Waste Management xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Waste Management

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

Comparison of ANN (MLP), ANFIS, SVM, and RF models for the online classification of heating value of burning municipal solid waste in circulating fluidized bed incinerators

Haihui You, Zengyi Ma *, Yijun Tang, Yuelan Wang, Jianhua Yan, Mingjiang Ni, Kefa Cen, Qunxing Huang

State Key Laboratory of Clean Energy Utilization, Zhejiang University, Hangzhou 310027, China

A R T I C L E   I N F O

Article history:
Received 9 October 2016
Revised 24 February 2017
Accepted 27 March 2017
Available online xxxx

Keywords:
Circulating fluidized bed incinerators
Heating value
MLP
SVM
ANFIS
RF

A B S T R A C T

The heating values, particularly lower heating values of burning municipal solid waste are critically important parameters in operating circulating fluidized bed incineration systems. However, the heating values change widely and frequently, while there is no reliable real-time instrument to measure heating values in the process of incinerating municipal solid waste. A rapid, cost-effective, and comparative methodology was proposed to evaluate the heating values of burning MSW online based on prior knowledge, expert experience, and data-mining techniques. First, selecting the input variables of the model by analyzing the operational mechanism of circulating fluidized bed incinerators, and the corresponding heating value was classified into one of nine fuzzy expressions according to expert advice. Development of prediction models by employing four different nonlinear models was undertaken, including a multilayer perceptron neural network, a support vector machine, an adaptive neuro-fuzzy inference system, and a random forest; a series of optimization schemes were implemented simultaneously in order to improve the performance of each model. Finally, a comprehensive comparison study was carried out to evaluate the performance of the models. Results indicate that the adaptive neuro-fuzzy inference system model outperforms the other three models, with the random forest model performing second-best, and the multilayer perceptron model performing at the worst level. A model with sufficient accuracy would contribute adequately to the control of circulating fluidized bed incinerator operation and provide reliable heating value signals for an automatic combustion control system.

1. Introduction

Municipal solid waste (MSW) incineration techniques have been developing rapidly due to the primary advantages of hygienic control, volume reduction, and energy recovery. Compared with other MSW incineration techniques, the circulating fluidized bed (CFB) incineration method is of great fuel flexibility, and has lower emissions (Van Caneghem et al., 2012; Liukkonen et al., 2012). There were more than 70 CFB incinerators with 64,000 T daily handling capacity in China by the end of 2014 (Specialized Committee of Urban Domestic Refuse of CAEPI, 2014), making an outstanding contribution to the harmless treatment of MSW.

The characteristics of physical and chemical composition of MSW in China are rather complicated due to the collection of unsorted MSW, with the physical components of Chinese MSW mainly comprising food residue, noncombustibles, plastics, paper, textiles, wood waste, and rubber, which are characterized by relatively high moisture and low (but varying) heating value (Zhou et al., 2014). These characteristics induce frequent fluctuation in incineration systems and result in undesired consequences, such as an increased level of emissions or sharp variations in bed temperature if effective measures are not adopted (Liukkonen et al., 2012, 2011). In addition, to improve the operation and

Abbreviations: MSW, municipal solid waste; HV, heating value; RF, random forest; SVM, support vector machine; DCS, distributed control system; PSO, particle swarm optimization; TT, training time; BP, back-propagation; NEB, negative extremely big; NM, negative medium; ZE, zero; PM, positive medium; CFB, circulating fluidized bed; MLP, multilayer perceptron; ANFIS, adaptive neuro-fuzzy inference system; ACCS, automatic combustion control system; CART, classification and regression tree; SC, subtractive clustering; PP, prediction precision; PEB, positive extremely big; NB, negative big; NS, negative small; PS, positive small; PB, positive big.

* Corresponding author.

E-mail addresses: 11327046@zju.edu.cn (H. You), mazy@zju.edu.cn (Z. Ma), 472721150@qq.com (Y. Tang), 11227044@zju.edu.cn (Y. Wang), yanjh@zju.edu.cn (J. Yan), mjn@zju.edu.cn (M. Ni), kfcen@sun.zju.edu.cn (K. Cen), hqx@zju.edu.cn (Q. Huang).

http://dx.doi.org/10.1016/j.wasman.2017.03.044
0956-053X/

management level of the waste incineration industry, and to enhance the safety, environmental friendliness, and economic efficiency of waste incineration technology, the Ministry of Housing and Urban-Rural Development of China issued a standard for the assessment of municipal solid waste incineration plants (Standard No. CJJ/T 137-2010), a grading tool to determine whether an incineration system has been implemented with an automatic combustion control system (ACCS) as proposed in the standard. However, the essential prerequisite to implementing an ACCS is obtaining the real-time lower heating value of burning waste (Shen, 2005; Xie et al., 2007). Meanwhile, the statistical analysis of HVs is required to acquaint plant managers with the variation tendency of HVs and support the management of the incineration plant. Therefore, it is of significant importance to establish a rapid, precise, and cost-effective online HV prediction approach.

