Prediction of the heating value of municipal solid waste: A case study of the city of Johannesburg

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In this study, a municipality-based model was developed for predicting the Lower heating value (LHV) of waste which is capable of overcoming the demerit of generalized model in capturing the peculiarity and characteristics of waste generated locally. The city of Johannesburg was used as a case study. Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy-Inference System (ANFIS) models were developed using the percentage composition of waste streams such as paper, plastics, organic, textile and glass as input variables and LHV as the output variable. The ANFIS model used three clustering techniques, namely Grid Partitioning (ANFIS-GP), Fuzzy C-means (ANFIS-FCM) and Subtractive Clustering (ANFIS-SC). ANN architectures with a range of 1-30 neurons in a single hidden layer were tested with three training algorithms and activation functions. The GP-clustered ANFIS model (ANFIS-GP) outperformed all other models with root mean square error (RMSE), mean absolute deviation (MAD), and mean absolute percentage error (MAPE) values of 0.1944, 0.1389 and 4.2982 respectively. Based on the result of this study, a GP-clustered ANFIS model is viable and recommended for predicting LHV of waste in a municipality.

Keywords: Physical Composition, Lower heating value, Municipal Solid Waste, Johannesburg, Clustering techniques, ANFIS, ANN

Nomenclature

P_a	Percentage composition of paper
Pl	Percentage composition of Plastic
C	Percentage composition of Carbon
H	Percentage composition of Hydrogen

O	Percentage composition of Oxygen
wo	Wood waste fraction
Tx	Textile waste fraction
Fw	Food waste fraction
S	Percentage composition of Sulphur
Cl	Percentage composition of Chlorine
N	Percentage composition of Nitrogen
Ga	Garbage waste stream composition
MC	Moisture Content
VM	Volatile Matter
org	Organic waste fraction
VIF	Variance Inflation Factor
FC	Fixed Carbon
$FFNN$	Feed Forward Neural Network
$RBFANN$	Radial Basis Artificial Neural Network

1. Introduction

Increase in population, urbanization, standard of living, and anthropogenic activities have increased the rate at which municipal solid waste (MSW) are generated. Statistic shows that about 3.5 million tonnes of waste was generated daily across the globe in 2010, it is further predicted to increase to about 6 million tonnes per day by 2025 (Hoornweg and Bhada-Tata 2012). This upsurge cannot be overlooked nor its impacts on the environment underestimated as long as the underlying causal components of MSW generation in the biosphere remain active. For instance, in Indonesia, one tonne of waste has the potential to generate power of about 21 kW and electricity capacity of 0.5 MWh which can lessen the use of coal by 19.5% (Anshar et al. 2015). The energy potential based on average incineration capacity of about 1500 tonnes/day and calorific value of about 2200 kcal/kg of MSW in Malaysia was estimated as 640 kW/day (Kathirvale et al. 2004). Islam and Nazmul (2016) forecasted the electrical energy potential of MSW at two cities in Bangladesh, Dhaka and Chittagong city in 2050 as 1444 GWh and 1394 GWh respectively through incineration. The total quantity of MSW generated in Africa has energy potential of 1125 PJ in 2012 and 2199 PJ in 2025 (Scarlat et al. 2015). Similarly, a total of 41998 tonnes of waste generated monthly in Kano, Nigeria has electrical energy potential of 805 MWh/day, which has the capacity to supply power to about 70009 houses in Kano, Nigeria assuming each house consumes 4200 kWh/year (Daura 2016). A similar study in Ilorin, Kwara state, Nigeria reveals that about 584 tonnes of waste has energy potential of 3244 MW covering about 15% of the total power demand in Kwara state (Ibikunle et al. 2019). Average energy content of waste was estimated in Ghana as 16.95 MJ/kg (Fobil, Carboo, and Armah 2005) and in Jordan as 2747 kcal/kg (Abu-Qudais and Abu-Qdais 2000).

In South Africa, like most developing countries, the prominent waste disposal method is uncontrolled landfill. About 54.2 million tonnes of general waste and 66.9 million tonnes of hazardous waste was generated in South Africa in 2017 (DEA, 2018). A larger percentage (about 90%) of the total general waste generated are disposed of in landfill which is identified as the major source of anthropogenic methane and it is believed to be 21 times weightier than carbon dioxide (CO_2) (Couth and Trois 2012). Average greenhouse gas (GHG) emission from landfilling of waste in South Africa depends on the landfill sites but it is in the range 145 – 1016 $kgCO_2$ equivalent (CO_2e) per tonne of waste when carbon storage is accounted for, more so landfill sites without engineered gas collection has the highest emission factor per unit of wet waste of all waste management associated emissions (Friedrich and Trois 2013). Methane emission from landfills in South Africa was predicted at about 531735 tCH_4 per annum and 635207 tCH_4 per annum in 2015 and 2020 respectively (Bhailall 2015). These emissions associated with landfill sites contribute to climate change and have adverse effect on the environment. In addition, leachate produced from landfill sites contaminates the ground water causing a serious water pollution (Vaish et al. 2019)

Globally, renewable energy accounts for 25% of the total electrical energy demand. It experienced an increase of about 6.3% in 2017, with China and US representing 50% of this increase, European Union covers 8%, while Japan and Indian covers 6% each (IEA 2018). The use of fossil fuel has consequently declined globally, however, despite this development, South Africa still depend largely on non-renewable sources mainly coal and nuclear-based energy to generate about 95% of its electricity (Alex and Pouris 2015). The renewable energy share of the total energy mix of South Africa is considerably low. About 244,364 GWh and 237,006 GWh of electricity was generated in 2013 and 2016 respectively, coal has a share of 88.3% and 85.67% in the total power generation capacity in 2013 and 2016 respectively, while hydro, wind, solar and Biomass has a share of 0.33 %, 0.89 %, 0.91 % and 1.24 % respectively in 2016 (Maluleke 2016). The rate of depletion of these fossil fuels and the increase in the burden of daily energy demands in South Africa have necessitated the search for sustainable and renewable energy sources.

Recovery of energy from waste has been efficient is combating both the challenges of waste management and energy crisis. It is a sustainable technique of managing the huge amount of waste generated and add to the share of renewable energy in the global energy mix. The calorific value of waste is an important indicator of the amount of energy inherent in the waste. The calorific value can be presented in two forms; the Gross Calorific Value (GCV) or the Higher Heating Value (HHV) and the Net Calorific Value (NCV) or Lower Heating Value (LHV). They are estimated in different units such as MJ/kg, Btu/lb and kJ/mol. The calorific value of different waste streams depends on the thermal and chemical properties of the waste stream such as elemental composition (carbon, Sulphur, hydrogen, oxygen), moisture content, volatile matter, fixed carbon and ash content. The technique of estimating the heating value of waste involves an experimental process using a sophisticated instrument i.e. bomb calorimeter by measuring the enthalpy change between the reactant and the product (Yin, 2011). However, this technique could laborious and expensive and are not always within the reach of researchers. More so, this instrument is limited in measuring the real-time heating value of waste due to the tendency of its variations during thermal process (Bagheri et al. 2019). Therefore, several empirical correlations and intelligent predictive models have been developed by researchers based on the ultimate analysis, proximate analysis and physical composition of the waste for estimating the heating value of MSW. The application of predictive model is cost-effective and it is a viable alternatives to the experimental procedure for estimating the heating value of waste.

Predictive models developed based on the ultimate analysis takes into account the elemental composition of the waste such as carbon, hydrogen, Sulphur and oxygen. Model based on proximate analysis takes into account waste properties such as Fixed Carbon (FC), Volatile Matter (VM), and Moisture Content (MC), while estimation based on physical composition uses the weight ratio of different streams in the MSW such as paper, plastics, textile etc. Prediction of HHV based on proximate analysis using MC, VM and FC as inputs were developed with linear regression models (Kathiravale et al. 2003; Titiladunayo et al. 2018) and Neural network model

(Hung et al. 2006). An ANFIS model optimized with Particle Swarm Optimization (PSO) was developed by Olatunji et al. (2019) to predict the HHV of MSW based on the elemental components, moisture and ash content.

Hung et al. (2006) used 220 experimental data of MSW to develop and compare the accuracy of predicting the LHV based on elemental composition, physical composition and proximate analysis using a Feed-Forward Neural Network (FFNN). The prediction result gave R-values of 0.93, 0.84 and 0.83 respectively, revealing the estimation of heating value using the elemental composition of waste as inputs gives as the most accurate. Similarly, Kathiravale et al. (2003) used 30 samples of waste to perform a comparative study of the effect of different waste properties on its HHV by developing an empirical model for heating value prediction based on proximate, ultimate analysis and physical composition of waste giving a prediction R-value of 0.625, 0.691 and 0.779 respectively and then concluded that prediction based on physical composition is the most accurate. More researches were found in literature based on waste elemental components using linear regression (Shi et al. 2016; Eboh, Ahlström, and Richards 2016; Khuriati, Nur, and Istadi 2015) and ANN (Abidoye and Mahdi 2014; Gong et al. 2017; Akkaya and Demir 2010). Mathematical equations were correlated for HHV prediction based on waste physical composition (Abu-Qudais and Abu-Qdais 2000; Lin et al. 2015; Chang et al. 2007; Drudi et al. 2019). Feed-forward neural network was developed for similar prediction using physical waste streams such as paper, Plastics, Textile, food waste (Ogwueleka and Ogwueleka 2010; Ozveren 2016; Dong et al. 2003). Table 1 and 2 present selected models in literature developed using linear regression and artificial intelligent approach respectively.

