Journal of Energy Technologies and Policy
ISSN 2224-3232 (Paper) ISSN 2225-0573 (Online)
Vol.4, No.5, 2014
www.iiste.org

Novel Linear and Nonlinear Equations for the Higher Heating Values of Municipal Solid Wastes and the Implications of Carbon to Energy Ratios

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ABSTRACT

Energy recovery from municipal solid wastes (MSW) offers economic benefits together with improved management of wastes. In the literature, attempts have been made to understand and quantify the potential energy benefits of MSW but the implications of the proportion of the elemental constituents on the heating value of the wastes are rarely discussed. In this investigation, novel linear and nonlinear equations were developed from artificial neural network (ANN) to predict the higher heating values (HHV) of MSW. The new equations perform equally well in comparison with the existing models in the literature for different HHV data from various MSW sources. They also showed consistency in satisfactory performances for predicting HHV values from new data as well as altered elemental compositions. Furthermore, it was found that the change in the proportion of elemental compositions have interesting relation to the magnitude of the HHV for different wastes. Results show that a change in percent hydrogen (%H) changes the HHV in some wastes that possess the thresholds of both HHV magnitude and the carbon to energy ratio (C/HHV). For the waste with low HHV but relatively high C/HHV value, increasing the %H does not significantly alter their HHV value. For those with high HHV value and moderate C/HHV value, HHV increases as the %H increases. Wastes with high HHV value but low C/HHV undergo reverse in the trend of HHV as the %H increases. Typical example of this is found in plastic wastes with high percentage carbon (%C) but low C/HHV. In this waste, as the %H increases the corresponding HHV decreases.

Keywords: Municipal solid wastes, linear, nonlinear, artificial neural network, carbon to energy ratio, higher heating values.

1. INTRODUCTION

Waste to energy is a sustainable and an economical choice in waste management. It is particularly important at the current time where the increasing cost of energy poses financial challenges to the poor populace. With increasing world population, waste generation is on the geometric rise. With human activities becoming diversified, wastes generated are also of various sources and compositions. Across many cities, the quantities and management of the wastes are posing difficult challenges. Thus, in the recent time, categories of wastes have included e-wastes which are the electrical and electronic wastes that include damaged and obsolete components, sub-assemblies, etc., that are considered unusable by owners (Qu et al. 2013). This category of wastes poses serious environmental challenges if not adequately managed. However, general solid wastes (e.g., municipal solid wastes) are still of considerable concerns in the developed and the developing countries. In the developing countries, increasing generation of wastes poses burden on the budget and management while the lack of understanding over a diversity of factors that affect the different stages of waste management and linkages necessary to enable the entire handling system functioning are serious issues (Guerrero et al. 2013).

Municipal solid wastes (MSW) are regular category of wastes that come from our cities and towns comprising of both combustible and incombustible materials (Speight 2014). They are generated in huge quantity at several urban places around the world. In 2007 alone, China treated about 152 million tons of MSW (Lai et al. 2011). With the huge quantity of MSW and the various compositions that are regularly gathered from various municipal sources, harnessing the derivable energy from them will be of immense benefits (Abila 2014). Advanced societies have largely replaced the biomass with fossil fuels for energy generation. However, the impacts of fossil fuels on climate change and the consequent global warming is calling for a rethink (Vargas-Moreno et al. 2012). Thermoelectric power can be feasibly generated from low grade fuel such as MSW (de Souza-Santos & Ceribeli 2013; Cheng & Hu 2010). To achieve maximum benefits, efficient designs of bio-energy systems and adequate knowledge of the higher heating values (HHV) derivable from these wastes are required (Nhuchhen & Abdul Salam 2012). Such knowledge will enhance the planning, design and optimization of the waste to energy projects. HHV indicates the worth of the wastes for fuel generations (Meraz et al. 2003). It is an important fuel property, which represents the overall enthalpy change when a compound is stoichiometrically burned at a reference temperature with the final products also at the reference temperature, and any water present in the liquid state. Aside the generation of energy, waste combustion also reduces the mass and volume of the waste considerably, making subsequent disposal more manageable. Such process usually takes place at high temperature (e.g., > 1000K) in the presence of abundant air to promote oxidation of the organic compounds (Tillman 2012; Walser et al. 2012; Galiano et al. 2011). Different material components of MSW have variable enthalpy of combustion and water content. The water content decreases the recoverable energy from them. The incombustible portion of the wastes eventually transforms into clinker after combustion resulting in solid residue; ash, with large metallic content (Meraz et al. 2003).

Heating values of MSW can be determined either directly or by using mathematical models. The direct determination often comes with some costs while the mathematical models are widely available in the literature. These models rely on elemental, proximal, structural, physical and chemical analyses (Vargas-Moreno et al. 2012). HHV is usually obtained via a mathematical relation using the reduced chemical composition of the fuels as parameters (Meraz et al. 2003). In this regards, many equations have been presented. While many of these equations perform quite well, investigators have not ceased to research into new and better-performing equations for HHV, especially in relations to MSW. Particularly, the deficiencies in the HHV estimation from pure substances, as given by physical chemistry texts (e.g., McQuarrie & Simon 1997) have been overcome with equations with capability for HHV estimation in complex mixture. These equations use linear combinations of the elemental compositions, which are often given on the percentage of dry basis.

Lloyd & Davenport (1980) established a linear equation for HHV estimation using multiple regression analysis of 138 liquid fossil fuels. The resulting relation is shown in equation (1):

$$\mathrm{HHV} = \left(1 - \frac{\%\mathrm{H_2O}}{100}\right)\left(-0.3578(\%\mathrm{C}) - 1.1357(\%\mathrm{H}) + 0.0845(\%\mathrm{O}) - 0.0594(\%\mathrm{N}) - 0.1119(\%\mathrm{S})\right) \qquad (1)$$

Similar correlation was presented by Boie (1953) as shown in equation (2):

$$\mathrm{HHV} = \left(1 - \frac{\%\mathrm{H_2O}}{100}\right)\left(-0.3517(\%\mathrm{C}) - 1.1625(\%\mathrm{H}) + 0.1109(\%\mathrm{O}) - 0.0628(\%\mathrm{N}) - 0.1109(\%\mathrm{S})\right) \qquad (2)$$

