C8_Heating value prediction for combustible fraction of municipal solid waste in Semarang using backpropagation neural network

by Ainie Khuriati

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Heating Value Prediction for Combustible Fraction of Municipal Solid Waste in Semarang Using Backpropagation Neural Network

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Abstract. Backpropgation neural network was trained to predict of combustible fraction heating value of MSW from the physical composition. Waste-to-Energy (WtE) is a viable option for municipal solid waste (MSW) management. The influence of the heating value of municipal solid waste (MSW) is very important on the implementation of WtE systems. As MSW is heterogeneous material, direct heating value measurements are often not feasible. In this study an empirical model was developed to describe the heating value of the combustible fraction of municipal solid waste as a function of its physical composition of MSW using backpropagation neural network. Sampling process was carried out at Jatibarang landfill. The weight of each sorting sample taken from each discharged MSW vehicle load is 100 kg. The MSW physical components were grouped into paper wastes, absorbent hygiene product waste, styrofoam waste, HD plastic waste, plastic waste, rubber waste, textile waste, wood waste, yard wastes, kitchen waste, coco waste, and miscellaneous combustible waste. Network was trained by 24 datasets with 1200, 769, and 210 epochs. The results of this analysis showed that the correlation from the physical composition is better than multiple regression method .

Keyword: backpropagation neural network, heating value, MSW, physical composition, stepwise multiple regression

INTRODUCTION

In the 2013, generation of Municipal solid waste (MSW) in Semarang reached 6219.2 m^3/day. Meanwhile, Jatibarang landfill is as the only one final disposal which has operated since 1994. The landfill is only capable to accommodate 4.15 million m^3 of MSW [1]. Figure 1 show the increasing of MSW generation per capita in the Semarang since 2003 [2]. It is estimated that just 64.57% people have access to the transport system and waste disposal [3]. Like the other cities in Indonesia, MSW management systems in Semarang are complex problem and diverse. MSW management has not been a high priority yet. These problems have motivated primarily to research study.

MSW is commonly known as trash or garbage. It comprises everyday items, such as tires, newspapers, plastic plates/cups, containers and packaging (e.g., milk cartons, plastic wrap), and other wastes (e.g., yard waste, food

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scraps) [4]. MSW can be a problem especially how to dispose it because of its large volume. One commonly adopted solution is to combust the MSW. Combustion both decreases the volume of material and creates energy that can be recovered in the form of heat or steam [5]. Because some materials have higher heat content than others, the amount of energy that can be produced by combusting MSW is a function of the composition of the waste stream

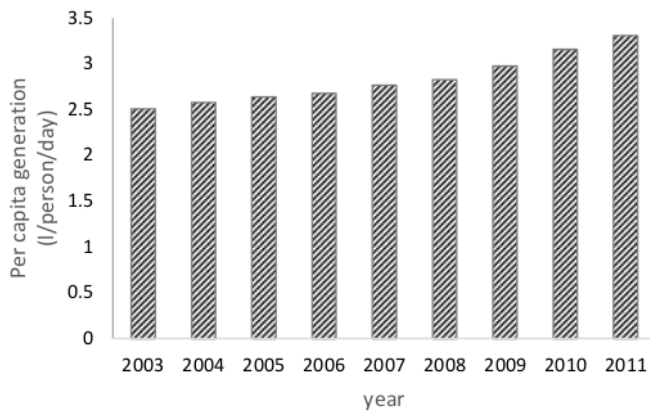

FIGURE 1. Per capita MSW generation in Semarang

The composition of MSW depends on a number of factors such as the lifestyles of the population, the relative standards of living, general consumer patterns, and the level of technological advancement of a particular country. The composition and properties of trash illustrate the diversity of human activity. Information about the solid waste physical composition data is very important to know to help the city in sizing of the facility waste to energy (WtE) based on the amount of waste remaining in the flow of the waste after recycling and composting [6]. To estimate the MSW composition in waste stream, it is necessary to classify the waste components [7]. The waste components were then classified into combustible and non-combustible groupings. Traditionally, combustible MSW fractions are divided into six groups, i.e. food residue, wood waste, paper, textiles, plastics, and rubber based on physical sources [8]. In this paper, 12 kinds of municipal solid waste components are selected. Non-combustible fractions include glass metal, electric, and electronics waste. The presence of incombustibles in MSW poses a serious challenge against the utilization as feedstock [9]. Typically, a physical separation system is included in order to remove these materials from municipal solid waste [9]. EIA divides the municipal solid waste stream into biogenic and non-biogenic components. Further, EIA identifies the biogenic component as renewable and the non-biogenic component as non-renewable [10].

