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Generalised models to predict the lower heating value of municipal solid waste

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Abstract

Accurately and efficiently predicting the lower heating value (LHV) of municipal solid waste (MSW) is vital for designing and operating a waste-to-energy plant. However, previous LHV prediction models have had limited geographically applicability. In this paper, we employ multiple linear regression and artificial neural network techniques to estimate models to predict LHV. These data-driven models utilize 151 globally distributed datasets, describing the wet physical composition of MSW and measured LHV, identifies during a systemic literature review. The results show that models generated using the two methods exhibited acceptable and compatible levels of performance in predicting LHV, based on the diagnostic tests on residuals (range and standard deviation), mean absolute percentage error and the standard error of the estimate. However, the ANN models proved to be more robust in their handling of datasets of diverse quality. Models developed from both methods indicated negative contribution of the wet weight of food waste to LHV. Supported by the strong and significant correlation between food waste and moisture content, we concluded that the impact of the high moisture content on LHV outweighed its calorific value. Thus separating food waste or any other waste with high moisture content from the MSW to be incinerated can be key to improved energy recovery efficiency. The models also reveal a higher contribution of paper waste to the LHV of MSW than plastic waste. This is contrary to our common sense and makes us rethinking the management of plastic waste.

Keywords: LHV prediction; physical composition of municipal solid waste; multiple regression; artificial neural network.

Nomenclature

LHV	Lower heating value

MSW	Municipal solid waste
ANN	Artificial neural network
MAPE	Mean absolute percentage error
SEE	Standard error of the estimate
WtE	Waste-to-energyVIF Variance inflation factors

1. Introduction

Waste-to-energy (WtE), especially incineration with energy recovery, is an increasingly popular municipal solid waste (MSW) management strategy [1]. Designing and operating an MSW incinerator requires the understanding of the heating value of MSW [2]. The lower heating value (LHV) is commonly used to evaluate the feasibility of using a particular composition of MSW as a fuel. It determines the energy that can be harvested from MSW in the form of heat and/or electricity in an incinerator [3-5]. LHV is usually estimated either using bomb calorimeter or empirical models. Three types of empirical models used to predict LHV are based on ultimate analysis, proximate analysis and physical composition [2, 6-12].

The contributions of this article are both practical and theoretical. Practically, a properly built model could save time, labour and investment in estimating the LHV of MSW. While performing ultimate analysis and proximate analysis is always time-consuming, costly, and requires staff that are skilled in chemical analysis [2, 13] models based on physical composition are less costly and less skill intensive, requiring only a relatively straightforward sorting and weighting of the waste [2, 4, 6, 14] to produce estimates of LHVs at an acceptable level of accuracy [13]. In practice, waste is usually sorted and reported on a wet-basis and moisture content in MSW is particularly influential [15]. Therefore, developing models based on the wet-based composition is practical and also less time- and money-consuming during the data collection phase of analysis.

Theoretically, an internationally applicable predictive model of the LHV of MSW has yet to the developed. Table 1 summarizes the existing LHV predictive models based on the wet-based physical composition of MSW from published literature. Eq. 1 was estimated based on data collected globally (86 cities in 35 countries), but the consistency between predicted and experimental LHVs were not evaluated [10]. Eq. 2 - Eq. 7 were estimated based on data collected from one or a small number of specific locations. They perform well when data used for validation was obtained from the same location as the training data collected from, but as one would expect, they perform less otherwise [14]. Besides, collinearity among independent variables has seldom been assessed in the evaluation of prior regression models. Therefore, developing an easy and rapid LHV predictive model for MSW which could be applied regionally or globally can be beneficial for designing, operating and importing an incinerator and associated waste management strategies. This may be especially important in light of the trend towards the rapid urbanized of developing countries, where the characteristics of waste change during the 15 to 20 year life span of an incinerator [16].

Table 1

Summary of empirical models for predicting LHV of MSW based on wet-based physical composition.

Country	Equation	NO.	Source
35 countries	$LHV = 53.50\ (F + 3.6Pa) + 372.16\ Pl$	Eq. 1	[10]
Jordan	$LHV = 621.04(Pl/Pa) + 5316.54$	Eq. 2	[17]
Malaysia	$LHV = 112.157F + 183.386Pa + 288.737Pl + 5064.701$	Eq. 3	[18]
Malaysia	$LHV = 81.209F + 285.035Pl + 8724.209$	Eq. 4	[18]
Taiwan	$LHV = 92.53Pa + 117.65Pl + 102.99\ T + 53.17\ W + 25.12\ F + 240.32R + 72.01Mi$	Eq. 5	[19]
China	$LHV = 219\ Pl + 112\ Pa + 108\ W + 115\ T$	Eq. 6	[14]
China	$LHV = 219\ Pl + 109\ (Pa + W + T)$	Eq. 7	[14]

Note: LHV, lower heating value (net calorific value) (Unit: kJ/kg); F, percentage of food waste; Pa, percentage of paper; Pl, percentage of plastics; R, percentage of rubble and leather; T, percentage of textile; W, percentage of wood; Mi: miscellaneous component.

1.1. Methods for developing a new LHV prediction model

Regression analysis is the commonly used method in building predictive models for estimating the heating value of MSW [6, 8, 20, 21], but it has limitations in estimating dependent variables (in this case LHV) when the resolution of independent variables (in this case, the composition of waste) is low, and regression models are sensitive to the precision of the input data [3, 22]. This issue tends to be amplified when LHV models are to be based on the physical compositions of MSW which are highly related to the environmental, geographical, social and economic factors and associated spatiotemporal variations [23]. Indeed, this limitation usually restricts the applicability of regression models to within the spatiotemporal boundary of the original datasets.

Equations built using regression analysis in previous studies are usually linear [2, 10, 19], but this is not always true. Eq. 2 indicates that the relationship between LHV and waste compositions is not necessarily linear [17]. Cross-plots between the individual physical composition and LHV also indicates that the linearity of relationships between some variables, for instance textile and wood, and LHV are not clear (Appendix A). Besides, regression analysis utilizes limited variables and the range of functions they can model is limited [24, 25], but MSW is a complex mixture with large numbers of distinct materials, and its complexity increases with the consumption of new products and technologies. Furthermore, as a standard statistical technique, regression analysis often ignores the variables not having statistically significant contributions. The insignificant contributions of these variables are because their small shares in MSW samples rather than their energy content. For example, wood and textile were included in Eq.5 – Eq.7 but not in Eq. 1- Eq.4. Even though these types of waste do not statistically contributes to LHV of MSW some cases, but their contribution cannot been ignored in others because they might take great proportions of MSW. Since we are trying to build an internationally applied model, we cannot ignore those materials and should include them in the model.

