# A MUNICIPAL SOLID WASTE HEATING VALUE PREDICTING MODEL BASED ON ARTIFICIAL NEURAL NETWORK

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*Abstract*. Proper management of waste produced by human activity has been one of the major environmental concerns of modern societies. The use of the waste as a source of renewable energy is an interesting option, increasing the country's energy matrix, reducing the volume of waste and mitigating its toxicity. However, for a proper design and operation of a waste-to-energy plant, it is essential to know the energy potential of the waste. This paper aims to develop a computer model to predict the higher heating value (HHV) of the municipal solid waste (MSW), based on the ultimate analysis, using an artificial intelligence technique known as artificial neural networks (ANN). With the use of ultimate analysis from the literature, we tested different ANN architectures until the best architecture was found. We performed comparative tests with mathematical models from the literature, and the ANN model got a considerably more accurate response than the mathematical models analyzed. The ANN model showed a superior precision in terms of mean absolute percentage error (MAPE = 2.9%) and in terms of the coefficient of determination (R2 = 0.996). Finally, we conclude that the forecasting of the HHV of the MSW could be improved through the use of ANN models, and the proposed model is very suitable to the task.

**Keywords**

Computational Prediction Model

Municipal Solid Waste Energy Recover

Artificial Neural Network

Higher Heating Value

Waste-to-Energy

# 1 Introduction

The proper final disposal of the municipal solid waste (MSW) is a growing concern for developing countries. The amount of waste generated has growth consistently due to the increasing of the consumption, the increasing of the income, and the population growth. The Fig. 1 compares the Brazilian population growth from 2007 to 2014 with the growth of waste generation in the same period [1]. In the figure, we can see that while the population grew less than 7%, the waste generation grew almost 30% in the same period.

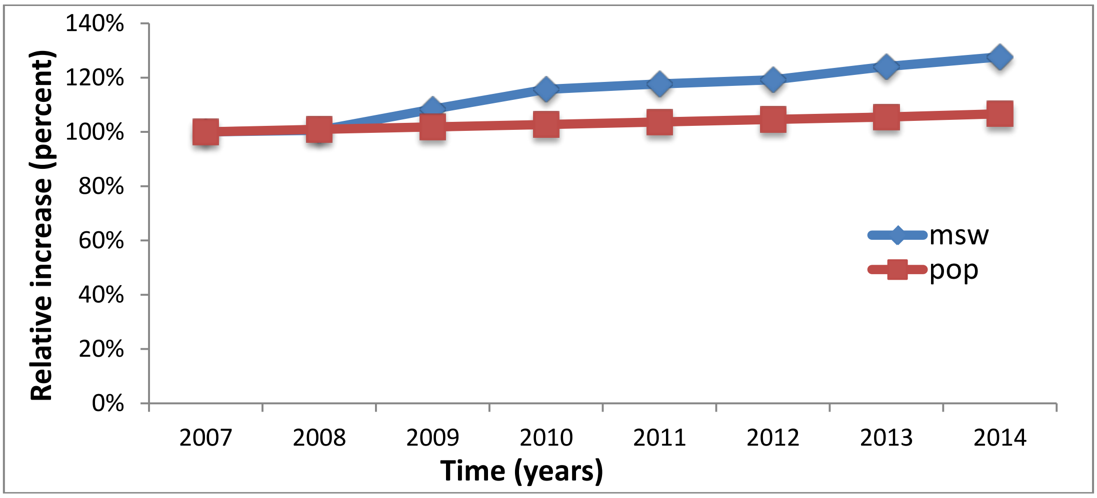


**Fig. 1 Brazilian population growth vs. MSW production growth**

The Fig. 2 shows the total amount of waste generated in Brazil (in tons/year) and the amount of waste generated *per capita* (in kg/year) [2]. It is possible to see that the increase in waste generation occurs not only by the increase in population as well as due to an increase in economic activity in the country.