The heating value determines how much fuel is required incinerator for energy recovery purposes. When direct heating value measurements are not feasible, empirical models can be useful to predict the calorific value of MSW [11]. Several models have been developed to describe and predict the energy content of commingled MSW.

Neural networks is widely used for applications in the problems relating to prediction or function approximation, pattern classification, clustering, and forecasting [12]. Neural networks are very powerful when fitting models to data. They can fit arbitrarily complex nonlinear models to multidimensional data to any desired accuracy; consequently, neural network predictors are called universal approximators [12]. ANN typically used to model complex relationships between inputs and outputs or to find patterns in the data [13]. The procedure of BPN repeatedly adjust the weights of the connections in a network to minimize the size of the difference between the actual output vectors and desired output vector network [12]. Neural network had been used to estimate the production of municipal solid waste [13]. ANN models were also developed to predict the value LHV municipal solid waste [14].

The purpose of this work is to introduce a new equation for HHV prediction from physical composition using stepwise regression and bakpropagation neural netwok. The result is compared.

TWO EMPIRICAL MODELS PUBLISHED

Lin et al. [15] established an empirical model for predicting a lower heating value (LHV) by multiple regression analysis. A wet-based physical components model (WBPCM) was developed and based on physical component analysis without dewatering. The LHV empirical prediction model can be described by the following equation

$$LHV = 22.1xP_{pa,w} + 28.1P_{pl,w} + 24.9P_{te,w} + 12.7P_{wo,w} + 6.0P_{fo.w} + 57.4P_{ru,w} + 17.2P_{mi,w} \text{ kcal/kg} \quad (1)$$

Where Ppa,w; Ppl,w; Pfo,w; Pte,w; Pwo,w; Pru,w; and Pmi,w represent paper and cardboard, plastics, food waste, textile, wood, rubber and leather, and miscellaneous materials respectively.

Lin et al [16] also developed LHV model based on wet physical composition. This work found that the effect food waste could been neglected. Therefore the equation as follow

$$LHV = 219P_{pl} + 112P_{pl} + 108P_{wo} + 115P_{Te} \text{ kJ/kg} \quad (2)$$

where P_{Pl}, P_{Pa}, P_{Wo}, and P_{Te} represent the plastic, paper, wood, and textile content (wt%), respectively

MATERIAL AND METHODS

Site characteristics and sampling

Jatibarang landfill is located in the Semarang city. The area is 46, 183 hectares which comprises 27.7098 ha (60%) of waste land and 18.4732 ha (40%) of infrastructures to leachate pond, green belt, and land cover. Landfill is located in the area is in the hill with a slope of more than 24%. Height varies between 63 to 200 meters above sea level. At the bottom flow river Kreo which is intake Semarang water [2].This research was carried out in Jatibarang landfill. MSW was classified into 12 nine combustible waste categories : paper wastes, absorbent hygiene product waste, styrofoam waste, HD plastics waste, plastics waste, rubber waste, textile waste, wood waste, yard wastes, kitchen waste, coco waste, and miscellaneous combustible waste. Samples for each combustible category were randomly collected from 24 trucks of MSW, the size of sample each truck was 102 kg. 100 kg was sorted and 2 kg was analized in laboratory. Samples of inert materials (non-combustible) were not collected.