$\%H_2O$, %C, %H, %O, %N, and %S refer to the percentage elemental composition of water, carbon, hydrogen, oxygen, nitrogen and sulphur, respectively. In addition, some existing HHV estimations were based on the thermochemical concepts. These include equations (3) and (4) given by Meraz et al. (2003) and Wilson (1972), respectively:

$$\mathrm{HHV} = \left(1 - \frac{\%\mathrm{H_2O}}{100}\right)\left(-0.3708(\%\mathrm{C}) - 1.1124(\%\mathrm{H}) + 0.1391(\%\mathrm{O}) - 0.3178(\%\mathrm{N}) - 0.1391(\%\mathrm{S})\right) \qquad (3)$$

$$\mathrm{HHV} = \left(1 - \frac{\%\mathrm{H_2O}}{100}\right)\left(-0.3279(\%\mathrm{C}) - 1.5330(\%\mathrm{H}) + 0.1668(\%\mathrm{O}) - 0.0242(\%\mathrm{N}) - 0.0928(\%\mathrm{S})\right) \qquad (4)$$

Many other models for predicting the heating values of MSW exist in the literature. Most of these can be found in the review by Vargas-Moreno et al. (2012). Observing the above equations, there exist similarities in the coefficients for almost all the elemental parameters. Not only that, they are all linear equations. Meraz et al. (2003) earlier investigated the performance of all the models and found them to perform well within acceptable error limits. Thus, one can assume them to be tested and trusted.

However, one assumption is common among the models listed above- that the relationship between elemental components of the MSW wastes and the enthalpy output from combustion is linear. This is the common form of the HHV models in the literature. They are hardly nonlinear. Also, an important phenomenon that is rarely addressed in the open literature is the sensitivity of these models to the change in the elemental compositions of the biomass. How does the HHV respond to a change in %H? Also, how does the value of carbon to energy ratio (C/HHV) affect the sensitivity of these models to the change in elemental compositions, e.g., %H, in relation to HHV and the waste type?

Answering the above questions require systematic investigations of the new and existing models together with further probe into the elemental compositions of various biomass wastes. This work aims to answer the above questions with new and novel equations as well as the existing models. As such, it is hoped that the results of this work will throw light at the relations between the proportion of the elemental compositions and the energy recoverable from the MSW wastes. Furthermore, it is envisaged that the results will enhance our understanding of the energy generation from synthetic fuels where elemental compositions can be manipulated.

2. Methods

The approach used in this work to address the questions raised above involves the design, implementation and validation of new models. The new models were obtained from the analyses of Artificial Neural Network (ANN) procedure as well as the Multivariate Regression (MVR) using XLSTAT (Microsoft Excel).

2.1 ANN

ANN is a powerful modelling tool that approximates functions between the dependent and the independent variables. It is a versatile tool to reduce the computational timescales as well as capture integrating effects inherent in the complex linear and nonlinear relationships among the variables. Yet, it has simple set up procedure (Brownlee 2011; Haykin 1999; Graupe 1999). Akkaya & Demir (2010) earlier demonstrated the use of ANN in the prediction of HHV for MSW. But, they did not develop any equation from the results. The procedures followed in the development of the new models from ANN involve data sourcing and pre-processing, different ANN configurations and network creation, network training, validation and testing as well as statistical evaluation of performances of the different ANN configurations. Different configurations were tested to obtain optimal performance. For each configuration, training, validation, and testing were performed together with post-training regression analysis. Among the well-performing ANN model configurations, those with simple network configurations were chosen for analyses to obtain the required linear and nonlinear models.

2.1.1 Data sources and pre-processing

Data used in this work were obtained from Meraz et al. (2003). These data pertained to MSW from various sources with materials ranging from food, paper, plastics, wood, textiles, yard, metals, glass and ash. Like the models discussed under the introduction, five elemental compositions (%C, %H, %O, %N and %S) were considered as the independent variables on a dry basis of the waste sample. The percentage of the water present in each MSW was subtracted from 100% of the original waste sample. The output variable remains the HHV value of each waste sample with unit of MJ/kg. Note that the HHV is exothermic and as such, negative sign is attached to its magnitude. Table 1 shows the statistics of the data. Pre-processing involves the data normalization using "mapminmax" function in MATLAB. This function scales the inputs and the output so that they fall into the range of -1 to 1.

Table 1: Statistics of the ultimate analyses data for MSW (Meraz et al. 2003)

Statistics	%C	%H	%O	%N	%S	%H_2O	-HHV (MJ/kg)
Maximum	87.10	14.18	47.84	10.00	4.08	78.70	0.39
Minimum	0.72	0.80	0.00	0.00	0.00	0.00	45.88
Average	43.25	5.63	25.84	1.15	0.30	14.13	15.89
Standard Deviation	18.73	2.66	15.55	1.77	0.49	21.73	9.66

2.1.2 ANN Models Configurations and Network Creation

Various ANN configurations were investigated before choosing from the simplest of the well-performing ones that suit the purpose of this work. The configuration procedure follows the proposal by Jain & Indurthy (2003). The network was created using single hidden layer. Different number of neurons was tested at the hidden layer. To implement this in MATLAB, program files were created with lines of code to create, train, validate and test the network as well as to generate the goodness of fit parameters of the data points using correlation coefficients and slope. The program divides the dataset randomly into 60, 20 and 20% corresponding to the data for training, validation and testing, respectively.

Levenberg-Marquardt function was used for the training of the network. It is a curve-fitting function that optimizes the parameter of the model curve in the nonlinear least squares problems. The function uses back-propagation algorithm that involves iterative adjustment of the weights and biases, which were used by the transfer function to relate the input layer to the hidden layer. The algorithm utilizes a gradient descent algorithm with such learning rule as described by Widrow (1962). The training process continues until the error between the input and the output reduces below the previously defined minimum. Also, the network used in our work is the feed forward type. It is the commonest network in engineering application (Haykin 2009). 'Purelin' and 'Tansig' transfer functions were used to develop the linear and nonlinear models, respectively. The transfer function calculates a layer's output from its net input. To obtain linear models from ANN structure, Purelin function was used as the transfer function between the input and the hidden layers as well as between the hidden layer and the output layer of the network. Also, to obtain the nonlinear models from ANN structure, Tansig function was used between the input and the hidden layers while Purelin function was used between the hidden and the output layers. Mean square error (mse) was employed as the network default performance criterion relating the calculated output from the model to the actual target.

In the training process, the epochs and goals serve as the stopping criteria of the number of iterations and the error tolerance, respectively. Epoch is the maximum number of times all of the training sets are presented to the network while goal refers to the maximum error tolerance between the predicted and the actual output. Thus, the training stops if the error goal is satisfactory or the maximum number of epochs is attained. In this work, an epoch of 200 and a goal of zero were used. The network trainings thus stopped when the number of iteration exceeded the stated epochs or if the error tolerance is achieved. The weights at various nodes in ANN network were randomly assigned leading to different output and performance at every training for the same dataset. To control the randomness, the number of network training for a single ANN configuration was limited to 10. The result from the training giving the best performance was then selected. Also, the training process generates the network object.