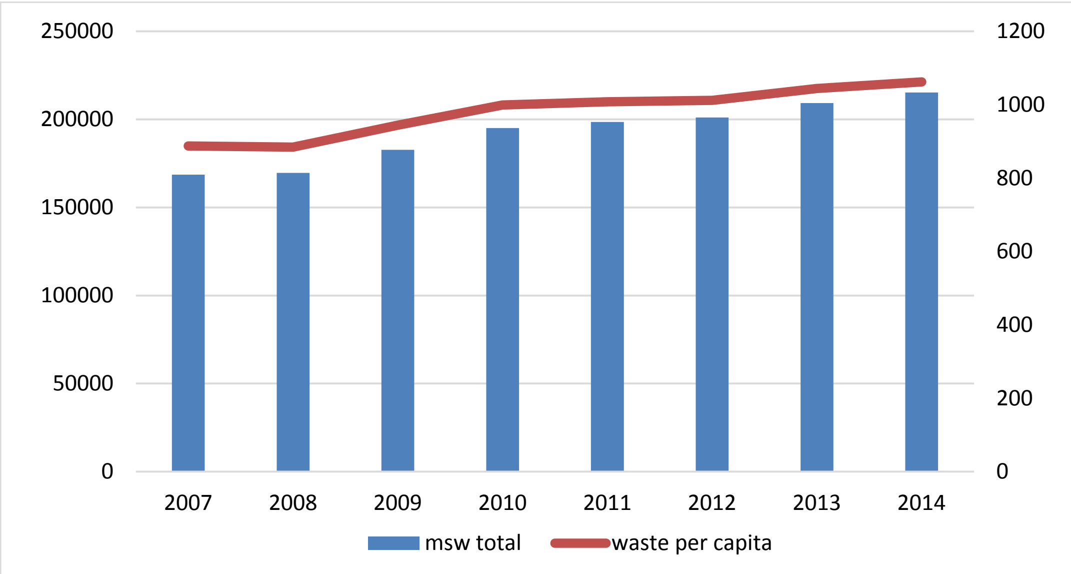


**Fig. 2 Total MSW and waste per capita generated in Brazil - 2007 to 2014**

One of the major consequences of this increase in waste generation is the large amount of waste disposed of in inappropriate places. In Brazil, waste disposal sites are divided into three types:

1) Landfills: places where waste has a correct treatment of deposition, with systems for soil and water resources protection and greenhouses gases emission control;

2) Controlled Landfills: places where there is some control in waste disposal, but without the proper effluents emission control;

3) Dumping Grounds: places where waste is disposed without any control or protection, with soil and water resources contamination and accumulation of animals and disease vectors.

The Fig. 3 shows the amount of waste disposed in each type of disposal site in Brazil in 2014 [2], where about 42% of the waste was disposed in inappropriate places, with considerable negative environmental and social impacts.

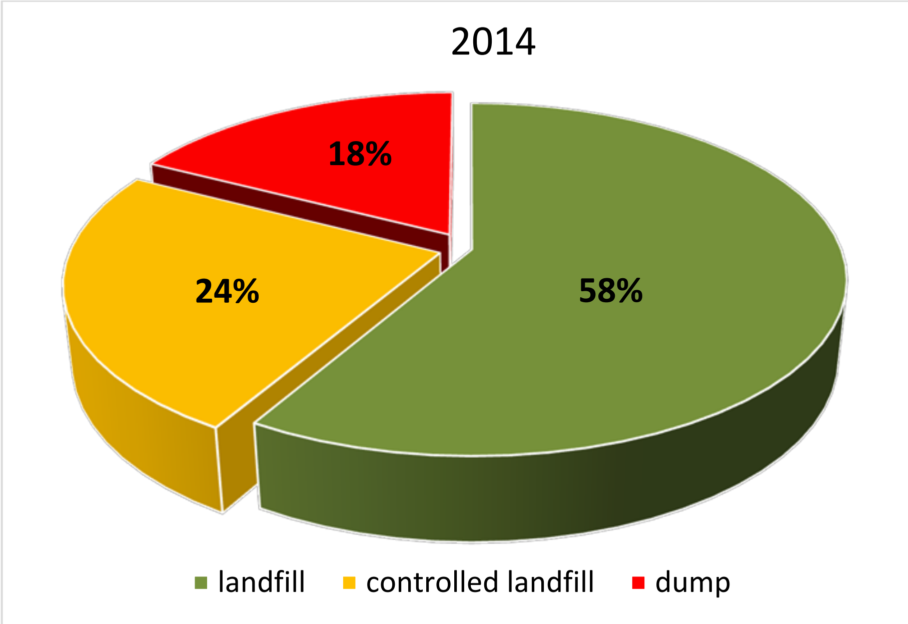


**Fig. 3 Final disposal of MSW in Brazil in 2014**

This situation, common in many developing countries, creates a challenging scenario for the government, and, in Brazil, specific laws about waste management have been introduced.

