Prediction of Municipal Solid Waste Generation: An Investigation of the effect of clustering techniques and parameters on ANFIS model Performance

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Abstract

The present waste management system and facilities in most developing countries are insufficient to combat the challenge of increasing rate of solid waste generation. To achieve success in sustainable solid waste management, planning plays a crucial role. Accurate prediction of waste quantities generated will immensely help to overcome the challenge of deficient-planning of sustainable waste management. This challenge has necessitated the need for modelling approach. In modelling the complexity within a system, a paradigm-shift from classical-model to artificial intelligent model has been necessitated. Previous researches which used Adaptive Neuro-Fuzzy Inference System (ANFIS) for waste generation forecast did not investigate the effect of clustering-techniques and parameters on the performance of the model despite its significance in achieving accurate prediction. This study therefore investigates the impact of the parameters of three clustering-technique namely: Fuzzy c-means (FCM), Grid-Partitioning (GP) and Subtractive-Clustering (SC) on the performance of the ANFIS model in predicting waste generation using South Africa as a case study. Socio-economic and demographic provincial-data for the period 2008-2016 were used as input-variables and provincial waste quantities as output-variable. ANFIS model clustered with GP using triangular input membership-function (tri-MF) and a linear type output membership-function (ANFIS-GP1) is the optimal model with Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE) and Correlation Co-efficient (R^2) values of 12.6727, 0.6940, 1.2372 and 0.9392 respectively. Based on the result in this study, ANFIS-GP with a triangular membership-function is recommended for modelling waste generation. The tool presented in this study can be utilized for the national repository of waste generation data by the South Africa Waste Information Centre (SAWIC) in South Africa and it is also applicable to waste-planners in developing countries for reliable and accurate prediction of annual waste generation

Keywords: Waste generation, Adaptive Neuro-Fuzzy Inference System, Clustering-techniques, South Africa, Grid-Partitioning, Subtractive-Clustering, Fuzzy c-means.

1. Introduction

The global upsurge in population, economic activities and commercialization has substantially influenced the increase in the rate of waste generated globally (Kamran et al. 2015). A study revealed that about 3.5 million tonnes of waste was generated daily across the globe in 2010 with a daily increase projection to about 6 million tonnes by 2025 (Hoornweg et al. 2012). However, in most developing countries, this increasingly generated waste has been poorly managed and consequently placed a burden on the collection, storage and disposal resources and operations (Al-Khatib et al. 2010). Waste is generated at every stages of material-flow, picking from the raw material extraction to the manufacture and production of consumer-goods, and finally to the stages in the cycle where the consumers discard the unwanted part of the materials, however since production cannot be stopped consumption is inevitable, consequently waste is generated (Ojeda et al. 2008). A well-planned management of solid waste generated aids the reduction of the quantity of waste that ends up in landfill, consequently mitigating the environmental effect of uncontrolled landfill-sites on human, soil, groundwater and air and also enhances material and energy recovery.

The quantity of waste generated is influenced by socio-economic factors such as income-level, Gross Domestic Product (GDP), employment-quota and expenditure, and demographic factors such as household-size, literacy-level, population (Intharathirat et al. 2015). Matheus (2018) investigated the influence of socio-economic factors such as population, life-expectancy, literacy-level, human development and income per capita on the quantity of waste generated in 39 municipalities in Sao Paulo using Pearson's correlation-coefficient. The influence of educational-level, family-size, income and employment type on household waste generated per capita per day in Bangalore city of India was investigated by Ramachandra et al. (2018).

South Africa like most developing countries is still faced with the challenge of waste management due to the increase in the population, urbanization and industrial-activities and rural-urban migration of the population. There is need for urgent attention and action to be taken to combat the repercussion of the increase in the rate of generation of waste in developing countries, this is because the current waste management strategy is inefficient to meet the collection and disposal need. A well-informed waste management planning and policy development for collection, treatment and disposal of waste are contingent on the custody of information on real-time data of waste generation. Accurate prediction of waste quantities generated will immensely help to overcome the challenge of inaccurate and scarce data of waste generation which has resulted into deficient planning of sustainable waste management.

Common traditional methods of quantifying waste generated in most developing countries are through direct sampling, load counts, volume and weight analysis (Shahabi & Khezri, 2012). These methods are insufficient to accurately estimate the quantity of waste generated, yet they are time-consuming and expensive. Therefore, they cannot be trusted as a bases for waste-management decisions and policy-making. This is because most of the time these techniques only estimate the amount of waste collected rather than waste generated (Younes et al., 2015). This challenge has necessitated the need for an alternative modelling-approach.

The literature is replete with researches on modelling MSW generation with several modelling techniques. The major setbacks for waste generation forecast in most developing countries are the scarcity of reliable historical-data of waste characteristics (Intharathirat et al. 2015, Kolekar et al. 2016) and the choice of suitable forecasting tool (Eleyan 2013, Rimaityte et al. 2011)**.** The data involved in waste generation modelling are mostly waste production, consumption or disposal related (Beigl et al. 2008, Kolekar et al. 2016) such as population (Chung 2010, Dai et al. 2011, Liu & Yu 2007, Thanh et al. 2010), income (Chung 2010, Liu & Yu 2007), education (Keser et al. 2012, Ojeda et al. 2008), age (Lebersorger & Beigl 2011) and employment (Keser et al. 2012, Lebersorger & Beigl 2011).

There are several modelling-techniques for predicting waste quantity generated such as times-series model (Mwenda et al. 2014, Xu et al. 2013), fuzzy-logic (Ojeda et al. 2008, Oumarou et al. 2012), system-dynamic models (Eleyan et al. 2013, Fu et al. 2015, Kollikkathara et al. 2010) and regression analysis (Chung, 2010, Dai et al. 2011, Keser et al. 2012, Kumar & Samadder 2017, Lebersorger & Beigl 2011). Auto-Regressive Integrated Moving Average (ARIMA) and Grey models are time-series model employed for medium-term and long-term forecast respectively (Xu et al. 2013). A multiple time-series hybrid-model was used by Xu et al. (2013) to develop a monthly-scale, medium-term and long-term waste generation forecast using Seasonal Autoregressive Integrated Moving Average (SARIMA) and Grey-model in Xiamen city of China. A long-term forecast of MSW collection using optimized multiple variate grey-model was developed by Intharathirat et al. (2015).

The linear regression model has found wide applications in MSW generation modelling, however, it is limited in application because of its inability to learn from new data which produces inaccurate prediction-outcomes (Thanh et al. 2010). Also, owing to the non-linearity and complexities in data of waste generation and related variables, classical-models are found inaccurate for prediction. Therefore to model the complexity within a given system, a paradigm shift from classical-model to more accurate artificial-intelligence model has been necessitated.

