

Comparative Analysis of Artificial Intelligence Algorithms for Solid Waste Volume Prediction in Support of SISWMS Design

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Abstract

Planning and designing a Sustainable Integrated Solid Waste Management System (SISWMS), as well as the decision on treatment technique to use, management policy to implement, requires an accurate and reliable forecast of the waste volume to deal with. The traditional forecasting methods, which depend solely on the demographics and socio-economic factors with few variables, can no longer handle the multifaceted and complex nature of the modern waste management system (WMS). This study mainly aims at forecasting waste volume to plan, design, and operate a SISWMS. Five artificial intelligence (AI) algorithms: Support Vector Machines (SVM), k-Nearest Neighbour (kNN), Artificial Neural Networks (ANN), Linear Regression (LR), and Adaptive Neuro Fuzzy Inference System (ANFIS) were applied on 120 months of waste data collected from Ibadan-North Local Government Area (LGA), Oyo state, South-West Nigeria. The performance of the algorithms was compared based on their respective coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Standard Error (MSE), and Mean Absolute Error (MAE). The results showed that ANFIS produced the most accurate forecast, which put the waste volume being generated in zones of Ibadan-North LGA to be 9.0947×10^4 kg/month, and by the year 2030, the peak waste volume will be 11.573×10^4 Kg/month. The results are in consonance with recent global indices and could be used as a benchmark for SISWMS and other waste management analyses.

Keywords

Artificial Intelligence, Machine Learning, Sustainable Integrated Solid Waste Management, Waste Volume Forecasting, Ibadan-North LGA

1. Introduction

Wastes are inevitable consequences of human, animal, and machine activities, which vary in size, nature, and characteristics from place to place all over the world. The amount of waste generated is never the same in different localities. Municipal Solid Waste (MSW), as well as other types of waste, differ from place to place and from country to country based on the source of generation, that is, the norm, economic status, and lifestyle of the people, as well as the physico-chemical properties of the waste [1]. The traditional waste management practices, having failed to handle the current trend, have given way to a sustainable integrated solid waste management system (SISWMS), which requires a quality prediction of waste volume for efficient design [2]. SISWMS involves the use of different waste treatment techniques, technologies, and versatile policies in waste management (WM). The planning, design, and management of SISWM have to do with many factors, like waste collection, waste treatment techniques to be used, policy to adopt, and the waste treatment technology to use (among others) [3]. There exists a complex network of interrelated functions between these factors, leading to a very complex non-linear system of operations in the waste management systems. The structure of an SISWM is presented in the figure below:

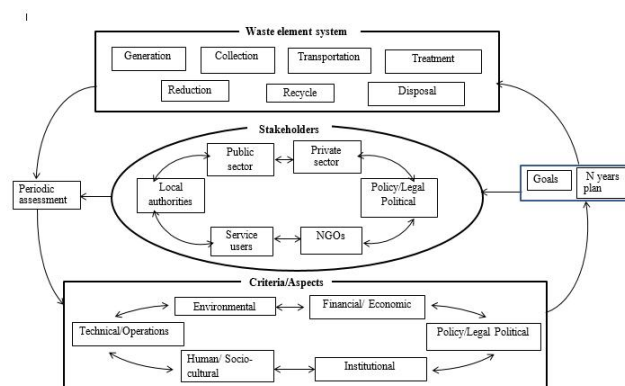


Figure 1. The Sustainable Integrated Solid Waste Management (SISWM) system

Source: Oluwanimifise and Anyaeche, 2021

The factors and variables involved in SISWM are numerous and complex to the extent that they cannot be handled without adequate knowledge of the quantity of waste in question [4]. Also, these issues can no longer be addressed with the traditional forecasting methods, which depend solely on the demographics and socio-economic factors on a per-capita basis alone [5]. These old tools and techniques cannot track and capture the trends in ever-dynamic factors involved in waste generation and management. Hence, data-driven model development for qualitative prediction of waste volume would be useful to enhance an SISWM system [6].

The WM literatures are inundated with many traditional forecasting models like the geometric average method, least square regression, curve extension, and saturation curve method, to mention a few [7]. These models lack the required flexibility to consider some inherent and germane factors in waste management practices. It is noteworthy that it is not possible to consider all the factors involved in waste generation (WG) and/or solid waste management (SWM), as that will require a large number of samples, which will involve a high cost. These facts necessitate the need for techniques or methods that can relate the input to the output, learn (or capture) the trend, to use it to make a meaningful forecast or predict the future values [8]. Artificial intelligence (AI) is a proven method that has shown superiority over the conventional traditional models, which rely heavily on probability and statistics alone [9]. AI entails the use of computers to mimic the human brain to perform a range of tasks and solve numerous life problems [10]. It replicates the structures and functions of the human brain using the graphic-based or data-based methods. AI, through one of its subsets-Machine Learning (ML), enables it to model non-linear complex systems like WG and SWM systems. ML is the science (and art) of programming computers so that they can learn from the data [11-12]. ML uses statistical models and algorithms to learn from data and perform tasks like predictions and classifications without explicit instructions [13]. There is a stream of literature about the linear regression machine learning algorithm being used to forecast waste volume generated [14]. Linear regression models the relationship between input(s) and output(s) variables by fitting a linear equation between the observed data. These variables are the dependent and the independent variables. Data visualization is first carried out on both the dependent and the independent variables to check whether there exist a relationship exists between them. The measurement of the relationship between two variables is the correlation coefficient, which ranges between 1 and -1.

ANN is a ML algorithm that is widely used in WM [15]. It comprises multiple layers of neurons that receive signals from the preceding neuron, process them, and pass them forward to the next neuron, with every link between any two neurons attached to an associated weight. These weights during the training are updated until a desired goal is reached using different algorithms available. The back-propagation algorithm trains the network by assigning the weights randomly. ANNs are updated on the basis of the error between the final output and the desired output. ANN models are data-driven models which can model complex and non-linear events like waste generation and management, and thus have been used severally with success to predict waste generation rates and waste volume. This work will apply each of the five machine learning algorithms mentioned above to the empirical data obtained from the location of the study to develop a model that could be used for the waste volume forecast. The models will be compared based on their performance metrics, and the best of the models will be used to forecast the average waste volume generation in the zones of the study area. Section 2 describes the algorithms used in the research. Section 3 presents the theory of the development of the algorithms used in the research work. Section 4 presents the results and the illustration, as well as the comparison of the work with previous studies to enable replicability, so as to boost subsequent research work in the field of solid waste management. The last section 5, presents the main conclusion and areas for future work.

