter plot of network throughputs by targets. As can be seen from Figure 6, the points in the scatter plot fell close to the 45° output=target line. Therefore, the fit is almost perfect.

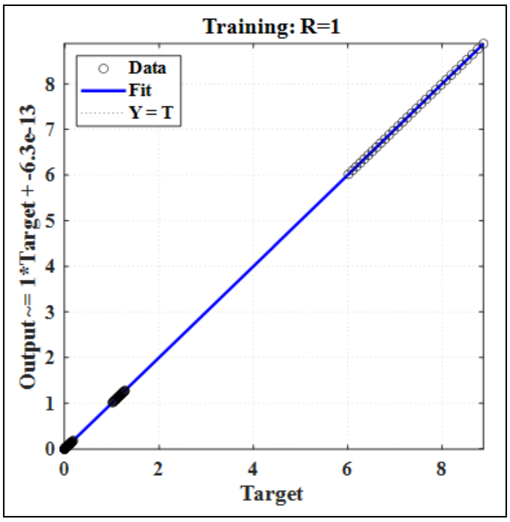

Figure 6. The network scatter graph of the most efficient network structure.

4 Conclusions

In this study, acorns, a non-wood forest product, were selected as biomass. Pyrolytic oil production was performed from this chosen biomass using the pyrolysis method in a fixed-bed reactor. ANN-based training for the pyrolytic oil production system was carried out by using the data obtained from the pyrolytic oil production system. In this context, a total of 164 trainings were performed for 20,000 iterations based on different hidden layers and neuron numbers, and ANN-based models were created.

- As a result of experimental studies with temperature, gas flow rate, heating rate, and biomass particle size parameters, the maximum pyrolytic oil yield was produced at 500 °C temperature, 1.5 L/min nitrogen gas flow rate, 5 °C/min heating rate and 0-2 mm biomass particle size and the amount of pyrolytic oil produced was obtained with a yield of 17.83% for 100 g sample used in 0-2 mm size,
- The analysis results of the pyrolytic oil showed an increase in kinematic viscosity, density, and sulphur values for 40 °C compared to diesel fuel. Despite this increase, the amount of water was found to be within the standard value range,
- According to the results obtained from the studies, the MLFNN-based Pyrolytic Oil Production System structure with one hidden layer containing LogSig nonlinear activation function in the hidden layers was the best-performing network structure with a value of 1.08E-15.

With this study, it has been shown that the pyrolytic oil production system can be realized safely based on ANN. In future research, by determining the most optimum parameter values of the model created and by using various optimization techniques, experimental studies can be carried out under these conditions. Additionally, designing and implementing the ANN-based modeled pyrolytic oil production system on FPGA and ARM-based digital platforms for real-time operation can be the subject of further studies.

5 Author contribution statements

In this study, Emirhan Yelekin, Ibrahim Mutlu created the idea, provided the materials, obtained the findings, created the experimental system; Murat Alcın evaluation of the idea, evaluation of the results, literature review, writing of the article; Murat Tuna and Ismail Koyuncu contributed to the writing and critical review, checking the article in terms of content, and general control of the article.

6 Ethics committee approval and conflict of interest statements

“There is no need to obtain permission from the ethics committee for the article prepared”.

“There is no conflict of interest with any person / institution in the article prepared”.

7 References

[1] Güney B, Aladağ A. "Microstructural analysis of liquefied petroleum gas vehicle emissions, one of the anthropogenic environmental pollutants". *International Journal of Environmental Science and Technology*, 19(1), 249-260, 2022.

[2] Abdeshahian P, Lim JS, Ho WS, Hashim H, Lee CT. "Potential of biogas production from farm animal waste in Malaysia". *Renewable and Sustainable Energy Reviews*, 60(C), 714-723, 2016.

[3] Güney B, Öz A. "Microstructure and chemical analysis of NOx and particle emissions of diesel engines". *International Journal of Automotive Engineering and Technologies*, 9(2), 105-112, 2020.

[4] Güney B, Aladağ A. "Microstructural characterization of particulate matter from gasoline-fuelled vehicle emissions". *Journal of Engineering Research and Reports*, 16(1), 29-39, 2020.

[5] Bridgwater AV. "Renewable fuels and chemicals by thermal processing of biomass". *Chemical Engineering Journal*, 91(2-3), 87-102, 2003.