Accurate prediction is important because inaccurate prediction of waste generation leads to underestimation and overestimation of disposal, collection and treatment capacities (Intharathirat et al. 2015). Common artificial-intelligence models used for waste generation forecast such as Adaptive Neuro-Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), K-Nearest Network (KNN) and Artificial Neural Network (ANN) are summarized in Table 1

Table 1 Artificial Intelligent model used for MSW generation prediction

S/N	Reference	Case-study	Type of waste	Model type	Performance metrics		
					R^2	RMSE	MAE
1	(Shahabi & Khezri, 2012)	Saqqez, Iran	MSW	ANN	0.69	364	298
2	(Jalili Ghazi Zade & Noori, 2008)	Mashhad, Iran	MSW	ANN	0.75	467	358
3	(Golbaz et al., 2019)	Karaj, Iran	Hospital Solid Waste	ANN ANFIS SVM LSSVM FSVM	0.74 0.78 0.89 0.82 0.84	- - - - -	0.031 0.009 0.009 0.007 0.004
4	(Younes et al., 2015)	Malaysia	MSW	ANFIS	0.99	4.39	0.741
5	(Abbasi & El Hanandeh, 2016)	Logan City, Australia	MSW	ANFIS SVM ANN	0.98 0.71 0.46	175.18 231.99 290.55	52.16 206.42 226.50
6	Soni et al., 2019	New Delhi, India	MSW	ANN GA-ANN Pure ANFIS DWT- ANFIS GA-ANFIS	0.72 0.87 0.56 0.73 0.56	165.5 95.7 224.99 155.48 393.8	- - - - -

7	(Kannangara et al., 2018)	Ontario, Canada	MSW	ANN	0.72	20	-
8	(Cubillos, 2020)	Herning, Denmark	Household-MSW	ANN	-	2.25	1.77
9	(Chhay et al., 2018)	China	MSW	ANN	0.931	0.014	228.53
10	(Singh & Satija, 2018)	Faridaba, India	MSW	ANN	R=0.839	0.019	0.005
11	(Abdoli et al., 2012)	Mashhad, Iran	MSW	ANN	R=0.86	MSE=0.26	-
12	(Sun & Chungpaibulpatana, 2017)	Bangkok, Thailand	MSW	ANN	0.96	252.8	-
13	(Adamović et al., 2017)	EU and non-EU countries	MSW	GRNN	R=0.956	41.7	29.9

ANFIS has found wide applications in different fields owing to its accuracy, adaptive-nature, swift learning-ability, computational-speed and its ability to capture the non-linearity in complex system. Several fields of applications of ANFIS model include, energy consumption (Kaveh et al., 2018), wind energy (Adedeji et al., 2020), petroleum engineering (Zamani et al., 2015), Agriculture (Ghadernejad et al., 2018), Biomass and bioenergy (Akkaya, 2016; Olatunji et al., 2019), stock-market (Cheng et al., 2009) and manufacturing (Zhang & Lei, 2017). The flexible computational structure of ANFIS allows its features and parameters such as number of rules, membership-function types and the method of generating the Fuzzy Inference System to be varied in order to improve its performance. The efficiency and accuracy of most soft-computing techniques of which ANFIS belongs are contingent on the optimal selection of model-parameters

(Adedeji et al., 2020). Therefore, careful choice of clustering-techniques and parameters are important steps in modelling using ANFIS as it influences the prediction accuracy of the model significantly.

Some applications of ANFIS model for forecasting solid waste generation found in the literature are presented in Table 1. However, these previous studies which used ANFIS for waste generation forecast do not investigate the effect of different parameters of the clustering-techniques on the performance of the ANFIS model despite its significance in achieving accurate prediction. Therefore the motivation of this study is to fill this gap by investigating the effect of model-parameters of three clustering-techniques namely: Fuzzy c-means (FCM), Grid-Partitioning (GP) and Subtractive-Clustering (SC) on the performance of the ANFIS model and then select the optimal-model to accurately predict provincial waste generation using South Africa as a case-study. This study compares and analyses the performance of three ANFIS model namely: ANFIS-GP, ANFIS-SC and ANFIS-FCM using GP, SC and FCM clustering-technique respectively. Several Sub-models were developed by stimulating some of the parameters of the models in each of the techniques. The performance of the sub-models in each techniques were evaluated using relevant performance-metrics in order to select the best sub-models in each clustering technique and the optimal-model for waste generation prediction in South Africa. This study proposes a tool which is also applicable in most developing countries for estimating waste quantities which will assist waste-related decisions and policies formulation

2. Materials and Method

2.1 Study Area: Waste Management and Solid waste generation

South Africa is a developing country having nine provinces with a total population of 58.78 million (StatsSA, 2019). The upsurge in population and urbanization has placed a burden on the waste management system in South Africa (Friedrich & Trois 2010). However, hierarchical waste management policies have been prioritized in South Africa under the National Waste Management Schemes, and National Environmental Management Waste Act to ensure diversion of waste from landfill (Nahman & Godfrey 2010). The establishment of the National Waste Management Strategy Implementation (NWMSI) in 2000 introduced the concept of Integrated Waste Management Planning (IWMP) with a major focus on enhancing the efficiency of solid waste management in South Africa. However, inconformity to the IWMP, the Department of Environmental Affairs (DEA) developed a guideline which stated that collection of reliable and updated waste-related data is an important course of action to organize integrated waste management-plan. Some of the data which are vital to the IWMP guidelines are waste characteristics, composition and quantity generated.

The South African Waste Information Center (SAWIC) manages national waste-related database in South Africa. SAWIC relies on the report of municipalities, treatment-facilities, public and private waste sector for publishing waste-data. However, the tonnage-report of waste received at the treatment-facilities at different provinces in South Africa which are published by SAWIC does not accurately represent the quantity of waste generated at each provinces annually, it rather represents the received collected-waste, recycled, and treated at the treatment-facilities in each provinces. The main aim is to create a single national-repository for accurate waste collection (DEAT, 2005)

Table 2 Waste generation rates at different income-level in South Africa

Income-level	Income-range	Waste-generated (kg/capita/day)		
		DEA, 2012	BPDM, 2009	Average
Low	R0 – R38600	0.41	0.45	0.46
Middle	R38601 – R153600	0.74	1.10	1.03
High	R153601 and above	1.29	1.85	1.68

Table 2 presents the variation in waste generation rate at different income-level in South Africa. Provincial waste generation in South Africa has been influenced by socio-economic and demographic data namely: Population, economic-level, household-size and employment. Table 3 presents the waste quantities, and the values of the influencing factors in the provinces in South Africa for the year 2016.

Table 3 Waste quantities, and influencing factors in South Africa Provinces for the year 2016

Province	Provincial Population (million)	Provincial contribution to national GDP (Billion rands)	Household-size (million)	Employment (15-64 ages) (million)	Waste generated (million tonnes per year)
Western Cape	6.374	596.1	1.771	2.386	4.988
Eastern Cape	6.492	331.1	1.648	1.447	3.146
Northern Cape	1.199	90.8	0.325	0.298	0.026
Free State	2.844	217.8	0.862	0.757	1.682
KwaZulu-Natal	10.941	692.2	2.752	2.541	1.342
North west	3.790	279.7	1.135	0.959	1.098
Gauteng	13.906	1507.1	4.546	5.111	11.518