2. Artificial Intelligence Application to Waste Management

The use of sophisticated AI forecasting systems has outperformed traditional models in waste management research and engineering problems [16-17]. Current research works in various aspects of waste management problems have demonstrated the use of AI algorithms to overcome the challenges of non-linearity in the historical data [18]. The choice of the best approach in any instance and in a particular place is a function of many factors, like the aim of the modelling, socio-economic factors, waste type, and composition. Hence, making a correct choice with the use of a correct training algorithm will enhance the development of a SISWM that fits the locality with its peculiarity. The application of various algorithms like LR, ANN, KNN, SVM, and ANFIS in the field of waste management is briefly discussed in this section.

2.1 The LR

Linear regression machine learning algorithm provides a check about the data properties apart from fitting the data to the model. The relationships, like the correlation, collinearity, errors, and residuals, as well as some statistical testing parameters of the predictors and explanatory variables, are easily obtained. In the real world of waste management, the relationships between the various interconnected factors are not linear. Also, with the present advances in AI, it is not to be used in isolation but in combination with other algorithms so as to compare the performance parameters as a form of checks and balances [19].

2.2 The ANN

ANN is a cellular information processing system designed and developed by mimicking the human brain and its neural system. One of the most significant and beneficial features of ANN in forecasting is its learning ability. ANN can construct a complex non-linear system through a set of inputs/outputs. The non-linear nature of waste management

problems makes ANN a vital and suitable tool to forecast MSW generation. Also, since the waste management operations and practices involve complex and complicated analysis, which changes over time in an unsuitable manner and rate, it will take the learning ability of ANN to obtain an accurate forecast of such trends [20].

2.3 The k-NN

Because of its ease of use and intuitiveness, kNN is frequently utilized for regression and classification. The idea behind using kNN to univariate time series is that regular data generation procedures frequently yield observations of recurring behavioral patterns. [21] states that once a prior pattern that is comparable to the present pattern of behavior of the time series is established, the behavior of that pattern can provide useful information to anticipate the behavior of the immediate future pattern. The objective variable in a time series forecasting issue is displayed as an interval scale value sequence. The technique discovers the k closest historical patterns and combines them with a pattern whose future value has to be forecasted.

2.4 The SVM

One type of neural network algorithm is SVM. Maximum margin classifiers, such as SVMs, look for a maximum margin hyperplane that is the closest network algorithm. One kind of maximum margin classifier that looks for the best line across the data is the support vector machine (SVM). According to [22-23], the training instances that are closest to the greatest margin hyperplane are referred to as support vectors, and the hyperplane that is thus created is known as the optimal separating hyperplane. SVM applies the structural risk minimization concept, whereas the majority of the traditional neural network models apply the empirical risk minimization principle. The neural network model seeks to minimize the misclassification error or deviation from the training data solution, whereas the SVM seeks to lower an upper bound on the generalization error. Studies have shown that SVM is most suitable in the prediction of MSW generation on a short term and that robustness and accuracy of SVM are optimized using wavelet transform of its inputs [24].

2.5 The ANFIS

ANFIS is a data-driven model modeling technique that uses fuzzy logic and an ANN. Antecedent and conclusion, the two components of ANFIS, are linked to one another via fuzzy rules based on the network form. Earlier research works have attempted to use ANFIS to forecast waste volume [25-27]. Some of those previous works compare the forecasting ability of ANFIS with SVM, ANN, and other algorithms. It was submitted that ANFIS can predict the volume of waste generated, even with a few data still, it is more reliable than ANN, SVM, and others in its ability to forecast MSW.

2.6 Waste Volume Forecasting Using AI Algorithms

Waste volume forecasting could be grouped into 3 groups based on the length of time involved in the forecasting period. These are: short-term forecasting, which often spans days to a few months; short-term forecasting, which usually spans a few months, and long-term forecasting, which spans more than 5 Below are a few of the recent studies about waste volume forecasting with the algorithms used and period of forecasting:

Table 1. Studies on waste volume forecast with their period and algorithms

Period	Algorithm	Data size	Disadvantage	References
Short term	ANN, LSTM	Not available	Choose only ANN as the ML algorithm	[28]
Mid term	ANN, SVM, ANFIS	252	Accuracy not high	[29]
	ANN	171,130,48(for different regions)	Not compared with any other algorithm	[18]
Long term	ANN, SVM	30	Susceptible to overfitting	[24]
	ANFIS-PSO	Not available	Susceptible to overfitting	[19]

3. Materials and Methods

3.1 Preprocessing of the Data

The data for waste generated from Ibadan-North LGA between the years 2014-2023 (10 years, 120 months) was collected and used in this study. Raw Time-series data from the field are non-stationary, that is, the mean, variance, and correlation coefficient change over time. Time series data can be decomposed into trend (which changes the mean), seasonal component (which changes periodically), and the random component on which the prediction is based. The trend and the seasonal component are removed through standardization before feeding the data into the networks(to make the data stationary), and then added to the predicted residual after training to obtain real values. Equation (1) is used to normalize the data [30-31].

$$N = 0.8 \times \frac{(X_i - MIN_{xi})}{(MAX_{xi} - MIN_{xi})} + 0.1 \quad (1)$$

3.2 Theory and Development of Linear Regression

Linear regression is used to fit the relationship between two or more variables, known as the predictor and explanatory variables. The mathematical equation of linear regression is given as :

$$Y = \alpha + \beta X \quad (2)$$

Where α is the intercept, β is the slope, Y is the dependent and X is the independent variable. For the accuracy of the model, the least squares error is obtained by finding the optimum parameter values of b that minimize the sum of squares (SSE). The residuals (r_i) which is the square of the sum of the actual minus the predicted values. The residual is represented mathematically as :

$$r_i = y_i - f(x_i, \beta) \quad (3)$$

The SSE is mathematically represented as:

$$SSE = \sum_{i=1}^n r_i^2 \quad (4)$$

3.3 The ANN Development

The literature on waste volume forecasting is a field with different approaches using ANN with various algorithms [32-35]. In this work, a feedforward neural network is constructed having one input layer, a hidden layer with 12 neurons, and one layer in output layer. The output layer is made up of all the neurons connected to all the neurons in the layer below it, with the weight coefficient W_{ij} characterizing the connections between the i th and j th neurons. Equations (5) and (6) yield the output value of x_i given as:

$$X_i = f(\eta_i) \quad (5)$$

$$\eta_i = \sum W_{ij} X_j \quad (6)$$

The function $f(\eta_i)$ is referred to as the transfer function; I th neuron's potential is represented by η_i .

