International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 6, December 2012

Prediction of Industrial Solid Waste with ANFIS Model and its comparison with ANN Model- A Case Study of Durg-Bhilai Twin City India

Manoj Kumar Tiwari, Dr. Samir Bajpai, Dr. U. K. Dewangan
Research Scholar, Associate Professor, Associate Professor
Department of Civil Engineering, National Institute of Technology, Raipur (Chhattisgarh)

Abstract:* This paper is an attempt to estimate the quantity of Industrial solid waste (ISW) that can be generated in the Durg-Bhilai Twin city (DBTC), C.G, India from 2010 to 2026. The prediction of Industrial solid waste generation plays an important role in solid waste management. Yet achieving the anticipated prediction accuracy with regard to the generation trends facing many fast growing regions is quite challenging. In addition to the population growth and migration, underlying economic development, household size, employment changes, and the impact of waste recycling would influences the solid waste generation interactively. The development of a reliable model for predicting the aggregate impact of economic trends, population changes, and recycling impact on solid waste generation would be a useful advance in the practice of solid waste management [7]. The four input variables considered in the ANFIS model to predict ISW in the study area are Population of Durg-Bhilai Twin City (DBTC), ISW generated at DBTC, Percentage of urban population of the nation and GDP per capita of the nation. ANFIS is used in function approximation, time series prediction, and control [1] [2] [4]. In the absence of the adequate past data on waste generation rates, it is extremely difficult to decide upon the methodology to make any kind of prediction for the future. Hardly any primary survey studies have been made in the study area, which indicates the actual waste quantum generated. As a result, except for data points from 1961 to 2001 population based on census , Industrial solid waste generated at DBTC from 1961 to 2001 and 2009 based on the data collected from the DBTC. The estimates of waste quantum for period from 2010 to 2026,shows that if the growth of industrialization and growth of percentage increase in per capita waste generation, are considered as per the nation projections, the ISW in the study area can be expected by ANFIS model using MAT Lab Version 7.8.0.347 as around 88,980 MT per year in DBTC by 2026. Due to the important role of Waste Generation (WG) prediction in ISWMS, a proper model was developed using ANN and ANFIS models [24][26] [30]. In this study, first WG in DBTC was predicted using ANN and ANFIS models; also uncertainty analysis was used to determine the uncertainty of two hybrid models.

Keywords: **Adaptive Neuro-Fuzzy Inference System (ANFIS), Industrial Solid Waste Management (ISWM), Prediction, Solid Waste, Waste Management Practices, Waste Minimization, Waste Generation (WG).**

I. INTRODUCTION

Civilization and industrialization are associated with numerous waste products. The issue of disposal of the waste products is a challenge. Some of these materials are not biodegradable and often lead to waste disposal crisis and environmental pollution. [9] The present article seeks the possibilities of utilization of these waste products for highway construction materials. Since the industrial revolution, industrial and mining operations have accompanied by a problem, industrial waste which could be toxic, ignitable, corrosive or reactive, if improperly managed; this waste can pose dangerous health and environmental consequences. Industrialization has caused serious problems relating to environmental pollution. Therefore, efforts are to be made to controlling pollution arising out of the disposal of wastes by conversion of these unwanted wastes into utilizable raw materials for various beneficial uses. The problems relating to disposal of industrial solid waste are associated with lack of infrastructural facilities and negligence of industries to take proper safeguards [16]. The large and medium industries located in identified industrial areas still have few arrangements to dispose solid waste. However, the problem lies with small scale industries. The major generators of industrial solid wastes are the thermal power plants producing coal ash, the integrated Iron and Steel mills producing blast furnace slag and steel melting slag [19]. This study looked at ISWM present practices in industrial sector, through a particular emphasis on in-house management practices, including resource recovery, reuse and final disposal practices. Bhilai or Bhilai Nagar is a city in Durg District of Chhattisgarh state, India with a population of 753,837 (2001 census). The city is located 25 km west of the capital Raipur on the Howrah –Mumbai main rail line, and in National Highway 6. Bhilai is famous for Bhilai Steel Plant which is the largest of its kind in India. Along with its sister city Durg, Bhilai was listed among the fastest growing cities in the world, in terms of the growing population. The economy of the town is centered around the massive Bhilai Steel Plant, one of the largest integrated steel plants in the world. Apart from this, Bhilai is also home to Bhilai Refractory Plant (BRP), another public sector organization. Durg is a city located in Chhattisgarh state, Central India. It is located in the east of the Seonath River and is one part of the Durg-Bhilai urban agglomeration. The city is an agricultural market and is heavily engaged in milling rice and pigeon peas. Durg gained importance as an industrial centre after the establishment of a large steel plant at Bhilai. Industries include brass working and bell-metal working, oil pressing, mining, and weaving. It is the headquarters of Durg District, the third largest district of Chhattisgarh. A literature survey was conducted to appraise the recent applications of artificial intelligence (AI)-based modeling studies in the environmental engineering field. A number of studies on artificial neural networks (ANN), fuzzy logic and adaptive neuro-fuzzy systems (ANFIS) were reviewed and important aspects of these models were highlighted [2] [6]. The results of the extensive literature survey showed that most AI-based prediction models were implemented for the solution of water/wastewater (56%) and air pollution (31%) related environmental problems compared to solid waste (14%) management studies. The real-life environmental problems are very complex and highly dependent on several process configurations, different influent characteristics and various operational conditions, such as organic loading rates, influent pH, toxic organic compounds, influent flow rate, hydraulic and sludge retention times, temperature variations, biomass concentration, and doses of applied chemicals, etc. For a sustainable control of environmental related problems, the proposed systems must be continuously monitored and properly controlled due to possible instabilities in circumstance conditions [8]. Therefore, the complicated inter-relationships among a number of system factors in the process may be explicated through a number of attempts in developing representative AI-based prediction models allowing the investigation of the key variables in greater detail.