The ANN models configurations in this work differ only in the number of neurons at the hidden layer. Typical model configuration was represented as ANN [I-H-T] where "I" represents the input layer and its number refers to the number of independent variables (5 in this work)."H" represents the hidden layer and its number represents the number of neurons used at this hidden layer (1 to 4 in this work). "T" represents the output layer and its number represents the number of corresponding dependent variable or target (1 in this work). The number of neuron was increased from 1 to 4 in this work. At each number of neurons, the network was trained, tested and validated ten times for each network configuration. The best performance in this set of training, in term of the correlation coefficient, was chosen. This procedure was followed for all the number of neurons used.

Criteria for the analyses of the performances of the ANN configurations include the coefficient of correlation (R^2), slope and intercept of the best line of fit.

2.1.3 Equations from ANN Models

Analysis of the ANN procedure was used to obtain the equations from the ANN structure. Among the simplest of the well-performing ANN configurations were used to generate the linear and nonlinear equations. The linear equation was obtained with the Purelin transfer function used in the input to hidden as well as at the hidden to output layers of the network, respectively while the nonlinear equation was obtained with Tansig and Purelin transfer functions at the former and latter positions, respectively. The procedure involved manual normalization of the independent variable data using the 'mapminmax' function procedure in MATLAB. This was then related with the weights and the biases obtained from the simulation of ANN model configuration of choice using the expressions for the 'Tansig' and 'Purelin' functions at the appropriate layers. The expression for 'mapminmax' is shown in equation (5):

$$y = \frac{2(x - x_{min})}{(x_{max} - x_{min})} - 1 \qquad (5)$$

where y is the normalized form of the variable x. xmax and xmin are the maximum and the minimum normalized values, respectively (typically 1 and -1) for the variable. Tansig function is shown in equation (6). The resulting relation is a normalized form of the predicted output, which can then be denormalized to get the actual predicted output. Thus, the resulting relation, from the above procedure, was denormalised to obtain the applicable models.

$$\tan sig(n) = \frac{2}{(1 + \exp(-2n))} - 1 \qquad (6)$$

2.2 Multivariate Regression (MVR)

The MVR model is one of the most widely used of all statistical methods. Regression techniques such as principal component regression (PCR) and partial least-squares regression (PLSR), are based on the inverse method (Gosasang et al. 2011; Fox et al. 2011) and they have been widely applied in many fields of study, e.g., anatomy (Schumann et al. 2013) . In this work, for the purpose of comparisons with the ANN models and other existing HHV models, multiple linear and nonlinear regression models were developed using XLSTAT (Microsoft Excel). The linear models (MVR-PCR, MVR-PLSR) and nonlinear model (MVR-nonlinear) are shown as equations (7), (8) and (9), respectively:

$$HHV = -0.132 - 0.326\%C - 1.242\%H + 9.148x10^{-2}\%O + 0.264\%N - 4.07910^{-2}\%S \qquad (7)$$

$$HHV = -0.270 - 0.256\%C - 1.746\%H + 9.364x10^{-2}\%O + 0.231\%N - 0.203\%S \quad (8)$$

$$HHV = -0.049 - 0.431\%C - 1.428\%H + 0.295\%O - 0.153\%N + 2.509\%S + 4.194x10^{-3}\%C^2 + 6.387x10^{-2}\%H^2 - 1.793x10^{-2}\%O^2 + 0.518\%N^2 - 8.265\%S^2 - 7.205x10^{-5}\%C^3 - 4.096x10^{-3}\%H + 5.881x10^{-4}\%O^3 - 0.1395\%N^3 + 6.611\%S^3 + 4.137x10^{-7}\%C^4 + 4.139x10^{-5}\%H^4 - 6.479x10^{-6}\%O^4 + 1.002x10^{-2}\%N^4 - 1.341\%S^4 \quad (9)$$

2.3 Model Performance Testing Criteria

The performances of all the models were tested using the criteria; R-squared (R^2), intercept and slope, of the regression or predicted line of fit to the actual HHV of the original dataset.

2.4 Sensitivity of HHV value to Change in %H and %C

In order to test the predictive ability of the models and estimate how change in the elemental composition affect the HHV values in the waste, %H was increased by 25 and 50%, respectively. In order to maintain the 100% total composition of the elements, the marginal change in the %H was deducted from the %C. Thus, %H increases by the same amount with which %C reduces in the original dataset.

3. Results and Discussions

The results of the various investigations are presented based on the applications of all models considered in this work for the prediction of HHV for MSW. The performances of the models were examined for different HHV data from literature. Also, the sensitivity of the HHV value to change in the elemental composition is tested with the new and existing models.

3.1 ANN

Figure 1 shows the training, validation and testing sessions of the network using 1 neuron in the hidden layer. The network uses the transfer functions- Tansig in the input layer and the Purelin in the output layer. It could be seen in Figure 1(A) that the network-learning rate is very fast resulting in near vertical drop in mean square error (mse). The best validation performance occurs at epoch 200 with very low mse. With just one neuron at the hidden layer, the coefficient of correlation (R) is very close to one (i.e., 0.991) as shown in Figure 1(B). Similarly, the performance of the network with two neurons at the hidden layer is shown in Figure 2. The performance at the post-regression analysis shows good correlation coefficient (approximately, 0.994). In comparisons, the performances of the above-mentioned ANN configurations are still approximately equal, despite the difference in the number of neurons at their hidden layers. The performances of the other ANN structures with different number of neurons are shown in Table 2. In the table, the parameters R and the slope are very close to one for all the configurations while the intercept is low. It will be appreciated that all the models have very good parameter values that are approximately equal for different ANN configurations. For all the

ANN configurations, the slopes and the Rs are closer to 1 by at least 98 and 99%, respectively. This indicates the strength of all the ANN configurations. Hanspal et al. (2013) acknowledges the fact that a well-trained ANN models, irrespective of the number of layers, can offer competitive performance. Thus, simple ANN models can be used to fit complex system, provided that sufficient training leads to good performance.