Table 1 Linear Regression model for prediction of heating value of MSW

S/N	Model	Performance	Correlation Equation	Reference

	Basis	index		
1	Physical Composition	R^2= 0.940	$LHV = 267.0\left({}^{Pl}/_{Pa}\right) + 2285.7$	(Abu-Qudais and Abu-Qdais 2000)
2	Ultimate Analysis	R^2= 0.936	$HHV = 0.350\ C + 1.01\ H - 0.0826\ O$	(Shi et al. 2016)
3	Physical Composition	MAPE= 18.21%	$LHV = LHV_{pl}P_{pl} + LHV_{pa}P_{pa}$ $+LHV_{wo}P_{wo} + LHV_{Tx}P_{Tx}$ $+LHV_{FW}P_{FW}$	(Lin et al. 2015)
4	Ultimate Analysis	R^2 = 0.92	$HHV = 0.364\ C + 0.863\ H - 0.075\ O$ $+0.028\ N - 1.633\ S + 0.062\ Cl$	(Eboh, Ahlström, and Richards 2016)
5	Ultimate Analysis	R^2 = 0.95	$HHV = 0.3491\ C + 1.1783\ H$ $+0.1005\ S - 0.1034\ O - 0.015\ N$ $-0.0211\ Ash$	(Channiwala and Parikh 2002)
6	Physical composition	R^2 = 0.9672	$HHV = 2229.21 + 28.16Pl + 7.09Pa +$ $4.87Ga - 37.38\mathrm{MC}$	(Chang et al. 2007)

7	Ultimate Analysis	$R^2 = 0.625$	$HHV = 416.638C - 570.017H$ $+259.031\,O + 598.955N - 5829.078$	(Kathiravale et al. 2003)
	Proximate Analysis	$R^2 = 0.690$	$HHV = 356.047VM - 118.035FC$ -5600.613	
	Physical composition	$R^2 = 0.779$	$HHV = 112.815Ga + 184.366Pa$ $+298.343Pl - 1.920MC + 5130.380$	
8	Ultimate Analysis	$R^2 = 0.9963$	$LHV = [(16.55org + 24.42\,S + 36.17Pl + 9.06Pa + 22.81Tx) \times (1 - MC)] - [(2.442 \times (9H + MC - (9H \times MC)]$	(Drudi et al. 2019)
9	Proximate Analysis	VIF>10%	$HV = -7.19477 + 0.116768FC$ $-0.3472MC + 0.151701VM$	(Titiladunayo et al. 2018)
10	Ultimate Analysis	$R^2 = 0.99$	$HHV = -2762.68 + 114.63C$ $+310.55H$	(Khuriati, Nur, and Istadi 2015)

Table 2 Artificial Intelligent Model for MSW Heating value prediction

S/N	Model Basis	Model type	Performance	Output	Reference
1	Physical composition	BRFF	R=0.993	LHV	(Ozveren 2016)
2	Physical Composition	FFNN	R=0.9557	LHV	(Ogwueleka and Ogwueleka 2010)

3	Physical Composition	FFNN	RE=5%	LHV	(Dong et al. 2003)
4	Ultimate Analysis	FFNN	R=0.9914	HHV	(Akkaya and Demir 2009)
5	Ultimate Analysis	FFNN	R=0.9914	HHV	(Abidoye and Mahdi 2014)
6	Ultimate Analysis	RBFANN	R=0.9924	HHV	(Gong et al. 2017)
7	Ultimate Analysis Physical Composition Proximate Analysis	MLP NN	R=0.93 R=0.84 R=0.83	LHV	(Hung et al. 2006)
8	Ultimate Analysis	ANFIS-PSO	R = 0.8673	HHV	(Olatunji et al. 2019)

Waste-to-energy (WTE) is gaining traction in most countries with more energy generated from waste and biomass resources through different conversion processes. This helps to manage the huge amount of waste generated and at the same time add to the share of renewable energy in the global energy mix. However, inadequate information regarding the heating value and other energetic properties of waste as potential feedstock in thermal plants is a major setback limiting the implementation of a large scale WTE projects in most countries (Bagheri et al. 2019). Owing to the heterogeneous nature of MSW, it is important to have a knowledge of its characteristics such as the heating value in a thermal process. The design, operation and the combustion efficiency of waste combustion systems depends largely on the heating value, therefore to monitor and control the combustion process for maximum energy recovery from waste, predictability of the heating value of MSW is vital because of the high cost and time involved in the experimental method of estimating the heating value. The literature is replete with models under the nomenclature of generalized global models for general application in predicting the heating value of MSW. However less attention has been given to municipality-based predictive model despite its significance. These generalized models are limited in applications owing to their deficiency in capturing the distinctiveness and peculiarity of locally generated waste at different municipalities which might result into inaccurate predictions. The characteristics of locally generated waste varies significantly across different municipalities in terms of its physical and elemental composition and its energy content. A report of characterization studies of MSW in the city of Johannesburg was given by Ayeleru et al. (2018) at both Daily Non-Compacted (DNC) and Round Collected Refuse (RCR) sources . The study of Masebinu et al. (2017) among others estimated the energy content of waste generated in Johannesburg calorimetrically based on its gross calorific value. Therefore, in order to capture the peculiarity in the characteristics, composition and energy content of waste generated in the city of Johannesburg, this study develops municipality-based artificial intelligent models using the physical composition of MSW generated in the city of Johannesburg to predict its LHV. To author's best knowledge, this has not been reported in literature.

Network topologies ranging from 1-30 neurons in a single hidden layer were selected for training and the best network was selected based on the prediction accuracy. Three ANFIS models with different clustering techniques: Grid Partitioning (ANFIS-GP), Fuzzy C-means (ANFIS-FCM) and Subtractive Clustering (ANFIS-SC) were developed for the modelling and the prediction accuracy of these models were compared. Subsequent sections in this paper are structured as follows; Section 2 introduces the methodology, the waste management service, waste generation and composition in the case study, data description, modelling tools, the processes followed to achieve optimal performance of the models and the statistical metrics used to evaluate the performance of the models. Section 3 discusses the results of the models while section 4 concludes the study with recommendations for further studies.

2. Methodology

2.1 Study area: The city of Johannesburg

The city of Johannesburg, also known as Joburg, Jozi and often referred to as city of Gold is the largest city and the constitutional headquarters of South Africa located in the Witwatersrand range of hills (Bwalya 2019). The latitude and longitude of the city of Johannesburg is $26^0 12^i 08^{ii}\ S$ and $28^0 02^i 37^{ii}\ E$ respectively with an area of 1645km^2 and elevation of 1767m (Masebinu et al. 2017). The city has a population of about 4.3 million, the largest in Gauteng Province. The city is the commercial and economic hub of South Africa as it contributes 17% to the total GDP of South Africa and 47% of Gauteng Province's (Mbuli 2015). The city of Johannesburg owns and operates a municipality-based waste management Service by Pikitup Company which carries out about 900,000 waste services and collects 1.6 million tonnes of waste per annum, operates four (4) different landfill sites with 8 years airspace (Mbuli 2015).

Landfill is the most prominent waste disposal method in this city, there are no large and commercial scale waste-to-energy (WTE) technological Projects that can recover energy from waste in the city through biological and thermal processes. However there are small scale WTE projects that are already implemented or at test-run stage. For instance, the recovery of 1756m^3/h landfill gas, flared at Marie Louise landfill sites in May 2011 to 2012 was meant to divert a considerable volume of landfill gas from escaping into the environment as Green House Gas (GHG) (Dlamini and Serge 2019).

A proposal of a 20 years no-cost Landfill gas structure was made to meet the power demand of 12500 middle income houses based on the agreement reached with Joburg EnerG System, (Baker and Letsoela 2016). There was an initiation of project to produce electricity from landfill gas by Joburg Department of Infrastructure and Service in 2007 to support the city's 2040 Growth and Development Strategy (GDS) goal of mitigating the environmental effect of landfill gas through transition to low carbon economy and climatic change (Baker and Letsoela 2016). Figure 1 represents the map of Gauteng Province showing major landfill sites in Johannesburg.

Based on the information available on the database of the Statistics South Africa (STATS SA) and the baseline waste quantity guideline provided by the Department of environmental affairs, the population of the city of Johannesburg in 2019 is 5.636 million, while the quantity of waste generated in the same year is 1.663 million tonnes. Figure 2 presents the population and the quantity of waste generated in the city of Johannesburg from 2013 to 2019. Some of the characteristics of waste generated in the city of Johannesburg is presented in Table 3

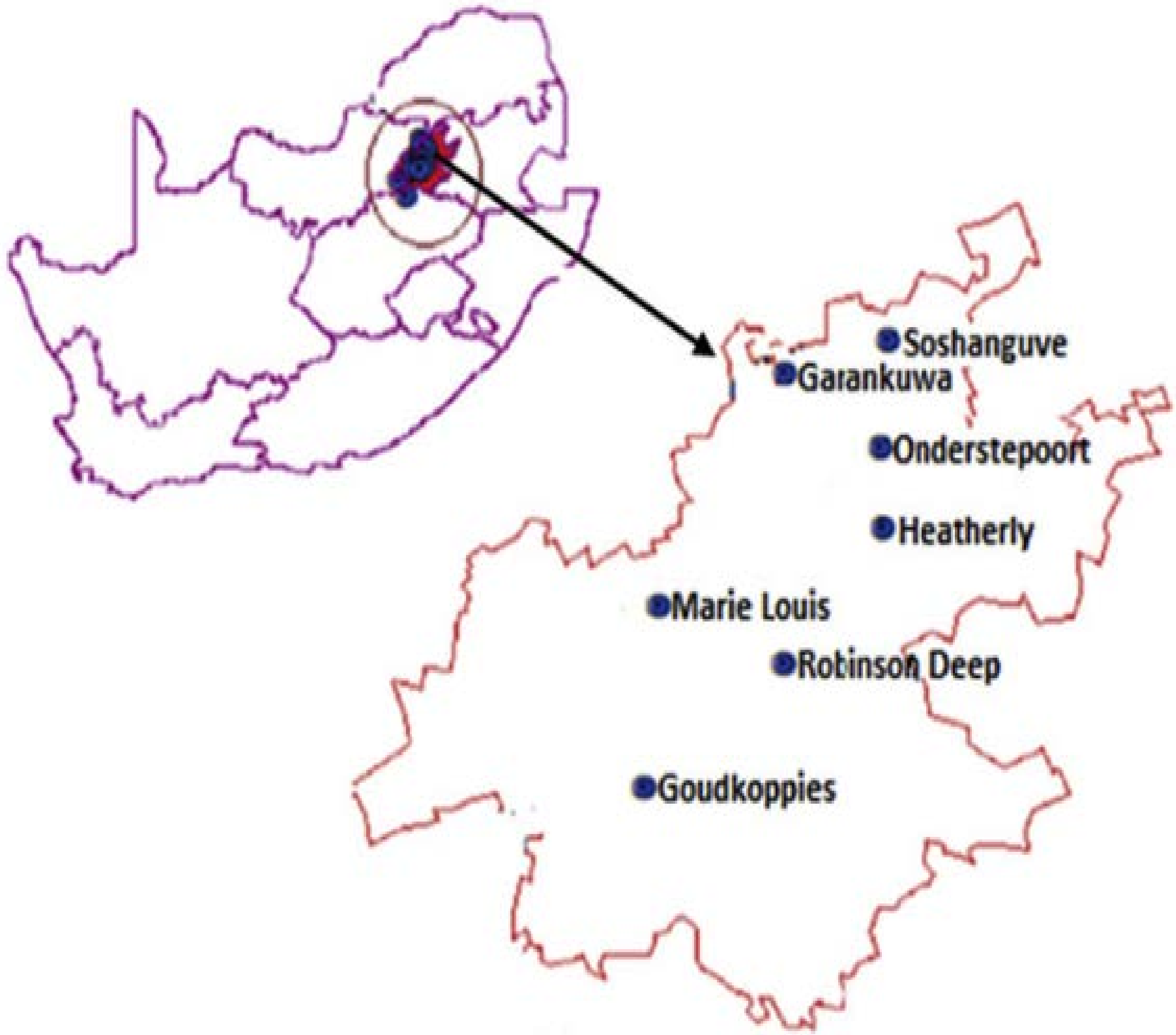

Figure 1 Map of Gauteng showing major landfill sites in Johannesburg (Sibiya, Olukunle, and Okonkwo 2017)