II. LITERATURE REVIEW

The prediction of Industrial solid waste generation plays an important role in a solid waste management. Yet achieving the anticipated prediction accuracy with regard to the generation trends facing many fast growing regions is quite challenging. In addition to population growth and migration, underlying economic development, household size, employment changes, and the impact of waste recycling would influence the solid waste generation interactively [7]. The development of a reliable model for predicting the aggregate impact of economic trend, population changes, and recycling impact on solid waste generation would be a useful advance in the practice of solid waste management. ANFIS represents a promising technology with a wide scope for potential applications [21]. They have received increasing attentions in time series prediction. There is growing interest in using ANFIS to forecast the future changes in prices of stocks, exchange rates, commodities, and other financial time series [24]. The planning of industrial solid waste management systems (ISWMS) to satisfy increasing waste disposal and treatment demands is often subject to a variety of impact factors, such as collection Technique to be used, service policy to be implemented, and management facilities to be adopted. Quantity of prediction of Industrial solid waste (ISW) is crucial for the planning of ISWMS, and the development of a reliable model (such as data-driven models) for this purpose would be a useful advance in the practice of ISWMS [31]. These models are called data-driven models. Two of the data-driven models are adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) models. ANN models can be modeled complex, and nonlinear events that use this model are successful in ISWMS. Jalili and Noori used feed-forward neural network to predict the weekly WG in Mashhad, Iran. Karaca and Özkaya used ANN to control leachate generation rate in landfills.

ANFIS-based models have recently been used for water treatment process. Chun et al. used an ANFIS-based model to optimize coagulant dosage used for turbidity removal in a water treatment plant. They obtained a better performance than in their previous works using ANN [1]. Similar to Chun et al., ANN and AN-FIS models were used by Wu and Lo to model poly aluminum chloride (PAC) dosing of the surface water of Northern Taiwan. They obtained results similar to those of Chun et al., indicating that the self-predicting model of ANFIS is better than the ANN model for PAC dosage predictions[5][36].

III. MODELING TOOLS

In this section, the basis of the widely used AI-based techniques, such as artificial neural networks, fuzzy logic and adaptive neuro-fuzzy inference systems [1] [2] [36], are briefly summarized and important mathematical aspects of these methods are highlighted. Moreover, computational issues, advantages and particular theoretical principles are described, and some methodological techniques are discussed to make a comparative assessment of the present AI-based prediction models.

A. Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

The ANN-based methods have been successfully used in various disciplines for modeling; however, the lack of interpretation is one of the major drawbacks of their utilization. Wieland et al. reported that one of the major shortcomings of ANNs is that they do not reveal causal relationships between major system components and thus are unable to improve the explicit knowledge of the user[2] [6] [15]. Another problem is due to the fact that reasoning is only done from the inputs to the outputs. In cases where the opposite is requested (i.e., deriving inputs leading to a given output), neural networks can hardly be used. There are also some basic aspects of fuzzy inference system that are in need of better understanding. In order to overcome the problematic combinations of ANNs and fuzzy systems, a new system combining ANN and the fuzzy system, called the adaptive network-based fuzzy inference system (ANFIS), was proposed by Jang. However, even before Jang published his paper, Lin and Lee and Wang and Mendel had already published their respective works on adaptive neuro-fuzzy inference systems. Jang and Sun expressed that adaptive neuro-fuzzy inference systems and the adaptive network-based fuzzy inference systems have the same aim. Therefore, they used adaptive neuro-fuzzy inference systems (ANFIS) to stand for adaptive network-based fuzzy inference systems [36]. Operation of the ANFIS looks like FFBP network. Consequent parameters are calculated forward while premise parameters are calculated backwards. The ANFIS is composed of two parts, antecedent and conclusion, which are connected to each other by fuzzy rules based on the network form. There are two learning methods in neural section of the system: Hybrid learning method and BP learning method. In fuzzy section, only zero or first order Sugeno inference system or Tsukamoto inference system can be used, and output variables are obtained by applying fuzzy rules to fuzzy sets of input variables.

