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ANFIS based prediction model for biomass heating value using proximate analysis components

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ABSTRACT

This paper proposes a new biomass higher heating value (HHV) prediction model using adaptive neuro-fuzzy inference system (ANFIS) approach. The 444 data related to wide range biomass based materials are composed from the open literature. The input set for the prediction model is involved of the proximate analysis components such as fixed carbon, ash and volatile matter. Three methods called grid partition, sub-clustering and fuzzy c-means are considered in the ANFIS model building process, in order to generate fuzzy inference system (FIS) structure. For determining the best ANFIS based prediction model, a number of simulation studies are performed for each FIS method. The optimal result obtained from each method is compared with each other and the results of the models given in the related literature by prediction performance criteria. The results show that sub-clustering based ANFIS model is the best biomass HHV prediction model. Its obtained coefficient of regression (R^2) and root mean square error (RMSE) are 0.8836 and 1.3006, respectively, in the testing phase. As a conclusion, it can be said that the proposed ANFIS based model is an efficient technique to obtain high accuracy biomass HHV prediction.

1. Introduction

Energy is one of the main entries for the social and economic development. In the last 100 years, the amount of energy consumption in the world has increased approximately 17 times [1,2]. Considering criteria such as energy efficiency, applicability, environmental impact and flexibility, the requirement for environmentally friendly alternative fuel sources and energy conversion methods is emerged. Since biomass based fuels meet these criteria, they become one of the attractive feedstocks for heat and electricity generation technologies [3,4].

In this point, biomass-heating value is needed to determine correctly their characterization and economic values. In addition, biomass-heating value is an essential parameter for design and operation of biomass-fueled technologies [5]. Determining HHV value directly (experimentally) by the essential apparatus becomes costly and time consuming [3]. The rapid, easy and economical way is to make efficient prediction of HHV. Therefore, in the literature, for predicting the heating value of biomass materials, there are a number of mathematical models depending on ultimate [3,4,6–9], proximate [4,6,10–13], structural [14–16], physical [17] and chemical [17,18] analyses. In the recent time, usage of the components of biomass proximate analysis has increased in significance among both researchers and engineers. The reason for this is that, obtaining the results of proximate analysis is easy, simple, quick and has a relatively low cost [3,7,8,19,20].

Table 1 summarizes the studies modeling heating value of various biomass-based materials using proximate analysis components since the year of 2000. As seen from this table, most of the modeling studies are based on linear regression method. However, relationship between some proximate analysis components of biomass and their HHV value is nonlinear. Therefore, the prediction of linear regression based models may be inadequate, especially when they are tested by different samples [5]. In the papers studying both linear and nonlinear regression approaches, the nonlinear-based models [13,20,24] generally gave better prediction results. Apart from these studies, Huang et al. [10] used artificial neural network (ANN) to develop predictive models that can provide prediction of heating value of straw samples for engineering applications. They concluded that the ANN model showed the best accuracy among the other proposed models. In addition to this, Ghugare at al. [5] proposed a novel artificial intelligence formalism for developing biomass HHV prediction models, namely genetic programming. They compared this novel model results with those of ANN based model. Their study revealed that the HHV prediction performance of the genetic programming and neural network models is consistently better than that of their existing linear and/or nonlinear counterparts.

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Table 1
Biomass heating value prediction models based on proximate analysis components (dry basis, wt.%) in the literature.

Authors	Year	Ref.	Material	Country	Number of data	Method	Model equation (dry basis, wt.%)	Eq. number	R^2
Cordero et al.	2001	[21]	Biomass/chars	Spain, Cuba	24	MLR	HHV = 35.430 – 183.5VM – 354.3A (kJ/kg)	(1)	na
Kathiravale et al.	2003	[22]	MSW	Malaysia	30	MLR	HHV = 356.047VM – 118.035FC – 5600.613 (kJ/kg)	(2)	0.691
Sheng and Azevedo	2005	[4]	WRB	DGL	209 (OL)	LR	HHV = 19.914 – 0.2324A (MJ/kg)	(3)	0.625
Parikh et al.	2005	[11]	Solid carbonaceous	DGL	550 (OL)	MLR	HHV = 0.3536FC + 0.1559VM – 0.0078A (MJ/kg)	(4)	na
Thipkhunthod et al.	2005	[23]	Sewage sludge	Thailand	219	LR	HHV = 259.83(VM + FC) – 2454.76 (kJ/kg)	(5)	0.899
Huang et al.	2008	[10]	Straw	China	222	ANN		na	0.896
Erol et al.	2010	[24]	Biomass	Turkey	20	MNR	LHV = –5.9 + 0.836FC – 0.0116FC^2 + 0.00209VM^2 + 0.0325A^2 (MJ/kg)	(6)	0.898
Callejón-Ferre et al.	2011	[3]	Biomass	Spain	8	MLR	HHV = –2.057 – 0.092A + 0.279VM (MJ/kg)	(7)	0.949
Yin	2011	[6]	Biomass	DGL	44 (OL)	MLR	HHV = 0.1905VM + 0.2521FC (MJ/kg)	(8)	0.995
Nhuchhen and Salam	2012	[20]	WRB	DGL	250(OL)	MNR	HHV = 20.7999 – 0.3214VM/FC + 0.0051(VM/FC)^2 – 11.2277A/VM + 4.4953(A/VM)^2 – 0.7223(A/VM)^3 + 0.0383(A/VM)^4 + 0.0076FC/A (MJ/kg)	(9)	na
Phichai et al.	2013	[25]	Biomass	Thailand	16	LR	HHV = 157.34(VM + FC) + 4243.97 (kJ/kg)	(10)	0.410
Kieseler et al.	2013	[26]	Chars	Germany	72	MLR	HHV = 0.4108FC + 0.1934VM – 0.0211A (MJ/kg)	(11)	na
Choi et al.	2014	[27]	Livestock waste	S. Korea	30	LR	HHV = 0.1970VM + 0.3955 (MJ/kg)	(12)	0.808
García et al.	2014	[13]	WRB	Spain	121	NR	HHV = 18,300 – 3.98A^2 – 112.10A (kJ/kg)	(13)	na
Ghugare et al.	2014	[5]	WRB	DGL	382 (OL)	GP	HHV = 0.365FC + 0.131VM + 1.397/FC + 328.658VM/[10283.138 + 0.531(FC)^{3}A – 6.863(FC)^{2}A] (MJ/kg)	(14)	0.962
Mohammed et al.	2014	[28]	WRB	DGL	300 (OL)	MLR	HHV = 1.999 + 0.248FC + 0.162VM – 0.137A (MJ/kg)	(15)	0.929
Soponpongpipat et al.	2015	[29]	Chars	Thailand	25	MLR	HHV = 35.4879 – 0.3023A – 0.1905VM (MJ/kg)	(16)	0.981