Alternatively, artificial neural networks (ANN) have the inherent ability to model prior hidden information in the training data that are not easily discernible by traditional statistical methods and to find patterns despite missing data [24]. ANN is an artificial intelligence technique that quantitatively analyzes information and builds models by learning and training from the input data in a way that mimics the neuron functions of the brain [3, 22]. It is widely applied to problems relating to predicting, forecasting, clustering, and pattern classification [26]. Predicting the LHV of MSW is one of its applications [3, 22]. ANN is able to straightforwardly capture non-linear relationships between dependent and independent variables [3, 22, 27], as they avoid the need to identify an appropriate data-fitting function before the models can be constructed [24, 28]. ANN models also allow for the inclusion of multiple inputs (or variables) and model adjustment of the models when new datasets are input [24]. Furthermore, the performance of ANN models is improved when the sample size and the number of groups or the number of variables increases [25]. This means that ANNs have the potential to take all MSW compositions into account to estimate the LHV; but only limited and fixed groups of MSW materials have been modeled in previous studies. Furthermore, previous ANN models were built based on datasets collected only locally and have not been verified using global or regional data.

Therefore, the objectives of this article are four-fold: (1) to build LHV predictive models of MSW, utilizing wet-based physical composition, and employing both regression analysis and ANN, (2) to display how model building methods compare in their accuracy in predicting the LHV of MSW, (3) to select the most reliable model for application to city, national and global scales, and (4) to provide reference for the choice and application of the most applicable model building techniques.

2. Materials and Methodology

This section discusses the processes for data collection, data pre-treatment, model building and validation, which are summarized in Fig. 1.

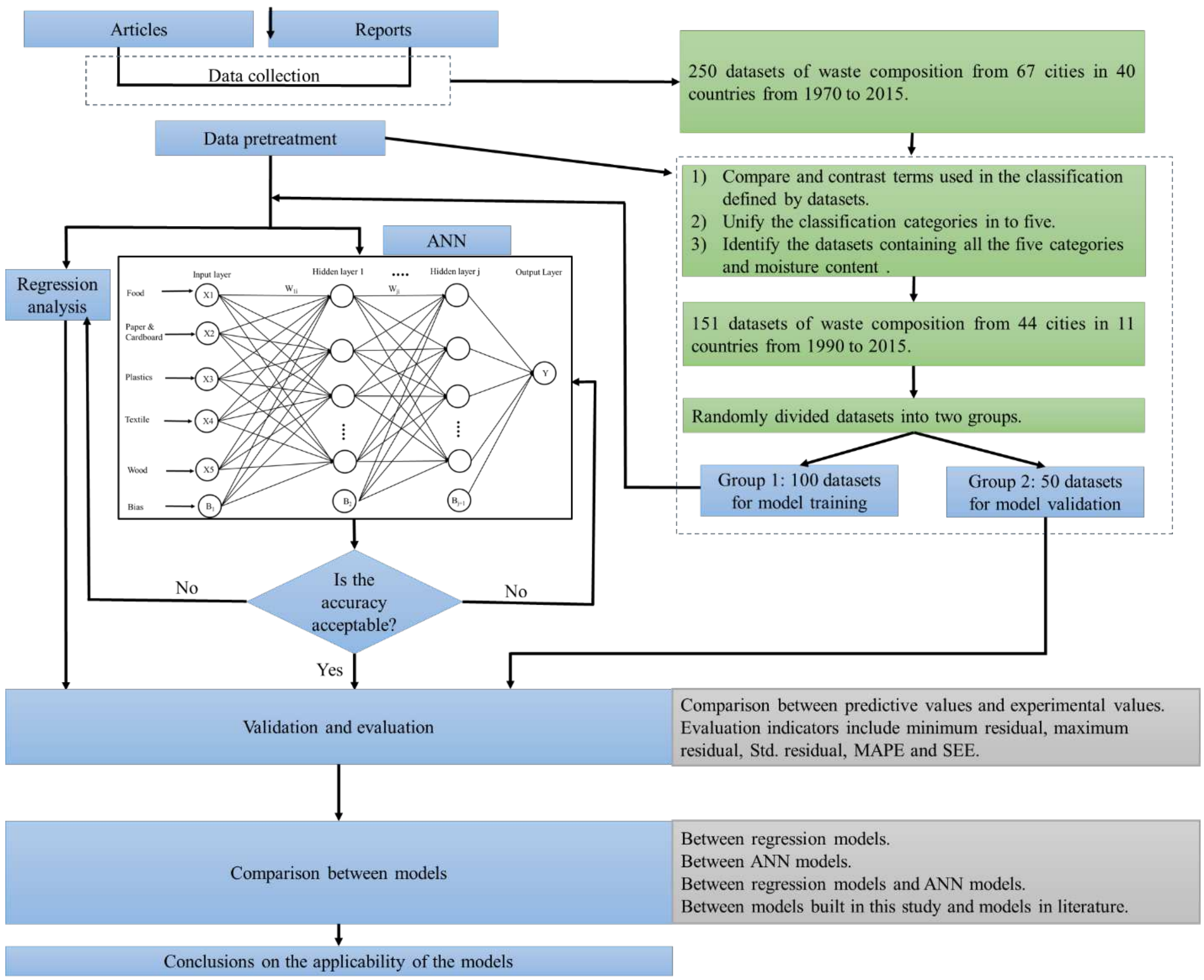


Fig. 1. Flowchart for building and validating the predictive model. MAPE, mean absolute percentage error; SEE, the standard error of the estimate.

2.1. Data collection and processing

MSW compositions and their associated LHVs were collected from a systemic literature review. Literature or statistical data were obtained from articles and reports published in English and Chinese since 1990. Keywords such as “lower heating value + municipal solid waste”, "characterization + municipal solid waste" and "energy + municipal solid waste" were used for searching articles and reports through Google, Google Scholar and Scopus. We were able to collect a total number of 250 datasets documenting average waste compositions and LHVs from 67 cities in 40 countries from 1970 to 2015.

Not all of these 250 datasets contained all of the five categories ('food', 'paper & cardboard', 'plastics', 'textile' and 'wood') of waste we intended to account for, because of the diverse waste classification systems used by the sources we identified, with some researchers using categories that are specific to their purposes e.g. Alam and Kulkarni [29] and Lin et al. [14]. In some research, a variety types of waste were grouped into the category of miscellaneous or others because they occupied a very small proportion or contributed little to LHV [30]. For the purpose of this analysis, we retain all datasets containing all the five categories, but the percentage of the five categories do not necessarily add up to 100%. Additionally, the categories of 'putrescible', 'organics', 'vegetable and fruit' in some research are considered as subcategories of food waste; the values of these compositions in the same dataset were added together to represent food waste. In one case garden waste was combined with the wood category, so that it became part of the statistic wood [31].