Since all the ANN models perform creditably well, irrespective of the number of neurons in the hidden layer, two of the simplest ANN structures with both having 1 neuron at the hidden layer were selected for the development of the equations for the prediction of HHV. These are the first two ANN structures in Table 2. The first ANN configuration in the table used Purelin function at both the input and the output layers. Thus, linear equation was obtained from this model. This is shown in equation (10) and it is henceforth referred to as ANN-linear. The second model used Tansig function at the input layer and the Purelin function at the output layer. Nonlinear equation was obtained from this model (shown in equation (11)) and it is henceforth referred to as ANN-nonlinear. The equations were obtained following the procedures described in section 2.1.3.

$$HHV = \left(1 - \frac{\%H_2O}{100}\right)\left(-0.334(\%C) - 1.15(\%H) + 0.091(\%O) + 0.285(\%N) + 0.091(\%S)\right) - 0.4105 \quad (10)$$

$$\mathrm{HHV} = \frac{-511.17}{1+\exp\left(\left(1-\frac{\%\mathrm{H_2O}}{100}\right)\left(-0.00291(\%\mathrm{C})-0.00872(\%\mathrm{H})+0.000678(\%\mathrm{O})+0.00243(\%\mathrm{N})+0.0011(\%\mathrm{S})\right)\right)}+178.464 \qquad (11)$$

The performances of the two equations are shown in Figure 3 in comparison with the target HHV. It is clear from the figure that the new equations, both linear and nonlinear provide good matches to the target HHV. Thus, reliable models can be obtained from ANN structures using the approach demonstrated in this work.

Furthermore, the performances of the linear and nonlinear MVR equations developed from XLSTAT were tested. This was done to obtain robust comparisons of the new equations with a range of other models. The performances of the MVR linear models (MVR-PCR and MVR-PLSR) and MVR-nonlinear equations also appear satisfactory. The performances of these equations are compared to the existing models in literature for the prediction of HHV values. The models selected from literature are expressed in equations (1) to (4). For the purpose of brevity, equations (1) to (4) will, henceforth be referred to, in this work, as; Lloyd, Boie , Meraz, and Wilson models, respectively.

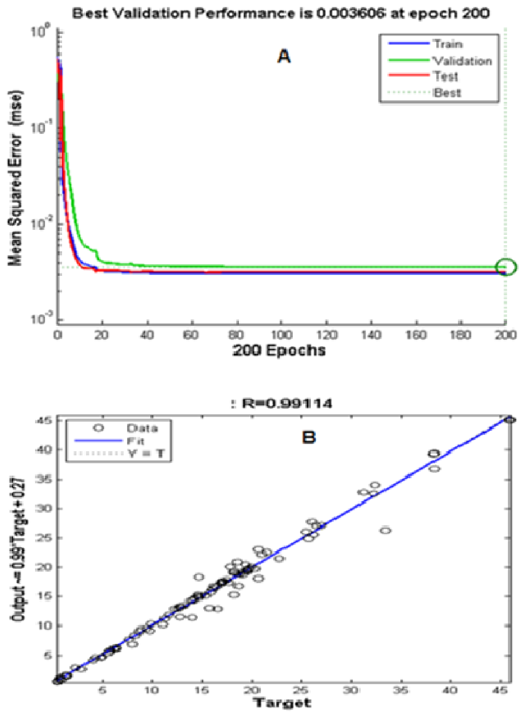

Figure 1: (A) Error reduction in trained network (B) Post-training regression analysis for ANN [5-1-1] using Tansig-Purelin transfer functions.

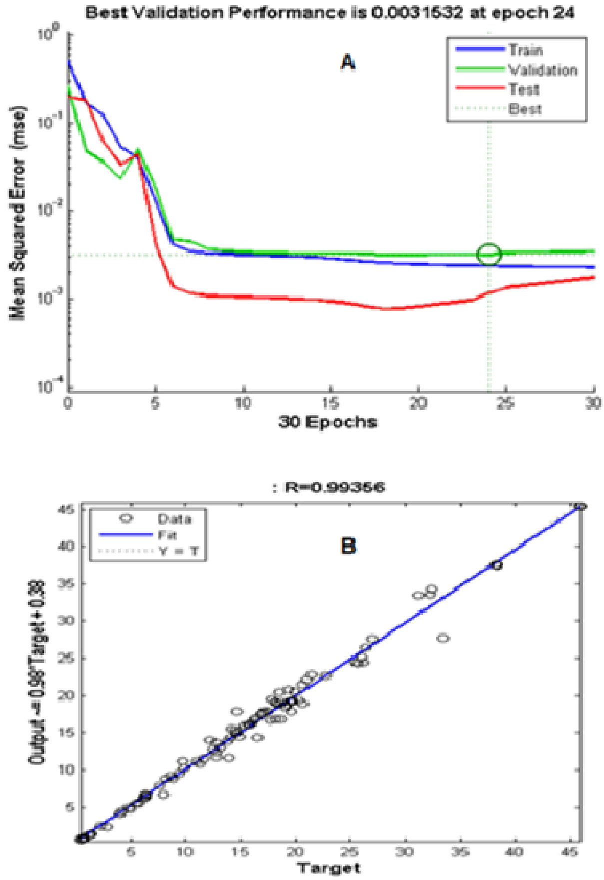

Figure 2: (A) Error reduction in trained network (B) Post-training regression analysis for ANN [5-2-1] using Tansig-Purelin transfer functions.

Table 2: Performances of the different ANN configurations.

S/N	ANN Configurations	R	Slope	intercept	Transfer functions
1	ANN[5-1-1]	0.9913	0.98	0.5	Purelin-Purelin
2	ANN[5-1-1]	0.9915	0.99	0.27	Tansig-Purelin
3	ANN[5-2-1]	0.994	0.98	0.38	Tansig-Purelin
4	ANN[5-3-1]	0.994	0.98	0.23	Tansig-Purelin
5	ANN[5-4-1]	0.9941	0.99	0.15	Tansig-Purelin

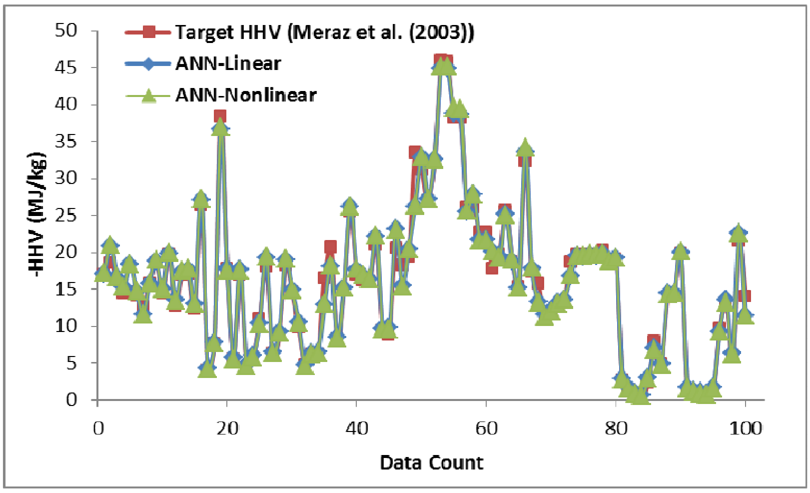

Figure 3: Target and the predicted HHV with new equations from ANN models.