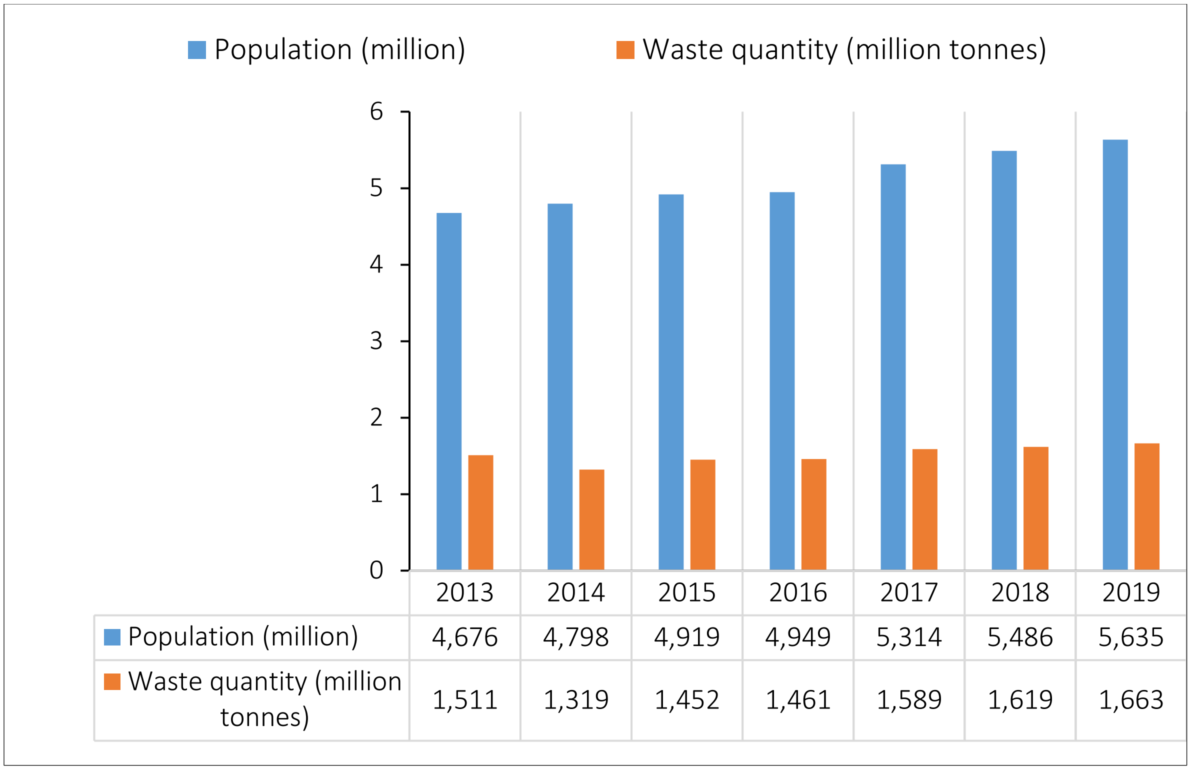

Figure 2 Population and waste quantity generated in the city of Johannesburg (2013-2019)

Table 3 Characteristics of waste generated in the city of Johannesburg (Adapted from Ayeleru et al., (2018))

Waste Characteristics	Range of values	Average
Recyclables (w/w)%	26.0 - 34.0	30.0
Non-recyclables (w/w)%	18.0 - 21.0	19.5
Moisture content (%)	60.9 - 67.1	63.9
Volatile Matter (%)	21.8 - 23.0	22.9
Fixed Carbon (%)	4.4 - 11.9	8.2
Organic (%)	13.9 - 28.7	21.4
Paper (%)	13.5 - 18.9	16.2
Plastic (%)	18.2 - 26.9	22.6
Textile (%)	4.9 - 7.8	6.4
Metals (%)	4.9 - 8.5	6.7

2.2 Methods of Data collection

The dataset comprises samples of waste collected from two landfill sites in the city of Johannesburg, which collects larger quantity of the total waste generated in Johannesburg. These landfill sites have waste collected from different collection points across the city from two different sources namely; Daily Non-Compacted (DNC) and the Round Collected Refuse (RCR) (Ayeleru, Okonta, and Ntuli 2018). The DNC are collected from hotels, restaurant and food stores on a daily basis while the RCR are collected weekly from households. The percentage composition of waste streams at these sources vary significantly, consequently the heating value and energy content varies depending on the source. The waste streams considered as input for this study are Plastics, Paper, Organics, Textile, Metal and Glass with Lower Heating Value, LHV (MJ/kg) as the output. The waste stream in the raw waste data set tagged "others" having constituents like Waste Electrical Products, Ceramics, bulky waste, car seat, composite wastes are believed to have a negligible effect on the heating value of waste and are therefore not considered in this study. Table 4 presents the statistical analysis of the input and output data.

Table 4 Statistical Description of Input and Output variables

Variables	Minimum	Maximum	Mean
Input Variables (%)			
Paper	1.90	46.70	15.02
Plastics	5.00	36.50	20.73
Organics	3.10	50.30	25.11

Metal	0.00	18.90	5.94
Textile	0.00	34.20	7.47
Glass	0.00	31.90	6.73
Output Variables			
LHV (MJ/kg)	1.039	5.795	3.6682

2.3 Modelling tools for Heating value Prediction

2.3.1 Artificial Neural Network

ANN is a machine learning tool that is inspired by the neurological system and functions of the human brain in such a way that it learns to carry out a task without being explicitly programmed (Dong et al. 2003). It consists of units called neuron which are intertwined with weighted communication strand and arranged in three layers; input layer, hidden layer and output layer (You et al. 2017). The network can be trained by adjusting the weights and bias assigned to each layer. It can be expressed mathematically using equation 1

$$y = F\left(\sum_{i=0}^{m} w_i . x_i + b\right) \qquad (1)$$

Where x_i = input value, w_i = Weight value, b = Bias, y = Output, F = Activation function

The activation function represents the rate of firing in the cell and determines the output from a set of inputs. It gives the mathematical relationship between input and output in terms of spatial or temporal frequency (Dorofki et al. 2012). It could be a linear or non-linear function. Non-linear transfer functions were used in this study and explained below:

(1) *Sigmoid (logsig) function*: Sigmoid function is a non-linear function existing in the range $0\ and\ 1$. The sigmoid function finds application in outcome probability prediction, since the probability of the outcome of an event lies between$0\ and\ 1$. This function is differentiable and mathematically expressed in equation 2

$$logsig = \frac{1}{1 + e^{-n}} \tag{2}$$

(2) *Tansigmoid (tansig) function:* This function is similar to hyperbolic tangent (tanh) function. It is a non-linear differentiable function in the range $-1\ and\ 1$. Tansigmoid (tansig) function is faster than the hyperbolic tangent (tanh) function, therefore it is used when speed is a priority (Dorofki et al. 2012), which is the case in this study. Equation 3 represents the tansigmoid function.

$$tansig = \frac{2}{1 + e^{-2n}} - 1 \tag{3}$$

(3) *Softmax function:* This function gives an output value which represents the probability outcome that adds up to 1. It has an output range between 0 and 1. It is represented in equation 4

$$softmax = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_j}} \tag{4}$$

The training data was normalized to fall within these transfer functions by using equation

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (5)$$

Where x the mean of the variable, x_{min} is the maximum variable and x_{max} is the minimum variable

The procedures in the process flowchart presented in figure 3 was carefully observed to obtain the best performing neural network in this study.