Applying the criteria described above, the 250 datasets identified from the literature were filtered. As a result, 151 datasets from 44 cities in 11 countries from 1990 to 2015 were identified as inputs for the ensuing model building work. Most of these datasets (around 90%) covered cities in developing countries such as China, India, Philippines and Thailand, with the remaining datasets relating to cities in developed countries such as the Finland, Italy, Spain, the USA and the UK.

2.2. Multiple regression analysis

Regression analysis was performed to establish a linear model for LHV prediction, is a similar style to the equations in Table 1. The average wet weight percentage of the five MSW categories were used as explanatory variables to estimate the overall LHV of the mixture of MSW. The collinearity between variables in models were diagnosed using condition indexes and variance inflation factors (VIFs). A condition index exceeding 15 indicates potential collinearity, while indices exceeding 30 suggest serious collinearity [32] and a VIF exceeding 10 indicates unacceptable collinearity [32].

2.2.1. Model development

The full model (Eq. 8), containing all the five variables, was established first. Moisture content was eliminated from the model to prevent double counting of its influence on LHV:

$$LHV = \alpha_1 F + \alpha_2 Pa + \alpha_3 Pl + \alpha_4 T + \alpha_5 W + C \quad (8)$$

The definitions of the variables in the equations are consistent with those in Table 1. The variable C was added to represent bias.

Some researches indicated that most of the LHV of MSW was contributed by the paper, food (or organics in some cases) and plastics in the mixture, with this accounting for over 70% of the MSW on a dry basis [2, 4, 27]. The contribution of the remaining ingredients is statistically insignificant and may be neglected in the model. On this basis, the full model (Eq. 8) can be simplified, as follows (Eq. 9):

$$LHV = \alpha_1 F + \alpha_2 Pa + \alpha_3 Pl + C \quad (9)$$

2.3. ANN

The ANN model consists of an input layer of neurons representing the behaviors of the explanatory variables, the compositions of MSW in this study, one or more hidden layers of neurons and a final layer of output predicting the value of the dependent variable, the LHV of MSW in this study (Fig. 1). Neurons within the same layer have no connection or interaction with each other. They only sequentially connect with the neurons in the next layer (Fig. 1). Each connection is associated with a weight by an activation function and the output value is calculated by multiplying the weight and input. The weights and bias values are not pre-determined. During the training phase, the ANN learns and adjusts the weights and biases to optimize the model based on the input of training data. The output y_i of neuron i is expressed as in Eq. 10 [13, 33]:

$$y_i = f(\sum_{i=1}^{n} (w_{ji})(x_i) + b_j) \qquad (10)$$

Where y_i is the output of neuron i which represents the LHV contributed by the composition i of MSW; x_i is the input of neuron i which represents composition i of MSW; w_{ji} is the connecting weight between neuron i of the input layer and the neuron j of the output layer; b_j is the bias; and f is the activation function.

Theoretically, ANNs can model any given type of waste composition, with the model's performance improving as the number of explanatory variables increases, as long as there is sufficient data. But unlike in our study, this has not been formally assessed in previous work.

Furthermore, in previous studies, ANN models often outperformed regression models since the training data was locally collected first-hand data. However, ANN models do not always outperform statistical techniques, especially when dependent variables are skewed [25]. Second-hand data is collected as alternative training and validation data in this study, since collecting first-hand data around the globe is challenging. Under this circumstance, the performances of ANN models need to be reassessed.

Initial training parameters are generally set based on experience, then adjusted to optimize the solution when all training data are input. In previous attempts to predict LHV using ANN, only one hidden layer was defined, with the number of nodes in the hidden layer varying from 3 to 35. The epoch (or number of iterations) varies from 200 to 4000, and the learning rate varies from 0.01 to 0.15 [3, 13, 22, 27]. According to Dong et al., changes in the sum-squared error of the ANN are minimal beyond 800 epochs [22]. Based on the literature, the ANN modeling in this study was set as: 3 – 35 nodes in one hidden layer, a maximum of 1000 epochs, and a learning rate of between 0.005 and 0.1, with an interval of 0.005.

2.4. Validation and evaluation

2.4.1. The contribution of compositions estimated by ANN

ANN modeling works like a black-box in comparison to conventional regression analysis. It is difficult to directly identify all the weights that were employed in the calculation of the LHV. To identify the contribution of each explanatory variable to LHV in the optimized ANN model we obtained, a simulation was conducted by inputting one variable in the range of 0% – 100% with an interval of 0.1% in the ANN model, while setting the value of all other variables to 0%. The results of the simulation are considered as the contribution of each explanatory variable to LHV at various levels of percentages in MSW composition.

2.4.2. Validation and evaluation

100 out of 151 pretreated datasets were randomly selected for model training in both regression analysis and ANN. The remaining 51 datasets were used for validation and evaluation. Models were evaluated and compared using statistical indicators include the minimum residual, maximum residual, the standard deviation of the residual (Std. residual), the mean absolute percentage error (MAPE) and the standard error of the estimate (SEE). The MAPE and SEE are expressed as follows [14, 19]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_{pi} - x_{ei}|}{x_{ei}} \times 100 \tag{11}$$

$$SEE = \sqrt{\frac{\sum_{i=1}^{n}(x_{pi} - x_{ei})^2}{n-1}} \tag{12}$$

where x_{pi} represents predicted LHV, x_{ei} represents experimentally measured LHV, and n represents the number of datasets. The evaluation of MAPE was divided into four levels: excellent (MAPE < 10), good (MAPE = 10 to 20), acceptable (MAPE = 20 to 50), and unacceptable (MAPE >50) [19]. In practice, smaller SEE indicates better performance.

3. Results

3.1. Regression analysis

Collinearity diagnostics indicate that collinearity is not observed in the explanatory variables of the regression models (Appendix B). The model containing the variables of food, paper, plastics, textile and wood content was developed first as the full model (Eq. 13). The coefficient of multiple correlation (R) is 0.73 within a 95% confidence interval. The regression model is statistically significant (F = 21.79, P <0.001).

$$LHV = -68.06\,F + 91.44Pa + 52.65\,Pl + 30.73\,T + 34.91\,W + 7{,}342.79 \qquad (13)$$

The coefficients of textile, wood and plastic are not statistically significant in this model (Appendix B). Considering that plastics are one of the three major compositions in most MSW and the sum of wood and textiles accounts less than 10% in most cases (results of the descriptive analysis of variables are depicted in Appendix C), the full model was simplified to the model without textile and wood (Eq. 14). The correlation coefficient R of Eq. 14 is 0.73, and it is statistically significant (F = 36.51, P <0.001). The coefficient of plastic became statistically significant ($p < 0.05$) after the variables were reduced.