R^2: coefficient of regression, HHV: higher heating value; LHV: lower heating value; MLR: multiple/multivariate linear regression; MNR: multiple/multivariate nonlinear regression; LR: linear regression; ANN: artificial neural network; GP: genetic programming; DGL: different geographic location; OL: open literature; MSW: municipal solid waste; WRB: wide range biomass; FC: fixed carbon; VM: volatile matter; A: ash; na: none available.

Recently, new models based on adaptive neuro-fuzzy inference system (ANFIS) have turned into a popular universal approximator representing highly nonlinear functions because their learning capabilities make them adaptive to system changes [30]. In fact, in fuzzy inference systems, the knowledge or experiments of human beings and the procedure of inference can be described and analyzed qualitatively through fuzzy if–then rules. Nevertheless, it is not able to perform a precise quantitative analysis. In addition, artificial neural network owns the ability to learn, organize and adapt by itself. However, it cannot deal with qualitative knowledge and the process of inference. The advantages of fuzzy inference systems and artificial neural networks were combined in ANFIS method that was described by Jang [31,32]. Therefore, this technique is capable of handling complex and nonlinear problems [33].

In this study, adaptive neuro fuzzy inference system (ANFIS) is applied with the aim of developing a prediction model of biomass heating value using the components of proximate analysis. The large biomass data set for wide range biomass based materials such as crops, forest trees, sludge, biomass chars, various waste types, etc. which are collected from open literature, are used to develop the ANFIS based models. Grid partition, sub-clustering and fuzzy c-means clustering methods are utilized for generating fuzzy inference system. For each method, a number of model structures are generated by changing their related parameters. The heating value prediction performances of the developed models are investigated by extensive simulation studies in order to find the best ANFIS based prediction model. Additionally, the developed ANFIS models are compared to the literature models to show their precision ability.

2. Adaptive neuro fuzzy inference system

Adaptive neuro fuzzy inference system (ANFIS) model is an architecture that consists of input–output variables and a fuzzy rule base of the Takagi–Sugeno type [31]. It is a class of adaptive, multi-layer and feed-forward networks. For simplification, it is assumed that the framework of ANFIS has two inputs x, y and one output z. Then, the corresponding rule set with two fuzzy if–then rules for a first-order Sugeno fuzzy model can be expressed as shown in Eq. (17). Entries are evaluated by linguistic variables (A_1, B_1). A linear combination of the input values with a constant term (r) is used to obtain each rule result.

$$\text{Rule1}: \text{ If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } z_1 = p_1x + q_1y + r_1$$

$$\text{Rule2}: \text{ If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } z_2 = p_2x + q_2y + r_2 \tag{17}$$

Fig. 1 illustrates the ANFIS architecture, which contains five layers with different functions. The function of each layer is described as follows.

Layer 1: The main purpose of layer 1 is to map input variables (x and y) into fuzzy sets, say $A = \{A_1, A_2, B_1, B_2\}$ through the process of fuzzification. Each node in this layer is a square node with node functions for generating membership grades. A and B are linguistic labels (such as "low" and "high") characterized by different membership functions such as generalized bell, sigmoid or triangular. Layer 2: In this layer, firing strength will be used after combining the fuzzy sets of each input. The Π-norm operator performing the fuzzy conjunction ("and"), is used to obtain the output. Layer 3: The main purpose of this layer is to calculate the ratio of ith rule is firing strength to the sum of all firing strength. Layer 4: In this layer, the output from the previous layer is multiplied with the function of Sugeno fuzzy rule. Layer 5: There is only one node in this layer. This single node computes the sum of all outputs of each rule from the previous layer. Then, the weighted averaged method is used to perform the process of defuzzification, which transforms the fuzzy result into a crisp output.