To collaborate on this issue, Petrobras, a Brazilian company responsible for the production, refining and distribution of oil in the country, developed a project with the aim of using MSW as an alternative source of energy, covering both the production of biogas as the build of a facility to generate electricity from the MSW incineration. Partnerships with MSW management companies and university community were created for the development of waste-to-energy technologies, and this paper (among others) is result of this partnership.

The aim of this work is to develop a predictive model of higher heating value of municipal solid waste, based on the ultimate analysis, and using artificial neural networks. The developed model will be compared with classical mathematical models of the literature, including a model developed from the same data set, in order to check the performance of the proposed ANN model.

## 2 Material and methods

For a proper MSW thermal conversion plant dimensioning, the amount of energy that can be obtained from waste combustion must be determined. The amount of recoverable energy of a fuel is called heating value, which can be measured as the higher heating (HHV) or lower heating value (LHV). The difference between the HHV and LHV is the phase of the water in the products of the chemical reaction. The HHV measurement considers the water in the liquid phase at the end of the process, whereas the LHV considers the water in the vapor phase [3].

The proximate analysis of the MSW determines their moisture, volatile combustible matter, fixed carbon and ash, while the physical analysis identifies the levels of the components of the waste, such as organics, plastics, papers, textiles, metals, etc. [4]. The ultimate analysis of the RSU determines the quantity (in weight percentage) of the main chemical elements of the waste. Nevertheless, due to its characteristics, the moisture content and the amount of ash found in waste are identified regardless of their chemical compositions. Therefore, the studies of MSW ultimate analysis usually provide the weight percentage of the moisture, ash, carbon, hydrogen, oxygen, nitrogen, chlorine and sulfur [5][6][7][8]. Here we chose to use data from the ultimate analysis, as a complement to other studies that uses the physical analysis as a database to determining the heating value of solid waste using artificial neural networks [9][10].

## 2.1 Artificial Neural Networks

Artificial Neural Networks (ANN) are one of the most used techniques of artificial intelligence and was created in 1943, in papers published by Warren McCulloch and Walter Pitts. ANN are based on human neurological system. ANN have a set of input patterns, a processing layer and a set of outputs. Each element of these sets is called a node, or a neuron, which are interconnected by linear equations with adjustable coefficients, called weights. A neural network is trained by the adjustment of the weights that connect neurons during the training phase [11].

In a Multi Layer Perceptron Neural Network (Fig. 4), the outputs of a layer are used as input pattern to the neurons of the next layer. At the end of each processing, the output error (difference between the expected value and the value calculated by the network) is distributed proportionally between the weights of the various network layers. The process of adjusting these weights that interconnect layers is the training of the network, and therein lies the knowledge acquired by the ANN.

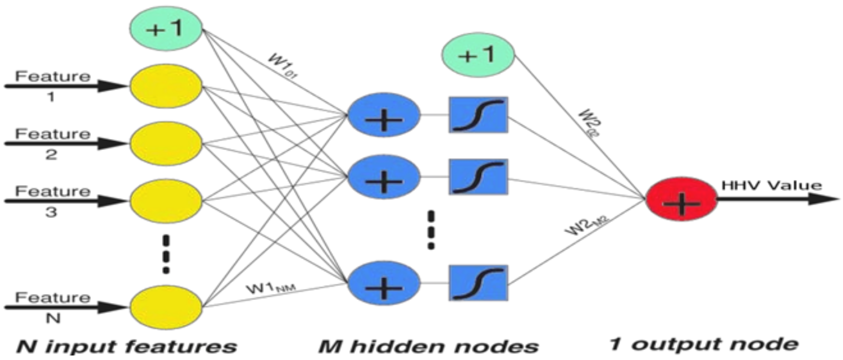


**Fig. 4 A Multi Layer Perceptron Neural Network**

There are many weights adjustment techniques, known as training algorithms, and here we tested four different training algorithms in order to determine what had the best fit for the HHV prediction.