[6] Kan T, Strezov V, Evans TJ. "Lignocellulosic biomass pyrolysis: A review of product properties and effects of pyrolysis parameters". *Renewable and Sustainable Energy Reviews*, 57, 1126-1140, 2016.

[7] Kar Y. "Catalytic cracking of pyrolytic oil by using bentonite clay for green liquid hydrocarbon fuels production". *Biomass Bioenergy*, 119, 473-479, 2018.

[8] Callioglu H, Muftu S, Koplay CN. "Comparison of vibration values of rotating discs with variable parameters obtained by finite element analysis modeling with different machine learning algorithms". *Multidiscipline Modeling in Materials and Structures*, 21(1), 98-118 2025.

[9] Boğar E, Boğar ZÖ. "Türkiye'nin sektörel CO2 gazı salınımlarının yapay sinir ağları ile tahmini". *Akademia Disiplinlerarası Bilimsel Araştırmalar Dergisi*, 3(2), 15-27, 2017.

[10] Akçay MŞ, Koyuncu İ, Alcin M, Tuna M. "FPGA tabanlı LogSig ve TanSig transfer fonksiyonlarının IQ-Math sayı standardında tasarımı ve gerçeklenmesi". *Journal of Materials and Mechatronics: A*, 3(2), 225-239, 2022.

[11] Le QN, Jeon JW. "Neural-Network-Based Low-Speed-damping controller for stepper motor with an FPGA". *IEEE Transactions on Industrial Electronics*, 57(9), 3167-3180, 2010.

[12] Alcin M, Koyuncu I, Tuna M, Varan M, Pehlivan I. "A novel high speed Artificial Neural Network-based chaotic True Random Number Generator on Field Programmable Gate Array". *International Journal of Circuit Theory and Applications*, 47(3), 365-378, 2019.

[13] Şahin M, Oğuz Y, Büyüktümtürk F. "ANN-based estimation of time-dependent energy loss in lighting systems". *Energy Build*, 116, 455-467, 2016.

[14] Ekici S, Jawzal H. "Breast cancer diagnosis using thermography and convolutional neural networks". *Med Hypotheses*, 132, 1-14, 2020.

[15] Koyuncu I, Yilmaz C, Alcin M, Tuna M. "Design and implementation of hydrogen economy using artificial neural network on field programmable gate array". *International Journal Hydrogen Energy*, 45(41), 20709-20720, 2020.

[16] Yilmaz C, Koyuncu I, Alcin M, Tuna M. "Artificial neural networks based thermodynamic and economic analysis of a hydrogen production system assisted by geothermal energy on field programmable gate array". *International Journal Hydrogen Energy*, 44(33), 17443-17459, 2019.

[17] Koyuncu I, Rajagopal K, Alcin M, Karthikeyan A, Tuna M, Varan M. "Control, synchronization with linear quadratic regulator method and FFANN-based PRNG application on FPGA of a novel chaotic system". *European Physical Journal Special Topics*, 230(7), 1915-1931, 2021.

[18] Tuna M, Karthikeyan A, Rajagopal K, Alçın M, Koyuncu İ. "Hyperjerk multiscroll oscillators with megastability: Analysis, FPGA implementation and A novel ANN-Ring-based true random number generator". *AEU-International Journal of Electronics and Communications*, 112, 152941, 2019.

[19] Panda AK, Rout SK, Das AK. "Optimization of diesel engine performance and emission using waste plastic pyrolytic oil by ANN and its thermo-economic assessment". *Environmental Science and Pollution Research*, 1, 1-15, 2023.

[20] Cao H, Xin Y, Yuan Q. "Prediction of biochar yield from cattle manure pyrolysis via least squares support vector machine intelligent approach". *Bioresource Technology*, 202, 158-164, 2016.

[21] Sun Y, Liu L, Wang Q, Yang X, Tu X. "Pyrolysis products from industrial waste biomass based on a neural network model". *Journal Analytical Applied Pyrolysis*, 120, 94-102, 2016.

[22] Sunphorka S, Chalermsinsuwan B, Piumsomboon P. "Artificial neural network model for the prediction of kinetic parameters of biomass pyrolysis from its constituents". *Fuel*, 193, 142-158, 2017.