Step wise Multiple Regression Model

Regression analysis is useful to know the direction of the relationship between independent variables and the dependent variable whether each independent variable associated positively or negatively, and to predict the value of the dependent variable when the independent variable values increase or decrease. Calorific value of waste (y) was a independent variable. Paper (*X1*), absorbent health product (*X2*), Styrofoam (*X3*), plastic HD (*X4*), plastic (*X5*), rubber (*X6*), textiles (*X7*), wood (*X8*), yard waste (*X9*), organics (*X10*), coco (*X11*), and miscellaneous combustible (*X12*) were dependent variables. Functional or causal relationship between these variables is expressed in function:

$$y = f(X) \quad (3)$$

Atau :

$$y = \alpha_1X_1 + \alpha_2X_2 + \alpha_3X_3 + \alpha_4X_4 + \alpha_5X_5 + \alpha_6X_6 + \alpha_7X_7 + \alpha_8X_8 + \alpha_9X_9 + \alpha_{10}X_{10} + \alpha_{11}X_{11} + \alpha_{12}X_{12} \quad (4)$$

While dealing with large number of independent variables, it is of significance importance to determine best combination of these variables to predict dependent variable. Stepwise regression serves as a robust tool for the selection of best subsetmodels i.e. the best combination of independent variables that best fits the dependent variable with considerably less computing than is required for all possible regressions.

BackPropagation Neural Network Model

Back propagation neural network model approach was selected for two reasons. Firstly, back propagation works far faster than earlier approaches to learning, making it possible to use neural nets to solve problems which had previously been insoluble. Secondly, neural networks are known to provide good modelling capabilities for complex, noisy environmental datasets where the relationships between input and output parameters are not well understood [17]. ANNs architecture is composed of three layers; input layer, hidden layer, and output layer. Figure 2 show the network architecture was of the form X: H: Y, where X was the number of input nodes, H was the number of hidden nodes, and Y was the number of output nodes. In this case, the ANN structure consists of eight input and one output, parameter setting given in table 1.

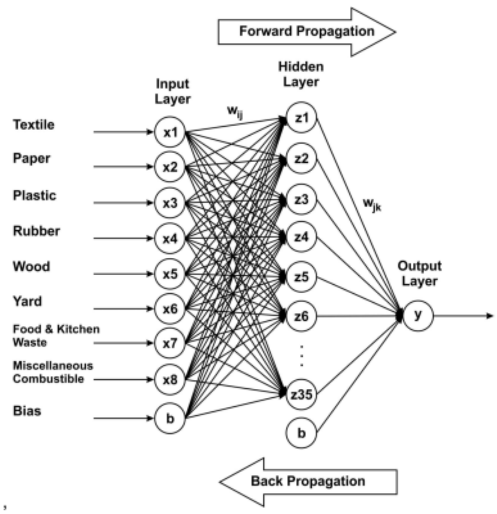

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FIGURE 2. The structure of a three-layer BPNN

TABLE 1. Setting of parameter of back propagation neural network model

Parameter	Setting		
Input layer node number	8	8	8
Hidden layer node number	11	23	35
Output layer node number	1	1	1
Activation function	$y_j(p) = \frac{2}{1+e^{-v_j(p)}} - 1$		
Normalized function	$z' = 0.8\frac{z - x_{min}}{x_{max} - x_{min}} + 0.1$		
Performance criteria	$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2$		
Learning rate	0.1		
Momentum	0.95		
Epoch max	1200		