Mpumalanga	4.367	323.7	1.208	1.155	6.899
Limpopo	5.707	311.7	1.495	1.414	1.569

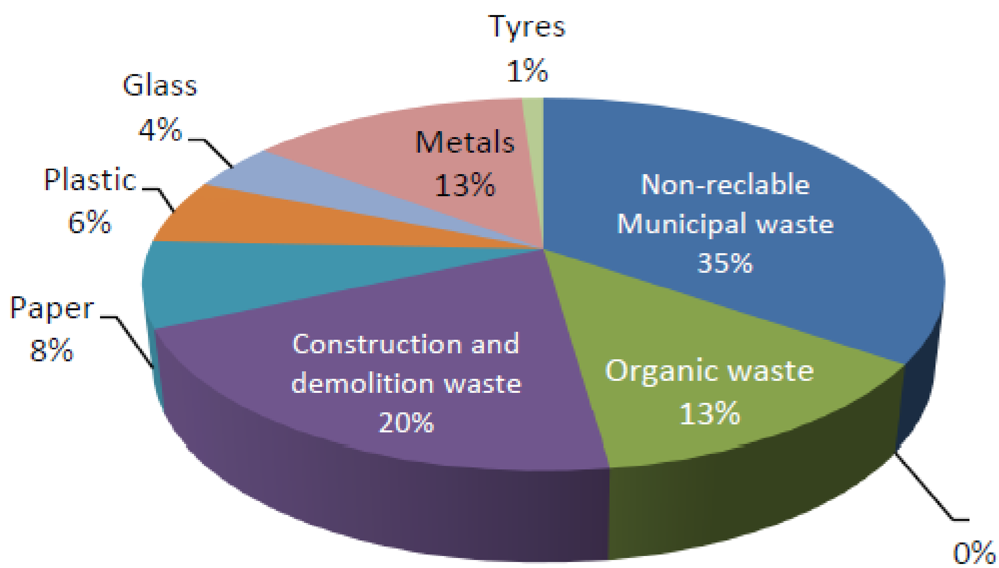
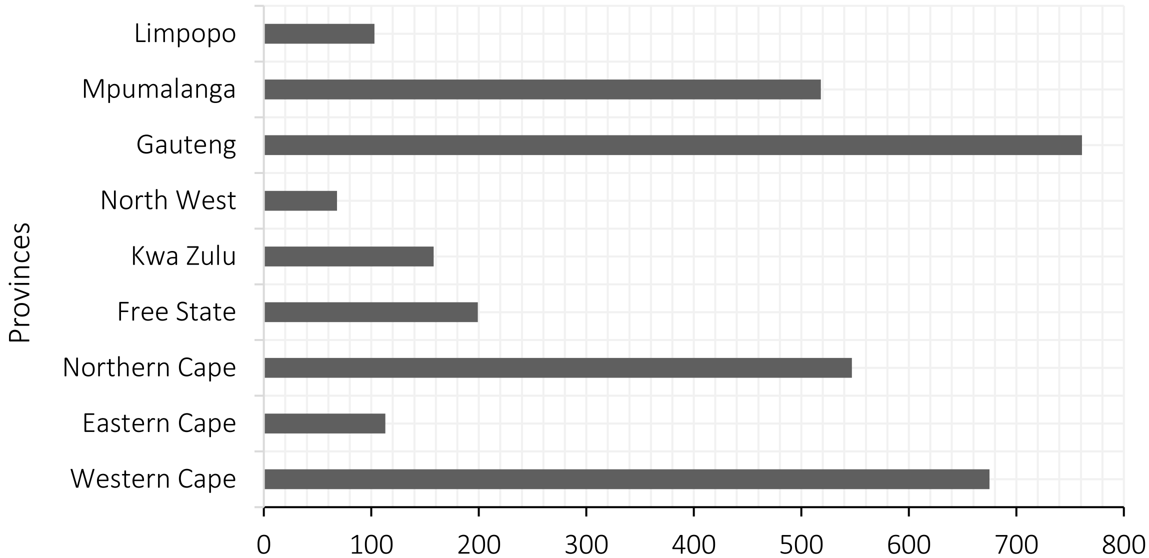


Figure 1 Composition of General Waste in South Africa (DEA, 2012)

Figure 1 represents the composition of general waste in South Africa. Larger fraction of the waste comprises the non-recyclable waste, the organic waste and the construction and demolition waste. Only about 10% of waste generated in South Africa was recycled, landfill still remain the prominent waste-disposal method. The rate of generation of waste generation per capita per annum is presented in figure 2



	Western Cape	Eastern Cape	Northern Cape	Free State	Kwa Zulu	North West	Gauteng	Mpumala nga	Limpopo
Series1	675	113	547	199	158	68	761	518	103

Figure 2: Waste generation rate (kg/capita/year) in South Africa Provinces

2.2 Dataset

Input and output variables used in this study are presented in Table 4. South Africa's provincial-population and household-size are both extracted from General Household Survey (GHS) report for the period 2008-2016. The number of employed adult between ages 15-64 in each province was extracted from Labour Force Survey, 2008-2016 and Provincial GDP report from South Africa GDP statistics, all provided by Statistics South Africa (StatSA). The tonnage-report of waste received at the treatment facilities in each province was extracted from the database of South Africa Waste Information Centre (SAWIC), DEA. However, these values represent the tonnage of waste recycled, treated and exported and do not accurately represent the actual waste generated in each province. The actual waste quantity generated was stimulated and interpolated between these values and the estimated-values based on 2011 baseline-guideline by National Waste Information Baseline Report (DEA, 2012) and used as the output-variable.

Table 4 Data statistical Description

Variables	Minimum	Maximum	Mean	Standard deviation
Input Variables				
Population (million)	1.07	13.90	5.75	9.39
Provincial contribution to national GDP (Billion-rands per annum)	39.50	1507.08	335.34	1208.50
Household number (million)	0.27	4.55	1.54	3.26
Number of employed person within the age 15-64 (million)	0.31	5.11	1.58	3.71
Output Variables				
Waste Quantity (million tonnes per annum)	0.2683	30.808	6.792	24.89

2.3 Adaptive Neuro-Fuzzy Inference System

Firstly proposed by Jang (1993), ANFIS is a common machine-learning algorithm which matches input to output by employing the Sugeno-type If-then rules and the neural network. It combines the fuzzy-logic theory commonly called Fuzzy Inference System (FIS) and the learning-approach of the neural network (Abdulshahed et al. 2015). It is a class of adaptive, multi-layer and feed-forward network that is capable of approximating real-continuous functions (Akkaya 2016). It uses a hybrid learning-algorithm, the least-square method and the back-propagation gradient-descent method which optimizes the linear consequent-parameters of the output and the non-linear premise-parameter with the fuzzy membership respectively (Güldal & Tongal 2010, Mustapha et al. 2016). The least-square method fixes the premise to optimize the consequent through a forward-learning and the parameters that defines the membership function (MF) in the premise is optimized by gradient-descent method through a back-learning after the optimum consequent-parameter is obtained in forward-learning (Yeom & Kwak 2018). A rule set which comprises two inputs, x_1 and x_2, two Sugeno-type and fuzzy-Takagi If-then rules and one output can be described by equations 2 and 3 (Azad et al. 2019)

$$\text{Rule 1: If } (x_1\ is\ A_1) \text{ and } (x_2\ is\ B_1) \text{ then } f_1 = P_1 x_1 + q_1 x_2 + r_1 \tag{2}$$

$$\text{Rule 2: If } (x_1\ is\ A_2) \text{ and } (x_2\ is\ B_2) \text{ then } f_2 = P_2 x_1 + q_2 x_2 + r_2 \tag{3}$$

Where A and B are fuzzy-sets, q, p and r are the nodal consequent-parameters.

The Architecture of ANFIS comprises five layers as shown in figure 3. These layers are described as follows;

In the first layer, all the nodes in this layer are adaptive and the output is defined by the MF. It is called the fuzzy-layer. The output function is given in equation 4 (Jang 1993)

$$O_{1,i} = \mu_{A_i} x_i \tag{4}$$

Where μ_{A_i} is the MF of node A.

In this second layer, the output of the nodes represents the firing-strength and product of the input. It has all nodes fixed.

$$O_{2,i} = w_i = \mu_{A_i} \times \mu_{B_i} \times \mu_{C_i} \tag{5}$$

Where $\mu_{A_i}, \mu_{B_i}, \mu_{C_i}$ represents the MF of node A, B and C respectively in the input layer.