$$f(\eta) = \frac{1}{(1 + \exp^{-f(\eta)})} \quad (7)$$

Reducing the total squared deviations between the output value (X_{or}) and the computed value (X_o), the weight coefficient, W_{ij} is obtained. The objective function denoted by E is given as:

$$E = \frac{1}{2(X_o - X_{or})^2} \quad (8)$$

Using a method that uses backpropagation to change the weight coefficients, the result is:

$$W_{ij}^{(k+1)} = W_{ij}^{(k)} - \tau \left(\frac{\partial E}{\partial W_{ij}} \right)^{(k)} \quad (9)$$

Where τ Is the pace of learning, the training mode runs iteratively, starting with random weight values. The major model's challenge is figuring out the optimal number of hidden units required for the best performance. The trial-and-error method, which is typically employed in the literature, is applied in the examination of this study. The training architecture in MATLAB is presented in the figure below:

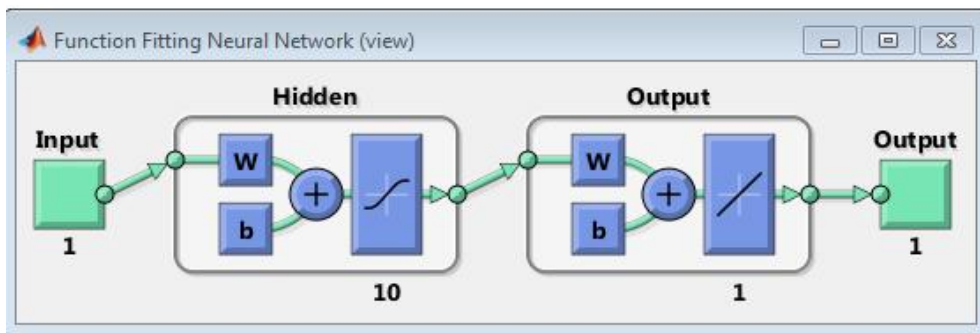


Figure 2. The ANN architecture

3.4 The KNN Development

Being a non-parametric method, KNN involves the placement of a new observation into a class of learning set observations that, with relation to the utilized variables, is more similar to the new observation in a class of observations

[18,36]. For instance, let:

$$L=\{(y_i, x_i), i=1 \dots n_L\} \quad (10)$$

Be a training or learning set of the observed data in which the predictor values are represented by the vector x_i ($x_1 \dots x_{ip}$) and class membership is indicated by $y_i \in (1 \dots c)$. The arbitrary distance function $D(x, x_i)$ serves as the basis for determining who the closest neighbors are. Subsequently, for a new observation (y, x) , the closest neighbor $(y(i), x(i))$ in the learning set is found using the formulas:

$$D(x, x_i) = \min(D(x, x_i)) \quad (11)$$

Where $\hat{y} = y_{(1)}$ It is in the class of closet neighbor selected for the prediction of y , also, the j th closest members of set y are $y(j)$ and $x(j)$ for set x . The user-specific parameters for the weighted include the weights applied to the closest neighbor and their number. The Gaussian kernel method is used in this work to determine the control parameter, K .

3.5 The SVM Development

The ε -type support vector regression approach was employed to forecast in [24]. Quantifying the functional dependency of the dependent variable y on a collection of independent variables x is done using a deterministic function $f(x)$ ($f(x) = w^T \cdot k(x) + b$) plus the addition of some noise ($y = f(x) + \text{noise}$). Usually, the error term (ε) may be used to define the noise. A sample set must be used to evaluate the SVM model to determine the functional form for $f(x)$. This procedure entails the sequential optimization of an error function. Next, the error function is minimized to determine w and b , subjecting (Eqn.(12)) to Eqn. (13)

$$C \sum_{i=1}^N \xi_i + C \sum_{i=1}^N \xi_i^* + \frac{1}{2} W^T W \quad (12)$$

$$W^T \cdot \phi(X_i) + b - y_i \leq \varepsilon + \xi_i^*$$

$$y_i - W^T \cdot \phi(X_i) - b \leq \varepsilon + \xi_i$$

$$\xi_i, \xi_i^* \geq 0, i=1 \dots N \quad (13)$$

Subject to an error term, the slack variables ξ_i and ξ_i^* define the upper and lower training error, ϕ is a collection of non-linear transformations, c is a positive constant, and N is the sample size. The majority of data instances in the regression issue should fall inside the ε -tube; otherwise, ξ_i and ξ_i^* errors will occur. By reducing the regularization term ($\frac{1}{2} w^T \cdot w$) and the training error term ($C \sum_{i=1}^N \xi_i + C \sum_{i=1}^N \xi_i^*$) in Equation (10), SVM eliminates under-fitting and overfitting issues. Equation (15) may be used to solve the optimization issue by maximizing the quadratic programming approach, then, Equation (14) is subject to the introduction of a dual pair of Lagrange multipliers, namely α_1 and α_2

$$\sum_{i=1}^N y_i (\alpha_i - \alpha_i^*) - \varepsilon \sum_{i=1}^N (\alpha_i - \alpha_i^*) - 0.5 \sum_{i=1}^N (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) \phi(x_i)^T \cdot \phi(x_j) \quad (14)$$

$$\sum_{i=1}^N y_i (\alpha_i - \alpha_i^*) = 0 \quad 0 \leq \alpha_i \leq C \quad (15)$$

$$0 \leq \alpha_i^* \leq c \quad i=1, 2, \dots, N$$

Equation (14) mentions an objective function that is convex and has a unique and optimal solution. Karush Kuhn Tucker complementarity condition may be applied to determine the support vector regression function's w and b parameters once a Lagrange multiplier in equation (14) has been determined [23], where $W = \sum_{i=1}^N (\alpha_i - \alpha_i^*) \phi(x_i)$. Hence, the support vector regression function is given as:

$$f(x) = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(x, x_i) + b \quad (16)$$