RESULT AND DISCUSSION

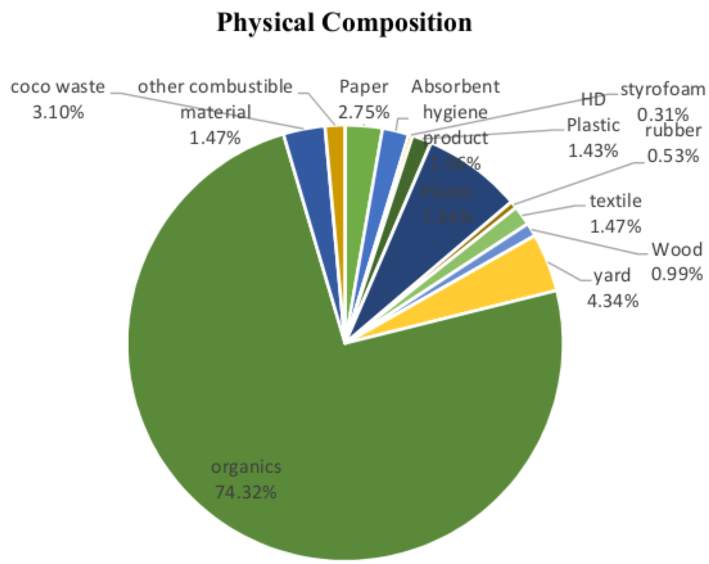


FIGURE 3. The mean combustible fraction physical composition of MSW

Figure 3 show the average combustible fraction physical composition in wet basis of MSW in Semarang city from samples (24 trucks). The contents of styrofoam, rubber, wood, HD plastics, textile, miscellaneous combustible, absorbent hygiene product, paper, coco waste, yard, plastics, organics in increase order were 0.305%, 0.523%, 0.989%, 1.426%, 1.464%, 1.481%, 1.953%, 2.752%, 3.069%, 4.324%, 7.338%, 74.376%. As most developing country, the MSW is dominated by organic waste. Organic components comprise food residue and kitchen waste. Coco waste was separated from organics since its large enough mass fraction. Miscelleneous combustible includes plastic packaging, aluminium foil packaging, and gunny sack. Table 2 show the physical characteristics of MSW in wet basis (as received). The samples were taken in dry season. In this study the heating value was only determined by combustible waste, the inert part (glass, metal, electronic waste) has no heating value.

However, MSWs contain more than 12 compositions. Too much samples will lead to difficulty and uncertainty in experiment process [15]. It is then simplified by using only 8 kinds of waste include paper, plastic (styrofoam, HD plastic, and plastic), Rubber, Textile+diapers, wood, yard+coco waste, Food+kitchen waste, and Miscellaneous combustible (table 1)

TABLE 2. The physical characteristic of MSW

Paper	Plastic	Rubber	Textile	Wood	Yard	Food +Kitchen Waste	Miscellaneous combustible	Moisture Content
6.08	8.34	0.00	9.64	0.00	1.80	74.47	8.01	61
10.15	9.88	0.00	10.98	0.00	15.16	63.47	0.35	57
2.74	6.17	0.00	6.17	0.00	6.78	66.99	17.53	62
5.26	5.74	0.00	6.08	0.00	12.07	76.20	0.40	62
3.82	9.18	0.00	9.18	0.00	3.09	83.13	0.81	63

4.28	8.22	0.00	9.69	0.00	1.23	84.25	0.95	62
6.88	7.72	0.00	11.15	1.05	5.13	75.69	0.11	62
7.22	15.98	0.35	16.30	0.75	18.30	56.70	0.40	60
1.89	11.22	0.00	17.22	0.00	7.37	73.48	0.05	62
2.04	8.79	0.00	10.35	0.00	1.69	85.53	0.40	61
4.93	6.48	0.00	8.38	1.10	8.43	77.13	0.03	62
4.10	7.27	0.00	9.90	1.28	3.71	79.75	1.26	63
8.38	9.24	0.00	10.57	0.00	1.28	79.42	0.35	63
4.04	8.09	0.00	8.09	0.00	34.31	53.22	0.35	62
5.22	4.65	0.00	5.94	0.69	8.14	79.97	0.06	60
5.89	4.69	0.00	10.09	4.87	5.42	73.33	0.40	60
2.93	8.11	0.00	9.82	4.33	5.00	77.56	0.43	63
1.90	6.51	0.00	7.44	0.73	0.84	88.50	0.60	61
6.63	10.29	0.83	10.61	0.00	5.52	76.35	0.08	62
5.63	17.84	0.00	17.21	0.00	0.00	75.16	2.05	63
5.45	6.51	0.00	6.44	0.04	4.91	83.28	0.12	59
2.87	17.78	0.00	17.78	0.00	15.13	63.86	0.35	59
6.38	12.17	0.26	7.88	4.45	6.12	74.47	0.45	56
6.62	6.81	11.10	8.55	4.44	6.01	63.24	0.06	61

Heating Value Model

Stepwise Regression Model

Based on multiple regression analysis, LHV empirical equation is derived, LHV as independent variable and physical compositions of MSW as dependent variables. The equation is

$$LHV = 2997 - 4.6P_{pa} + 7P_{pl} + 11P_{ru} - 27P_{te} + 20P_{wo} - 28P_{yr} - 26P_{fo} - 6P_{mi} \quad \text{kcal/kg} \tag{5}$$

Paper, textile, yard waste, food scarps, and miscellaneous exert a negative influence on the LHV of the MSW because they have high moisture content. The statistical evaluation is RMSE = 197, R^2= 0.491, Adjusted R-Squared = 0.22, and p-value = 0.153. The model is not fully satisfactory. Figure 4 demonstrate the graphical of the multiple regression model based on Eq. 4.

