Journal of the Energy Institute xxx (2016) 1–11

Contents lists available at ScienceDirect

Journal of the Energy Institute

journal homepage: http://www.journals.elsevier.com/journal-of-the-energy-institute

An artificial intelligence approach to predict gross heating value of lignocellulosic fuels

Ugur Ozveren*

Department of Chemical Engineering, Faculty of Engineering, Marmara University, Istanbul 34722, Turkey

ARTICLE INFO

Article history:
Received 11 September 2015
Received in revised form
22 March 2016
Accepted 4 April 2016
Available online xxx

Keywords:
Biomass
Gross heating value
Artificial neural network
Proximate analysis

ABSTRACT

The gross heating value (GHV) is one of the most significant properties of biomass fuels in designing and operating any fuel processing systems. This study deals with a new method to calculate the GHV from the proximate analysis of different kinds of lignocellulosic fuels by using Levenberg–Marquardt trained artificial neural network (ANN) as an artificial intelligence method. Furthermore, a new nonlinear regression model was developed for this study. The published correlations were employed with the various biomasses to obtain a comparison with the ANN model and developed nonlinear correlation in this study. The results indicate that the artificial intelligence approach offers a high degree of correlation and its robustness and capability to compute GHV of any lignocellulosic fuels from its proximate analysis. Therefore, the proposed artificial intelligence is highly promising tool to use in designing and operating of any thermolysis process for lignocellulosic fuels.

1. Introduction

The accelerating rate of industrialization coupled with the rising standards of living and the population growth results in the constant increase of energy demand. In such a situation, biomass sources such as the renewable energy sources serve as promising alternatives in the production of sustainable energy. The energy generation from biomass is of utmost importance, considering the decreasing availability of fossil fuels [1]. The higher sensibility towards the greenhouse effect from carbon dioxide generated by conventional methods of energy production also makes biomass favorable due to it having net zero carbon dioxide emissions.

The design of biomass thermal conversion systems significantly relies on the characteristics of biomass such as heating value, elemental composition, ash properties, etc. The GHV, also known as gross calorific value (GCV), refers to the heat released by the complete combustion of a unit volume of biomass leading to the production of water vapor and its eventual condensation; the total energy released is measured at this point [2].

The GHV of biomass samples can be generally determined by using a bomb calorimeter. However, the measurement of GHV is a costly and time-consuming process that requires a set-up; therefore, empirical models are used for predicting the gross heating value of biomass samples. According to the input parameters, the empirical correlations can be classified into three groups: the proximate analysis based model [3–7], ultimate analysis based model [3,6–8], and the lignocellulosic component based model [4,9].

The ultimate analysis based correlations have proved to have a strong ability in estimating GHV conveniently and accurately. However, the models from the ultimate analysis results require specific and expensive instrumentation [10]. The literature relating to the correlation between the heating values and lignocellulosic contents was also presented [11–13]. On the other hand, the lignocellulosic components of biomass, except cellulose, have a different chemical structure and composition, consequently, leading the heating values of these components to vary a lot among different biomass species [3,4]. For that reason, there exists an alternative approach in the literature, which uses proximate analysis data for the GHV estimation. The proximate analysis includes measurements of volatile matter (VM), ash (ASH) and fixed carbon (FC), which can be easily determined and attained during the most industrial usage [14]. Thus, the GHV prediction of biomass fuels

* Tel.: +90 535 8837701; fax: +90 216 3480293.
E-mail address: ugur.ozveren@marmara.edu.tr.

http://dx.doi.org/10.1016/j.joei.2016.04.003
1743-9671/

using the proximate analysis results has been investigated by many researchers [7,8,15,16]. The empirical correlations used to predict GHV, found during a literature review, are presented in Table 1.

The variability of the biomass chemical structure determines reduction in the accuracy of the GCV prediction [6]. The artificial neural networks as an artificial intelligence approach provide an alternative method to describing the complex relationships between variables without choosing the correct form of the nonlinear data fitting function [18]. Therefore, the ANN has gained wide popularity in the intelligent prediction systems and has also been applied in the heating value estimation [18,19].