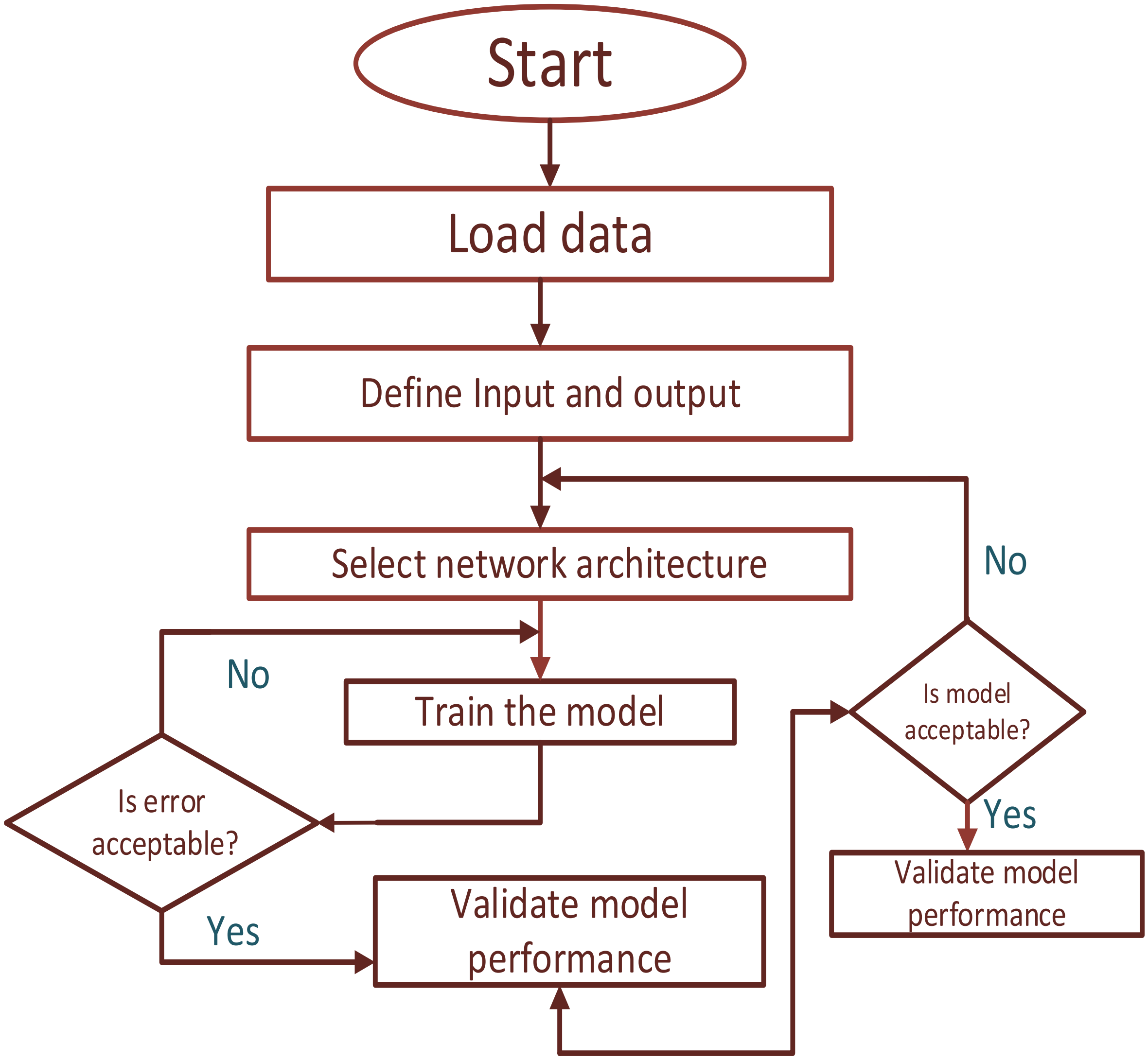

Figure 3 Neural Network Modelling Process flowchart

The model structure of the optimal network in this study is represented in figure 4. A single hidden layer was used because of its proven accuracy and requirement for a lower size of training data which affect the network efficiency (Elhewy, Mesbahi, and Pu 2006). A range of 1-30 neurons in the hidden layer were tested. Each network topology was tested with the combinations of three different activation functions namely; logsig, tansig and softmax and three different training algorithms; the Leverberg-Marquardt (LM), Scaled-Conjugate (SCG) and the Gradient Descent Algorithm (GDA). This was carried out to investigate the influence of the choice of training and activation function on the prediction accuracy of the model. In all the trials, the best 20 networks were selected based on the result of the performance evaluation. The generalization capacity of the developed model is of utmost importance in this study, therefore the performance of these models developed to predict heating value was evaluated and compared using the following performance metrics; Root Means Square Errors (RMSE), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and determination Co-efficient (R) represented in equations 5-7. The dataset was divided into 70 % for training and 30 % for validation in each of these trials.

$$RMSE = \left(\sum_{i=1}^{N} \frac{(P_i - O_i)^2}{N}\right)^{1/2} \tag{6}$$

$$MAD = \sum_{i=1}^{N} \frac{(O_i - P_i)}{N} \tag{7}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left|\frac{O_i - P_i}{O_i}\right| \times 100\% \tag{8}$$

Where i = sample index, N=number of samples, P_i = Predicted LHV value for the i^{th} sample and O_i = Observed LHV for the i^{th} sample.

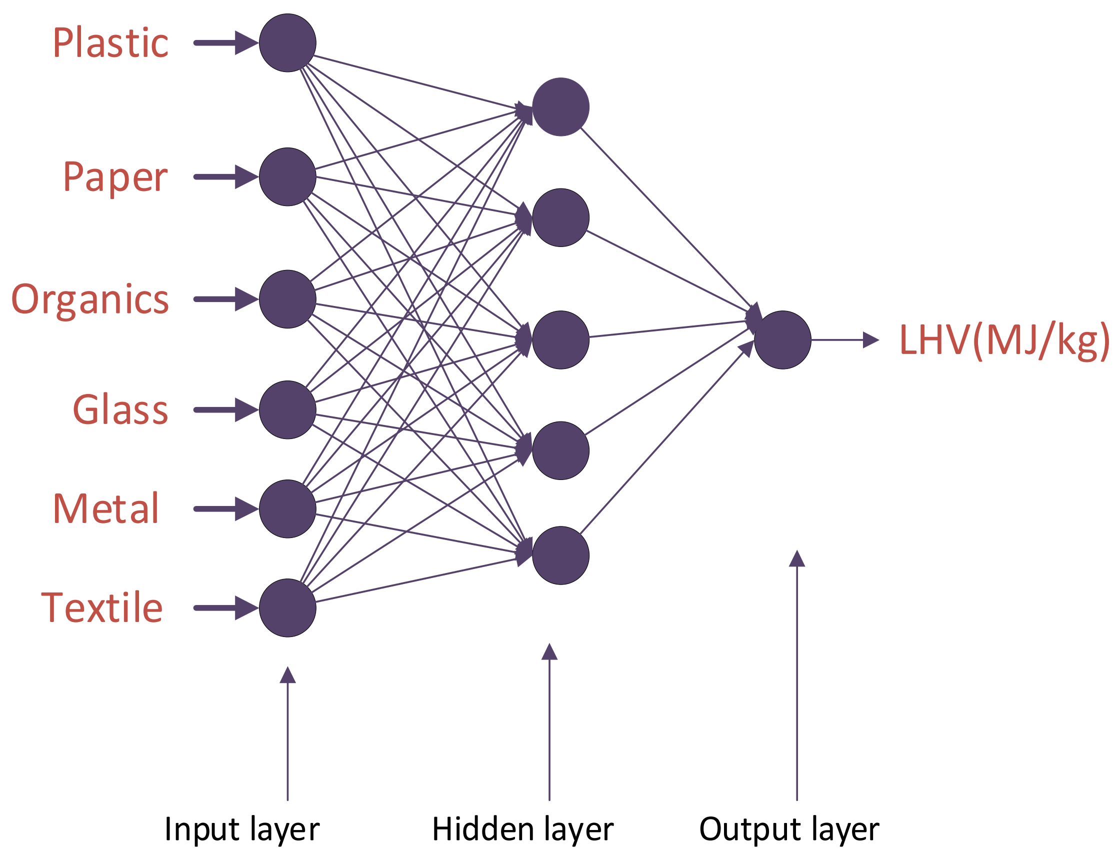

Figure 4 Optimal Neural Network structure with 6 inputs and 5 neurons in a hidden layer

2.3.2 Adaptive Neuro Fuzzy Inference System

ANFIS is a multilayer feedforward network which uses neural network learning algorithm and fuzzy reasoning for mapping input to output, thus integrating the benefits of both neural network and fuzzy logic in a single network (Chang and Chang 2006). It has five layers as shown in Figure 5. For optimization of premise and consequent parameters, ANFIS employs hybrid learning rule which involves back-propagation gradient descent and least square method (Azad et al. 2019)

A system with two inputs, x_1 and x_2, two Sugeno-type and fuzzy Takagi If-then rules and one output can be described by the set of Equations 9 and 10 (Azad et al. 2019)

Rule 1: If $(x_1\ is\ A_1)$ and $(x_2\ is\ B_1)$ then $f_1 = P_1x_1 + q_1x_2 + r_1$ (9)

Rule 2: If $(x_1\ is\ A_2)$ and $(x_2\ is\ B_2)$ then $f_2 = P_2x_1 + q_2x_2 + r_2$ (10)

Where B and A are fuzzy sets, $q, p\ and\ r$ are the nodal consequent parameters

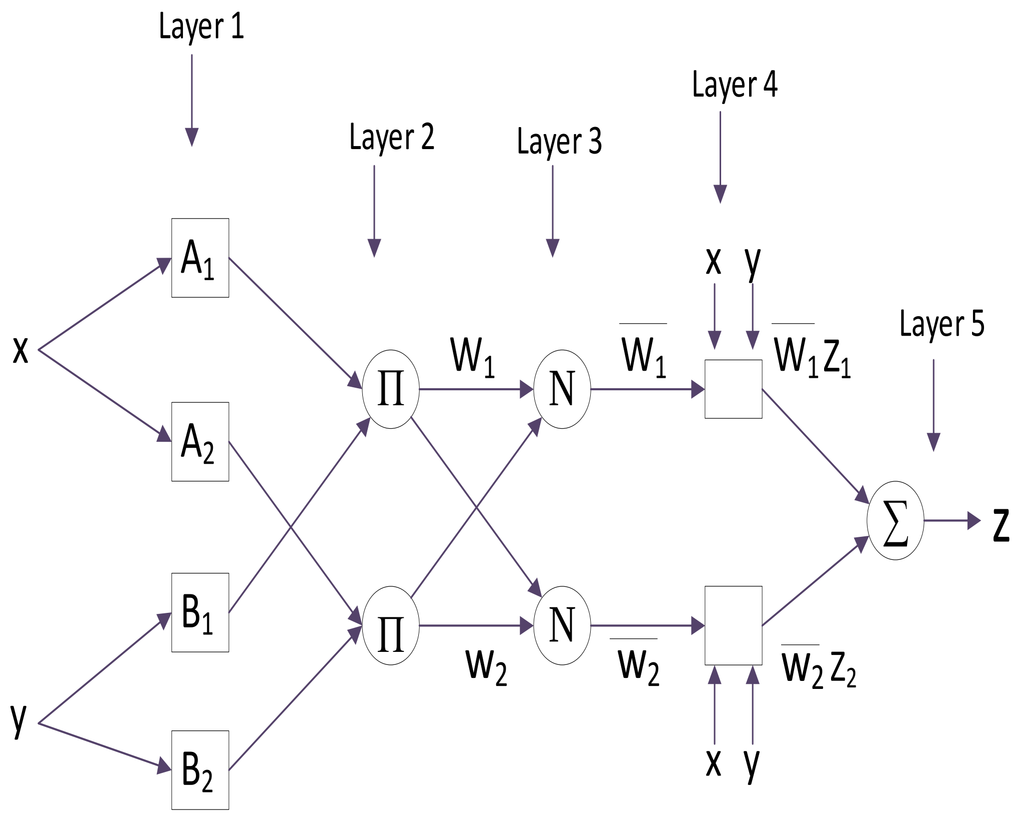

Figure 5 ANFIS architecture with two rules and two inputs

Layer 1: This layer is called the fuzzy layer with premise parameters and consists of fuzzy membership functions. Each node has an output function as given in Equation 11

$$O_{1,i} = \mu_i x_i \tag{11}$$

Layers 2: The output of the nodes in this layer represents the firing strength and product of the input. It has all nodes fixed. A multiplication operator is used for computing in this layer as represented in equation 12, thus;

$$O_{2,i} = w_i = \prod_i \mu_j \tag{12}$$

Layer 3: This is called the normalized layer. Nodes in this layer are adaptive. Output in this layer is computed using equation 13