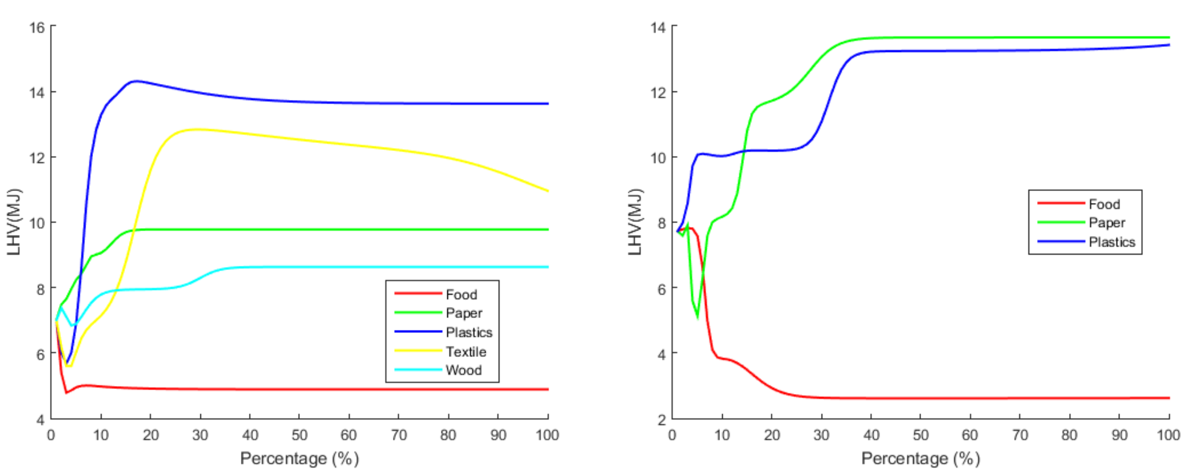
$$LHV = -72.42F + 83.20Pa + 67.90Pl + 7{,}669.08 \qquad (14)$$

Food waste is negatively correlated with LHV (P <0.01 for the coefficient in both Eq. 13 and Eq. 14). This negative contribution to LHV is discussed later. The reduction of the number of dependent variables did not reduce the coefficient of multiple correlations; keeping the three explanatory variables has not reduced the power of the model to explain the variability of the dependent variable.

3.2. The development of ANN models

Model ANN1 was generated using the same explanatory variables as regression model Eq. 13; its nodes in the hidden layer, learning rate and epoch were 31, 0.08 and 40, respectively. Similarly, model ANN2 was generated using the variables of Eq. 14. Without the two variables of wood and textile, fewer nodes (25) in the hidden layer and a lower learning rate (0.005) but more epochs (650) were required in ANN2 to model LHV: fewer epochs and a larger learning rate are required as the number of ANN input variables increases, as more information is provided for each sample point.

The contribution of each variable to the modeled LHV was estimated as illustrated in Fig. 2. When the proportions of all waste compositions were set as 0, the models still return estimations of LHV at around 7 MJ/kg; we consider this to be the systemic bias of the model. The bias in ANN models are similar to the constants in the regression models (Appendix B). This bias is partly derived from the nature of the input data: the waste categories we used as input variables did not account for 100% of MSW.



(a) ANN1 (b) ANN2

Fig. 2. Comparison of the contribution significance of each variable to LHV in ANN models. For the convenience of simulating, the unit of LHV was changed from kJ/kg to MJ/kg.

The estimated LHV is lower for MSW with a higher proportion of food waste, quite consistent with the results obtained from the linear regression analysis. Models generated using both methods indicate that food waste negatively contributes to LHV because of its high moisture content. Moisture content is significantly and positively correlated with the percentage of food waste ($r=0.88$, $p<0.001$). The negative contribution results from the increased latent heat required during combustion to evaporate the water. Plastics have the greatest contribution to LHV, as it has the highest energy content amongst all waste streams [14]; however, its contribution to LHV is estimated to be smaller than paper when its proportion is greater than 15% in ANN2 (Fig. 2b), or smaller than paper and wood when its fraction is smaller than 5% in ANN1. A similar situation arises in the regression models, as paper has larger standardised coefficients than plastic. The possible reasons for these results are discussed in Section 4, considering chemical composition and the basis of the models.

3.3. Evaluation and comparison of models

Model performance was evaluated using statistical evaluators (Table 2). The MAPE and SEE indices suggest that the ANN models performs better and could give more accurate results when being compared with the regression models. However, the Std. deviation and range of the residuals (Min-Max) of the regression models are smaller than those of the corresponding ANN model. This indicates that the regression models may produce predictions that are closer to the measured LHVs. However, their performance may have been affected by non-linear cases. While ANN models may not give as precise predictions as the regression models, they are more robust in their ability to handle non-linearity.

Table 2

The evaluation of predictive models.