For obtain a satisfactory model is used stepwise regression. The model suggested by stepwise has just one variable. Rubber is highly significant (p=0.007) but explain just 29% compared to full model. There is necessary to adding variables. Eq. 4 can be simplified as follow:

$$LHV = 141 + 23P_{pa} + 8P_{pl} + 40P_{ru} + 49P_{wo} + 2.5P_{fo} + 22P_{mi} \quad \text{kcal/kg} \tag{6}$$

Eq. 5 show that not all predictors contribute to the model, and R^2 is a same (49%) for the full model, R^2-adjusted is greater (0.31 vs 0.22), the overall model has a smaller p-value (0.04) than the original (0.153), and RMSE of model is smaller than full model RMSE (185 vs 197). The graphical representations of Eq. 5 and 6 are presented in Figs. 4 (a) and (b).

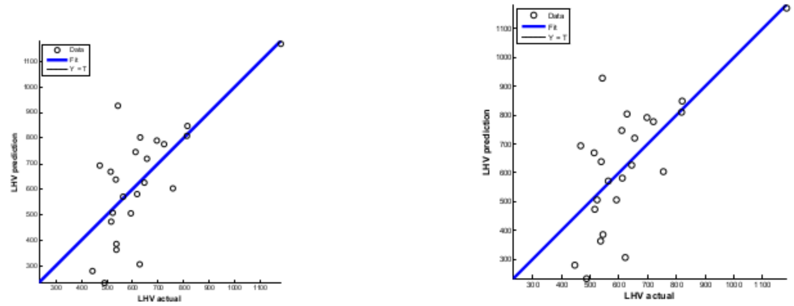
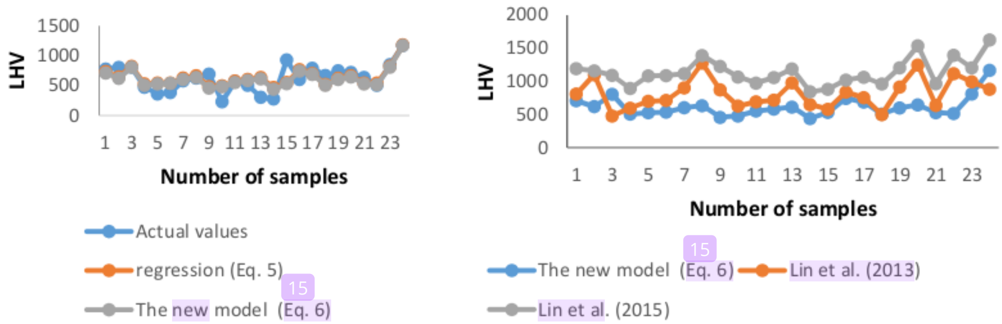


FIGURE 4. Comparison of actual LHV and prediction model (a). Multiple linear regression (b). stepwise regression model

Figure 5 (a) and (b) demonstrate the trend of the measured values as compared to the predicted values. The comparison of LHV predicted by the model, Eq. 5, and actual values shown in Fig. 5(a). While, Fig. 5(b) show the comparison of LHV predicted, Eq. 1, and Eq. 2 which indicates that the heating values for Eq. 1 and Eq. 2 greater than Eq. 6.



(a) (b)

FIGURE 5. LHV values from regression models based on physical composition

Back propagation Neural Network Model

The training process was stopped after 1200 epochs. 11, 23, and 35 neurons in the hidden layer for network training were used to predict the heating values. Figure 6 (a)-(c) represent the graphical of the actual versus predicted lower heating value for n = 24 samples. The network training was run on Intel core i5-4430 CPU @ 3GHz with 4GB RAM, realized in MATLAB R 2014. These result show that there is a high correlation between the measured data to the empirical model. The correlation coefficient (R) increased 0.9763, 0.98551, and 0.98577 respectively. The BPNN architectures associated are 8:11:1, 8:23:1, and 8:35:1. The results indicate that Fig. 6(c) highest accuracy in prediction.

