ARTICLE IN PRESS

Waste Management xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Waste Management

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

Artificial neural network based modelling approach for municipal solid waste gasification in a fluidized bed reactor

Daya Shankar Pandey [a], Saptarshi Das [b], Indranil Pan [c], James J. Leahy [a], Witold Kwapinski [a,*]

[a] Carbolea Research Group, Chemical and Environmental Science Department, Bernal Institute, University of Limerick, Ireland
[b] Department of Physics, University of Cambridge, JJ Thomson Avenue, Cambridge CB3 0HE, United Kingdom
[c] Department of Earth Science and Engineering, Imperial College London, Exhibition Road, London SW7 2AZ, United Kingdom

ARTICLE INFO

Article history:
Received 16 May 2016
Revised 4 August 2016
Accepted 23 August 2016
Available online xxxx

Keywords:
Municipal solid waste
Gasification
Artificial neural networks
Feed-forward multilayer perceptron
Fluidized bed gasifier

ABSTRACT

In this paper, multi-layer feed forward neural networks are used to predict the lower heating value of gas (LHV), lower heating value of gasification products including tars and entrained char (LHV_p) and syngas yield during gasification of municipal solid waste (MSW) during gasification in a fluidized bed reactor. These artificial neural networks (ANNs) with different architectures are trained using the Levenberg–Marquardt (LM) back-propagation algorithm and a cross validation is also performed to ensure that the results generalise to other unseen datasets. A rigorous study is carried out on optimally choosing the number of hidden layers, number of neurons in the hidden layer and activation function in a network using multiple Monte Carlo runs. Nine input and three output parameters are used to train and test various neural network architectures in both multiple output and single output prediction paradigms using the available experimental datasets. The model selection procedure is carried out to ascertain the best network architecture in terms of predictive accuracy. The simulation results show that the ANN based methodology is a viable alternative which can be used to predict the performance of a fluidized bed gasifier.

1. Introduction

According to World Bank data, about 4 billion tonnes of waste is generated per year, out of which cities' alone contribute 1.3 billion tonnes of solid waste. This volume is forecast to increase to 2.2 billion tonnes by 2025. Three-fourths of this waste is disposed of in landfills, with only one fourth being recycled. It is expected that in lower income countries waste generation will double in the next 25 years (Hoornweg and Bhada-Tata, 2012). With rapid industrial growth and growing world population, most developing countries are facing acute disposal problem for municipal solid waste (MSW). MSW refers to the discarded materials from household wastes such as kitchen garbage, paper, wood, food waste, cotton as well as materials derived from fossil fuels such as plastic and rubber (Cheng and Hu, 2010). In urban areas significant environmental problems are arising from the disposal of MSW which have led to major concerns regarding human health and environment. These issues are common to both developed as well as developing countries (Pires et al., 2011). Furthermore, these issues are stimulating the need for further development of treatment technologies to meet these global challenges. The new European sustainable development strategy (EU, 2009) promotes thermal treatment processes to recover energy from MSW while tackling the issues related to climate change.

There are several processes that could treat MSW including thermal, biochemical and mechanical processes. Incineration technology is widely used to process MSW, but the control of NOx, SOx, nano-particle, dioxins and furans emissions are challenging (Cheng and Hu, 2010). In a quest for a sustainable waste treatment technology, waste to energy (WtE) technology has been reviewed by Brunner and Rechberger (2015). The study concluded that due to the advancement in combustion and air pollution control technologies WtE plants are useful for energy and material recovery from waste without having adverse effects on environment.

Abbreviations: LHV, lower heating value; LHV_p, lower heating value of product gas including tars and entrained char; MSW, municipal solid waste; ANN, artificial neural network; LM, Levenberg–Marquardt; WtE, waste to energy; FFNN, feed forward neural network; CFD, computational fluid-dynamics; ER, equivalence ratio; SCG, scaled conjugate gradient; BFGS, Broyden-Fletcher-Goldfarb-Shanno quasi-Newton; GDX, gradient descent with momentum and adaptive learning rate; MIMO, multiple input and multiple output; MISO, multiple input and single output; tansig, hyperbolic tangent sigmoid function; logsig, logarithmic sigmoid function; purelin, pure linear function; MSE, mean squared error; MAE, mean absolute error; RMSE, root mean squared error; NMSE, normalised root mean squared error; IQR, Interquartile range.

* Corresponding author.
E-mail address: witold.kwapinski@ul.ie (W. Kwapinski).

http://dx.doi.org/10.1016/j.wasman.2016.08.023
0956-053X/

Please cite this article in press as: Pandey, D.S., et al. Artificial neural network based modelling approach for municipal solid waste gasification in a fluidized bed reactor. Waste Management (2016), http://dx.doi.org/10.1016/j.wasman.2016.08.023

The impact on the environment of thermal treatment of waste with energy recovery was evaluated by Pavlas et al. (2010) who concluded that thermal treatment of MSW with energy recovery was undoubtedly one of the best techniques. WtE not only offers an alternative to treat the waste but also produces clean energy which can offset primary energy consumption in conventional heat and power units. In general, WtE plants are considered as carbon neutral but they are not. The total carbon content present in the MSW is bound with various materials present in the waste. It was found that more than half of the carbon present is biogenic in nature but the remaining part originates from fossil fuels which cannot be considered as biogenic carbon (Gohlke, 2009). As per the EU's new directive, each WtE plant has to report how much electricity was produced from the renewable sources present in the waste feed. The measured biogenic CO_2 fraction in the flue gas from an incinerator plant in The Netherlands was between 48% and 50% (Palstra and Meijer, 2010) whereas, in Austria the ratio of biogenic to anthropogenic energy content in MSW was reported in the range 36–53% (Fellner et al., 2007).