Some of the main configurable parameters of a neural network are the number of layers, the number of neurons in each layer, the training algorithm, and the activation function of each neuron. In general, different architectures and network configurations are tested for each application, in order to find out the best solution to the analyzed problem. In this paper, many ANN configurations were tested, and the possible configurations are listed in the table.

**Table 1 ANN configuration parameters**

| ANN Parameter | Configuration Tested |
|---|---|
| Number of layers | 2 / 3 |
| Nodes in the input layer | 3 / 4 / 5 / 6 / 7 |
| Nodes in the hidden layer | 2 / 3 / 4 / 5 / 6 / 7 / 8 / 10 / 12 / 14 |
| Training algorithm | Descendent Gradient with *Momentum*<br>Resilient Propagation<br>Levenberg-Marquardt<br>BFGS Quasi-Newton |
| Activation Function | Linear<br>Hyperbolic tangent<br>Logistic |

## 2.2 Datasets

Here we used data of the ultimate analysis of many MSW components from the literature, compiled by Meraz *et al* [5] from studies of other three different authors, collected in different locations and times. These dataset contains a set of 100 ultimate analysis of MSW components and their high heating value (HHV) in MJ/kg. This set of 100 analysis proved quite heterogeneous and brought a great variety of components, divided into categories such as paper, food waste, pruning remains of trees, domestic waste, and others. The Fig. 5 shows the compilation of the dataset and the groups that compose it.

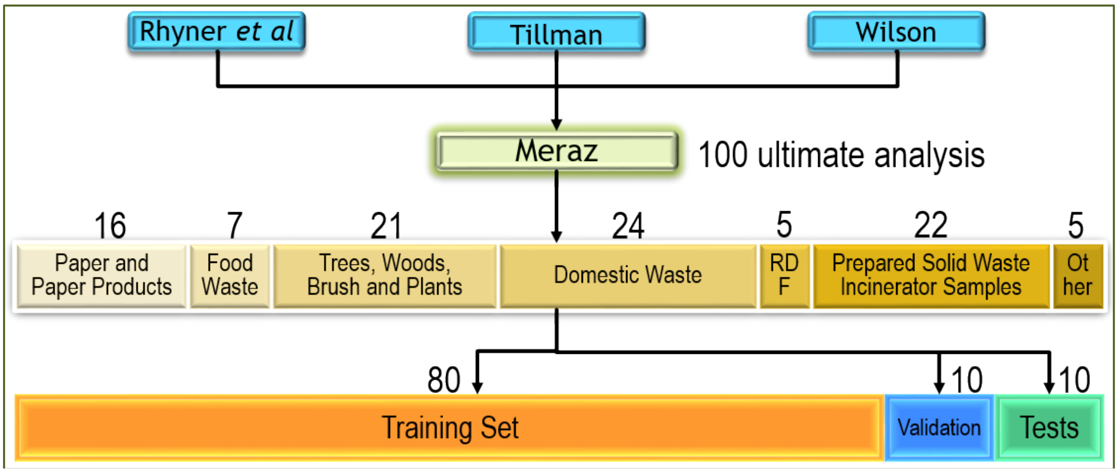


**Fig. 5 The dataset compilation and the sets of the ANN**

The Table 2 shows the variables of the ultimate analysis in the dataset. The input pattern of the neural network was formed by the components of MSW, including moisture, ash, carbon, hydrogen, oxygen, nitrogen and sulfur present in the samples. The expected value used as the output standard for the training of the network was the HVV of the MSW sample.

**Table 2 Components of the ultimate analysis dataset**

| Pattern | Item | Example |
|---|---|---|
| | Group | Paper and Paper Products |
| | Component | Waxed milk cartons |
| Input | Moisture (wt%) | 3.45 |
| | Carbon (wt%) | 59.18 |
| | Hydrogen (wt%) | 9.25 |
| | Oxygen (wt%) | 30.13 |
| | Nitrogen (wt%) | 0.12 |
| | Sulfur (wt%) | 0.1 |
| | Ash (wt%) | 1.22 |
| Output | HHV (MJ/kg) | 26.34 |

## 2.3 Data Analysis

With the dataset compilation, some data analysis were carried out to ensure the reliability of the results. The first step was to verify the statistical significance of each one of the variables of the ultimate analysis. A p-Value test was carried out, and the Table 3 shows the level of significance of the components of the MSW.