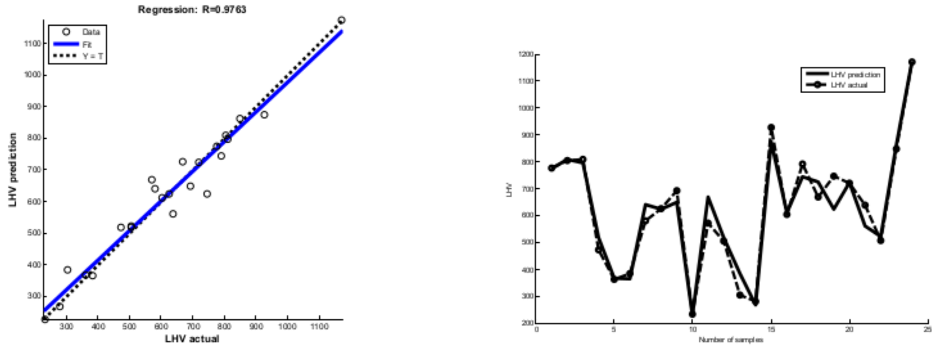


FIGURE-6 (a). The comparison of the calculated LHV values by BPNN with 11 neurons and 1200 epochs and actual LHV

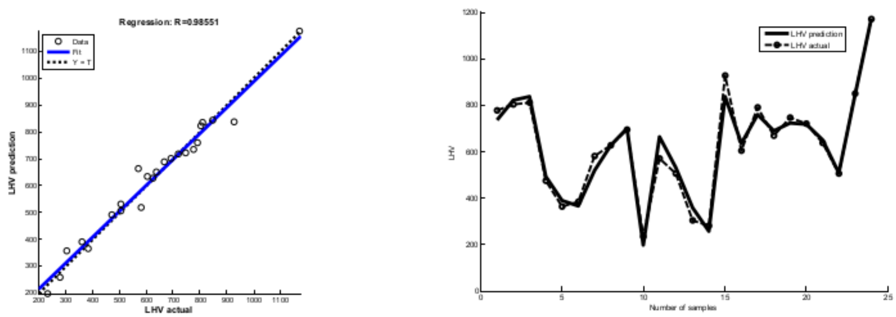


FIGURE-6(b). The comparison of the calculated LHV values by BPNN with 23 neurons and 769 epochs and actual LHV

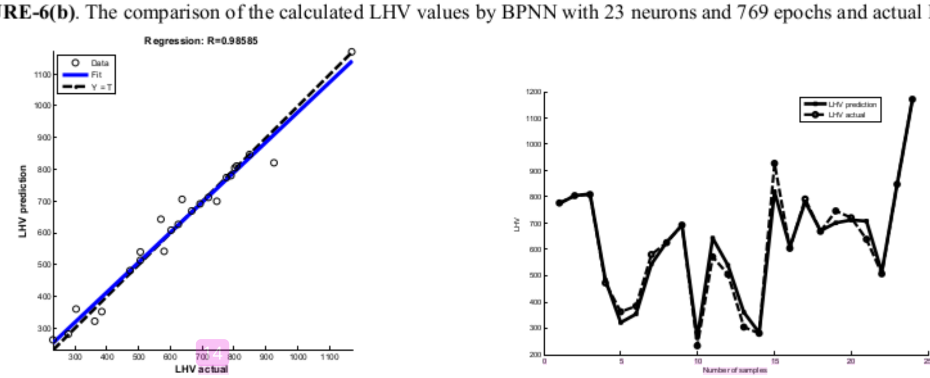


FIGURE-6(c). The comparison of the calculated LHV values by BPNN with 35 neurons and 210 epochs and actual LHV

CONCLUSION

The composition and the heating value of mixed MSW were studied. The composition was dominated by organics waste. The average LHVar is 626 kcal/kg. The high composition of organic waste increase the moisture content and decrease the heating value of MSW. The food waste exerts a negative influence on the LHV of the MSW. The result show that the LHV prediction using BPNN is better than multiple regression model.

ACKNOWLEDGMENTS

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