There has been no reliable online measuring instrument for detecting HVs of MSW up to now, and the conventional approaches include offline experimental methods, empirical prediction models based on MSW test results and mass and energy balances based models. In the experimental method, the HVs are determined using a bomb calorimeter, which is accurate but costly and time consuming (Lin et al., 2015). Additionally, MSW is a heterogeneous material, and the sample masses required for ultimate analysis and proximate analysis are considered to be inadequate due to the vast variance in MSW composition (Zhou et al., 2014; Lin et al., 2015). Another approach is to predict HVs by empirical models; three types of empirical models applied to forecast HVs, namely those based on ultimate analysis (Chang et al., 2007; Ebru and Ahmet, 2009; Akkaya and Demir, 2010), proximate analysis (Moh'd et al., 2000), or physical composition analysis (Zhou et al., 2014; Lin et al., 2015; Dong et al., 2003; Ozveren, 2016). All of these models are developed by multiple regression analysis methods or nonlinear data-mining techniques (e.g., artificial neural networks), and have a certain degree of accuracy. However, these approaches inherit defects of the experimental method, and thus are incapable of measuring the HVs constantly and in real time. Some researchers proposed a modeling approach based on mass and energy balances to predict HVs (Van Kessel et al., 2004, 2002; Belkhir and Frey, 2016), these models is easy to apply and has been assessed as to their practical reliability and accuracy, but they depend heavily on the real-time weighing of MSW feedstock and/or concentration measuring. However, due to the imbalanced industrial development and complexity of MSW feeding system in China, the real-time weighing of MSW stock is not available in all incineration plants, and some plants are lack of concentration measurements, these limits the application of mass and energy balances based prediction models.

Accurate HVs of MSW remain unknown in the process of operating incineration systems by incinerator operators, but they are capable of evaluating the trend of the HV by analyzing operating conditions of incinerators comprehensively, and by further estimating the fuzzy level (e.g., high, medium, or low) of HVs according to their professional knowledge and accumulated experience. Consequently, it is effective and convenient to construct online prediction models for HVs based on operator expertise and experience by utilizing nonlinear data-mining techniques, and thus avoiding experimental testing of MSW.

As a product of the development boom in electronic techniques, computer science, and information technology, distributed control systems (DCSs) have been widely applied in waste-incineration power plants, and abundant process-parameter data are stored in databases since such systems produce a surfeit of data that is not easily interpreted using conventional data-analysis methods (Liukkonen et al., 2011). These data archives offer a useful source of information and, in fact, have potential uses in constructing data-driven models. Data-based modeling techniques, such as MLP, SVM, ANFIS, RF, etc., all have simultaneously benefited from the progress in computer science. These modeling techniques are broadly used in many fields, such as energy, construction, biology, economics, medicine, etc. (Matin and Chelgani, 2016; Tuğru and Yiğit, 2005; Xu et al., 2010; Chen, 2013), and it is convenient and advantageous to implement these algorithms in cases in which just a little knowledge about a mechanism is required, particularly when there is insufficient understanding of a process mechanism or the properties of the object of study are quite complicated. The training time for a reasonably designed model is on an acceptable level, and a well-trained model can realize real-time computing. All of these features make these data-driven models an attractive tool for practical application. Nonetheless, it is important to bear in mind that the performance of these models varies with the object of study. Comparative research of these models has captured research attention (Najafi et al., 2016; Moghaddamnia et al., 2009; Roohollah et al., 2010; Zhang et al., 2008; Yang and Ross, 2012; Yilmaz, 2010; Khalilia et al., 2011) since it is important to choose a relatively optimal HV prediction model by carrying out comprehensive comparative studies. Additionally, the continuous increase in CPU computation speed has shortened the computation time spent on training these models, supplying a reliable hardware platform for subsequent popularization and application.

This study presents several rapid and cost-efficient HV forecasting models developed with the aid of MLP, SVM, ANFIS, and RF models. First, the input variables of the model were selected by analyzing the operational mechanism of CBFIs, and the corresponding HV was classified into one of nine fuzzy expressions according to expert advice. Then, training and testing samples were collected from the DCS databases for modeling HV prediction models based on MLP, SVM, ANFIS, and RF. To improve the MLP, SVM, ANFIS and RF performance, a series of optimization schemes were implemented, including (1) conducting trial-and-error experiments and employing particle swarm optimization (PSO) to search for optimal MLP parameters; (2) utilizing a subtractive clustering (SC) algorithm to initialize the ANIFS structure and parameter settings and conducting trial-and-error experiments to select the optimal clustering radius (r_α); (3) applying a PSO algorithm to optimize the penalty parameter (C) and kernel function parameters (g) of the SVM; (4) applying a PSO algorithm to optimize number of trees (*ntree*) and number of input variables tried at each split (*mtry*). Finally, the performance of all models was compared in detail using the training time (*TT*) and prediction precision (*PP*).

2. Background

2.1. MLP

MLP is one of the most popular feed-forward artificial neural network architectures in the literature for forecasting problems, among which the back-propagation (BP) model is the most extensively used, and it is a supervised learning model. It is a network inspired by the neural system of the human brain, consisting of processing elements called neurons and connections, which are arranged in three or more layers: an input layer, a single or more hidden layer(s), and an output layer. In this study, a three-layer BP model is adopted because many theoretical and experimental works have shown that a single hidden layer is sufficient to approximate a complex nonlinear function (Yilmaz, 2010; Jalili and Noori, 2008); the architecture of the three-layer BP model is shown in Fig. 1.

The core of the BP model consists of two parts: transforming the input signals forward through a nonlinear activation function to the output layer, and back-propagating the prediction error energy to tune the weighting. The two processes run in a cyclical alternat-