The third layer has an output which is a quotient of the firing-strength of the node to the sum of all firing-strength of the other nodes. This layer is called the normalized layer.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{\sum_j w_i} \tag{6}$$

Where w_i is the firing-strength of node i

The fourth layer called the de-fuzzing layer uses a nodal-function to compute the effect of rule at each node towards the output. The sum of the linear input-signals and the normalized signals from previous nodes gives the output as in equation 7.

$$O_{4,i} = O_{3,i} f_i = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \qquad (7)$$

Where, $\overline{w}_i$ is the normalized firing-strength of layer 3, and p, q, r are parameter-sets and f_i is the fuzzy rules.

The output layer is the fifth-layer. It has a single node which sum the signals from previous layers to give the output.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} = f_{out} \qquad (8)$$

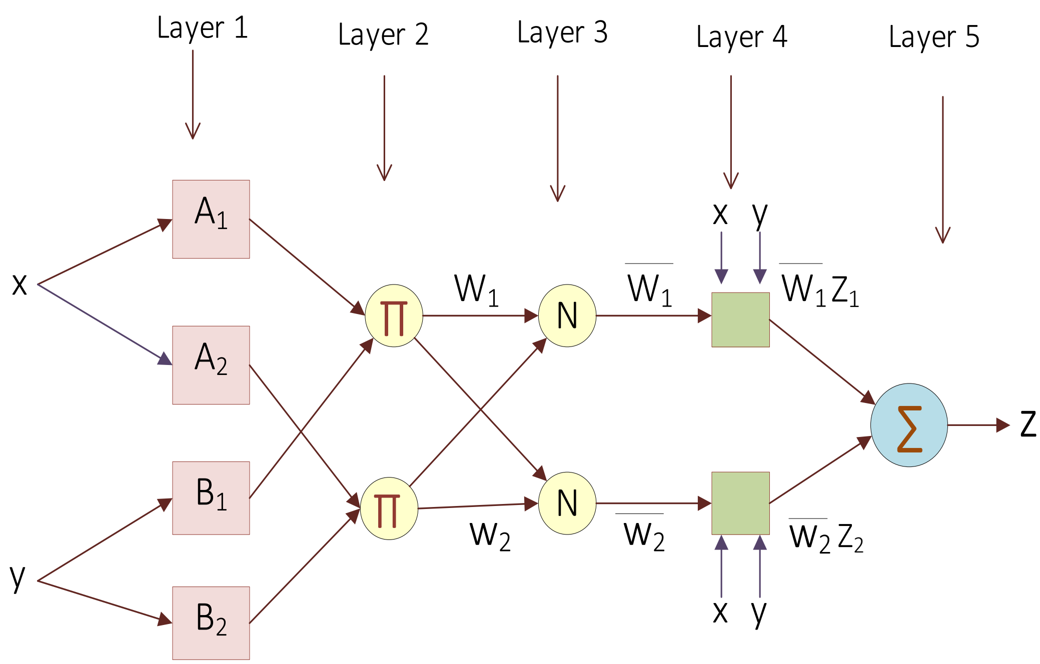


Figure 3 ANFIS architecture with two rules and two inputs

2.4 Clustering techniques

Clustering is an important task in data-mining and statistical analysis which involves grouping of data-sets into groups and assigning them into a cluster, such that object in one cluster is different from another cluster. Clustering-techniques are used in ANFIS for grouping data into similar fuzzy-cluster to assign MF and generate the FIS structure from the data (Adedeji et al. 2020). The common clustering-techniques in ANFIS are; Grid-partitioning (GP), Fuzzy C-means (FCM) and subtractive-clustering (SC).

2.4.1 Grid-Partitioning

This technique clusters by diving the input-space into rectangular subspaces using some local fuzzy regions by axis-paralleled partition based on a predefined number of MF and their types in each dimension (Wei et al. 2007). There exists an exponential relationship between the input and the number of fuzzy-rules. This implies that the number of fuzzy rules in a system with n inputs and m MF for each variable will be m^n (Wei et al. 2007), consequently, this requires a very massive memory on the computer. This is a major demerit of the GP-technique and such limitation can be termed curse-dimensionality (Adedeji et al. 2020). The size of the input affects the performance of the system, hence an adaptive-GP can be used to optimize the size and location of the fuzzy grid-regions (Benmouiza & Cheknane 2019).

2.4.2 Subtractive-Clustering

This technique works based on the assumption that each data-point is a potential cluster-center and computes the probability that each data point will establish a cluster-center, depending on the density of the surrounding data point. Given a n data points in a M dimensional-space and assuming that the data-point has been normalized in each dimension, the potential P_i of data-point x_i is given by equation 9

$$P_i = \sum_{j=1}^{n} e^{-\alpha\|x_i - x_j\|^2} \tag{9}$$

Where α = Euclidean distance and $\alpha = {}^{4}/_{{r_a}^2}$, $\left\|x_i - x_j\right\|^2$, r_a is a positive-constant which is a radius that determines the neighbouring data-point. Therefore Potential for a data-point depends on the distance to other data-point. It is important to select carefully, radius for clustering the data space as it decides the number of cluster$s$. The SC-algorithms performance is affected by different parameters such as cluster-radius, squash factors, accept and reject ratio (Adedeji et al. 2020)

2.4.3 Fuzzy C-means clustering

FCM clustering-technique enables a piece of data to belong to two or more clusters by minimizing objective-function based on the assumption that the number of clusters is known or fixed (Benmouiza & Cheknane, 2019). A major merit of FCM is that a partial membership of an object to different groups is permitted instead of belonging entirely to a single group (Abdulshahed et al. 2015). FCM is preferred when speed is a priority because it improves the speed of the algorithm (Mustapha et al. 2016). The FCM aims at minimizing the distance between the data-center to each data-point by the objective function in equation 10.

$$E = \sum_{i=1}^{N} \sum_{j=1}^{C} {U_{ij}}^{m} \left\| x_i - c_j \right\|^2 \qquad (10)$$

Where $m =$ Fuzzier i.e. any real number greater than one $(1 \leq m \leq \infty)$

$U_{ij} =$ Degree of membership, $U_{ij} \in (0,1)$

$x_i =$ Data-points

$c_j =$ Centroid of clusters

C = Number of clusters.

The degree of membership of the data point x_i in j cluster at any iteration is given by equation 11

$$U_{ij} = \left(\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_j \right\|} \right)^{\frac{2}{m-1}} \right)^{-1} \qquad (11)$$

2.5 Building the ANFIS model

ANFIS model developed in this study was computed on MATLAB (R2015a) installed on a computing-device with 64bits, 4GB ram Intel(R) Core(TM)i3 configuration. The process flow-chart in Figure 3 represents the processes followed to build an optimal ANFIS model. The resulting ANFIS models using the three techniques then becomes ANFIS-FCM, which uses the FCM-clustering technique, ANFIS-GP, which uses the GP-clustering technique, and the ANFIS-SC, which uses the SC-clustering technique. The data-set was divided into two; 70% of the data was used for training the model and 30% was used to test the model's performance.