Corresponding kernel function k given as:

$$K(x_i, x) = \phi(x_i)^T \cdot \phi(x) \quad (17)$$

Any symmetric function that satisfies Mercer's criterion can be a kernel. It is possible to create many SVM types by using different kernels. The following are typical cases [24,29]:

- The kernels of polynomials $k(x \text{ and } x_i) = [x \cdot x + 1]^a$
- The kernel of Radial Basis Function (RBF) $K(x \text{ and } x_i) = \exp(-\gamma \|x - x_i\|^2)$
- The Linear Kernel $K(x, x_i)$ which is defined as (x, x_i)

When each training input is represented by x and the unlabeled input by x_i , where α and γ stand for the kernels' parameters and the constants, respectively. The Gaussian radial basis function was used as the kernel function in this

study due to its widespread application. SVM generalization requires proper values of the meta parameters, especially the kernel parameter (γ), regularization parameter (c), and accuracy parameter (ϵ). Penalties to estimate errors, ϵ , are determined by the regularization parameter (c). The radius of the tube around the regression function is indicated by parameter ϵ . The selection of ϵ dictates the extent of faults that may be overlooked; hence, an incorrect selection will lead to issues with over-fitting or under-fitting. Ten-fold cross-validation is the most used technique in data mining and machine learning [37]. Using the two-step grid search method, this strategy has been used to find the best SVM parameters. Using c , γ , and ϵ 's set of values, a coarse grid search is conducted in the first phase; the ideal values discovered in the first phase are the focus of a tighter grid search in the second step.

3.6 The ANFIS Development

The Sugeno-Takagi method used in this work is the most popular of the ANFIS. To find the best fuzzy decision rule for a task, this work uses a feed-forward network. It creates a fuzzy inference system (FIS) with membership function parameters that may be changed using a back-propagation technique, a least-squares approach, or both, as demonstrated by [38-39]. Assuming a Gaussian membership function, which is computed as:

$$\mu_{A1}(X) = \exp[-0.5(X - C_i)^2 / \sigma_i^2] \quad (18)$$

Considering the set of parameters known as premise(antecedents) given by (σ_i, c_i) , Figure 3a below illustrates the five layers that make up the whole FIS. According to [40], there are five layers in the total system. The summary of an ANFIS with one output and two inputs(x and y), and two rules is presented below:

$$\text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1 \quad (19)$$

$$\text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2 \quad (20)$$

Fuzzy sets A_i and B_i , the training step determines the design parameters p_i , q_i , and r_i as well as the outputs f_i inside the fuzzy region delineated by the fuzzy rule. The degree to which each rule in the second layer is activated is determined by each node, after which the membership function is multiplied.

$$W_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \quad i=1,2 \quad (21)$$

Whereas μ_{B_i} indicates the membership degree of y in the B set, $\mu_{A_i}(x)$ indicates the membership degree of x in the A_i set. The ratio of a rule I 's activity degree to the total activation degree of all rules w is determined by the third layer of the i th node. W_i is the normalized membership degree of the I rule.

$$\bar{W} = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \quad (22)$$

Fourth layer calculation of the node is given by:

$$\bar{W}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (23)$$

Fifth layer node calculation for the final outputs of all nodes is given by:

$$\text{Overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (24)$$

The details of the development of ANFIS, the inputs and output relationships, the nodes, and weights are presented in [31]. The ANFIS architecture and reasoning mechanism are presented in Figures 3a and 3b below:

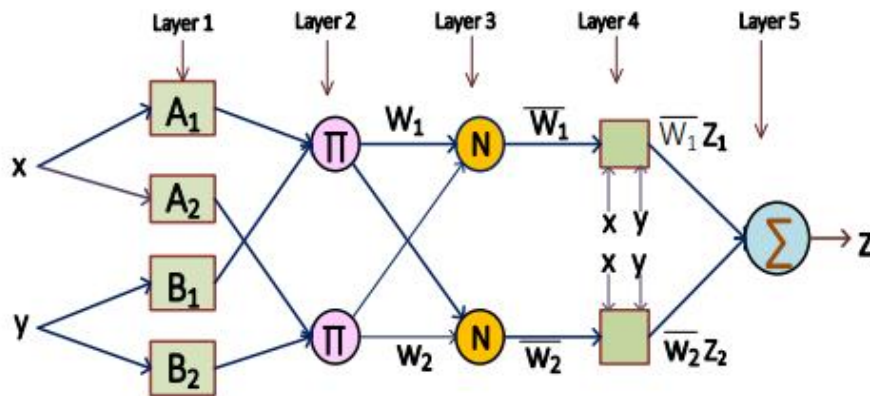


Figure 3a. The ANFIS architecture

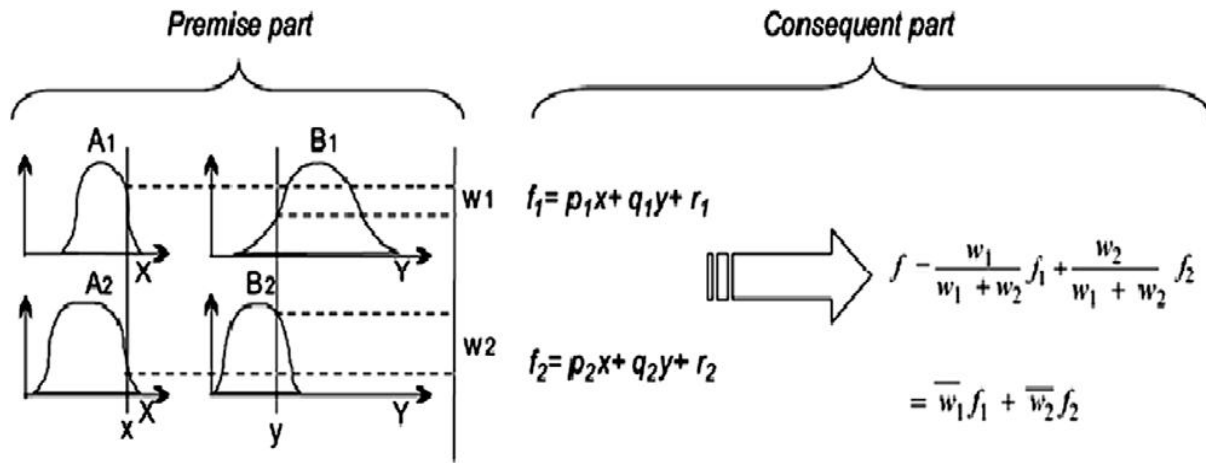


Figure 3b. Sugeno-Takagi's if-then rules and fuzzy reasoning mechanism

3.7 The Performance Evaluation of the Models

The Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Standard Error (MSE), Root Mean Standard Error (RMSE), and the coefficient of determination (R^2) are used in this work to examine the performance of each model. With n number of observations given the weight of waste generated as W and the model output as W^* , then:

