Journal of Analytical and Applied Pyrolysis 122 (2016) 84–94

Contents lists available at ScienceDirect

Journal of Analytical and Applied Pyrolysis

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

A study to predict pyrolytic behaviors of refuse-derived fuel (RDF): Artificial neural network application

Özge Çepelioğullar[a,*], İlhan Mutlu[b], Serdar Yaman[a], Hanzade Haykiri-Acma[a]

[a] Istanbul Technical University, Faculty of Chemical and Metallurgical Engineering, Department of Chemical Engineering, 34469, Istanbul, Turkey
[b] Istanbul Technical University, Faculty of Electrical and Electronics, Department of Control and Automation Engineering, 34469, Istanbul, Turkey

ARTICLE INFO

Article history:
Received 1 March 2016
Received in revised form 7 October 2016
Accepted 13 October 2016
Available online 14 October 2016

Keywords:
RDF
Pyrolysis
Artificial neural network (ANN)
Prediction
TGA
Characterization

ABSTRACT

The present study demonstrates the thermal behaviors of refuse-derived fuel (RDF), a highly-heterogeneous fuel, at high temperature region by bringing experimental and modelling studies together. In the first part, RDF was pyrolyzed in thermal analyzer from room temperature to 900 °C at varying heating rates as well as the evolved gas analysis was monitored by using TG-FTIR-MS. Afterwards, obtained data was used to develop an artificial neural network (ANN) model that can predict thermal behaviors of RDF at a new heating rate without performing any experiments. The temperature and heating rate were selected as input parameters while temperature dependent weight loss was selected as output parameter. The effects of parameters such as neuron number, training number, and the transfer function type on the network performance were investigated in detail to optimize network topology. Optimization studies showed that the best performance was achieved with ANN that had 7-6 neurons trained 25 times with tansig-logsig non-linear function combination. Prediction performance of the optimized ANN was tested by introducing a new experimental dataset. The good agreement between experimental and predicted values revealed that ANN can be a promising tool in pyrolytic behaviors estimation of even heterogeneous fuels such as RDF.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

Serious disadvantages of fossil fuel utilization such as sudden price changes in the market, unevenly distribution of these sources, as well as their negative impact on the environment motivate countries to increase the share of sustainable and alternative energy sources as a part of their future energy plans. From the current perspective, alternative solid fuels especially wastes have gained serious attention in energy utilization [1,2]. Thermal treatment methods such as combustion [3], pyrolysis [4] and gasification [5] are the significant processes where the wastes can be utilized as fuel. Compared to gasification and combustion, pyrolysis has some superiorities. For instance, it requires lower temperature, oxygen-absent environment and it enables not only energy production but also high value-added products, such as char, oil and gas [6,7]. Moreover, pyrolysis is known as the common step of the thermal processes. Therefore, a detailed thermal characterization of fuels' pyrolytic behaviors is really important for the further steps of the operation.

Thermogravimetric Analysis (TGA) has become an ordinary and necessary laboratory procedure to analyze thermal behaviors of different materials [8,9]. TGA provides information on the continuous mass loss characteristics of the samples to clarify their behaviors at high temperature region. Nowadays, most of the researchers are attempting to apply computational methods for the prediction of thermal data to reduce the number of the ordinary laboratory procedures in terms of time and energy saving. At this point, artificial neural network (ANN) becomes prominent as one of the widely accepted methods that generally deal with solving non-linear problems. Furthermore, ANN also allows analyzing the effects of different parameters on process performance, predicting and generalizing the overall system behaviors to make accurate predictions at high speed [10].

ANNs are originally inspired by the functionality of human brain. A typical biological neuron as part of a human brain transfers information (data) from synapses towards to the axon by

Abbreviations: ANN, Artificial neural network; BP, Back propagation; DTG, Derivative thermogravimetry; FT-IR, Fourier transform infrared spectrometer; LM, Levenberg-Marquardt; MS, Mass spectrometer; MSE, Mean square error; RDF, Refuse derived fuel; TGA, Thermogravimetric analysis; Logsig, Log-sigmoidal nonlinear function; Purelin, Linear transfer function; Tansig, Tan-sigmoidal nonlinear function.

* Corresponding author.
E-mail addresses: cepeliogullar@itu.edu.tr (Ö. Çepelioğullar), mutlui@itu.edu.tr (İ. Mutlu), yamans@itu.edu.tr (S. Yaman), hanzade@itu.edu.tr (H. Haykiri-Acma).

http://dx.doi.org/10.1016/j.jaap.2016.10.013
0165-2370/© 2016 Elsevier B.V. All rights reserved.