Sub-models were developed through several stimulations of some of the model parameters in each of the clustering-techniques studied. Sub-models developed using the GP-method used eight different input MF-types. Since a sugeno-FIS structure is used, only one output is involved. Each input MF-type was tested with the two output MF-type namely: linear and constant, but the best was reported in each case. Two input MF for all input parameters were tested in all the sub-models, this is due to the large-memory requirement of a higher number of rules consequent upon the choice of higher input MF. Parameters specified in the ANFIS-GP model are presented in Table 5

The cluster-radius (CR) is a vector which specifies a cluster center's range of influence in each of the data-dimensions. Sub-models developed using SC-techniques used tested ranges of CR between 0.2 and 0.5 (recommended by Mathwork Inc.) in an incremental step of 0.05. Each sub-models tested ranges of squash-factors (SF) between 1.2 and 1.4. Default values of accept-ratio and reject-ratio presented in Table 5 were used, this is because variation in these values had no significant impact on the model outcomes. The rule-extraction method assigns a default gauss and linear MF for the input and output respectively.

The FCM-techniques tested different number of clusters. The number of clusters consequently specifies the number of rules and MF. Other parameters specified for the ANFIS-FCM are presented in Table 5. The training-data was normalized before building the model using equation 12 to ensure that it falls in the same range.

$$y_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{12}$$

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

Table 5 Parameters specification in all clustering-techniques

ANFIS-GP		ANFIS-FCM		ANFIS-SC	
Parameters	Value/range of values	Parameters	Value/range of values	Parameters	Value/range of values
Number of input MF	2	Number of clusters	2 – 9	Cluster radius	0.2 – 0.5
Number of rules	8	Number of exponent for partitioning matrix	2	Squash factors	1.2 – 1.4
Input MF-type	tri, gauss, gauss2, psig, dsig, trap, gbell and pi	Maximum iteration	50	Accept ratio	0.5
Output MF-type	Linear, constant	Minimum improvement	1e-5	Reject ratio	0.15

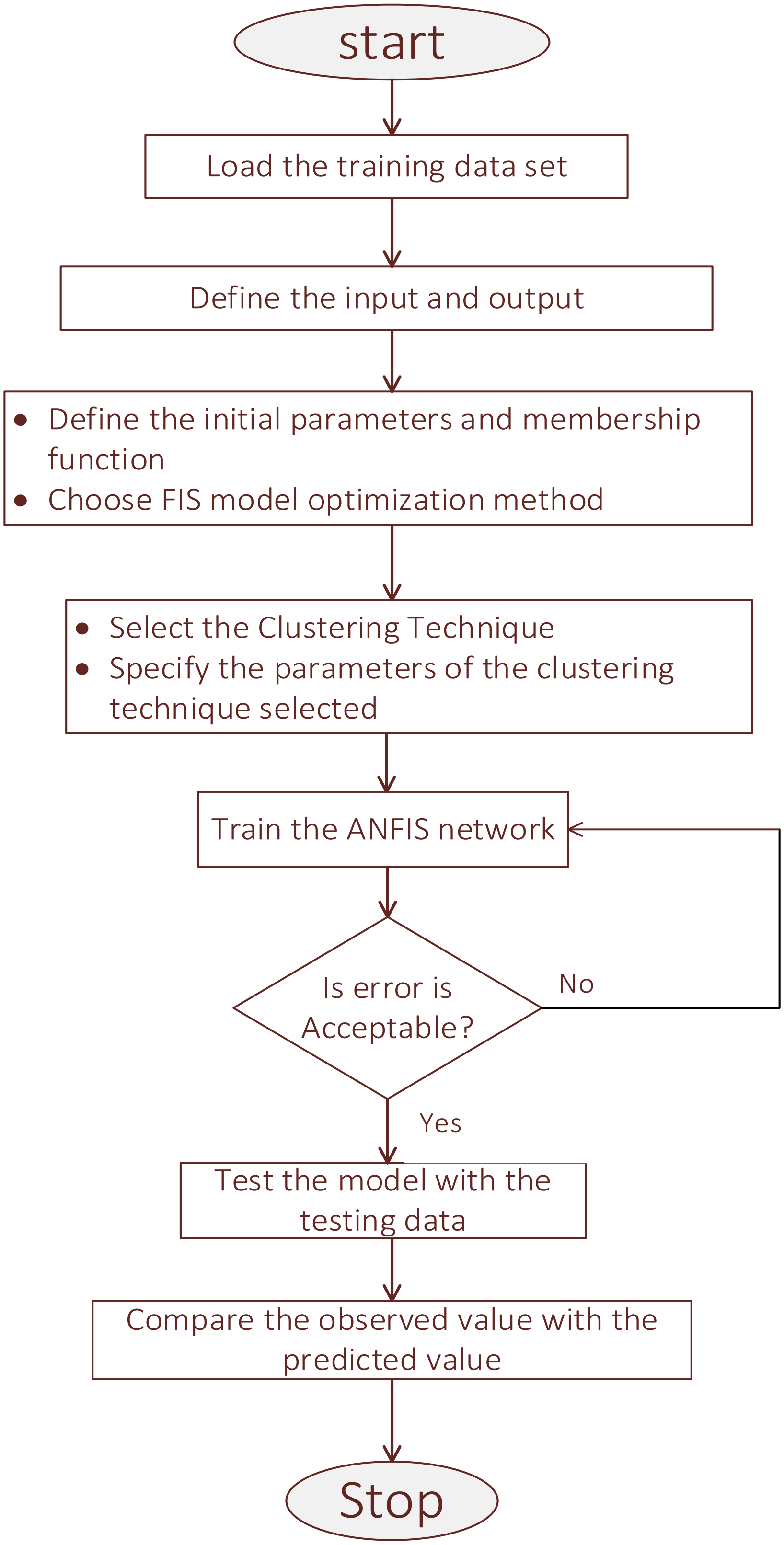


Figure 4 Process flowchart for building the ANFIS model

2.6 Performance Evaluation

An integral part of this study is the model evaluation. Statistical-indicators are used to evaluate the fitness between the model and the data. The following performance-metrics, Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE) and Correlation Co-efficient (R^2) represented in equations 12-15 are used to evaluate the accuracy of all sub-models developed in this study and to select the optimal-model

$$RMSE = \left(\sum_{i=1}^{N} \frac{(P_i - O_i)^2}{N}\right)^{1/2} \tag{12}$$

$$MAD = \sum_{i=1}^{N} \frac{(O_i - P_i)}{N} \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left|\frac{O_i - P_i}{O_i}\right| \times 100\% \tag{14}$$

$$R^2 = \left[\frac{\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}}(O_i - \bar{O})^{\mathbf{2}} \times \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}}(P_i - \bar{P})^{\mathbf{2}}}}\right]^{\mathbf{2}} \tag{15}$$

Where i = sample index, N=number of samples, P_i = Predicted waste generation value for the i^{th} sample and O_i = Observed waste generation for the i^{th} sample, $\bar{O}$ and $\bar{P}$ are observed and predicted average value respectively.