$$R^2 = 1 - \frac{\sum_{i=1}^n (W_i - W_i^*)^2}{\sum_{i=1}^n (W_i - \bar{W})^2} \quad (25)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n ((W_i - W_i^*))^2 \quad (26)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (W_i - W_i^*)^2} \quad (27)$$

$$MAPF = \frac{1}{n} \sum_{i=1}^n \left| \frac{W_i - W_i^*}{W} \right| \quad (28)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |W_i - W_i^*| \quad (29)$$

3.8 The Study Area

Ibadan-North LGA, located between latitude $7^{\circ} 23'N$ and longitude $3^{\circ} 52'$ and $3^{\circ} 56'E$. It is situated within an area of 27 Km^2 with an estimated population of 622772 persons (based on the 1991 census at an annual growth rate of 2.32%). It has the largest land area among the urban LGAs. It is divided into 12 wards for easy political administration. It is the biggest Centre of commerce and economic activities apart from being the seat of state government, academic institutions (like the University of Ibadan, Polytechnic, and others), and medical institutions (University College Hospitals and others).

Ibadan-North LGA operates a variety of waste management operations between the public and private waste companies. Oyo State Waste Management Agency (OYWMA) oversees the activities of the private waste collection companies and partners with some private waste companies to operate and maintain the dumpsites located at Awotan, Lapite, and Ajakanga, since the other dumpsite is moribund already. The monthly average MSW is 294921.9kg. The waste characterization in Ibadan-North is 42% organic (food and garden) waste, 4% glass and ceramics, 5% metal, 9% plastic, 9% rubber, 2% textiles, 10% paper, 5% miscellaneous, with the rest unknown components. The data for 120 months (January 2014 to December 2023) were collected and used in the study. The graph of Ibadan-North LGA showing the wards and the waste generated areas is presented below:

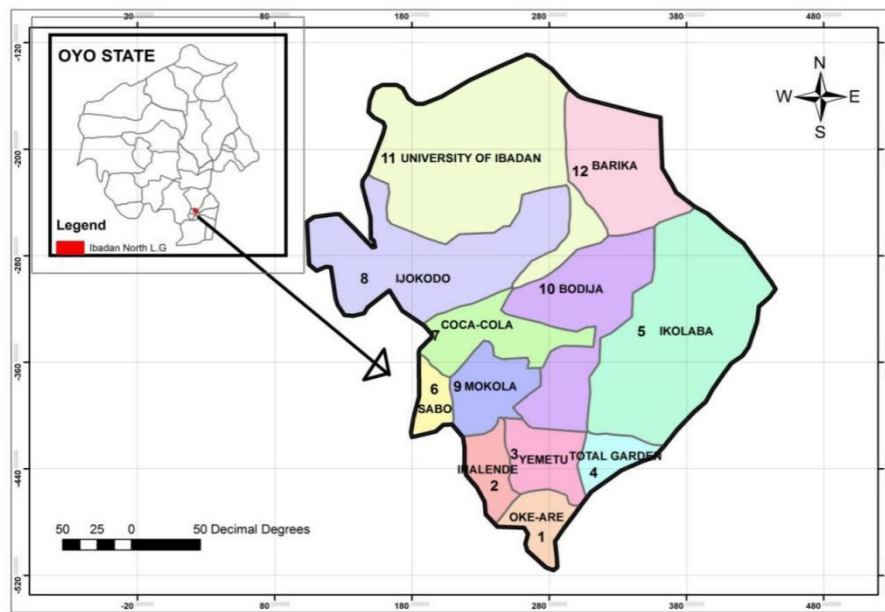


Figure 4a. Wards in Ibadan-North LGA

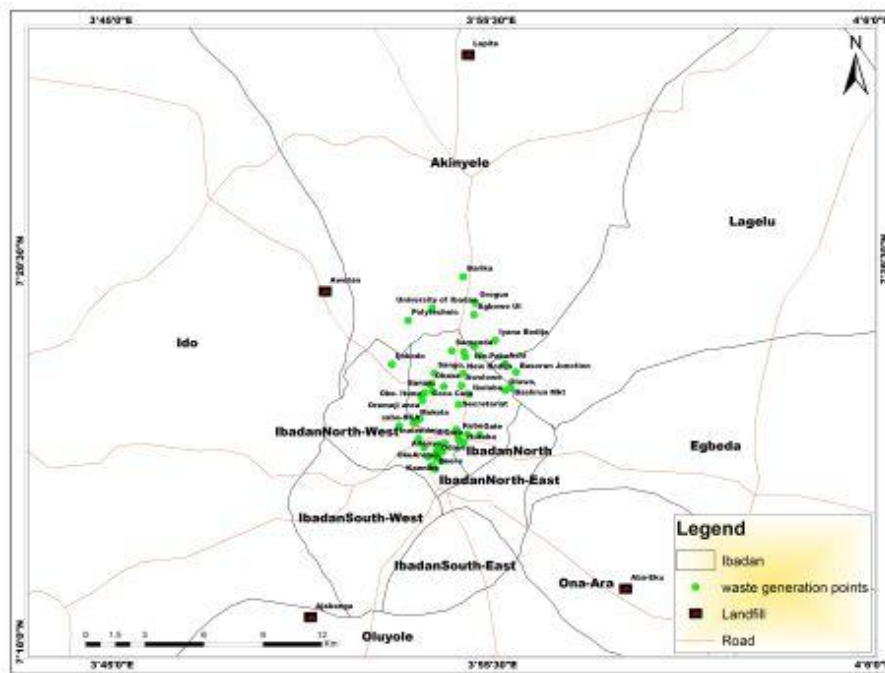


Figure 4b. The selected SISWM planning areas(waste generation sources) in Ibadan- North LGA