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_j w_i} \tag{13}$$

Layer 4: The de-fuzzing layer uses a nodal function to compute the effect of rule at each node towards the output as represented in equation 14. It has consequent parameters.

$$O_{4,i} = O_{3,i} f_i = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{14}$$

Where, $\bar{w}_i$ *is* the normalized firing strength of layer 3, and p, q, r are parameter sets

Layer 5: This is the output layer. It has a single node which sum the output as represented in equation 15

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{15}$$

Building and effective ANFIS model requires the following steps (Zounemat-kermani and Teshnehlab 2008).

1. Selection of fuzzy model type
2. Selection of model input and output variables
3. Determining the number and type of membership function per variable
4. Determination of the number of initial fuzzy rules

5. Identification of fitting parameters, antecedent and consequent

In this study, these processes were considered to design the optimal ANFIS model to predict the heating value of waste.

2.3.2.1 Clustering technique

The key element in the ANFIS modelling techniques is the data clustering which involves grouping of data sets into similar group and assigning them a cluster. It also entails assigning membership function to each cluster and generating a fuzzy inference system from the data (Adedeji et al. 2020). Clustering techniques has found applications in image segmentation (Dhanachandra, Manglem, and Chanu 2015), fault diagnosis (Zuo et al. 2010) and pattern recognition (Rezaei and Zarandi 2011). Commonly used clustering techniques in ANFIS modelling are, Grid Partitioning (GP), Subtractive clustering (SC) and Fuzzy c-means clustering (FCM).

2.3.2.1.1 Grid Partitioning

Grid Partitioning is one of the three fuzzy partitioning technique. The other two are, tree and scatter partitioning. They are used to obtain fuzzy member from a data set (Adedeji et al. 2020). This techniques clusters by diving the input space into rectangular subspaces using some local fuzzy regions by axis-paralleled partition based on predefined number of membership function and their types in each dimension(Wei et al. 2007). Only a small number of membership function is required for each input as an exponential relationship exists between the number of input and number of fuzzy rules. A problem of prohibitively large fuzzy rules may be encountered at a moderate or higher number of input, this phenomenon is termed as curse dimensionality (Roger et al. 2000). This is a major demerit of this technique. A finer grid definition often produce a better performance in Grid partitioning (Adedeji et al. 2020). More details for grid partitioning in ANFIS application can be found in Abonyi et al. (1999)

2.3.2.1.2 Subtractive Clustering

The subtractive clustering technique computes tendency that each data point will establish a cluster center, depending on the density of the surrounding data point (Chiu 1994) and identifies the highest potential as a cluster centre (Adedeji et al. 2020). The potential for the each data set is computed when the distributed over a grid point, the grip point with the highest potential is selected as the first cluster. The potential P_i of the ith data and n data point is given by;

$$P_i = \sum_{j=1}^{n} e^{-\alpha P^i - P^{j^2}} \tag{16}$$

Where α = Euclidean distance= $4/_{r_a{}^2}$, r_a is a positive constant which defines the radius of cluster in the dimensional space, while $P^i \ and \ P^j$ are data vectors. Second or next cluster center is selected by computing the new potential in the remaining grid as;

$$P_i = P_i - P_k{}^* \zeta \tag{17}$$

Where ζ= $e^{-\beta P^i - c^{k^2}} \ and \ \beta = \frac{4}{r_b{}^2}, r_b = n^* r_a$. P_k is the potential of kth cluster, c^k is the kth cluster center, n is the squash factor. Potential subtracted from each data point is a function of the distance from first data point (Dhanachandra, Manglem, and Chanu 2015). The number of clusters is influenced by the radius for clustering in the data space, therefore a meticulous effort is needed is selecting the radius, a small radius implies a small cluster in data and consequently more rules and vice versa (Sanikhani et al. 2012). The numbers of rules and performance of the subtractive cluster can be impacted by cluster radius, squash factor, reject ratio and aspect ratio (Adedeji et al. 2020)

2.3.2.1.3 Fuzzy c-means clustering

FCM clustering technique is a soft clustering technique and a fuzzy form of k-means clustering algorithm which assigns a data point to a cluster and membership degree to each data (Adedeji et al. 2020). Instead of wholly belonging to a single group, FCM clustering technique allows a partial membership to different group as no acute boundary exists between clusters (Abdulshahed, Longstaff, and Fletcher 2015). FCM determines a cluster for each fuzzy group of n vectors $x_i, i = 1,2 \ldots\ldots n$ and the distance of data center to each data point is minimized using a goal function:

$$E = \sum_{i=1}^{N} \sum_{j=1}^{C} {U_{ij}}^{m} \left\| x_i - c_j \right\|^2 \qquad (18)$$

Where $m =$ Fuzzier i.e. any real number greater than one $(1 \leq m \leq \infty)$, U_{ij} is degree of membership, $U_{ij} \in (0,1)$, x_i is the data points, c_j is the centroid of clusters and c is the number of clusters. The degree of membership of the data point x_i in j cluster at any iteration is given by equation 3

$$U_{ij} = \left(\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_j\|} \right)^{\frac{2}{m-1}} \right)^{-1} \qquad (19)$$

In this study ANFIS models were developed using three different clustering techniques, thus presenting three-clustering based ANFIS models. The resulting ANFIS models then becomes ANFIS-FCM model, which uses fuzzy c-means clustering technique, ANFIS-GP model, which uses the grid partitioning clustering technique, and the ANFIS-SC model, which uses the subtractive clustering technique.

3. Results and Discussion

The models developed in this study were computed on MATLAB (R2015a) installed on a computing device with 64bits, 4GB ram Intel(R) core(TM)i3 configuration. Presented in Table 5 is the performance evaluation result of the best 20 neural network model selected based on minimum error values and maximum R-values. The network with 5 neurons in a single hidden layer trained with a Leverberg-Marquardt training algorithm and logsig activation function is selected as the optimal network. The performance of the optimal network expressed in terms of RMSE, MAD, MAPE and R-value were 0.0279, 0.0178, 0.0886 and 0.9998 respectively at the training phase and 0.5168, 0.3051, 0.9660 and 12.7157 respectively at the testing phase. These performance metric values of the optimal network show that the network is the most eligible and most accurate in predicting the lower heating value of MSW generated in the city of Johannesburg. Based on the MAPE value of 12.7157, the optimal model is 87.3% accurate, this shows an acceptable fit between the experimental and the predicted value of the lower heating value. The RMSE and MAD values of the optimal model present it as an eligible model for predicting lower heating value.

Table 5 Performance metrics of the best 20 neural networks

S/N	Training	Performance indicator

	Network topology	Activation Function	Algorithm		RMSE	MAD	MAPE	R
1	6-30-1	LOGSIG	SCG	Training	0.1821	0.0763	1.9959	0.9904
				Testing	0.8087	0.4644	16.4436	0.9374
2	6-30-1	LOGSIG	LM	Training	0.2810	0.1180	2.0088	0.9911
				Testing	0.9089	0.3822	16.6166	0.7741
3	6-29-1	TANSIG	LM	Training	0.2688	0.0999	2.5369	0.9845
				Testing	0.9570	0.6503	26.7820	0.8434
4	6-28-1	TANSIG	GDA	Training	0.8020	0.3120	2.7431	0.9613
				Testing	1.2097	0.9214	21.5321	0.8076
5	6-28-1	LOGSIG	GDA	Training	0.3278	0.2382	4.8905	0.9784
				Testing	0.6495	0.4423	18.9525	0.8929
6	6-27-1	LOGSIG	GDA	Training	0.4065	0.2882	4.8541	0.9821
				Testing	0.8282	0.5669	21.1348	0.9289
7	6-26-1	LOGSIG	SCG	Training	0.2857	0.0863	4.0450	0.9833
				Testing	0.9110	0.5461	18.8067	0.9218
8	6-25-1	LOGSIG	LM	Training	0.2453	0.1518	1.8338	0.9960
				Testing	1.1717	0.5798	8.77237	0.9762
9	6-24-1	LOGSIG	LM	Training	0.1569	0.0942	0.4729	0.9993
				Testing	0.7087	0.4094	14.6502	0.9537
10	6-22-1	LOGSIG	GDA	Training	0.3272	0.2393	5.5423	0.9796
				Testing	1.1288	0.7223	14.4229	0.9426
11	6-21-1	LOGSIG	SCG	Training	0.2100	0.1147	1.6912	0.9900