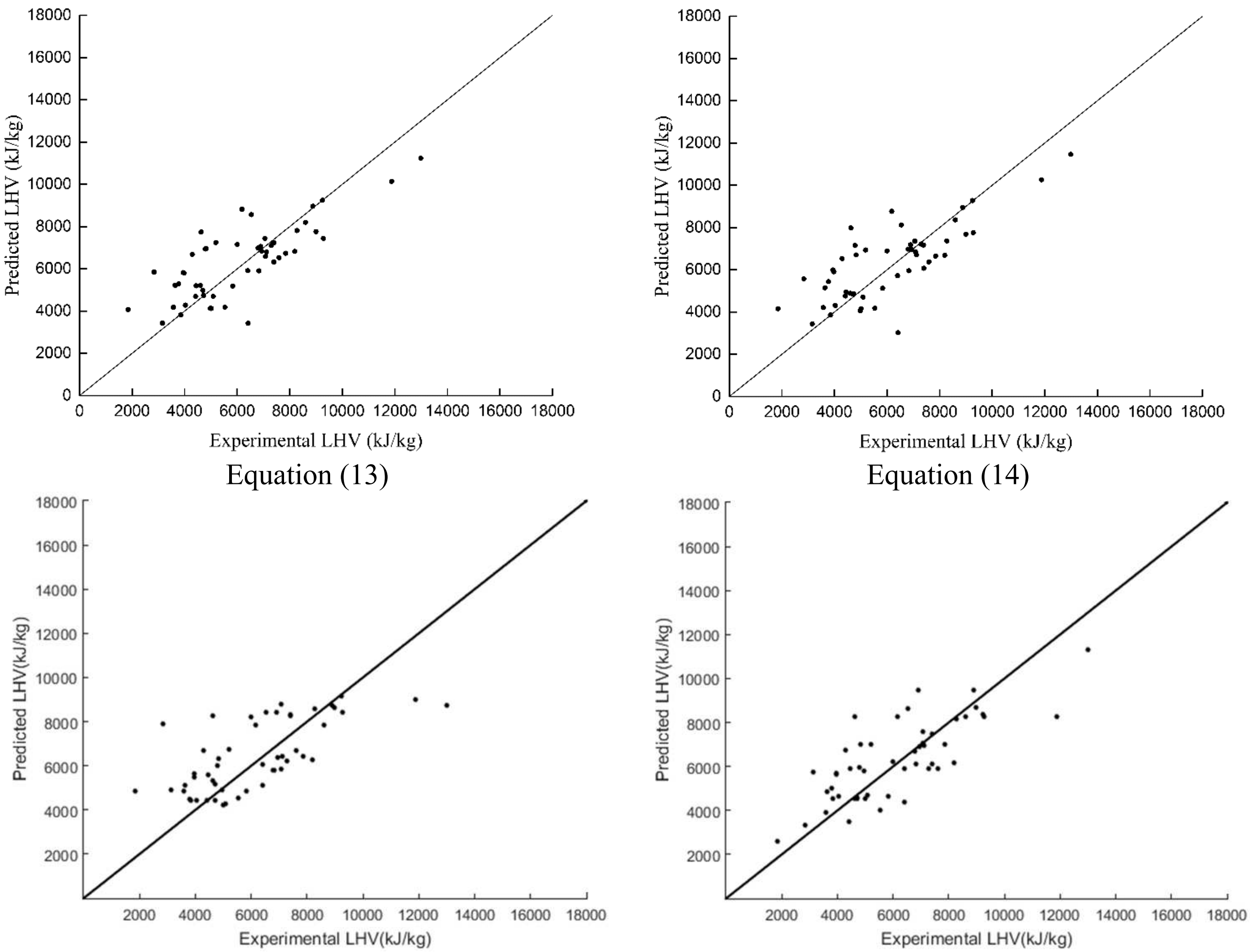
Model	Residual(kJ/kg)			MAPE (%)	SEE (kJ/kg)
	Min.	Max.	Std. Deviation		
Eq. 13	-3,003.60	3,117.46	759.64	22.18	1,414.69
Eq. 14	-3,401.10	3,352.51	803.07	21.94	1,410.36
Eq. 3	3,308.02	14,527.80	2,670.02	197.39	10,544.60
Eq. 7	-4,393.90	2,264.43	1,684.63	24.09	1,918.04
Eq. 3*	-16.46	13.57	8.88	-	-
Eq. 7*	-69.42	67.79	-	18.16	1,111.44
ANN1	-2,183.37	4,261.35	1,246.94	18.38	1,296.94
ANN2	-2,960.11	4,171.90	1,301.92	15.92	1,357.92

Note: *: The values of indicators are from the original research as shown in Table 1. -: Data deficient.

Of the two ANN models, ANN1 performs better than ANN2 based on the range and Std. deviation of the residual and SEE, but not MAPE (Table 2). As more complete information in terms of waste composition was input to ANN1, the behavior of the model is expected to more closely match reality. On the contrary, the regression model which contains fewer explanatory variables performs better than the full model (Table 2). The restricted linear relationship between explanatory variables and the dependent variable reduced the likelihood of overfitting.

The performances of models built in this study were also compared with models in the literature containing similar explanatory variables, but built on data collected in specific geographic regions. These models did not perform as satisfactorily as documented in previous studies and performed less well than the models built in this study when the data we collected globally was used as input (Table 2).

To better illustrate the performance of the models, predicted and measured LHV are compared in Fig. 3. LHVs estimated using regression models are qualitatively closer to the best fit line than those estimated using ANN models. Models from the literature appear to be considerably less accurate than the models generated in this study; Eq. 3 in particular. Our models appear to be more universally applicable and they may have higher tolerance to less precise dataset.

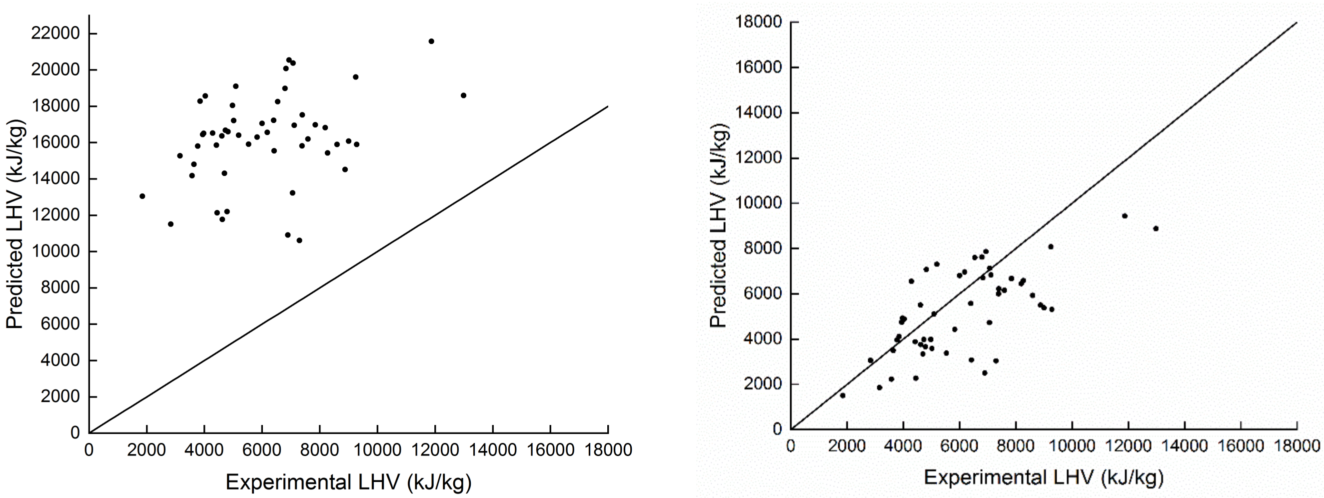


Equation (13)

Equation (14)

ANN 1

ANN 2



Equation (3) Equation (7)

Fig. 3. Comparison between predicted LHV and experimental LHV. Lines in figures represent the best fit line where predicted LHVs equals experimental LHVs.

4. Discussion

The primary aim of this study is to develop a generally applicable model to predict LHV based on wet composition of MSW, using data that is relatively easy to acquire. A secondary aim is to compare two distinct methods to generate such models: linear regression and ANN. With those aims, our discussion is focused on the following points.

4.1. Data quality and availability

The quality of collected data clearly affects the performance of data-driven models, like linear regression and ANN. As mentioned earlier (section 2.1), most data is based on the average percentage of MSW composition and LHV in a city or country. Though these point estimations could represent well the general MSW characteristics in that city or country, they cannot reflect the variability of this MSW composition. Moreover, is these point values are not representative of the broader sample mean, the resultant models could be seriously in error in aggregate terms. In statistical terms, this could produce the effect named ecological fallacy. This may influence the prediction accuracy of the models built based on the point of estimation. The ecological fallacy may even create false model if individual data point were used.