3.2 *Performances of the Models to the Target HHV (Meraz et al. 2003)*

The performances of all models in predicting the target HHV were compared as shown in Figure 4. As said earlier, the closeness to value 1 of the slope and the R^2 and the closeness to zero of the intercept define the quality of prediction by the model. In the figure, all the models posed very good values for slope, each having approximate value close to 1. Similarly, the R^2 values for all the models are, at least, 98% closest to 1. MVR-nonlinear leads with value of 0.985 followed by MVR-PCR with 0.983. These are followed closely by ANN-linear with value of 0.983 and MVR-nonlinear with value of 0.982. In term of the intercept, the Boie model has the best value with value 0.086 closest to zero. This is followed by the ANN-nonlinear model with value of 0.272. The performance analyses above show that the new ANN models perform equally well in comparison with the existing models. The new MVR-PCR and MVR-nonlinear presented have minimal edges over the ANN models in term of the R^2 criterion while they all perform better than the selected existing models in the literature as shown in Figure 4. Predictions by ANN-linear and MVR-nonlinear are shown in Figures 5 and 6, respectively. The figures show good predictions by the two models with the target HHV data points clustering well around the lines of fit.

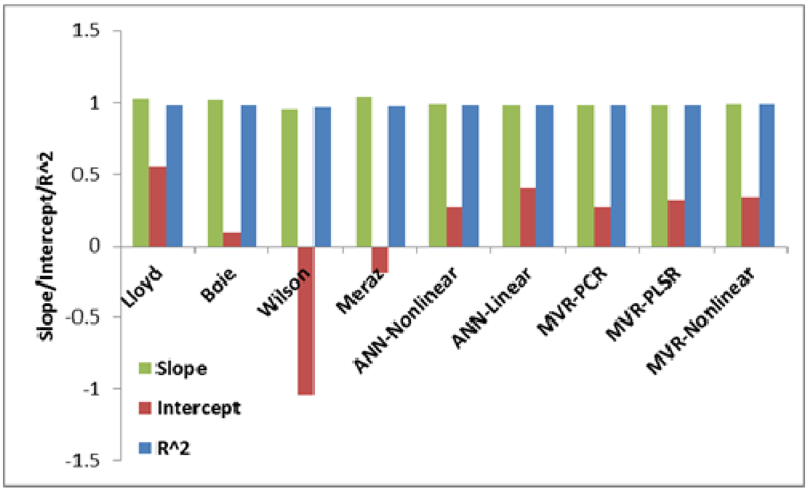

Figure 4: Performances of all models based on target HHV data (Meraz et al. 2003)

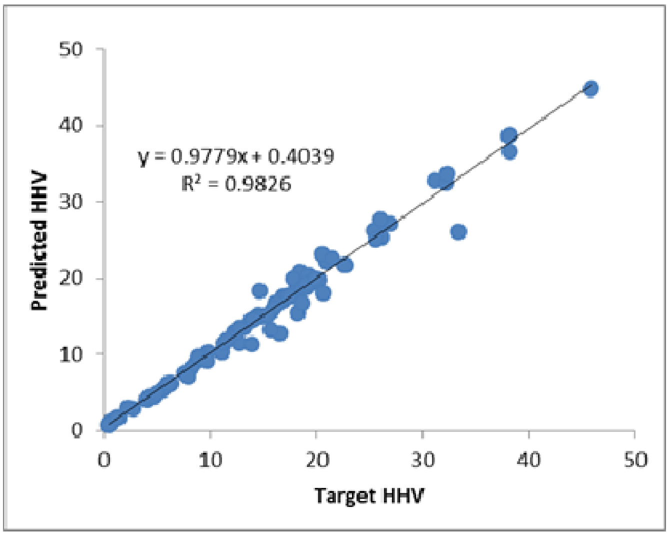

Figure 5: Output of ANN-linear model compared to target HHV data (Meraz et al. 2003)

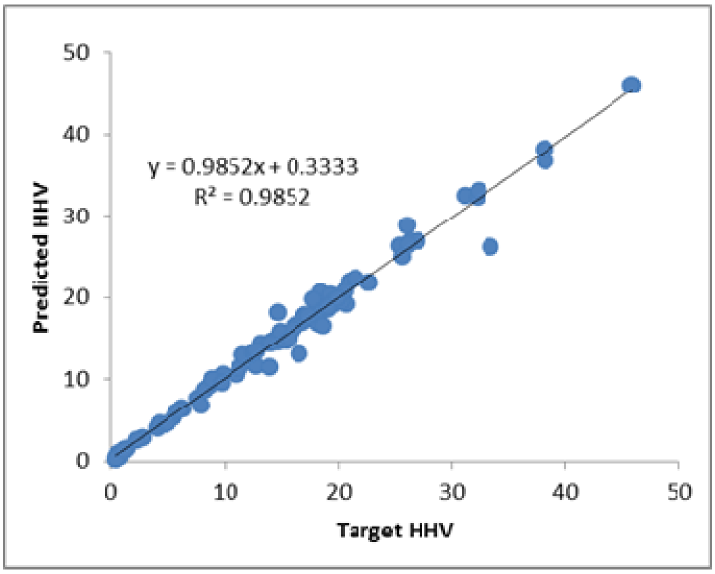

Figure 6: Output of MVR-nonlinear model compared to target HHV data (Meraz et al. 2003)