				Testing	0.8624	0.4646	18.8678	0.8701
12	6-20-1	SOFTMAX	SCG	Training	0.0821	0.0347	0.4016	0.9992
				Testing	0.6095	0.3328	14.6339	0.9525
13	6-19-1	SOFTMAX	SCG	Training	0.0180	0.0094	0.6239	0.9991
				Testing	0.5370	0.3078	13.5715	0.9614
14	6-18-1	LOGSIG	SCG	Training	0.0775	0.0408	4.2388	0.9885
				Testing	0.5671	0.3576	18.5921	0.9352
15	6-18-1	TANSIG	SCG	Training	0.0624	0.0374	5.6882	0.9275
				Testing	0.7652	0.5172	24.3393	0.8702
16	6-13-1	TANSIG	LM	Training	0.1188	0.0619	1.8836	0.9944
				Testing	0.9027	0.5367	18.0932	0.8611
17	6-9-1	SOFTMAX	LM	Training	0.0640	0.0318	0.5261	0.9993
				Testing	0.5791	0.3381	12.8556	0.9710
18	6-7-1	SOFTMAX	LM	Training	0.0541	0.0219	0.2626	0.9998
				Testing	0.5991	0.3095	12.7709	0.9575
19	6-5-1	SOFTMAX	SCG	Training	0.0306	0.0160	0.2523	0.9998
				Testing	0.6183	0.3337	13.6189	0.9542
20	***6-5-1***	***LOGSIG***	***LM***	***Training***	***0.0279***	***0.0178***	***0.0886***	***0.9999***
				Testing	***0.5168***	***0.3051***	***12.7157***	***0.9660***

Evaluating the performance of the networks based on the activation functions used in this study, Softmax function gave the most accurate results. All networks trained with the softmax function have a RMSE value between 0.0180-0.082 at the training phase and 0.5370-0.6183 at the testing phase. The best prediction result using the logsig activation function was with the topology 6-5-1, with RMSE of 0.0279 for training while the least accurate prediction using the logsig activation function was with the 6-27-1 topology giving a RMSE value of 0.4065 for training. The tansig function based network predicted with a lesser accuracy compared with logsig function. However, the best prediction result based on the tansig function was obtained with the topology 6-13-1, with RMSE and MAPE of 0.1188 and 0.1619 respectively for training, while tansig function tested with 6-28-1 predicted with the least accuracy with RMSE and MAPE value of 0.8020 and 0.3120 respectively for training.

It can be observed from Table 5 that the training R-value increased as the number of neurons in the hidden layer reduced which implies that the network trained better when the numbers of neurons in the hidden layer reduced. The training was stopped at 30 neurons, because no significant improvement was noticed in the network performance above 30 neurons. It was also observed that all the networks trained with the softmax activation function gave the highest R-values ranging from 0.9991-0.9998. Based on MAPE, the network with a topology 6-29-1 trained with LM algorithm and tansig activation function was considered the least accurate network, it is 78.2% accurate (MAPE=26.7820). The network trained with LM training algorithms were observed to be best trained, while the GDA trained the least with the data set. Generally, the performance of the network improved as the percentage error reduces when the number of neurons in the hidden layer reduced progressively from 30 to 5. The post regression plot of the training state and the testing plot of the best network are shown in figures 6 and 7

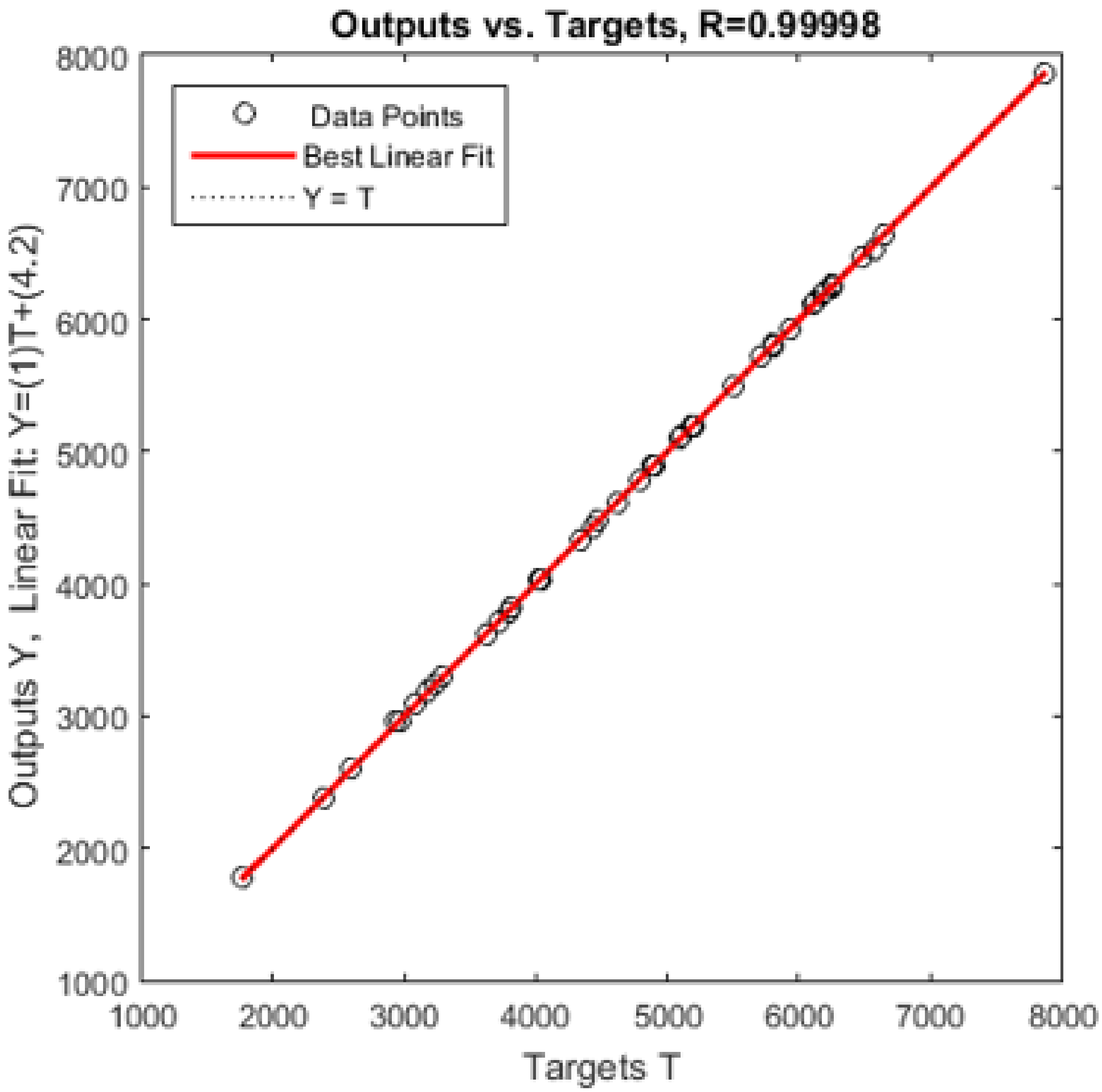

Figure 6 Post regression training plot for the optimal neural network

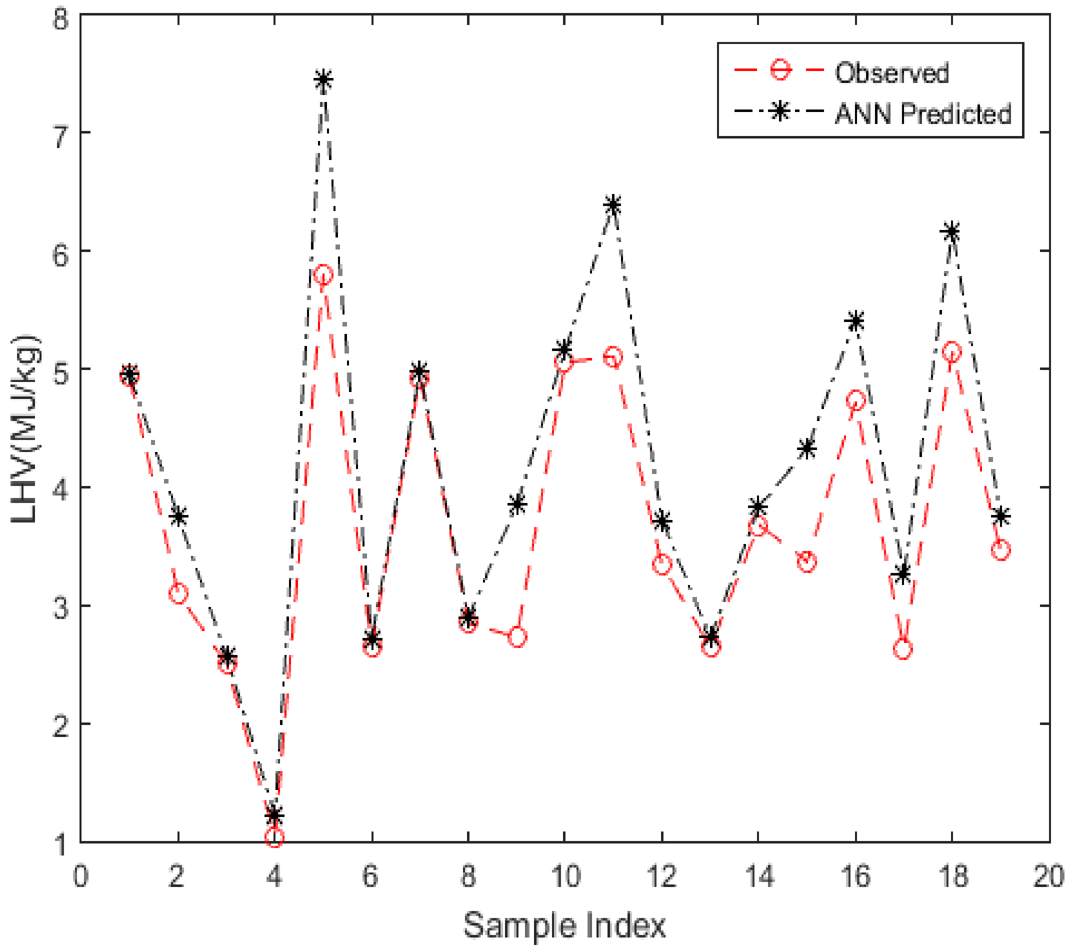

Figure 7 Test Plot of the optimal neural network

In training the ANFIS network, 70% of the data was used for training and 30% for testing. Two input membership function was used for training the ANFIS-GP model using grid partitioning clustering technique and a gaussian-type input membership function. In training the ANFIS FCM model, the parameters of the network were specified, the fuzzy C-means clustering technique with Sugeno-type Fuzzy Inference System were selected. The FCM clustered ANFIS model was developed with 10 cluster numbers. Other parameters of the FCM clustering like the exponent was set at 2 and the maximum Iterations was set at 20. The cluster radius of the subtractive clustering for the ANFIS-SC model was set at the recommended value of 0.55. The accuracy of the three models were also assessed using the performance indicator Root Means Square Errors (RMSE), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and Correlation Co-efficient (R)

Table 6 presents the result of the performance of the best ANN network, ANFIS-FCM, ANFIS-GP and ANFIS-SC in term of the RMSE, MAD, MAPE, and R. Given the Mean Absolute Percentage error of the four models, the selected ANN model predicted with an accuracy of 87.3% and considered the least accurate model. The ANFIS-GP predicted with the highest prediction accuracy of 95.1%, ANFIS-FCM and ANFIS-SC were 93.6% and 91.6% accurate respectively. Owing to the nature of the data and the computational complexity of the ANFIS-GP, a lower number of membership function was selected, however this model recorded the longest computational time. Comparatively, the ANFIS models trained better, all having correlation co-efficient of training of 1.000, and predicted more accurately than the ANN models. In the overall performance of the four models, ANFIS-GP is the most accurate in predicting the heating value of MSW generated in Johannesburg. It trained and predicted with the lowest error. Its RMSE, MAD, MAPE and R-values for testing were 0.2916, 0.2286, 8.4736 and 0.9731 respectively.