[23] Selvarajoo A, Muhammad D, Arumugasamy SK. "An experimental and modelling approach to produce biochar from banana peels through pyrolysis as potential renewable energy resources". *Modeling Earth Systems and Environment*, 6, 115-128, 2020.

[24] Çepelioğullar Ö, Mutlu İ, Yaman S, Haykiri-Acma H. "Activation energy prediction of biomass wastes based on different neural network topologies". *Fuel*, 220, 535-545, 2018.

[25] Mayol AP, Maningo JMZ, Chua-Unsu AGAY, Felix CB, Rico PI, Chua GS, Manalili EV, Fernandez DD, Cuello JL, Bandala AA, Ubando AT, Madrazo CF, Dadios E, Culaba AB. "Application of artificial neural networks in prediction of pyrolysis behavior for algal mat (LABLAB) biomass". *IEEE 2018 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, Baguio City, Philippines, 29-02 December 2018.

[26] Aydinli B, Caglar A, Pekol S, Karaci A. "The prediction of potential energy and matter production from biomass pyrolysis with artificial neural network". *Energy Exploration and Exploitation*, 35(6), 698-712, 2017.

[27] Bridgwater AV. "Review of fast pyrolysis of biomass and product upgrading". *Biomass and Bioenergy*, 38, 68-94, 2012.

[28] Xiu S, Shahbazi A. "Bio-oil production and upgrading research: A review". *Renewable and Sustainable Energy Reviews*, 16(7), 4406-4414, 2012.

[29] Fernandez-Akarregi AR, Makibar J, Lopez G, Amutio M, Olazar M. "Design and operation of a conical spouted bed reactor pilot plant (25 kg/h) for biomass fast pyrolysis". *Fuel Processing Technology*, 112, 48-56, 2013.

[30] Erdem F. "Parameter estimation in Crystal Sugar production with MLR, ANN and ANFIS". *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 28(7), 987-992, 2022.

[31] Gürgen S, Altın İ. "Bütanol-Diesel yakıtı kullanılan bir sıkıştırma ateşlemeli motorda motor performansı ve egzoz emisyonlarının yapay sinir ağları ile tahmini". *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 24(4), 576-581, 2018.

[32] Abdelkareem MA, Soudan B, Mahmoud MS, Sayed ET, AlMallahi MN, Inayat A, Radi MAl, Olabi AG. "Progress of artificial neural networks applications in hydrogen production". *Chemical Engineering Research and Design*, 182, 66-86, 2022.

[33] Nawaz A, Kumar P. "Optimization of process parameters of Lagerstroemia speciosa seed hull pyrolysis using a combined approach of Response Surface Methodology (RSM) and Artificial Neural Network (ANN) for renewable fuel production". *Bioresource Technology Reports*, 18, 101110, 2022.

[34] Keskin RSO. "Predicting shear strength of reinforced concrete slender beams without shear reinforcement using artificial neural networks". *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 23(3), 193-202, 2017.

[35] Sahin I, Koyuncu I. "Design and ımplementation of neural networks neurons with RadBas, LogSig, and TanSig Activation Functions on FPGA". *Electronics and Electrical Engineering*, 4(120), 51-54, 2012.

[36] Bhattacharjee N, Biswas AB. "Pyrolysis of alternanthera philoxeroides (alligator weed): Effect of pyrolysis parameter on product yield and characterization of liquid product and bio char". *Journal of the Energy Institute*, 91(4), 605-618, 2018.

[37] Santos J, Ouadi M, Jahangiri H, Hornung A. "Valorisation of lignocellulosic biomass investigating different pyrolysis temperatures". *Journal of the Energy Institute*, 93(5), 1960-1969, 2020.

[38] Kim P, Weaver S, Noh K, Labbé N. "Characteristics of bio-oils produced by an intermediate semipilot scale pyrolysis auger reactor equipped with multistage condensers". *Energy & Fuels*, 28(11), 6966-6973, 2014.

[39] Tabal A, Belyazid O, Dahman H, Berrich E, Jeguirim M, El Achaby M, Aboulkas A. "Intermediate pyrolysis of Ficus nitida wood in a fixed-bed reactor: effect of pyrolysis parameters on bio-oil and bio-char yields and properties". *Comptes Rendus Chimie*, 26(S1), 1-17, 2023.