3. Results and Discussion

The capability, eligibility and accuracy of the developed model with each clustering-techniques using the 30% hold-out data were evaluated using the statistical-metrics values previously described. The results based on clustering parameters and its effects on the model's performance are briefly discussed. The performance result of the ANFIS-GP sub-models are presented in Table 6 in the order of their increasing performance results. Table 7 presents the performance-metrics of ANFIS-SC sub-models developed using parameters of the SC-clustering. Table 8 presents the result of the ANFIS-FCM sub-models in order in their increasing performance accuracy

Table 6 ANFIS-GP Model features and performance-metrics

Sub-models	Input MF-type	Output MF-type		Performance-metrics				
				MAPE	MAD	RMSE	R^2	CT
ANFIS-GP1	tri-MF	linear	Training	9.735	0.189	0.279	0.945	3.37
			Testing	12.673	0.694	1.237	0.939	
ANFIS-GP2	guass2-MF	constant	Training	10.596	0.158	0.242	0.914	3.94
			Testing	19.085	1.015	1.708	0.904	
ANFIS-GP3	Psig-MF	linear	Training	14.209	0.177	0.271	0.911	3.64
			Testing	15.226	0.939	1.788	0.893	
ANFIS-GP4	gauss-MF	constant	Training	12.608	0.198	0.276	0.898	4.58
			Testing	18.028	1.736	3.478	0.861	
ANFIS-GP5	dsig-MF	constant	Training	14.223	0.177	0.271	0.901	3.91
			Testing	15.291	0.955	1.832	0.855	
ANFIS-GP6	gbell-MF	constant	Training	14.887	0.212	0.293	0.880	3.71
			Testing	17.013	1.104	2.308	0.842	

ANFIS-GP7	pi-MF	linear	Training	29.824	0.379	0.544	0.874	3.14
			Testing	38.220	1.578	2.588	0.839	
ANFIS-GP8	trap-MF	linear	Training	29.627	0.373	0.542	0.852	2.99
			Testing	46.068	2.982	8.195	0.798	

Table 7 ANFIS-SC Sub-model features and performance-metrics

Sub-models	CR	SF		Performance-metrics				
				MAPE	MAD	RMSE	R^2	CT
ANFIS-SC1	0.20	1.2	Training	14.736	0.236	0.325	0.863	2.64
			Testing	23.444	1.933	2.430	0.823	
ANFIS-SC2	0.25	1.4	Training	15.639	0.285	0.384	0.845	2.56
			Testing	28.432	2.365	2.658	0.779	
ANFIS-SC3	0.30	1.3	Training	14.059	0.189	0.294	0.894	2.55
			Testing	19.452	1.886	1.835	0.864	
ANFIS-SC4	0.35	1.2	Training	17.328	0.281	0.414	0.865	2.53
			Testing	25.476	3.147	2.775	0.843	
ANFIS-SC5	0.40	1.3	Training	18.463	0.312	0.408	0.823	2.55
			Testing	26.535	3.246	2.738	0.793	
ANFIS-SC6	0.45	1.4	Training	23.305	0.351	0.524	0.806	2.61
			Testing	29.617	3.326	4.144	0.784	
ANFIS-SC7	0.50	1.2	Training	28.458	0.415	0.544	0.814	2.49
			Testing	35.168	3.533	6.305	0.776	

Table 8 ANFIS-FCM Sub-model features and performance-metrics

Sub-models	Number of clusters		Performance-metrics				
			MAPE	MAD	RMSE	R^2	CT
ANFIS-FCM1	2	Training	50.091	1.135	1.423	0.833	2.47
		Testing	57.697	1.616	1.621	0.809	
ANFIS-FCM2	3	Training	34.953	0.683	0.887	0.840	2.43
		Testing	41.680	1.216	1.075	0.812	
ANFIS-FCM3	4	Training	31.179	0.643	0.785	0.855	2.41
		Testing	34.816	0.918	0.846	0.811	
ANFIS-FCM4	5	Training	26.969	0.489	0.674	0.863	2.48
		Testing	28.306	0.863	0.788	0.818	
ANFIS-FCM5	6	Training	23.312	0.374	0.554	0.872	2.69
		Testing	26.291	0.789	0.608	0.822	
ANFIS-FCM6	7	Training	16.512	0.312	0.468	0.880	2.45
		Testing	23.922	0.922	1.363	0.832	
ANFIS-FCM7	8	Training	12.709	0.155	0.238	0.919	2.55
		Testing	22.412	0.544	0.987	0.892	
ANFIS-FCM8	9	Training	9.506	0.127	0.189	0.935	2.55
		Testing	15.735	0.456	0.921	0.928	

3.1 Effect of clustering-parameters on models performance

The MF-type in GP-clustering are vital to fuzzy-set theory and affects the FIS. This consequently affects the accuracy and capability of the model in approximating an output (Adil et al., 2015). In this study, tri-MF is the most accurate while trap-MF is the least accurate based on

MAPE at the testing-stage. The accuracy in decreasing order are; tri-MF (87.4%), dsig-MF (84.8%), psig-MF (84.8%), gbell-MF (83%), gauss-MF (82%), guass2-MF (80.9%), pi-MF (61.8%), trap-MF (54%).

There was no significant variation in the model's performance using the linear and constant output MF-type. However, the CT was the basis for the MF presented for each sub-model in Table 6. CT is an important evaluation metrics for GP owing to the computational-intensity of the technique associated with a large rule-base thereby resulting into curse-dimensionality which consequently affect the time of computation (Adedeji et al. 2020). Based on the CT, tri-MF, trap-MF and pi-MF computed in the least time which are 3.37 secs, 3.14 secs and 2.99 secs. Gauss-MF computed in 4.58 secs being the highest, this is similar to the result of the study of Adil et al. (2015). An unexpected variation in the trend of RMSE and MAD across different parameters of GP compared with the MAPE wass observed. However, the lowest error-value was obtained with tri-MF at testing-phase ($RMSE_{tri\text{-}MF}$ =1.2372 and $MAD_{tri\text{-}MF}$ =0.6940) while trap-MF had the highest error-value ($RMSE_{trap\text{-}MF}$ =8.1952 and $MAD_{trap\text{-}MF}$ =2.9816).

It was observed that the performance of the ANFIS-FCM models improved as the number of clusters increased from 2 to 9, this might be due to the increased recovery strength of the true cluster structure at higher cluster number. This is similar to the result in the study of Wiharto & Suryani (2019). FCM clustered model with 9 clusters outperformed others ($RMSE_{cluster9}$ = 0.9207, $MAD_{cluster9}$ = 0.4563, $MAPE_{cluster9}$ = 15.7352 and $R^2_{cluster9}$ = 0.9278). No significant improvement was observed in the prediction outcome at cluster-number greater than 9. A further increase in cluster-number might result in higher uncertainty, noise and overfitting.

The variation in the values of accept ratio and reject ratio were found to have no effect on the SC-clustered model performance, therefore the default value presented in Table 5 were used for all ANFIS-SC models. Irregular trend is observed in the performance of the SC-clustered model as the CR increased from 0.2-0.5. SF between 1.2-1.4 were tested with each cluster radius while the optimal is presented. However, SC-model with the combination of CR 0.3 and SF 1.3 had the best performance (RMSE = 1.8348, MAD=1.8854, MAPE=19.4524, R^2=0.8645).

Table 9 compares the performance of the optimal sub-models in each techniques at the testing phase. ANFIS-FCM shows a lesser variability in the observed and predicted values based on RMSE and MAD values, presenting ANFIS-FCM to be more eligible to predict waste generation ($RMSE_{ANFIS\text{-}FCM8}<RMSE_{ANFIS\text{-}GP1}<RMSE_{ANFIS\text{-}SC3}$ and $MAD_{ANFIS\text{-}FCM8}<MAD_{ANFIS\text{-}GP1}<MAD_{ANFIS\text{-}SC3}$). However, ANFIS-GP1 has a more accurate fit between the observed and predicted value based on the MAPE-values ($MAPE_{ANFIS\text{-}GP1}<RMSE_{ANFIS\text{-}FCM8}<RMSE_{ANFIS\text{-}SC3}$) and produced the model with the strongest agreement between the observed and the predict values based on R^2-values.