Table 6 Comparison Performance of the optimal ANN and ANFIS model

Model		RMSE	MAD	MAPE	R
ANN (6-5-1)	training	0.0279	0.0178	0.886	0.9999
	testing	0.5168	0.3051	12.7157	0.9660
ANFIS-SC	training	4.16×10^{-7}	1.88×10^{-7}	5.03×10^{-6}	1.0000

	testing	0.2916	0.2286	8.4736	0.9731
ANFIS-GP	training	8.61×10^{-8}	0.64×10^{-8}	1.77×10^{-6}	1.0000
	testing	0.1944	0.1389	4.2982	0.9874
ANFIS-FCM	training	1.56×10^{-7}	1.08×10^{-7}	2.9×10^{-6}	1.0000
	Testing	0.1944	0.1389	4.2982	0.9874

Figure 8-10 presents the regression test plot of the observed and predicted values by the ANFIS models. Both the predicted and experimental heating value had no significant variation and are highly correlated with co-efficient 0.9731, 0.9874 and 0.9766 for ANFIS-SC, ANFIS-GP and ANFIS-FCM respectively. The ANFIS-GP was more computationally intensive with the highest computational time, this is due to the large computer memory requirement that may result from the exponential relationship that exist between fuzzy rules and number of input (Roger et al. 2000), hence two (2) membership functions were selected in this study. The ANFIS-FCM computed in the shortest time. The computational time were 4.2, 6.19 and 3.76 seconds for ANFIS-SC, ANFIS-GP and ANFIS-FCM models respectively