4. Results and Discussions

This work evaluates the performance of the trained models, having determined their respective structures. From the literature, the most current studies utilize 10% of the data for validation, 15% for testing, and 75% for training. MATLAB (version 2019a, Mat. Incorp) and the Microsoft Windows 10 operating system were used for all calculations. This structure is used for the LR model; the R^2 , MAE, MAPE, and RMSE are 0.68, 430.1, 0.058, and 0.48. The performance evaluation of the Linear Regression model is presented in the table below:

Table 2. Performance evaluation of Linear regression

Adjusted R^2	R^2	Sum of squares	Mean Squared Error	Root Mean Squared Error
0.56	0.68	27.648	0.2304	0.48

The ANN parameters were determined using the generally accepted and commonly used trial-and-error method for avoiding overfitting or underfitting. The optimal number of hidden neurons is found to be 10, and after which the performance of the model begins to decrease. The R^2 is 0.73, and then the performance decreases immediately after 10

due to the over-fitting problem. The MAE, MAPE, and RMSE were found to be 217.8, 0.039, and 0.321, respectively. The architecture, structure, and results are presented in the table below:

Table 3. The ANN structures and parameters

S/N	Training structure				Architecture	Neurons in the Hidden Layer	RMSE	R ²
	Training set %	Test set %	data	Validation data set %				
1	70	15		15	1-7-1	7	0.412	0.43
2	70	15		15	1-8-1	8	0.375	0.58
3	70	15		15	1-9-1	9	0.346	0.61
4	70	15		15	1-10-1	10	0.321	0.73
5	70	15		15	1-11-1	11	0.338	0.64
6	70	15		15	1-12-1	12	0.342	0.58
7	70	15		15	1-13-1	13	0.364	0.46

For the SVM model, the grid search method was used for the optimization of the key performance indicators (KPIs). The values for the regularization parameter (C), Kernel parameter (γ), and precision parameter (ϵ) are obtained to be 98, 36 and 0.001, respectively. The performance value is presented in the table below:

Table 4. The performance value of the SVM model

	Train					Test				
	MAE	MAPE	MSE	RMSE	R ²	MAE	MAPE	MSE	RMSE	R ²
SVM	228.9	0.041	0.081	0.285	0.86	226.2	0.36	0.031	0.231	0.84

For the KNN, a large value of k reduces the noise and provides a more precise prediction. The optimum k was found to be 11 with $R^2=0.72$, $MAE=318.5$, and $MAPE=0.042$, $RMSE=0.72$.

Table 5. The performance values of the KNN network

	Train					Test				
	MAE	MAPE	MSE	RMSE	R ²	MAE	MAPE	MSE	RMSE	R ²
kNN	224.1	0.039	0.067	0.257	0.71	318.5	0.042	0.157	0.397	0.72

For the ANFIS model, the outcome showed that the neural-fuzzy network's optimal fuzzy structure was obtained when the cluster radius (r) is 0.35, where MAE, MAPE, RMSE, and R^2 are 198.4, 0.35, 0.211, and 0.97, respectively. The properties of the trained ANFIS network are presented in the table below:

Table 6. The properties of the ANFIS network

Training data pair	Epoch number reached	Number of parameters	linear	Number of Non-linear parameters	Total Number of parameters	Number of Nodes	Number of rules
84	20	10		20	30	24	5

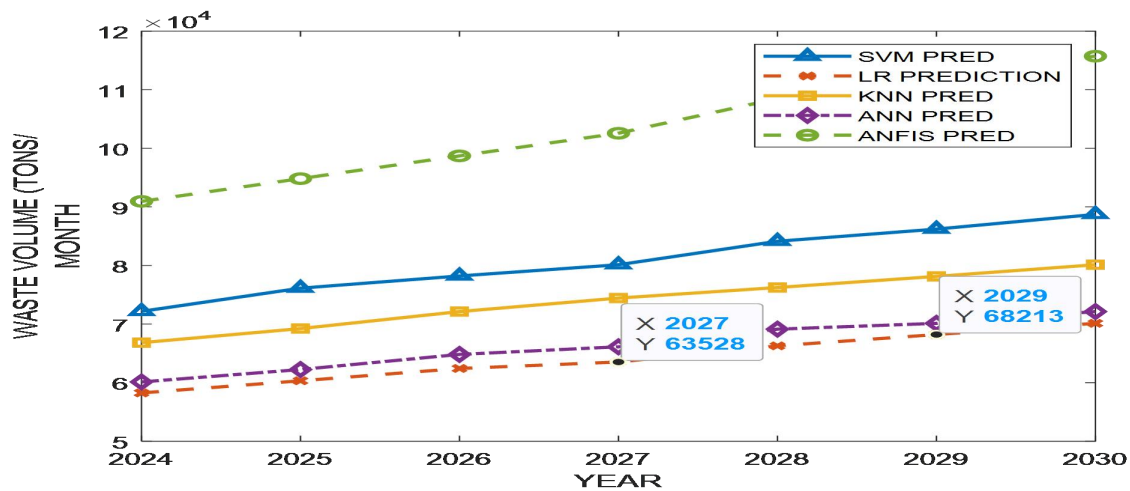
4.2 Projection of Waste Volume Generated in Ibadan-North LGA

As shown in the previous section, ANFIS presents the best estimate of waste volume, better than ANN and LR. The four models are used to predict the waste generation from 2024 to 2030. Although the LR gives good performance characteristics, but lesser than that of ANN and VM, the LR prediction can not capture the complex non-linear systems like waste management problems. This is a major advantage of ANN, k-NN, SVM, and ANFIS over LR. ANFIS demonstrated the best ability to learn from the data and reduce the bias to the barest minimum, apart from handling the uncertainty better than the duo of ANN, SVM, and LR. The SVM performs better than the ANN, k-NN but less than ANFIS. The table below presents the performance of the models.