Thermal treatment technologies for MSW have been extensively reviewed by Arena (2012), Leckner (2015), Lombardi et al. (2015), Malkow (2004) and it was proposed that an alternative to combustion is to gasify the MSW for energy recovery. To date, gasification processes have been investigated by several contemporary researchers and extensively reviewed by Gómez-Barea and Leckner (2010). Thermal gasification provides flexibility for the production of heat and power based on clean biomass derived syngas (Basu, 2010). In addition, thermochemical conversion technologies can reduce the original volume of wastes disposed by 80–95% along with energy recovery (Rand et al., 1999). Lately, gasification of solid wastes which originates from the household or industrial sectors have received increasing attention by researchers. The syngas from MSW can be used for heating and production of electricity to offset the use of fossil fuels. However, gasification of MSW is not widespread. The major barrier that has prevented the widespread uptake of advanced gasification technologies for treating MSW has been the higher ash content in the feed making the gasification operation difficult. In addition, high amounts of tar and char contaminants in the produced gas make it unsuitable for power production using energy efficient gas engines or turbines.

A comprehensive review of fluidized bed biomass gasification model was presented by Gómez-Barea and Leckner (2010). In the past, different modelling approaches starting from black box modelling to thermodynamic equilibrium, kinetic rate, fluid-dynamics, neural network and genetic programming models (Pandey et al., 2015; Puig-Arnavat et al., 2010) and Gaussian process based Bayesian inference (Pan and Pandey, 2016) were applied for modelling gasification. These models were validated using pilot scale gasification data. Simulating MSW gasification is computationally expensive and fast meta-models are required. In this paper an artificial intelligence technique namely feedforward neural network is used to predict the heating value of gas (LHV), heating value of gasification products (LHV_p) as well as the syngas (product gas) yield. LHV_p is defined as the sum of the LHV of gas and the calorific value of unreacted char (entrained) and tar.

ANN models are not based on modelling the physical combustion and transport equations governing the reactor but they are a class of generic nonlinear regression models which learns the arbitrary mapping from the input data on to the output to obtain computational models with high predictive accuracy. Although ANN based models have been extensively used in other scientific fields, it has only recently gained popularity in renewable energy related applications (Kalogirou, 2001). ANN based models were developed for predicting the product yield and gas composition in an atmospheric steam blown biomass fluidized bed gasifier (Guo et al., 2001). It was concluded that the feed forward neural network (FFNN) model has better predictive accuracy over the traditional regression models. An FFNN model was employed to predict the lower heating value of MSW based on its chemical composition (Dong et al., 2003). ANN was applied for predicting the gasification characteristics of MSW (Xiao et al., 2009) and tested for its feasibility. ANN methodology was used to predict future MSW quality and composition in Serbia to achieve the targets for waste management set by national policy and EU directive by 2016 (Batinic et al., 2011). Two different types of ANN based data-driven models have been developed for the prediction of gas production rate and heating value of gas in coal gasifiers (Chavan et al., 2012). Recently, ANN based predictive tools have been used in fluidized bed gasifiers to predict the syngas composition and gas yield (Puig-Arnavat et al., 2013). The ANN technique has been applied in the gasification area and has shown better results compared to the conventional process modelling approaches. A brief overview of different modelling approaches and their pros and cons is presented in Table 1.

Most of the mathematical models for fluidized bed gasifier are based on the law of conservation (mass, energy and momentum) and other boundary conditions (Gómez-Barea and Leckner, 2010). Depending on the complexity, the model can be a 3-D fluid dynamic model or kinetic rate based model or less complex such as an equilibrium based model. Due to the inherent complexity of gasification processes, development of mathematical models are still at a nascent stage. The aim of this research is to develop neural network based models which can be used to simulate the gasification process with improved accuracy. In this study, computational

Table 1
Pros and cons of different gasification modelling approach (Gómez-Barea and Leckner, 2010; Robert et al., 2014).

Modelling approaches	Advantages	Disadvantages	Models using this approach
Black Box model	Independent of gasifier type Easy to implement Fast convergence Widely used for the gas prediction and heating value	Only applicable for stationary process Does not provide insight into the gasification process	Equilibrium model, Thermodynamic model, Pseudo-equilibrium model
Kinetic model	Realistic model, which can be used for process design and scaling-up	Depend on reaction kinetics and gasifier type	Uniform conversion model, Shrinking core model *etc.*
Fluidization model	Offers a trade-off between precision and numerical complications	Applicability of the correlations used has limited scope	Davidson–Harrison model, Kunii–Levenspiel model *etc.*
Computational fluid-dynamics (CFD) model	Useful in improving the details of the gasifier	Computationally expensive, time consuming and uncertainty involved with the parameters in closure	Direct numerical simulation, Large eddy simulation, Two fluid model, Euler-Euler model, Euler-Lagrange model *etc.*
ANN model	Does not need extensive understanding of the process. High predictive accuracy	Dependent on quantity of datasets. No proper physical interpretation of models can be made	Feed-forward neural network, Hybrid neural network *etc.*