The best way to verify the model is to verify the results using individual point data to further examine the relationship between the waste composition and LHV. However, such data is difficult to obtain at the global scale. The best we can do to then, is to separate data into training and validation datasets, and then to evaluate the models, performance using relevant statistical indices that measure the deviation between prediction and observation, such as MAPE, SEE and residuals (Table 2). Using such indices, we have shown that our models can estimate LHVs reasonably well, so that the relationship between the MSW composition and LHV can be verified. Furthermore, the results of LHV estimation using two totally different methodologies have both confirmed the positive contribution of plastic and paper waste and the negative contribution of food waste. Thus, we may be confident that the models have some discriminatory power, in terms of the physicochemical properties of the constituent parts of MSW.

In addition to the issues of using average values of MSW compositions and LHVs from cities, the data we collected are from various sources, so the quality of data is unavoidably inconsistent. The diverse characters in the same categories of MSW from different data sources or geographical region (e.g. the characteristics of food waste) may have adversely effected the performance of our estimated models. However, collecting high quality primary MSW data, using consistent measurement and recording methodologies is like to be prohibitively time and labor consuming; and sometimes access to these data are simply not permitted. Under these circumstances (the absence of international standardisation), the use of publicly accessible secondary data is seen as a reasonable and necessary compromise to developing a model of wide geographical applicability.

The geographical distribution of the cities where these types of secondary data are available is uneven. In our case, most of our datasets were obtained from developing countries in Asia. We found that our models performed better than the models built based on the data only collected from local areas or small regions where the composition of MSW is less variable. This suggested that previous regression models built based on local and regional data only may not be generalized and applied with confidence elsewhere. Indeed, models generated from limited numbers of sites may be spatially skewed, and unrepresentative in terms of the MSW composition, reducing their utility both beyond and within their spatial bounds of applicability. Furthermore, the size of these samples is usually small, increasing the likelihood of overfitting and thus reducing the utility of models, even *within* their spatial bounds of applicability. Thus, the predicted LHV using our models for developed countries need to be interpreted with extra caution. The models may be further refined when additional data can be collected from developing countries/cities from regions such as Africa and Latin America.

Standardising the categories of MSW and the units of LHV measurement from a variety of sources and may also have introduced uncertainties. As mentioned in section 2.1, food waste is classified as a standalone category in many cases, but merged with other green waste in others [18, 29].

All the quality issues relating to input data affect the performance of the models generated. Based on the results of our performance evaluation, ANN methods seem to be good at accommodating a variety of data quality and return a model that can produce acceptable overall predictions. ANN also makes better use of more categories of data that may be considered insignificant in regression models (textile and wood) to further improve model performance.

4.2. Possible reasons for higher contribution of paper

We established the models based on the waste categories commonly used in openly available statistics that most relevant to energy recovery during the incineration process. In this way, the models may be conveniently used to estimate the LHV of MSW at an initial stage in designing incinerators in any place in the world. However, our data does include MSW dataset whose contents under the same or similar categories are diverse and sometimes inconsistent. An obvious example of some biodegradable waste has been noted previously (Section 2.1.2 and Section 4.1). The uncertainty of the diversified compositions within the categories may also have contributed to the inconsistency between our models and the commonly known heating values estimated based on combustion theory. Our models mostly showed reduced contribution of plastic to the heating value of MSW compared paper; except for one model generated based on ANN (ANN1). We only identified limited studies showing similar patterns in their models. For example, based on the MSW samples and their LHVs collected by Lin, et al. from eastern and middle regions of China from 1996 to 2012 [14], Ozveren derived a model depicting lower than expected contribution of plastics to LHV [34].

One possible explanation for this seemingly counterintuitive result could be that the presences of the types of plastics that produce relatively low LHV in the MSW dataset we collected is higher than generally expected. Among the commonly used types of plastics, the heating values of PVC can be half of other plastic ingredients such as LDPE, HDPE, PP and PS [35]. The lower end of heating value among the range of the plastics materials (17.8MJ/Kg – 47.5 MJ/Kg) can be lower than the higher end of the heating values produced by paper (10.4MJ/Kg – 27.3MJ/Kg) or wood (14.6MJ/Kg – 28.6MJ/Kg) [9]. Ragaert, et al. indicated that PVC, as the major ingredient in some soft-packages, is usually not the target plastic ingredient for mechanical sorting for recycling/recovery and may be sent for incineration [36]. Thus, it is quite possible that with well-organized recycling activities in a city, the proportion of plastic materials with a high energy content in the MSW to be incinerated may be reduced. Furthermore, the non-plastic ingredients may be attached on the surface of the plastic waste. Taking Nottingham city as an example [37], the main plastic materials remaining in the residual waste sent to incineration for energy recovery are packaging waste, plastic films, refuse sacks and carrier bags; these types of plastics waste are usually contaminated and moisturized easily by other wet waste with low energy contents, such as food waste. In addition, moisturized plastic products is more difficult to dry than paper products. As a result, the contribution of plastic materials to the LHV of MSW may be reduced. This may have been reflected in our models.

4.3. Applying ANN in LHV estimation

Given the varieties of MSW recycling and incineration methods (as mentioned in section 4.2) as well as the types of waste generated based on the life-styles and economic development among municipalities, the LHV contributed under each category may not be as unified as we originally considered according to the theory of combustion that describes a linear relationship between chemical elements and energy contents [38, 39]. From this aspect, the use of an ANN methodology that can accommodate non-linear relationships in establishing predictive models may be advantageous. This may be explained by the MAPE and SEE values of ANN models that showed an overall better performance amongst the models we built.

Indeed, ANN has advantages in learning from new data, taking potential non-linear relationship and ingredient variabilities into account, and handling multiple variables and processing big data, but these advantages of ANN haven't been harnessed in previous and current research. Thus, the suitability of ANN in building LHV predictive model needs to be further assessed and discussed by increasing the number of input variables and the size of training data.