3.3 Sensitivity of HHV to change in % H

The sensitivities of the HHV values and models to change in elemental compositions were investigated for selected wastes. The %H in the data obtained from Meraz et al. (2003) was separately increased by 25 and 50%. The marginal changes in %H were deducted from the composition of carbon. Thus, in the data, %H increases by a certain amount while the %C decreases by the same amount. Figure 7 shows the plot of HHV predictions for selected wastes at 50% increase in %H. Also, Figure 8 depicts the carbon to energy ratios (C/HHV) for the selected wastes in Figure 7. Selected data points are used in the figures for the purpose of clarity. In Figure 7, with 50% increase in %H, all the models predict the change in HHV values in the same way. Though Wilson model shows lower value of HHV, compare to other models. For waste with high HHV values, the models predict increase in HHV values for 50% increase in %H. This is, however different at the last data count (9) where all the models predict reduction in HHV value for increase in %H. This point represents the waste for the mixed plastics. Possible reason for this is the low ratios of carbon to energy (C/HHV) for this category of waste. This is shown in Figure 8 for the selected waste samples. Among all the wastes shown in the figure, mixed plastics have the least C/HHV. Thus, in this waste, reducing the carbon content drives down the HHV value irrespective of the increase in the %H. Furthermore, for some waste samples in Figure 7 (see, data count 2, 3, 6, 7) with low values of HHV, the predictions indicate no significant change in HHV values with change in the %H. As earlier inferred, since these categories of wastes have high C/HHV but low HHV values they are unaffected by the reduction in carbon composition unlike the mixed plastic waste (data count 9) with low C/HHV having high HHV value. Figure 9 shows the predicted HHV values at 25 and 50% increase in %H composition using ANN-nonlinear model. The model shows good performance in forecasting HHV values with consistency.

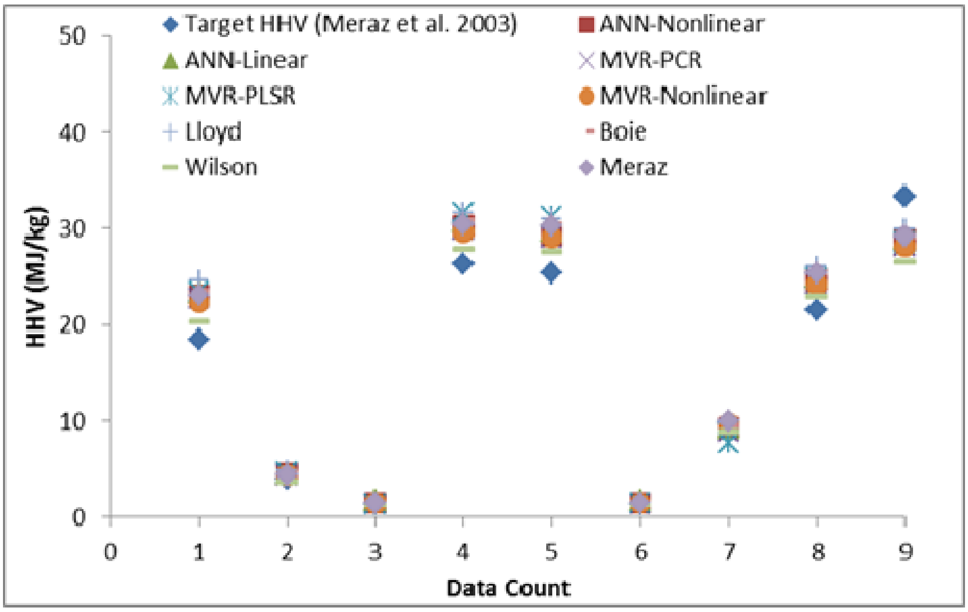

Figure 7: HHV predictions for 50% change in %H for all models (Original Data from Meraz et al. 2003)

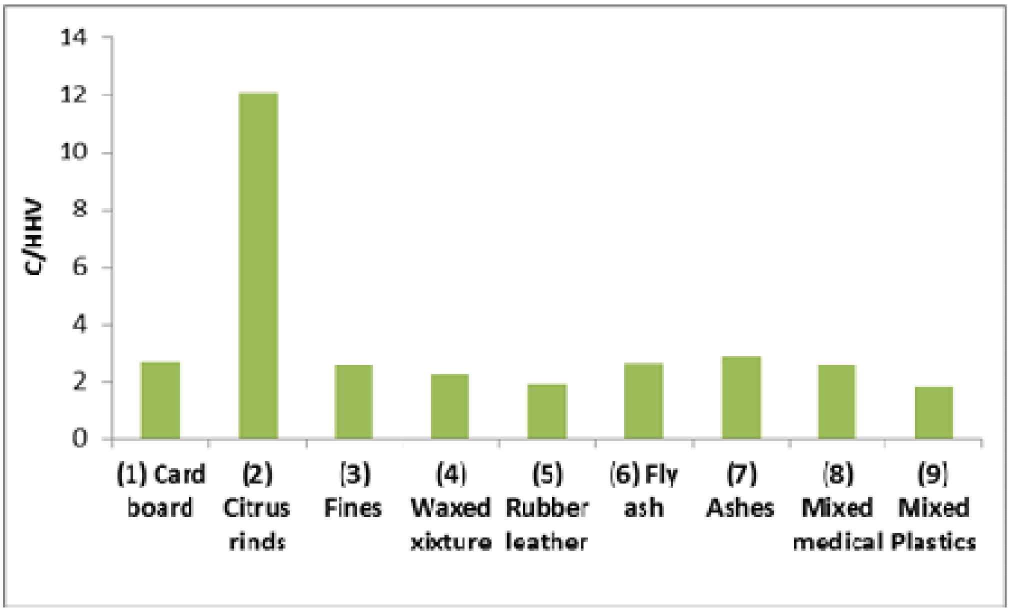

Figure 8: Carbon to energy ratios for randomly selected waste samples (Original data from Meraz et al. 2003)

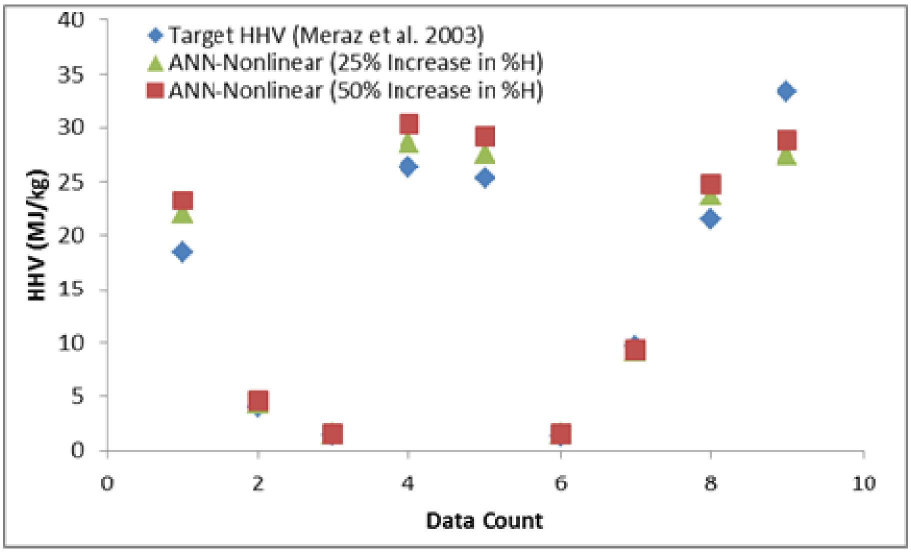

Figure 9: HHV predictions for 25 and 50% Change in %H using ANN-nonlinear (Meraz et al. 2003)