The second column of the Table 3 shows the p-Value of the component, and usually a p-Value greater than 0,05 shows that the component is loosely related with the dependent variable, in this case, the HHV. Hence, the moisture content (%$H_2O$), the carbon content (%C), the hydrogen content (%H) and the ash content (%Ash) are tightly related with the HHV, and the %C and %H have the higher significance to the determining of the HHV. Although it is not objective of this study the analysis of the thermodynamics of the incineration process, this result was expected, since it is precisely the oxidation of carbon and hydrogen, as exothermic chemical reactions, the most responsible for the release of heat during the combustion process. On the other hand, the oxygen content (%O), nitrogen content (%N) and sulfur content (%S) were not significant for determining the HHV.

**Table 3 Level of statistical significance of the variables of the dataset**

| Component | p-Value |
|---|---|
| $\%H_2O$ | $2.583 \times 10^{-5}$ |
| %C | $1.447 \times 10^{-28}$ |
| %H | $1.042 \times 10^{-24}$ |
| %O | 0.4325 |
| %N | 0.7143 |
| %S | 0.7492 |
| %Ash | $5.885 \times 10^{-10}$ |

A significant correlation between variables and the HHV is shown in Fig. 6, where the independent variables (weight percentage) are on the horizontal axis and the correspondent HHV is on the vertical axis.

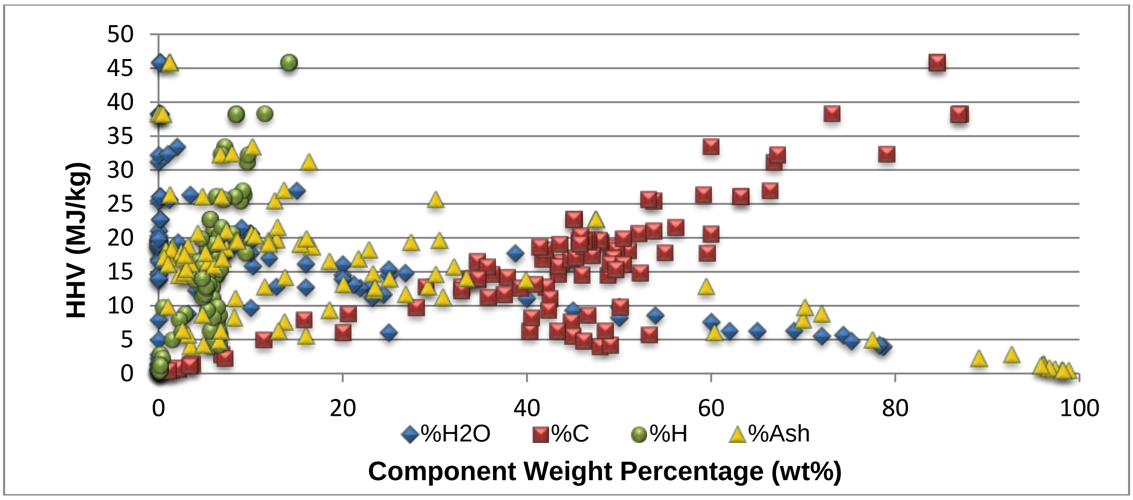


**Fig. 6 Correlations between the components of MSW and the HHV**

Fig. 6 shows that %C has a positive correlation with the HHV (the higher the weight percentage of carbon the higher the HHV of the MSW). The %H has also has a positive correlation with the HHV, and the correlation of the %H is higher than the correlation of the %C. On the other hand, $\%H_2O$ and %Ash have a negative correlation with the HHV (the higher the weight percentage of the component, the lower the HHV).

The last step of the preprocessing was the division of the 100 samples of the dataset in 3 subsets: a set of training, validation set and test set. The training set is called input patterns, and it is used to adjust the network weights accordingly to the selected algorithm. The validation set is used as network performance criteria. After the ANN training, the weights of the connections of the network neurons used in the final configuration are those that offer the best results in the forecasting of the validation set samples. Furthermore, the validation set can be used as a network training stop criteria, when the training of the network is interrupted when the result of the forecasting of the validation set is better than a predefined value. Finally, the test set is used to establish the network performance in relation to a data pattern not previously known. If the samples of the test set was not separated from, the input patterns, the network could lost the ability of generalization. The Table 4 shows the distribution of the 100 samples among the 3 datasets used in the ANN.