Table 9 Comparison between the optimal sub-models in each clustering-techniques

Model	Clustering Parameters	Performance			
		MAPE	MAD	RMSE	R^2
ANFIS-GP1	tri input-MF, Linear output-MF	12.673	0.694	1.237	0.939
ANFIS-FCM8	9 clusters	15.735	0.456	0.921	0.928
ANFIS-SC3	CR=0.3, SF=1.3	19.452	1.886	1.835	0.864

3.2 Discussion

The scatter-plot of the observed against the predicted waste-quantity by the optimal sub-models developed are presented in figures 5, 6 and 7. Presented in figure 8 is the combined test-plot of the optimal ANFIS-GP1, ANFIS-SC3 and ANFIS-FCM8 predicted values. A similar trend is observed depicting a strong-agreement between the actual and predicted values of the waste quantity by the optimal ANFIS-GP, ANFIS-SC and ANFIS-FCM. The under-fitting observed at test sample 12 and 24 may be due to the model's response to unusual variation characterized by a drastic decrease in the the employment and Gross Domestic Product of some provinces at a particular year despite the increase in the waste generated.

Table 10 compares the performance result of ANFIS models in this study with the previous researches which used ANFIS to forecast waste generation. The stimulation of sub-models carried out in this study using the three clustering techniques parameters produced models with relatively better performance indicating its capability to accurately forecast waste generation in developing countries

Table 10 Comparison of performance of this study and previous studies which used ANFIS for waste generation forecast

S/N	Reference	Case study	Model	Performance metrics			
				R^2	RMSE	MAE	MAD
1	Younes et al. (2015)	Malaysia	Modified-ANFIS	0.98	3.988	0.673	-
2	Abbasi & El Hanandeh (2016)	Logan, Australia	ANFIS	0.99	0.002	0.001	-
3	Golbaz et al. (2019)	Karaji, Iran	ANFIS	0.66	-	0.005	-
4	Soni et al. (2019)	New Delhi, India	Pure ANFIS DWT-ANFIS	0.56 0.73	224.99 155.47	-	-
5	Tiwari et al. (2012)	Durg-Bhilai, India	ANFIS	0.49	2465	-	-

6	This study	South Africa	ANFIS-GP1	0.939	1.24	-	0.69
			ANFIS-SC3	0.864	1.84	-	1.89
			ANFIS-FCM8	0.928	0.92	-	0.46

Gauteng province generated the highest quantity of waste in 2016 while Northern Cape Province which generated the lowest quantity of waste. Using predicted value of the influencing factors for a medium-term prediction of waste quantity, Gauteng province and Northern cape province still remain the highest and lowest waste generator respectively. It has been observed that KwaZulu-Natal province is a relatively highly populated province, however a lower waste quantity is generated. This could be attributed to the economic level of the province compared to other provinces which is also depicted in the provincial waste generation rate presented in figure 2. Because of the increase in the rate of urbanization and migration to the urban areas which would consequently alter the trend in the population and economic level differently from what is experienced currently, significant variations would be observed in the trend of the waste generation patterns at some provinces.

The increase in the population of the high income provinces such as the Gauteng and Western Cape Province that might be experienced due to rural-urban migration will bring about an increase in the usual trend of waste generated. The relationship between the influencing factors of waste and waste quantity has been expressed in this study. These factors have been predicted to increase across all provinces in the next decade, hence the consequent increase in waste quantity over the same period indicates a direct relationship between these factors and waste generated.

The laudable outcomes of the ANFIS model used in this study has presented it as a useful tool to waste management sector in South Africa and other developing countries to make a waste-related decisions and planning such as allocation of resources, treatment and recovery facilities, strategizing collection and disposal of waste. Also the study will be of immense help to the South Africa Waste Information Centre (SAWIC) which manages the waste national waste database.