Table 7. The performance values of all the models for MSW generation in Ibadan-North LGA

	Training					Testing				
	MAE	MAPE	MSE	RMSE	R ²	MAE	MAPE	MSE	RMSE	R ²
LR	432.6	0.065	0.282	0.531	0.70	430.1	0.058	0.230	0.480	0.68
ANN	236.7	0.042	0.112	0.334	0.74	217.8	0.039	0.103	0.321	0.73
SVM	228.9	0.041	0.081	0.286	0.86	226.2	0.036	0.031	0.231	0.84
kNN	224.1	0.039	0.066	0.257	0.71	318.5	0.042	0.157	0.397	0.72
ANFIS	196.4	0.284	0.055	0.234	0.98	198.4	0.035	0.044	0.211	0.97

The figure below shows the monthly projection of MSW in Ibadan-North LGA for the next six years (2025-2030). The results show that waste generated grows by 0.06% annually and that the waste flow will reach a monthly turnout of 72.2 tons in most of the zones in Ibadan-North LGA.

**Figure 6.** Waste volume forecast using LR, ANN, KNN, SVM, and ANFIS

4.3 Comparison with Recent Studies

Evaluation of effectiveness is carried out by conducting comparison experiments. This is important to develop a baseline and produce a transparent description that will enhance the reproducibility of the work in the near future. This work presents a comparison of the results with some recent findings in the table below:

Table 8. Comparison of the performance values with the previous studies

Reference	Algorithm/performance values			
	ANN R ²	SVM R ²	KNN R ²	ANFIS R ²
[29]	0.85	-	-	0.68
[18]	-	-	-	0.92
[28]	0.5	-	-	-
[24]	0.99	-	-	-
[9]	-	-	-	0.98
This work	0.73	0.84	0.72	0.97*

The best model in this study (ANFIS) is in trend with the recent studies, hence confirming the reliability of the forecast. The other models could be improved upon by adjusting the parameters of the model, that is, finding new optimum points for the model parameters.

5. Conclusion

A solid waste management system's planning, design, and operation all depend on the ability to forecast the development of solid waste. Therefore, stakeholders, decision-makers, and solid waste managers must create a tool for precise waste amount estimation. Selecting a single statistical model may restrict the capacity to identify the most effective prediction model for waste generation data due to the drawbacks of traditional waste generation estimating techniques. Instead of enforcing a certain model a priori, artificial intelligence models choose the model. This study assessed and compared the prediction accuracy of the five artificial intelligence algorithms. The trash volume in Ibadan North local government, Ibadan, Oyo state, South-West Nigeria, was then predicted using the five algorithms. The findings demonstrated that artificial intelligence models offer potential instruments that might enable decision makers to accurately predict the MSW generation trend for SISWM planning and design.

The study finds that while all of the models produced good and accurate forecasts, the ANFIS model produced more accurate forecasts than Linear regression, ANN, KNN, and SVM. These models can be used to create forecasting models that might produce accurate and reliable monthly MSW generation predictions. Other machine learning algorithms could be explored to address the need for reliable data for effective and efficient waste management design. More work is needed for updates and to handle the dynamism in the art of performance measurement.

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Conflict of Interest

There is no conflict of interest or financial support for this work from anywhere.

References

- [1] Tchobanoglous, G., Eliaseen, R. and Theisen, H., Solid Waste: Engineering Principles and Management (1st Ed).Tokyo: McGraw-Hill;1977.
- [2] Alessio Campitelli and Liselotte Schebek, "How is the Performance of Waste Management Systems assessed globally? A Systematic Review", *Journal of Cleaner Production*, 2020 272(1):122986.
- [3] Oluwanimifise, M.K. and Anyaeche, C.O. A framework for addressing the challenges of Sustainable solid waste management in an urban area in south-west Nigeria. *Proceedings of Nigerian Institute of Industrial Engineering*, held at the University of Ibadan, Nov.2021.
- [4] Paulauskaite-Taraseviciene, A., Raudonis, V., and Sutiene, K. Forecasting municipal solid waste in Lithuania by incorporating socioeconomic and geographical factors. *Waste Management*, 2022, 140, 31-39.
- [5] Vu, H. L., Ng, K. T. W., Richter, A., and An, C. Analysis of input set characteristics and variances on k-fold cross-validation for a Recurrent Neural Network model on waste disposal rate estimation. *Journal of Environmental Management*, 2022. 311, 114869.
- [6] Velis, C.A., Wilson, D.C, Gavish, Y., Grimes, S.M., and Whiteman, A. Socio-economic development drives solid waste management performance in cities: A global analysis using machine learning. *Science of the Total Environment*, 2023;872,161913.
- [7] Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdallah, H., and Mahfood, B. Artificial intelligence application in solid waste management: A systematic research review. *Waste Management*, 2020.109,231-246.
- [8] Almomani, F. Prediction of biogas production from chemically treated co-digested agricultural waste using an artificial neural network. *Fuel*, 2020. 280, 118573.
- [9] Adeleke, O., and Jen, T. C. Provincial waste generation prediction using evolutionary-based neuro-fuzzy model: A South African case study. *Materials Today: Proceedings*, 2023. 122, 32-42.
- [10] Malviya, A., and Jaspal, D. Artificial intelligence as an upcoming technology in wastewater treatment: a comprehensive review. *Environmental Technology Reviews*, 2021, 10(1), 177-187.
- [11] Hussain, A., Draz, U., Ali, T., Tariq, S., Irfan, M., Glowacz, A., and Rahman, S. Waste management and prediction of air pollutants using IoT and a machine learning approach. *Energies*, 2020, 13(15), 3930.
- [12] Nguyen, X. C., Nguyen, T. T. H., La, D. D., Kumar, G., Rene, E. R., Nguyen, D. D., and Nguyen, V. K. Development of machine learning-based models to forecast solid waste generation in residential areas: A case study from Vietnam. *Resources, Conservation and Recycling*, 2021,167, 105381.
- [13] Guo, H. N., Wu, S. B., Tian, Y. J., Zhang, J., and Liu, H. T. Application of machine learning methods for the prediction of organic solid waste treatment and recycling processes: A review. *Bioresource technology*, 2021. 319, 124114.
- [14] Xia, W., Jiang, Y., Chen, X., and Zhao, R. Application of machine learning algorithms in municipal solid waste management: A minireview. *Waste Management and Research*, 2022.40(6), 609-624.
- [15] Xu, A., Chang, H., Xu, Y., Li, R., Li, X., and Zhao, Y. Applying artificial neural networks (ANNs) to solve solid waste-related issues: A critical review. *Waste Management*, 2021. 124, 385-402.
- [16] Hosseinzadeh, A., Baziar, M., Alidadi, H., Zhou, J. L., Altaee, A., Najafpoor, A. A., and Jafarpour, S. Application of artificial neural network and multiple linear regression in modeling nutrient recovery in vermicompost under different conditions. *Bioresource technology*, 2020, 303, 122926.
- [17] Ihsanullah, I., Alam, G., Jamal, A., and Shaik, F. Recent advances in applications of artificial intelligence in solid waste management: A review. *Chemosphere*, 2022, 309, 136631.
- [18] Wu F, Niu D, Dai S, et al. New insights into regional differences of the predictions of municipal solid waste generation rates using artificial neural networks. *Waste Management*, 2020, 107: 182-190.