**Table 4 Distribution of samples among the ANN datasets**

| Component Group | Set Training | Validation | Test |
|---|---|---|---|
| Paper and Paper Products | 14 | 1 | 1 |
| Food and food waste | 5 | 1 | 1 |
| Trees, woods, brush and plants | 17 | 2 | 2 |
| Domestic waste | 20 | 2 | 2 |
| Refuse derived fuels | 3 | 1 | 1 |
| Prepared solid waste incinerator samples | 18 | 2 | 2 |
| Other wastes | 3 | 1 | 1 |
| **Total** | **80** | **10** | **10** |

## 2.4 Statistical Performance Indexes

The MSW HHV forecasting has been the subject of research for a long time, and several mathematical models can be found in the literature. Thereby, when a new forecast model is proposed, it is necessary to do some statistical analysis to check if the new model can really contribute with the subject, by a better accuracy of the predictions, or proposing an easy way to forecast the HHV of the MSW. Here we use two very common statistical performance indexes: the mean absolute percentage error (MAPE) and the coefficient of determination ($R^2$).

The MAPE provides an indication of the average error, expressed as a percentage of the observed value, regardless of the error be positive or negative. This index has the advantage of being dimensionless and proportional to the observed value, and it is calculated according to equation (1). The lower the MAPE, the smaller the difference between the expected and measured values of the HHV, and better the model performance. Chang *et al* [6] proposed that models with MAPE <10% can be considered excellent.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|HHV_{predicted} - HHV_{measured}\right|}{HHV_{measured}} \times 100 \qquad (1)$$

The index $R^2$ shows how much of the measured values can be explained by the proposed model, and it is used as a metric for the adjustment of the model [12]. Hence, a $R^2$ of 0.90 means that the analyzed model explains 90% of the measured value of the HHV, and the remaining 10% are due to other factors that are not included in the model. Therefore, the higher the $R^2$ the better the model performance. Equation (2) shows how the $R^2$ is calculated.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(HHV_{measured} - HHV_{predicted}\right)^2}{\sum_{i=1}^{n}\left(HHV_{measured} - HHV_{average}\right)^2} \qquad (2)$$

# 3 Results and Discussion

From the analysis of the components that have the greatest significance on the determination of the HHV of MSW, several ANN architectures were tested, and the results were compared with mathematical forecasting models found in the literature [5]. The mathematical models used for comparison are listed in Table 5.

For the comparison, we used the 10 samples of the test set were randomly selected from the set of initial 100 samples. For each sample, the value of the measured HHV was compared with the predicted HHV by the model, and then the performance indexes were determined. Table 6 shows the results of the comparison among the proposed ANN based model and the mathematical models tested.

**Table 5 Mathematical Forecasting Models**

| Model | Equation | Author |
|---|---|---|
| 1 | $HHV = \left(1 - \frac{\%H_2O}{100}\right)(-0{,}3578\ (\%C) -\ 1{,}1357(\%H) + 0{,}0845(\%O) - 0{,}0594(\%N) - 0{,}1119(\%S))$ | Lloyd and Davenport |
| 2 | $HHV = \left(1 - \frac{\%H_2O}{100}\right)(-0{,}3517\ (\%C) -\ 1{,}1625(\%H) + 0{,}1109(\%O) - 0{,}0628(\%N) - 0{,}1109(\%S))$ | Boie |
| 3 | $HHV = \left(1 - \frac{\%H_2O}{100}\right)(-0{,}3279\ (\%C) -\ 1{,}5330(\%H) + 0{,}1668(\%O) - 0{,}0242(\%N) - 0{,}0928(\%S))$ | Wilson |
| 4 | $HHV = \left(1 - \frac{\%H_2O}{100}\right)(-0{,}3708\ (\%C) -\ 1{,}1124(\%H) + 0{,}1391(\%O) - 0{,}3178(\%N) - 0{,}1391(\%S))$ | Meraz |

The proposed ANN model had better performance than the mathematical models for both statistical indexes (Table 6). This result was expected because mathematical models are usually developed from a mathematical technique known as multiple linear regression. As the name states, this technique captures only the linear relationships between the input variables (the contents of MSW components) and the output variable (measured HHV). Multiple linear regression analysis also assumes that the input variables are independents, i.e., a change in one variable does not imply a change in the others variable, which is not correct when the variables are the elemental composition of the MSW. Furthermore, a neural network is able to capture non-linear relationships between the variables [11], and does not require that the variables are independent, which is the case.