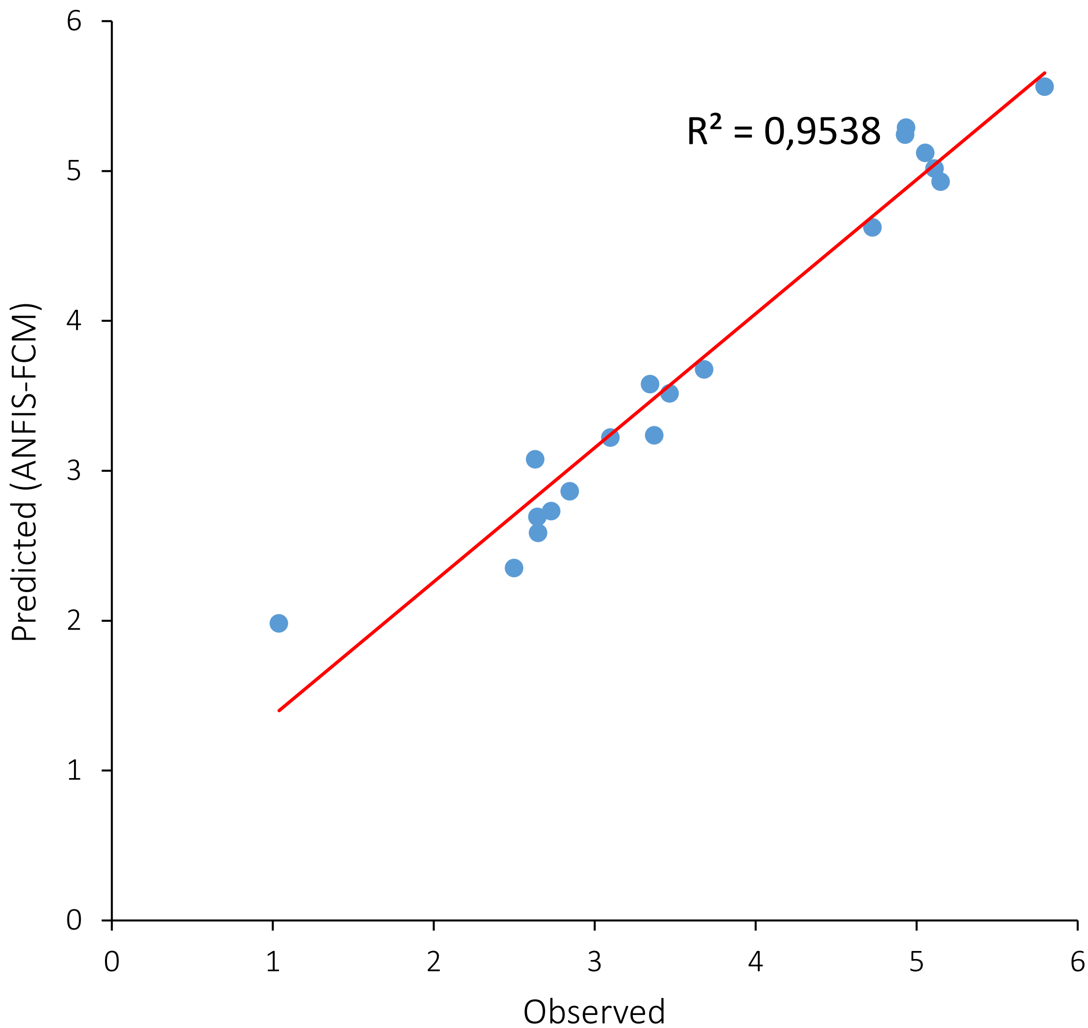

Figure 8 Regression plot of ANFIS-FCM Predicted LHV versus observed LHV

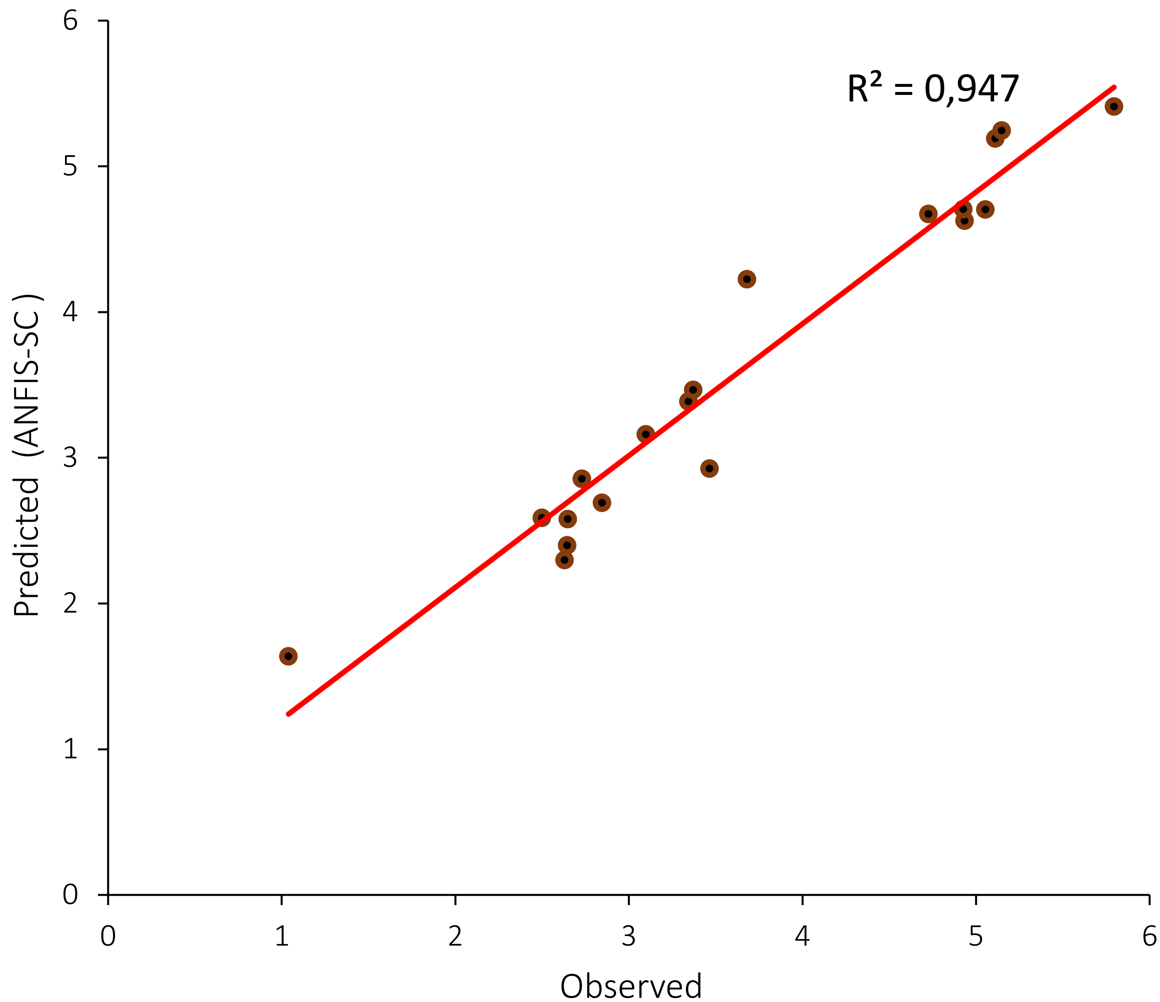

Figure 9 Regression of ANFIS-SC Predicted LHV versus observed LHV

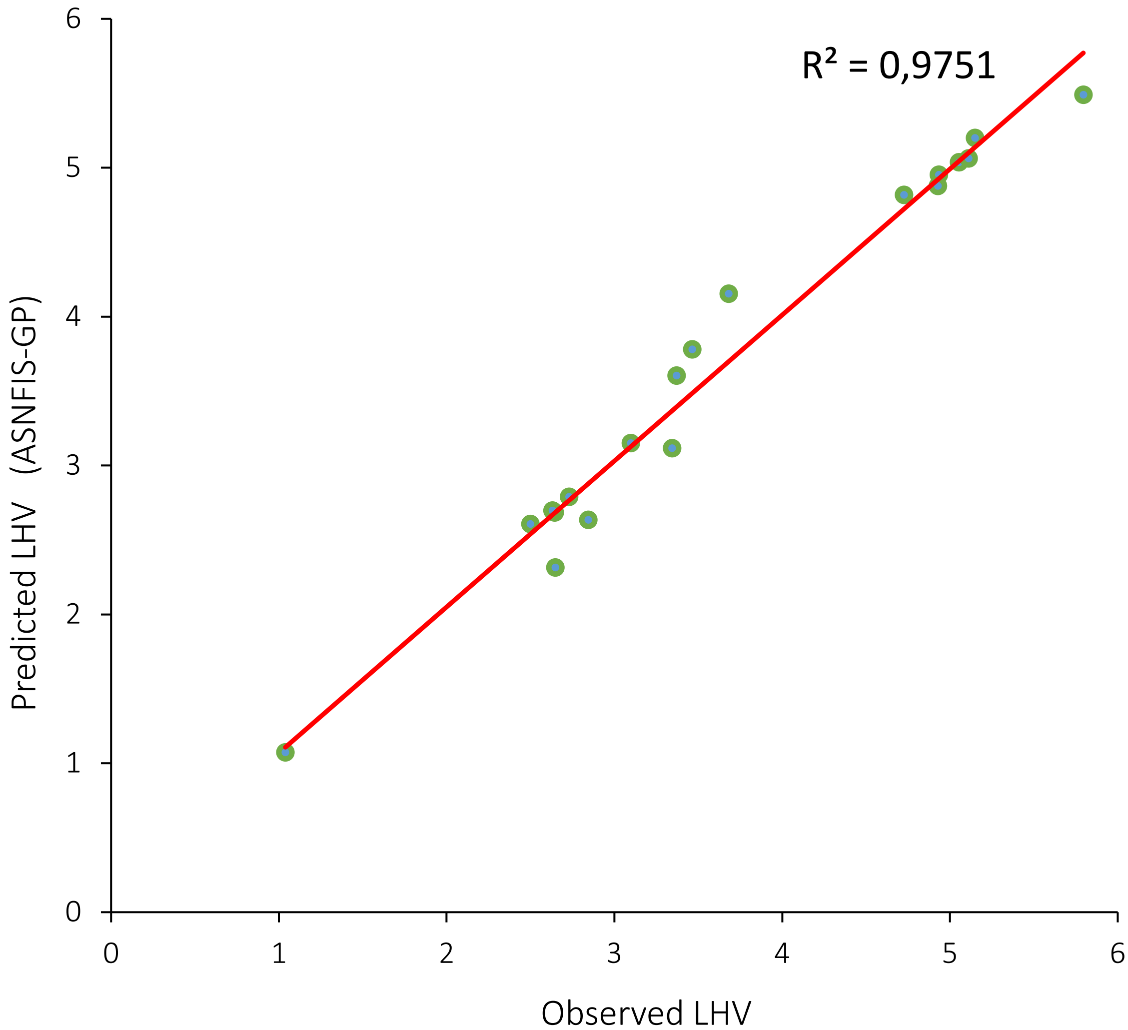

Figure 10 Regression plot of ANFIS-GP Predicted LHV versus observed LHV

The combined test sample plots of the four models used in this study is presented in figure 11. There is a similar trend noticed in the four model plots with a very slight variation in the predicted values. The rise and fall trend depicted in the plot of the predicted values of the four models in figure 11 is similar to the trend in the experimental heating values. This reveals the significant variation in the energy content of the waste collected at the landfill sites in

Johannesburg. This noticed trend resulted from the variation in the composition of plastic and organic waste from the DNC and RCR sources. Averagely, waste from DNC sources has about 28% plastics and 13% organic, while RCR waste has about 29% organics and 18% plastics (Ayeleru, Okonta, and Ntuli 2018). The highest points in figure 11, especially at samples index 5, 11, 16 and 18 with the maximum heating values are identified as waste samples from the Daily Non-Compacted (DNC) source with the higher plastic waste streams and low organic waste stream. Plastic waste streams have higher calorific value, therefore more plastic waste stream in waste, indicates higher energy content. The lowest points in figure 11, especially at samples 4, 6, 8, 9, 13, 17 and 19 with the minimum heating values represent waste from the RCR source with lesser plastic waste and a higher fraction of organic waste. More organic waste stream in a waste, indicates a lesser energy content, due to the lower calorific value of organic waste. The ANN model over-predicted LHV values especially at samples 5, 11 16 and 18, this may be due to the sensitivity of the ANN model to sudden changes in the data samples of LHV at these points, resulting in over-prediction

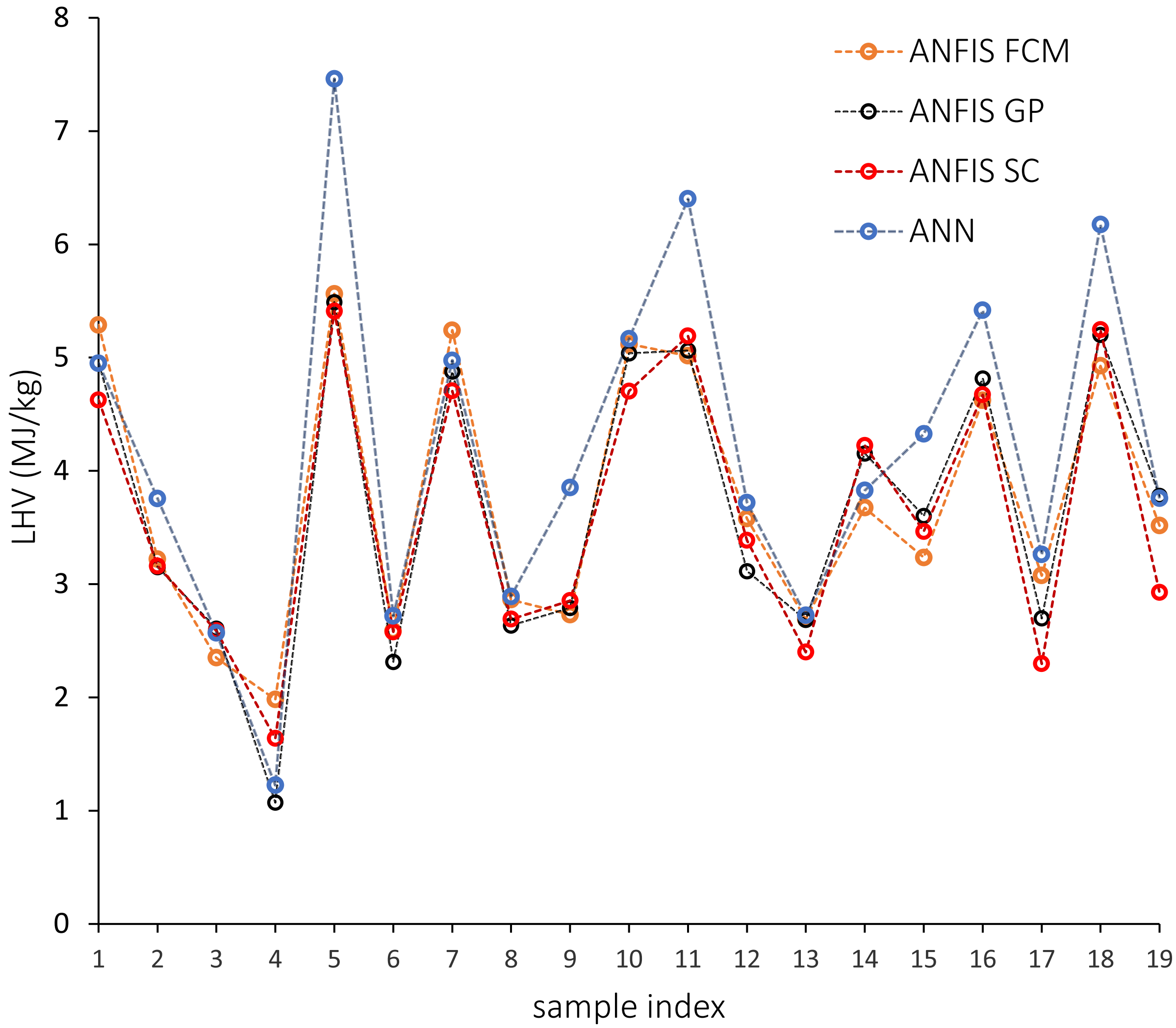

Figure 11 Combined Prediction test plot of the four models

4. Conclusion and Recommendations

This study evaluated the relationship between the physical composition and energy content of waste generated in Johannesburg, South Africa. The accuracy of the ANN and ANFIS model to predict the heating value of waste has been unveiled. Four models were developed with laudable performance, ANN, ANFIS-GP, ANFIS-FCM and ANFIS-SC. It was observed that the performance of the network improved as the neurons in the hidden layer reduced. The network with a topology 6-5-1 trained with a Levenberg-Marquardt algorithm and logsig transfer function emerged as the best network predicting with minimum errors values RMSE, MAD and MAPE of 0.5168, 0.3051 and 12.7157 respectively. The ANFIS-GP performed better than all other models with 95.1% accuracy, and RMSE and MAD value of 0.1944 and 0.1389 respectively. More so, it was noted that the percentage composition of some waste streams like plastics and organic waste had a significant impact on the energy content of the waste. Waste from the DNC, with about 28% plastic waste were identified as having the highest heating value while the RCR source with about 19% plastic had the lowest heating value. This trend was depicted in the predicted values using the four models. Due to limited availability of calorimetric heating value published data of waste in Johannesburg, this study was constrained to the use of meagre sample data set. The use of a large experimental waste data set is hereby recommended for further researches into prediction of the energy content of waste in Johannesburg. ANFIS model optimized with an evolutionary algorithm like Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) is recommended for further researches.

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Declaration of Conflicting Interest

The authors declare that there is no potential conflict of interest

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