Nomenclature

b	Bias
f	Transfer function
a_i	Output
R^2	Regression
t_i	Target
w	Weight
β_i	Predicted values
λ_i	Experimental values

neurotransmitters. Likewise, ANNs are comprised of group of interconnected neurons which are known as input layer, hidden layer(s) and output layer. They have ability to learn the relationship between input/output layers, restore this relationship and generalize it for the further problems [11,12]. Therefore, ANNs can be very useful tools for the prediction of the thermal data. Although it is possible to find studies about the application of ANN on thermal data prediction, these have been mostly focusing on materials which have more predictable decomposition paths such as polymers or composites which was summarized in Table 1. For instance, Burgaz et al. [13] employed ANN method for the prediction of thermal stability, crystallinity and thermochemical properties of poly(ethylene oxide)/clay nanocomposites. In another study, Bezerra et al. [14] used ANN for the determination of the kinetic parameters of the composites while Conesa et al. [15] tried to apply ANN to determine the reaction kinetics of different polymeric materials by producing data in TGA at multiple heating rates. Yildiz et. al also employed ANN method for the estimation of the co-pyrolytic behaviors of hazelnut husk/lignite mixtures [16]. At this point, the question that should be asked is "*Is an ANN system sufficient enough to predict the pyrolytic data of more heterogeneous materials/mixtures?*" There is no certain answer for this question, because the more complicated the data introduced to ANN system, the more difficult to make accurate estimations without significant modifications in ANN structure. The present paper discusses ANN performance in data estimation from the perspective of refuse derived fuel (RDF) pyrolysis. It is already known that RDF is produced from municipal solid wastes (MSW) through a number of processes. The majority fraction of RDF is paper, card, wood, plastics and textiles [17]. This variety in the composition creates diversities in thermal degradation behaviors. Each component in the RDF has different degradation temperature intervals and, mostly these intervals may overlap, since many reactions occur simultaneously during pyrolysis. Therefore, estimation of pyrolytic behaviors of heterogeneous materials such as RDF becomes more complicated, because it is difficult to complete each run of experiments with evenly distributed samples in thermal analyzer due to its working principle with small quantities. Therefore, the present paper investigates the ANN performance on thermal data estimation from several standpoints; i) selection of the material in terms of its compositional variety which results in complexity in the prediction problem, ii) optimization of ANN topology for the best prediction performance, iii) testing prediction capability of ANN for new cases based on built ANN topology. Additionally, it is already known that evolved gas analysis always plays an important role to understand the pyrolysis process in detail. Therefore, TG-FTIR-MS analysis was also carried out to monitor the RDF pyrolysis in terms of product gases. Consequently, the current study provides an insight by bringing experimental and modelling studies together and introduces a different approach to the field.

2. Materials and methods

Within the scope of this study, two subsequent parts were included. In the first part, RDF pyrolysis was conducted at eight different heating rates to monitor the effect of varying heating rates on pyrolysis process. In addition, thermal decomposition studies were supported with TG-FTIR-MS as a complementary tool to analyze the evolved gas during pyrolysis. In the second part of the study, obtained data from thermal experiments were used to create an ANN model that predicts pyrolytic behaviors of RDF. The parameters such as neuron number, training number and transfer function type were discussed in detail to make sure that the developed model is robust and reliable for the generalization of new cases.

2.1. Material

In the present paper, RDF obtained from ISTAÇ Co. Compost and Recovery Plant in Istanbul-Turkey was selected as fuel. The main fractions were identified as textile (66%), paper (17.1%) and plastic derivatives (13.3%) [18]. RDF was first dried in open containers under laboratory conditions. After drying process, it was grinded and sieved to below 250 μm and particles were shaken very well to make a more uniform distribution of the particles. In order to determine the features of the selected fuel, characterization studies were carried out before thermal step. Proximate, ultimate and component analyses were completed according to the procedures that were explained in our previous study [19]. RDF was analyzed with 71.5% volatiles, 7.1% of moisture and 15.6% of ash contents. From these results, it is possible to say that the moisture content was under the limits for thermal processes. However, the ash con-

Table 1
Literature summary of ANN applications in thermal data estimation.

Material	*Thermal Decomposition Conditions*			*ANN model properties*					*Reference*
	Final Temp. (°C)	Heating rate (°C/min)	Atmosphere	Input	Output	Algorithm	Network topology $[x\text{-}y]_z$	Training function	
Poly(ethylene)/clay nanocomposites	630	10	N_2	–Temperature –Clay wt.%	Weight loss	LM	$[4\text{–}3]_2$	Tansig-logsig	[13]
Carbon reinforced fiber composites	1000	2.5, 5, 10, 20, 40	N_2	–Temperature –Heating rate	Mass retained	LM	$[3\text{–}3]_2$ $[21\text{–}21]_2$	–	[14]
Polymeric materials	500	5, 10,25	N_2	–20 points in TG curves at different heating	Kinetic constants	–	$[10]_1$	Sigmoid	[15]
Hazelnut husk/lignite	900	5, 10, 20, 50	air	–Heating rate –Blend ratio –Temperature	Mass loss	LM	$[15\text{–}5]_2$	Tansig-Tansig	[16]

LM:Levenberg-Marquardt.
x,y: number of neurons in hidden layers.
z: number of hidden layers in network.

Download English Version:

https://daneshyari.com/en/article/5134757

Download Persian Version:

https://daneshyari.com/article/5134757

Daneshyari.com