3.4 Comparison of the performances of models on the new HHV data

New data from the feasibility study of waste to energy by Pasek et al. (2013) were obtained for further test of the models performances. Figure 10 shows the bar chart for all models in terms of the criteria earlier discussed. Clearly, all the models perform well judging from the view of the slope and the R^2 which are very close to 1 in all cases. But, the intercept vary for some of the models. For example, the intercept value of MVR-nonlinear model is very close to 5, which indicates wide deviation. Similarly, the intercept for the Lloyd model also shows wide deviation from origin with value greater than 3. The ANN models and the linear MVR models show high value of intercepts, though, they are lesser in values than the earlier models mentioned. This is also the case with Boie and Wilson models. In all, Meraz et al. (2003) model performs best on new data with intercept value very close to zero and the R^2 as well as the slope being in the acceptable range. Figures 11 and 12 show the outputs of the predicted HHV using the ANN-nonlinear and Meraz et al. (2003) models, respectively. Both models show good predictions as indicated with their R^2 values as well as the fair cluster of the data points around the lines of fit. Thus, the new equations from ANN can compete equally well with the existing models in predicting HHV values.

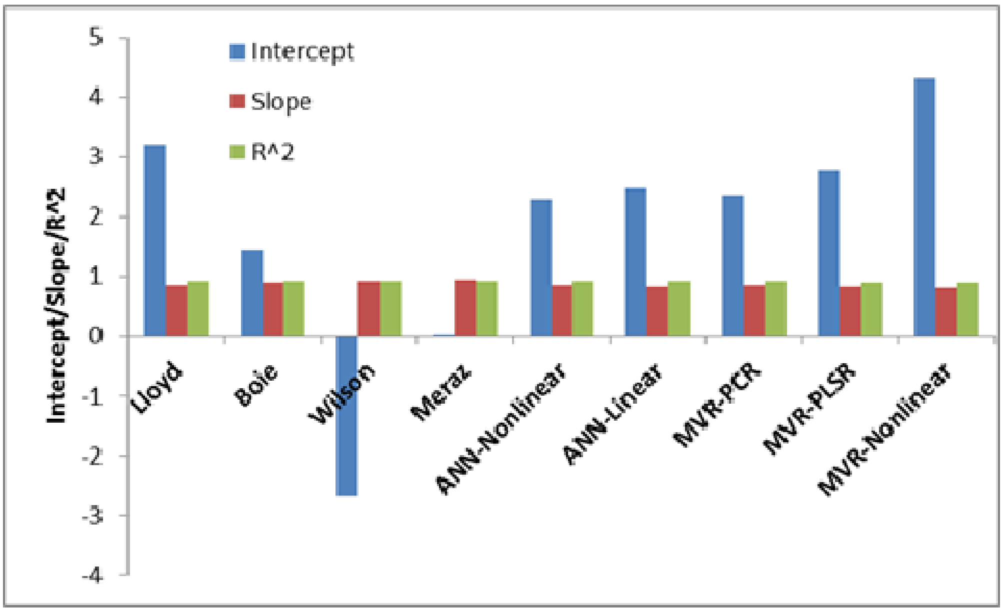

Figure10: Performances of all models based on new HHV data (Pasek et al. 2013)

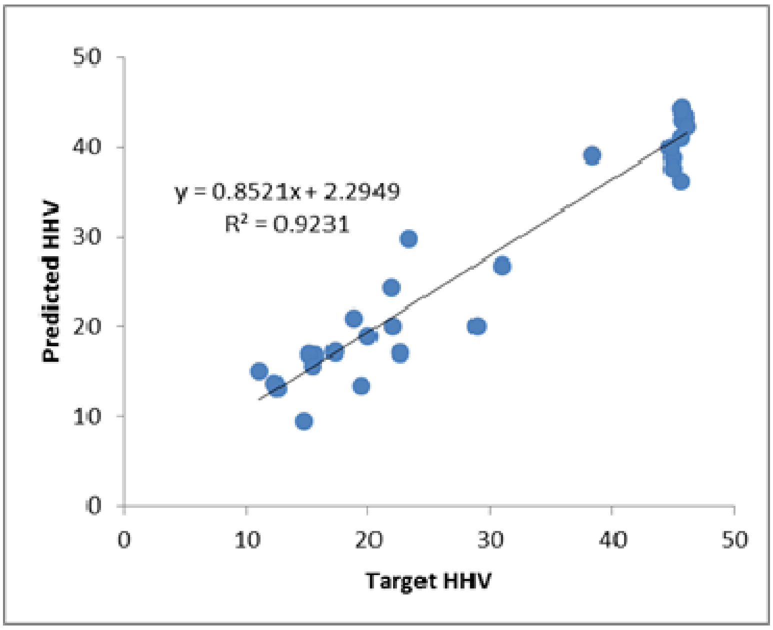

Figure 11: Output of ANN-nonlinear model compared to new HHV data (Pasek et al. 2013)

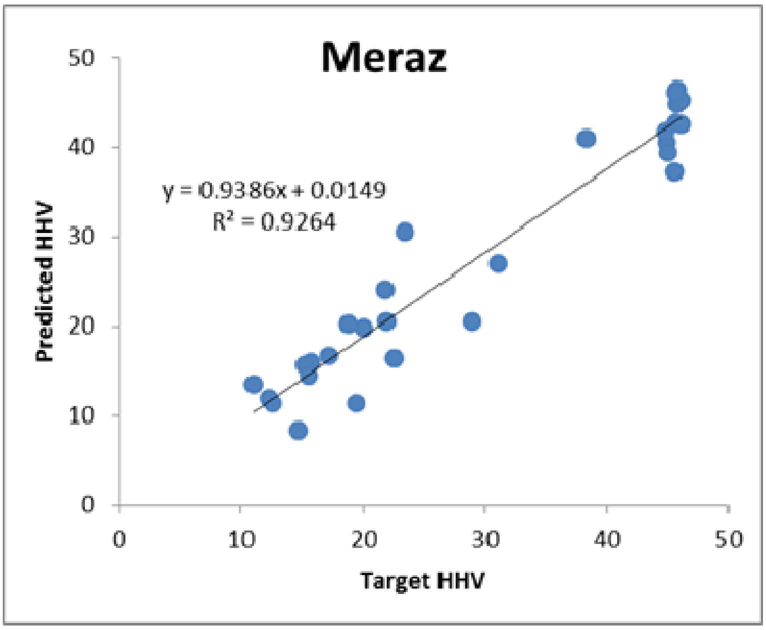

Figure 12: Output of Meraz et al. (2003) model compared to new HHV data (Pasek et al. 2013)