The first objective of this study is to estimate the GHV by using a Levenberg–Marquardt trained back-propagation ANN model through the proximate analysis of biomass fuels. The second aim is to develop a nonlinear model, and validates the artificial intelligence approach against the developed predictive model and previous published correlations in literature for the reliability and robustness of model.

2. Materials and methods

2.1. Experimental data

The data of 250 biomass samples with their GHVs were taken from the study of Nhuchhen and Salam [15], who acquired the data from previous studies in this field. All 250 samples as well as a split of the samples into a training set with 174 samples, training validation set with 38 samples and a testing set with 38 samples were randomly selected by using the MATLAB software. The training dataset was employed for generation/training of the ANN model. The training dataset is presented in Table 2.

Table 2 shows that, in the training dataset, the ash content varies from 0.10% to 70%, volatile matter content varies from 12.70% to 91.98% and fixed carbon contents range from 1.90% to 68.10%, while the range of GHV varies from 5.63 to 23.46 MJ/kg.

The validation dataset in this study is utilized for checking the generalization ability of the ANN and for stopping the training before any over-fitting occurs. When the validation error reaches the maximum validation failures in the training step, the algorithm stops the network training automatically. Thus, the problem of over-fitting is effectively controlled during the training step. The validation dataset that includes the proximate analysis results of biomass samples with their GHVs is presented in Table 3.

The volatile matter of the validation samples varies between 9.09% and 87.30%, the ash content between 0.10% and 77.70%, the fixed carbon content between 5.96% and 24.6%, and the heat content between 5.70 and 21.59 MJ/kg (on dry basis).

2.2. Artificial neural network (ANN)

An ANN is a massively parallel-distributed information processing system that simulates the functions of neurons using artificial neurons, inspired by the studies of the brain and the nervous system [20]. An artificial neuron is the fundamental processing element of an ANN and can be implemented in many different ways. The general architecture of an artificial neuron is shown in Fig. 1.

In this figure, input from the output (out_i) of the preceding layer neuron is multiplied by its weight value (W_{ji}). Then, results of these multiplications are added to the bias value (B_j). Usually, the initial weights and biases are randomly assigned. The output of a neuron, which is in Fig. 1, can be described by Eq. (12).

$$out_j = h\left(\sum_{i=1}^{N}(W)_{ji}X_i + B_j\right) \tag{12}$$

where h is the activation (transfer) function. The activation function can be found in different forms, either linear or non-linear. In this work, logarithmic sigmoid, $h(x)$, function was used as an activation function, which is defined as:

$$h(x) = 1/(1+\exp(-x)) \tag{13}$$

Table 1
Some of the models used to predict GHV, found during a literature review.

Equation	Equation no	Ref.
Proximate analysis		
GHV = −3.0368 + 0.2218VM + 0.2601FC	1	[3]
GHV = −10.81408 + 0.3133(VM + FC)	2	[4]
GHV = 0.3543FC + 0.1708VM	3	[5]
GHV = 0.312FC + 0.1534VM	4	[17]
GHV = 0.196FC + 14.119	5	[17]
GHV = 19.2880 − 0.2135VM/FC − 1.9584ASH/VM + 0.0234FC/ASH	6	[15]
GHV = 20.7999 − 0.3214VM/FC + 0.0051(VM/FC)^2 − 11.2277ASH/VM + 4.4953(ASH/VM)^2 − 0.7223(ASH/VM)^3 + 0.0383(ASH/VM)^4 + 0.0076FC/ASH	7	[15]
Ultimate analysis		
GHV = −1.3675 + 0.3137C + 0.7009H + 0.0318O (MJ/kg)	8	[3]
GHV = 0.3491C + 1.1783H + 0.1005S − 0.10340O − 0.0151N − 0.0211A (MJ/kg)	9	[8]
Lignocellulosic components		
GHV = (1 − Ash/(100 − Ash)) × (0.1739Ce + 0.2663Lig + 0.3219He)	10	[4]
GHV = 0.0979Lig + 16.292	11	[9]

C, H, S and O, the fractions of the elements of carbon, hydrogen, sulfur and oxygen in the substance, on a dry basis, respectively. Ce, Lig, He weight percent of cellulose, lignin, hemicellulose, on dry basis respectively.