- [19] Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdallah, H., and Mahfood, B. Artificial intelligence application in solid waste management: A systematic research review. *Waste Management*, 2020 .109,231-246.
- [20] Jawad, J, Hawari, A.H., Zaidi, S.J. Artificial neural network modeling of wastewater treatment and desalination using membrane processes: A review. *Chemical Engineering Journal*. 2021;419.
- [21] Nguyen, X. C., Nguyen, T. T. H., La, D. D., Kumar, G., Rene, E. R., Nguyen, D. D., and Nguyen, V. K. Development of machine learning-based models to forecast solid waste generation in residential areas: A case study from Vietnam. *Resources, Conservation and Recycling*, 2021 167, 105381.
- [22] Dai, F., Nie, G., and Chen, Y. The municipal solid waste generation distribution prediction system based on-GA-SVR model. *Journal of Material Cycles and Waste Management*. 2020. <https://doi.org/10.1007/s10163-020-01022-5>
- [23] Rahbar, A., Mirarabi, A., Nakhaei, M., Mahdi Talkhabi, and Jamali, M. A Comparative Analysis of Data-Driven Models (SVR, ANFIS, and ANNs) for Daily Karst Spring Discharge Prediction. *Water Resources Management*, (2022). 36(2), 589-609. <https://doi.org/10.1007/s11269-021-03041-9>
- [24] Ayeleru O.O., Fajimi L.I., Oboirien B.O., Olubambi P.A. Forecasting municipal solid waste quantity using artificial neural network and supported vector machine techniques: A case study of Johannesburg, South Africa. *Journal of Cleaner Production*. 2021 Mar; 289:125671.
- [25] Adeleke, O., Akinlabi, S. A., Adedeji, P. A., and Jen, T. C. Energy Content Modelling for Municipal Solid Waste Using Adaptive Neuro-Fuzzy Inference System (ANFIS). In *Advances in Manufacturing Engineering: Selected articles from ICMMP 2019* (pp. 177-185). 2020. Springer Singapore.
- [26] Okwu, M. O., Samuel, O. D., Ewim, D. R. E., and Huan, Z. Estimation of biogas yields produced from a combination of waste by implementing response surface methodology (RSM) and adaptive neuro-fuzzy inference system (ANFIS). *International Journal of Energy and Environmental Engineering*, 2021. 12, 353-363.
- [27] Khoshand, A., Karami, A., Rostami, G., and Emaminejad, N. Prediction of e-waste generation: Application of modified adaptive neuro-fuzzy inference system (MANFIS). *Waste Management and Research*, 2023. 41(2), 389-400.
- [28] Cubillos M Multi-site household waste generation forecasting using a deep learning approach. *Waste Management* 2020 .115: 8-14.
- [29] Abbasi M, Rastgoo M.N., Nakisa B. Monthly and seasonal modeling of municipal waste generation using radial basis function neural network. *Environmental Progress and Sustainable Energy*. 2018 Oct 25;38(3):13033.
- [30] Jang, J.S.R., and Sun, C.T. *Neuro-fuzzy modelling and con.* NJ: Prentice Hall: troll. *Proceedings of the IEEE*, 1995, 83,378-406.
- [31] Jang, J.S.R., Sun, C.T., and Mizutani, E *Neuro fuzzy and soft computing: A computational approach to learning and machine intelligence.* Eaglewood cliffs, NJ: Prentice Hall. 1997. pp 503-534.
- [32] Haykin, S. *Neural networks: A comprehensive foundation* (2nd ed.) New York. Macmillan.1994.
- [33] Bishop, C.M. *Neural network for pattern recognition* (2nd ed), Oxford University Press. Pp22-37.1995.
- [34] Demuth, H. and Beale, M. (1998). *Neural network toolbox for use with MATLAB.* Natick. The Mathworks Inc.
- [35] Heydari, B., Sharghi, E. A., Rafiee, S., and Mohtasebi, S. S. (2021). Use of artificial neural network and adaptive neuro-fuzzy inference system for prediction of biogas production from spearmint essential oil wastewater treatment in up-flow anaerobic sludge blanket reactor. *Fuel*, 306, 121734.
- [36] Namoun, A., Hussein, B. R., Tufail, A., Alrehaili, A., Syed, T. A., and BenRhouma, O. An ensemble learning based classification approach for the prediction of household solid waste generation. *Sensors*, 2022, 22(9), 3506.
- [37] Zaghoul MS, Hamza RA, Iorhemen OT, Tay JH. Comparison of adaptive neuro-fuzzy inference systems (ANFIS) and support vector regression (SVR) for data-driven modelling of aerobic granular sludge reactors. *Journal of Environmental Chemical Engineering*. 2020;8(3):103742.
- [38] Brown, M. and Harris, C. *Neuro-fuzzy adaptive modelling and control* (2nd ed).Upper Saddle River, New Jersey: Prentice-Hall. 1994.
- [39] Chiu, S.L. Fuzzy and model identification based on cluster estimation, *Journal of Intelligent and Fuzzy Systems* 1994,2, 267-278.
- [40] Jang, J.S.R. and Gulley, N. *The fuzzy logic toolbox for use with MATLAB.* Natick, Massachusetts: The Mathworks Inc.1995.