4. Conclusion

Energy recovery from municipal solid wastes (MSW) offers economic benefits together with improved management of wastes. This investigation demonstrated the ability of novel linear and nonlinear models from artificial neural network (ANN) to predict the higher heating values (HHV) of the MSW. Investigations of the suitable ANN configurations for the development of the models show that well-trained simple ANN structures give satisfactory performances. As a result, simple ANN structures are utilized to develop the new models. The new equations perform equally well in comparison with the existing models in the literature for different HHV data on various MSW sources. The new equations also showed consistency in satisfactory performances in predicting HHV values with new data as well as change in elemental compositions. The sensitivities of the HHV to change in elemental composition display interesting scenarios. Results show that change in percent hydrogen (%H) composition change the HHV in some wastes that possess a threshold of both HHV magnitude and the carbon to energy ratio (C/HHV). For the waste with low HHV and relatively high C/HHV value, increasing the %H does not significantly alter their HHV value. For those with high HHV value and moderate C/HHV value, HHV increases as the %H increases. Wastes with high HHV and very low C/HHV undergo reverse in the trend of HHV as the %H increases. Typical example of this is found in plastic waste with high %C but low C/HHV. In this waste, as the %H increases the corresponding HHV decreases.

References

Abila, N., 2014. Biofuels adoption in Nigeria: Attaining a balance in the food, fuel, feed and fibre objectives. Renewable and Sustainable Energy Reviews, 35, pp.347–355.

Akkaya, E. & Demir, A., 2010. Predicting the Heating Value of Municipal Solid Waste-based Materials: An Artificial Neural Network Model. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 32(19), pp.1777–1783.

Boie, W., 1953. Fuel technology calculations. Energietechnik, 3, pp.309–316.

Brownlee, J., 2011. Clever Algorithms: Nature-Inspired Programming Recipes, Jason Brownlee.

Cheng, H. & Hu, Y., 2010. Municipal solid waste (MSW) as a renewable source of energy: Current and future practices in China. Bioresource technology, 101(11), pp.3816–3824.

Darmawan Pasek, A., Gultom, K.W. & Suwono, A., 2013. Feasibility of Recovering Energy from Municipal Solid Waste to Generate Electricity. Journal of Engineering & Technological Sciences, 45(3).

Graupe, D., 1999. Large memory storage and retrieval (LAMSTAR) network.

Guerrero, L.A., Maas, G. & Hogland, W., 2013. Solid waste management challenges for cities in developing countries. Waste management, 33(1), pp.220–232.

Hanspal, N.S. Allison, B.A., Deka, L., Das, D. B., 2013. Artificial neural network (ANN) modeling of dynamic effects on two-phase flow in homogenous porous media. Journal of Hydroinformatics, 15(2), p.540.

Haykin, S., 1999. Neural Networks – A Comprehensive Foundation. 2nd edn. Prentice-Hall, Englewood Cliffs, NJ.

Haykin, S., 2009. Neural networks and learning machines, 3rd ed. Prentice Hall.

Jain, A. & Indurthy, S., 2003. Comparative Analysis of Event-based Rainfall-runoff Modeling Techniques—Deterministic, Statistical, and Artificial Neural Networks. Journal of Hydrologic Engineering, 8(2).

Lai, Z. Ma, X., Tang, Y., Lin, H., 2011. A study on municipal solid waste (MSW) combustion in N2/O2 and CO2/O2 atmosphere from the perspective of TGA. Energy, 36(2), pp.819–824.

Lloyd, W.G. & Davenport, D.A., 1980. Applying thermodynamics to fossil fuels: Heats of combustion from elemental compositions. Journal of chemical education, 57(1), p.56.

Luna Galiano, Y., Fernández Pereira, C. & Vale, J., 2011. Stabilization/solidification of a municipal solid waste incineration residue using fly ash-based geopolymers. Journal of hazardous materials, 185(1), pp.373–381.

McQuarrie, D.A. & Simon, J.D., 1997. Physical chemistry: a molecular approach, University Science Books.

Meraz, L. Domínguez, A., Kornhauser, I., Rojas, F., 2003. A thermochemical concept-based equation to estimate waste combustion enthalpy from elemental composition☆. Fuel, 82(12), pp.1499–1507.

Nhuchhen, D.R. & Abdul Salam, P., 2012. Estimation of higher heating value of biomass from proximate analysis: A new approach. Fuel, 99, pp.55–63.

Qu, Y., Zhu, Q., Sarkis, J., Geng, Y., Zhong, Y., 2013. A review of developing an e-wastes collection system in Dalian, China. Journal of Cleaner Production, 52, pp.176–184.

Schumann, S., Nolte, L.-P. & Zheng, G., 2013. Comparison of partial least squares regression and principal component regression for pelvic shape prediction. Journal of biomechanics, 46(1), pp.197–199.

De Souza-Santos, M.L. & Ceribeli, K., 2013. Technical evaluation of a power generation process consuming municipal solid waste. Fuel, 108, pp.578–585.

Speight, J.G., 2014. Gasification of Unconventional Feedstocks, Gulf Professional Publishing.

Tillman, D.A., 2012. Incineration of municipal and hazardous solid wastes, Elsevier.

Vargas-Moreno, J.M. et al., 2012. A review of the mathematical models for predicting the heating value of biomass materials. Renewable and Sustainable Energy Reviews, 16(5), pp.3065–3083.

Walser, T., Limbach, L., Brogioli, R., Erismann, E., Flamigni, L., Hattendorf, B., Juchli, M., Krumeich, F., Ludwig, C., Prikopsky, K., 2012. Persistence of engineered nanoparticles in a municipal solid-waste incineration plant. Nature nanotechnology, 7(8), pp.520–524.

Widrow, B., 1962. Generalization and information storage in network of adaline'neurons'. Self-organizing systems-1962, pp.435–462.

Wilson, D.L., 1972. Prediction of heat of combustion of solid wastes from ultimate analysis. Environmental Science & Technology, 6(13), pp.1119–1121.