In addition, constructing a good network for a particular application is a non-trivial task. It involves choosing an appropriate architecture (the number of layers, the number of nodes in each layer, and the connections among nodes), selecting the transfer functions of the middle and output units, designing a training algorithm, choosing initial weights, and specifying the stopping rule [40]. To a non-modeler, ANN also appears to work as a black box. It is difficult to verify or validate the model based on knowledge of the chemical mechanism involved in incineration. Thus, we suggest applying ANN models only to predict the LHV for MSW composition, of which the percentage in each waste category is within the range covered by the dataset used to generate the model. Beyond (or rather below) these ranges, the explanatory power of the model decreases dramatically. As Fig. 2 illustrated, The LHV changes little with increased percentage of waste composition after it exceeds a certain value, for instance 35% for wood in ANN1 and 30% for food waste in ANN2. When the influence of variables on predicted LHV of MSW in ANN models was analyzed, the range of the proportion of waste compositions that the model can be applied needs to be specified. We randomly selected 100 from the 151 datasets for modeling while leave the remaining 51 datasets for validation to ensure the performances are evaluated based on the collection of data that are reviewed and organized under the same criteria. The waste composition ranges between training and validation datasets overlap. As such, the MAPE values indicate that ANN models in this study performed well, even slightly better than the regression models. However, the time invested to build ANN models may be several times longer than to build linear regression model. Whether this level of improvement is worth the time may need to be further evaluated based on benefits of improved prediction of the energy recovery efficiency in designing and operating the incinerator.

4.4. The selection of model building techniques

Researchers often treat regression analysis and ANN as competing techniques for model building. However, these two methods may mutually assist each other, resulting in better decision making. Models built using these two distinct techniques can be validated and assessed against one another with the best performing model selected to support case-specific decision. In this study, both regression and ANN models have consistent performance. There is no single model that overwhelmingly out performs the other. Either Eq.14 or ANN1 can be selected to predict LHV of MSW for researchers without or with ANN model building experience.

Whilst both techniques have their strengths and limitations (as mentioned in section 1.1 and section 4.3), neither can be guaranteed to always perform better than the other [41]. It is thus valuable to employ both techniques, selecting that which performs best, based on the specificities of the available training data. However, when big datasets and/or multiple independent variables are available, ANNs (ANN1 is recommended) are a better choice; otherwise, regression analysis (Eq.14 is recommended) can be applied to save time. Considering the complex nature of MSW and likely improvements in MSW management in the future, ANNs have greater potential of application than regression analysis in this field.

4.5. The implication of the models in MSW management and policy making

The negative or low contribution of food waste to the overall LHV in both regression analysis and ANN illustrates that food waste is not suitable for incineration. Because of the lower carbon content and higher oxygen content in food waste (or organic waste in some cases), in comparison to materials like plastics, combustion is an ineffective means of disposal of or energy recovery from food waste [27]. The positive correlation between the proportion of food waste and moisture content of MSW in our datasets also confirms the unsuitability of incinerating moisture-rich food waste for energy recovery. Apart from the unrecoverable energy as latent heat, substances with high moisture content require a high energy input to increase the unit temperature and this makes self-sustained combustion more difficult, more energy intensive and also readily produces incomplete combustion [15, 42]. This latter increases the risk of producing pollutants such as dioxins and carbon monoxide [43, 44]. Thus, reducing the proportion of food waste in the MSW for incineration may improve combustion efficiency and reduced pollutants by not only increasing LHV but also by enhancing the combustion processes. Hence, based on the results of our model, we recommend separating food waste or any other waste with a high moisture content at the point of collection, and applying alternative disposal methods for this type of waste, such as composting and anaerobic digestion [45]; otherwise, the pre-treatment to dehydrated MSW before incineration may be needed. At the same time, efforts needs to be invested in planning and decision making to assist the separate collection and treatment of food waste. We recommend that authorities set targets on the separation rate and biological treatment rate of food waste, as with the recycling rate that is set in many waste management regulation. Economic incentives and investments in technical facilities may facilitate the achievement of these target.

Plastic waste has a higher LHV than paper waste does, and incineration is the most suitable choice to treat plastic waste. However, the inherited diverse composition of plastic waste means that its LHV is highly variable. This might make the LHV of incinerated plastics waste unstable and make self-sustained combustion difficult. Therefore, we recommend that policies and actions should be undertaken to refine the classification of plastic waste, seeking alternative treatment options for plastics that have relatively lower LHV, such as those that can be easily moisturized, such as plastic films and packaging waste. As mentioned in section 4.1, the inconsistency of waste classification is an important factor influencing the building and application of an international

LHV predictive model. To this end, further effort would be welcome in the standardisation of MSW classification.

5. Conclusions

In this study, we demonstrated that models built via linear regression analysis and ANN show acceptable and similar performance in predicting LHV, but not as good as locally built models because of the uncertainties and inconsistency of training data. Model building in this study can be applied in a regional level, especially in developing countries, to estimate the LHV of MSW. The selection of model building methods should base on their advantages and inputting data. Our results also indicated that waste with higher moisture content, such as food waste, reduced the overall LHV of MSW, and thus reduced energy recovery efficiency for incineration. Separating this type of waste from waste to be incinerated at the collection point and applying an alternative method to treat it is recommended for more efficient and environmentally friendly MSW management. Besides, we might need to change our original perception of separation and treatment of plastics.

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Reference

[1] Brunner PH, Rechberger H. Waste to energy–key element for sustainable waste management. Waste Manage 2015; 37: 3-12.

[2] Chang YF, Lin CJ, Chyan JM, Chen IM, Chang JE. Multiple regression models for the lower heating value of municipal solid waste in Taiwan. J Environ Manage 2007; 85(4): 891-899.