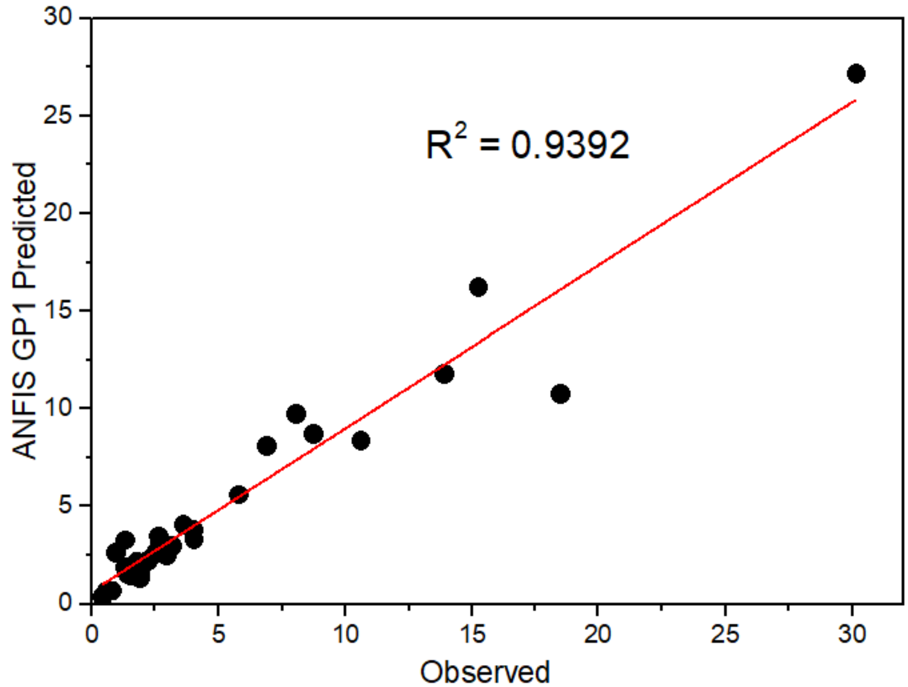


Figure 5 Observed against optimal ANFIS-GP predicted waste quantity

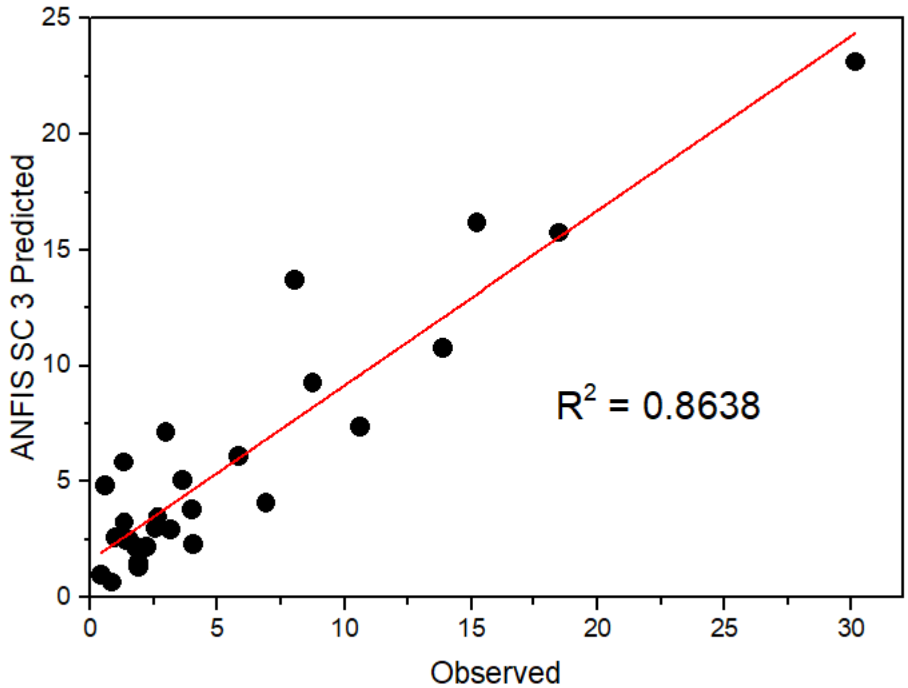


Figure 6 Observed against optimal ANFIS-SC predicted waste quantity

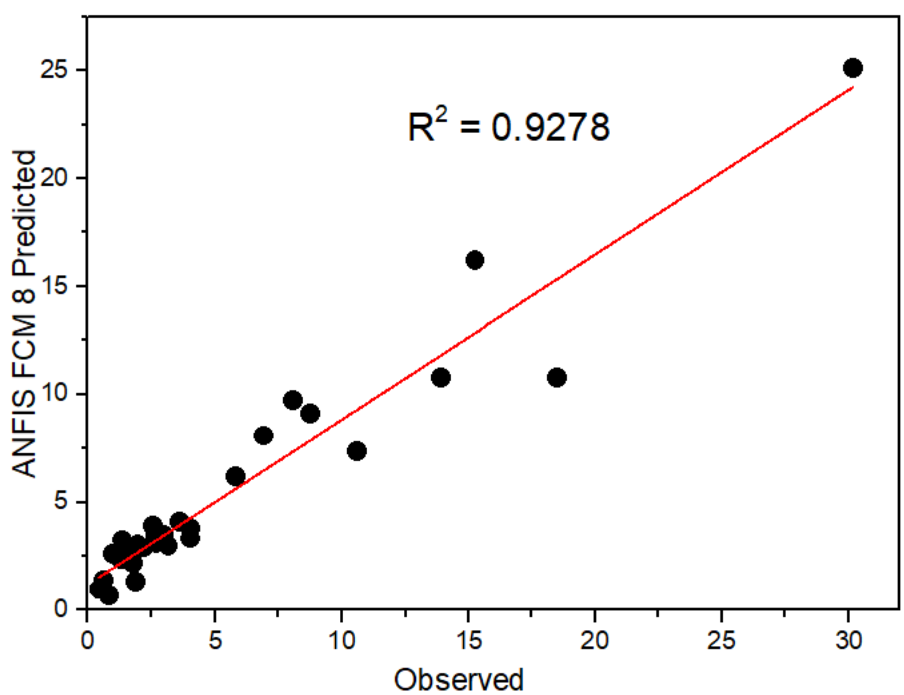


Figure 7 Observed against optimal ANFIS-FCM predicted waste quantity

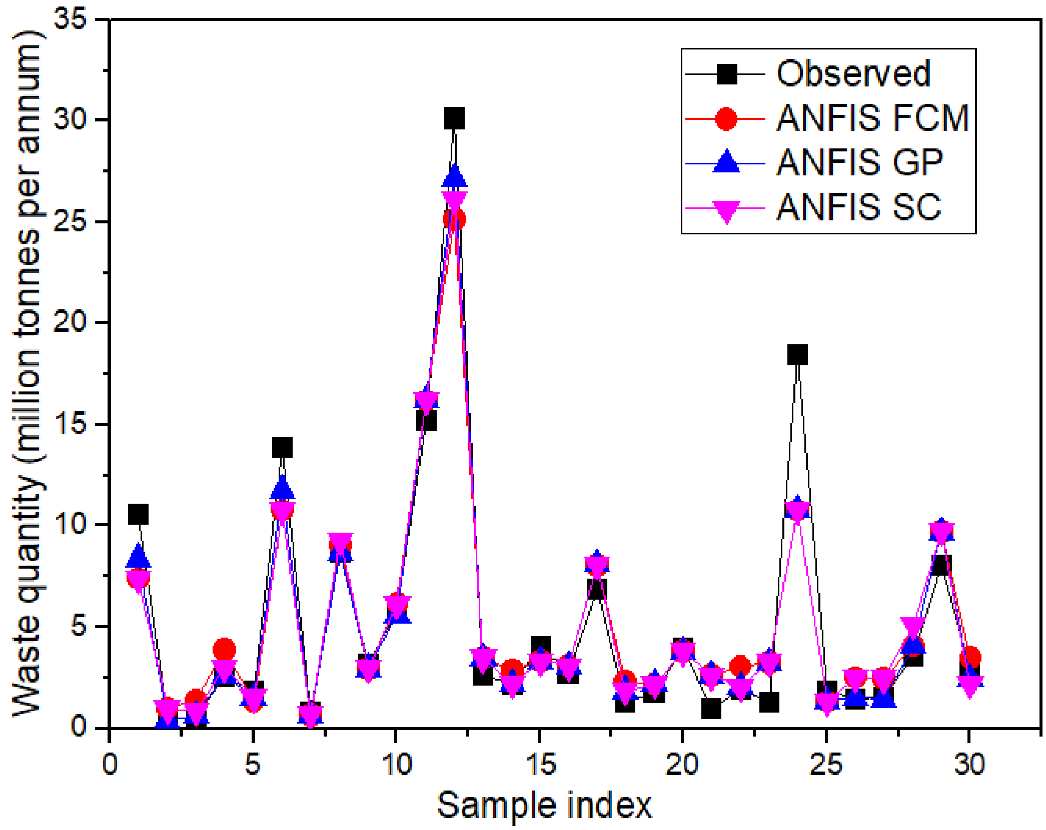


Figure 8 Combined test plot of all optimal sub-models with the observed value

4. Conclusion

A comparative study of the performance of clustering-techniques of ANFIS model in predicting provincial waste generation was carried out in this study. We studied the influence of the choice of different parameters of the three clustering-techniques, GP, SC and FCM on the outcomes of the ANFIS model in waste generation forecast in South Africa using provincial socio-economic and demographic dataset. The accuracy of all sub-models stimulated were evaluated using the statistical-metrics, all the sub-models gave a laudable prediction outcomes, and then the optimal-model was selected. The sub-models with the best performance outcomes using the GP, SC and FCM clustering-techniques are ANFIS-GP1, ANFIS-SC3 and ANFIS-FCM8 with R^2-values of 0.9392, 0.8638 and 0.9278 respectively at the testing-phase. The ANFIS-GP1 which was tested with a triangular input MF-type outperformed others and was selected as the optimal model with MAPE, MAD, RMSE and R^2-values of 12.6727, 0.6940, 1.2372 and 0.9392 respectively. Based on the result in this study, ANFIS-GP with a triangular MF is recommended for modelling waste generation

Sustainable waste-management is contingent on reliable information of waste volumes and composition. The model presented in this study will help to combat the challenge of limited and inaccurate data of waste generation in South Africa. It can be utilized for the national repository of waste related data by the South Waste Information Centre (SAWIC) for accurate and reliable publications of annual waste generation at South Africa provinces. This study is generally useful to waste management planners and policy makers to assist with effective waste management planning for allocating resources and facilities especially at regions where waste data are not available or scarce in developing countries.

This study recommends the use of Hybrid ANFIS model with Particle Swamp Optimization (PSO) and Genetic Algorithm (GA) to increase the accuracy of the ANFIS model to predict waste quantity in South Africa in future research

Declaration of Conflicting Interest

The authors declare that there is no potential conflict of interest

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