**Table 6 MAPE and $R^2$ of the HHV prediction models**

| Model | MAPE | $R^2$ |
|---|---|---|
| ANN | 2,9% | 0,9958 |
| Boie | 4,6% | 0,9881 |
| Wilson | 5,1% | 0,9803 |
| Meraz | 7,4% | 0,9732 |
| Lloyd and Davenport | 8,7% | 0,9908 |

Figure 7 shows the correlation coefficients obtained by the neural network model for all sets: the training set (80 samples), the validation set (10 samples), the test set (10 samples) and the complete dataset (100 samples). In these charts, you can see that the highest correlation coefficient was obtained with the test set, which is significant of the good adaptation of the ANN as a HHV prediction model, and shows the ability of generalization of the network.

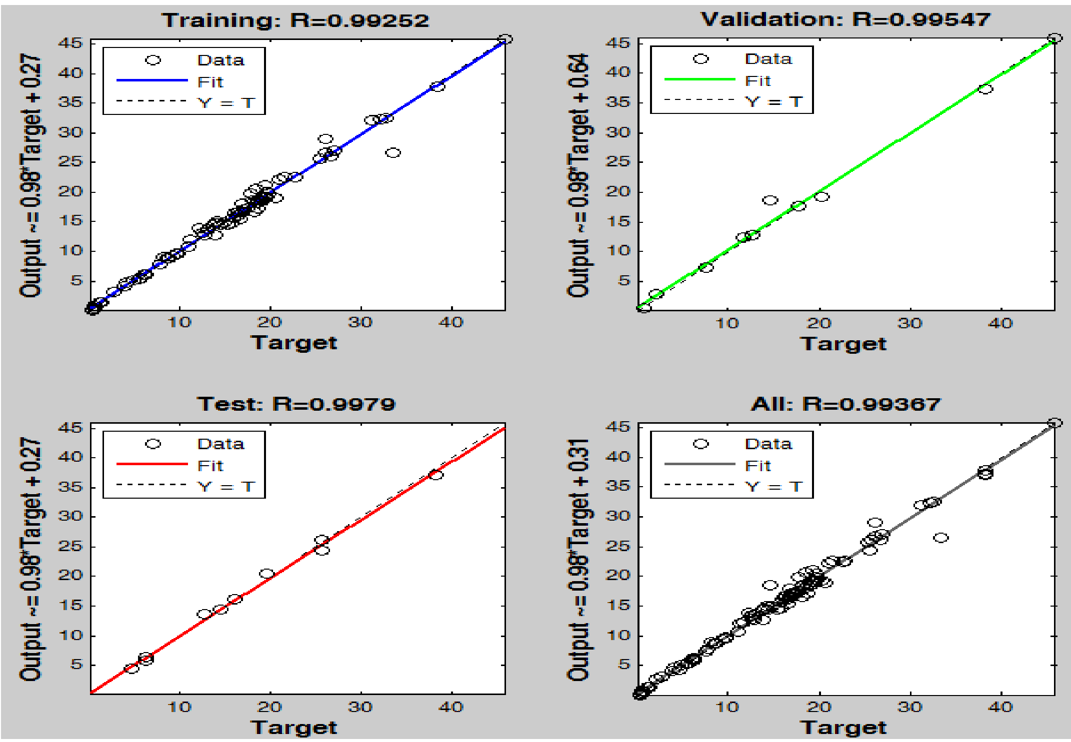


**Fig. 7 Coefficients of correlation of the ANN model and the samples sets**

# 4 Conclusions

The higher heating value prediction models of the municipal solid waste based on the ultimate analysis are better (more accurate) than those based on proximate analysis or physical analysis [6]. Here we expected to have demonstrated that artificial neural networks models can make even better predictions based on ultimate analysis, when compared with classical mathematical models. Further studies in this subject should be developed with other network settings and other databases, but the initial results seem promising.

With this work, we hope to have succeeded in demonstrating that the technique of artificial neural networks can contribute to better HHV prediction models. Therefore, ANN models could provide better information to the design and operation of waste-to-energy plants, helping to reduce the caused by the inappropriate MSW disposal, as well as contributing to the increase in renewable energy production in developing countries.

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