[3] Ogwueleka TC, Ogwueleka N. Modelling energy content of municipal solid waste using artificial neural network. Iran J Environ Healt 2010; 7(3): 259-266.
[4] Drudi KC, Drudi R, Martins G, Antonio GC, Leite JTC. Statistical model for heating value of municipal solid waste in Brazil based on gravimetric composition. Waste Manage 2019; 87: 782-790.
[5] Pavlas M, Touš M, Klimek P, Bébar L. Waste incineration with production of clean and reliable energy. Clean Technol Envir 2011; 13(4): 595-605.
[6] Liu JI, Paode RD, Holsen TM. Modeling the energy content of municipal solid waste using multiple regression analysis. J Air Waste Manage 1996; 46(7): 650-656.
[7] Boumanchar I, Chhiti Y, Alaoui FEMH, Sahibed-Dine A, Bentiss F, Jama C, Bensitel M. Municipal solid waste higher heating value prediction from ultimate analysis using multiple regression and genetic programming techniques. Waste Manage Res 2019; 37 (6):578-589.
[8] Ibikunle R, Titiladunayo I, Akinnuli B, Lukman A, Ikubanni P, Agboola O. Modelling the energy content of municipal solid waste and determination of its physico-chemical correlation using multiple regression analysis. International Journal of Mechanical Engineering and Technology 2018; 9: 220-232.
[9] Shi H, Mahinpey N, Aqsha A, Silbermann R. Characterization, thermochemical conversion studies, and heating value modeling of municipal solid waste. Waste Manage 2016; 48: 34-47.
[10] Khan MA, Abu-Ghararah ZH. 1991. New approach for estimating energy content of municipal solid waste. J Eviron Eng 1991; 117(3): 376-380.
[11] Akkaya E, Demir A. Energy content estimation of municipal solid waste by multiple regression analysis. In: 5th international advanced technologies symposium (IATS'09); 2009. Karabuk, Turkey.
[12] Özyuğuran A, Yaman S. Prediction of calorific value of biomass from proximate analysis. Energy Procedia 2017; 107: 130-136.
[13] Shu HY, Lu HC, Fan HJ, Chang MC, Chen JC. Prediction for energy content of Taiwan municipal solid waste using multilayer perceptron neural networks. J Air Waste Manage 2006; 56(6): 852-858.
[14] Lin X, Wang F, Chi Y, Huang Q, Yan J. A simple method for predicting the lower heating value of municipal solid waste in China based on wet physical composition. Waste Manage 2015; 36: 24-32.
[15] Komilis D, Kissas K, Symeonidis A. Effect of organic matter and moisture on the calorific value of solid wastes: An update of the Tanner diagram. Waste Manage 2014; 34(2): 249-255.
[16] DEFRA. Municipal solid waste incineration, http://www.wtert.co.uk/content/Defra%20report.pdf; 2013 [accessed 20 March 2019].
[17] Abu-Qudais MD, Abu-Qdais HA. Energy content of municipal solid waste in Jordan and its potential utilization. Energ Convers Manage 2000; 41(9): 983-991.
[18] Kathiravale S, Yunus MNM, Sopian K, Samsuddin AH, Rahman RA. Modeling the heating value of Municipal Solid Waste☆. Fuel 2003; 82(9): 1119-1125.
[19] Lin CJ, Chyan JM, Chen IM, Wang YT. Swift model for a lower heating value prediction based on wet-based physical components of municipal solid waste. Waste Manage 2013; 33(2): 268-276.
[20] Nwankwo CA, Amah VE. Estimating Energy Content of Municipal Solid Waste by Multiple Regression Analysis. International Journal of Science and Research 2016; 5(6): 687-691.

[21] Drudi KCR, Drudi R, Martins G, Antonio GC, Leite JTCL. Prediction of Lower Heating Value of Wastes of Santo Andre Using Multivariate Regression. In: 25th European Biomass Conference and Exhibition; 2017. Stockholm, Sweden.
[22] Dong C, Jin B, Li D. Predicting the heating value of MSW with a feed forward neural network. Waste Manage 2003; 23(2): 103-106.
[23] Das S, Lee SH, Kumar P, Kim KH, Lee SS, Bhattacharya SS. Solid waste management: Scope and the challenge of sustainability. J Clean Prod 2019; 228: 658-678.
[24] Eftekhar B, Mohammad K, Ardebili HE, Ghodsi M, Ketabchi E. Comparison of artificial neural network and logistic regression models for prediction of mortality in head trauma based on initial clinical data. BMC Med Inform Decis 2005; 5(1): 1-8.
[25] Kumar UA. Comparison of neural networks and regression analysis: A new insight. Expert Syst Appl 2005; 29(2): 424-430.
[26] Samarasinghe S. Neural networks for applied sciences and engineering: from fundamentals to complex pattern recognition. 2016. Auerbach publications.
[27] Khuriati A, Setiabudi W, Nur M, Istadi I. Heating value prediction for combustible fraction of municipal solid waste in Semarang using backpropagation neural network. In 2n International Conference on Chemical and Material Engineering; 2015. Phuket, Thailand.
[28] Patel SU, Kumar BJ, Badhe YP, Sharma B, Saha S, Biswas S, Chaudhury A, Tambe SS, Kulkarni BD. Estimation of gross calorific value of coals using artificial neural networks. Fuel 2007; 86: 334-344.
[29] Alam T, Kulkarni K. Municipal Solid Waste Management and its Energy Potential in Roorkee City, Uttarakhand, India. Journal of The Institution of Engineers (India): Series A 2016; 97: 9-17.
[30] Zhou H, Meng A, Long Y, Li Q, Zhang Y. An overview of characteristics of municipal solid waste fuel in China: physical, chemical composition and heating value. Renew Sust Energ Rev 2014; 36: 107-122.
[31] Liu Q, Sun Y, Kou W, Cao Y, Wang X, Liu Z, Zhang H. Compositions analysis and anaerobic digestion characteristics on seasonal municipal solid waste. Chinese Jounal of Environmental Engineering 2013; 7: 4507-4512.
[32] James G, Witten D, Hastie T, Tibshirani R. An introduction to statistical learning (Vol. 112). New York: Springer; 2013.
[33] Bunsan S, Chen WY, Chen HW, Chuang YH, Grisdanurak N. Modeling the dioxin emission of a municipal solid waste incinerator using neural networks. Chemosphere 2013; 92(3): 258-264.
[34] Ozveren U. An artificial intelligence approach to predict a lower heating value of municipal solid waste. Energ Source Part A 2016; 38(19): 2906-2913.
[35] Zevenhoven R, Karlsson M, Hupa M, Frankenhaeuser M. Combustion and gasification properties of plastics particles. J Air Waste Manage 1997; 47: 861-870.
[36] Ragaert K, Delva L, Van Geem K. Mechanical and chemical recycling of solid plastic waste. Waste Manage 2017; 69: 24-58.
[37] Waste Research Limited. Compositional and chemical analysis of waste entering Nottingham Energy Recovery Facility (ERF) for FCC Environment. 2014.
[38] Ryu C, Sharifi VN, Swithenbank J. Thermal waste treatment for sustainable energy. In Proceedings of the Institution of Civil Engineers-Engineering Sustainability. Thomas Telford Ltd; 2007.

[39] Giusti L. A review of waste management practices and their impact on human health. Waste Manage 2009; 29(8): 2227-2239.
[40] Alon I, Qi M, Sadowski RJ. Forecasting aggregate retail sales: a comparison of artificial neural networks and traditional methods. J Retail Consum Serv 2001; 8(3): 147-156.
[41] Wang YM, Elhag TM. A comparison of neural network, evidential reasoning and multiple regression analysis in modelling bridge risks. Expert Syst Appl 2007; 32(2), 336-348.
[42] Van Caneghem J, Block C, Vandecasteele C. Destruction and formation of dioxin-like PCBs in dedicated full scale waste incinerators. Chemosphere 2014; 94: 42-47.
[43] McKay G. Dioxin characterisation, formation and minimisation during municipal solid waste (MSW) incineration. Chem Eng J 2002; 86(3): 343-368.
[44] Tsai WT, Chou YH. An overview of renewable energy utilization from municipal solid waste (MSW) incineration in Taiwan. Rene Sust Energ Rev 2006; 10(5): 491-502.
[45] Papargyropoulou E, Lozano R, Steinberger JK, Wright N, Bin Ujang Z. The food waste hierarchy as a framework for the management of food surplus and food waste. J Clean Prod 2014; 76: 106-115.