B. ANFIS Architecture Equivalent to Sugeno Fuzzy Model

For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs x and y and one output z. For a first order Sugeno fuzzy Model, a common rule set with two fuzzy if-then rules is the following [36],

Rule 1: If x is A_1 and y is B_1, then

$$Z_1=f_1\,\overline{\overline{w}}_1 = \overline{\overline{w}}_1(p_1x+q_1y+r_1)$$

Rule 2: If x is A_2 and y is B_2, then

$$Z_2=f_2\,\overline{\overline{w}}_2 = \overline{\overline{w}}_2(p_2x+q_2y+r_2)$$

Fig 1 illustrates the reasoning mechanism for this Sugeno model, the corresponding equivalent ANFIS architecture is as shown in Fig2, where nodes of the same layer have similar functions, as described in further text. There O_1, i is denoted by the output of the i^{th} node in l^{th} layer.

Layer1: Every node in this layer is an adaptive node with a node function

O_1, i = $\mu_{Ai}(x)$, for i = 1, 2 or

O_1, i = $\mu_{B_{i-2}}(y)$ for i =3, 4 … (1)

Where x (or y) is the input to node i and Ai (or B_{i-2}) is a linguistic label, such as small or large, associated with this node. In other words, $O_{1,}$ i is the membership grade of a fuzzy set A (A=A_1, A2, or B=B_1, B_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A.

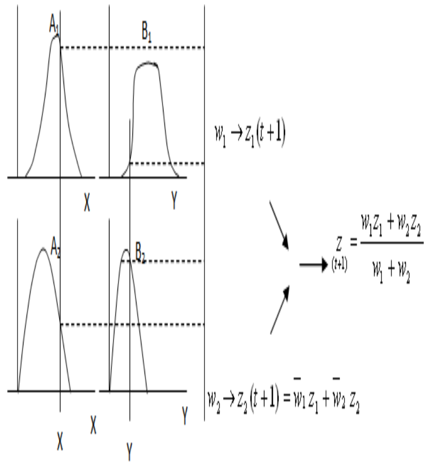

Fig. 1 A Two Input First Order Sugeno Fuzzy Model

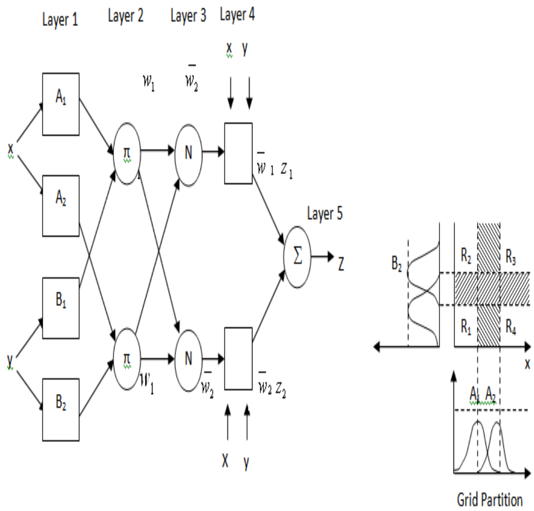

Fig. 2 Equivalent ANFIS Architecture (Equivalent to fig. 1)

The membership function for A can be any appropriate parameterized membership function. Here it is a generalized bell function[13].

$$\mu_{A^i}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_{ii}}} \quad \dots (2)$$

Where (a_i, b_i, ci) is the parameter set. As the values of these change, the bell-shaped function vary accordingly, thus exhibiting various forms of membership to as premise parameters for fuzzy set A parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a fixed node labelled π , whose output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{A_i}(x), \mu_{B_i}(y), i = 1,2.\ldots n \qquad \ldots (3)$$

Each node output represents the firing strength of a node

Layer 3: Every node in this layer is a fixed node labelled N, this denotes that the i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1,2. \qquad \ldots (4)$$

For convenience output of this layer is called normalized firing strengths (hence denoted N).

Layer 4: Every node i in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w}_i z_i (\in +1), i = 1,2.........n \qquad \ldots (5)$$

$$= \overline{w}_i (p_i x + q_i y + r_i)$$

Where $\overline{w_i}$ is a normalized firing strength output of layer 3 denoted by N, (p_i, q_i, r_i) is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: The signals node in this layer is a fixed node labeled $\sum$, which computes the overall output as the summation of all incoming signals.

$$\text{Overall Output } O5_{,i} = \sum \overline{w_i} z_i$$

$$= \frac{\sum_i w_i z_i}{\sum_i w_i} \qquad \ldots (6)$$

Evaluation criteria

We used root mean square error (RMSE) to comparison of the efficiency of models that expressed as:

$$\text{RMSE} = \sqrt{\sum_{k=1}^{n} (Zs - Zo)^2 / n} \qquad \ldots$$

$$\text{RMSE} = \sqrt{\sum_{k=1}^{n} (Zs - Zo)^2 / n} \qquad \ldots (7)$$

The Mean Square Error (MSE) is expressed as:

$$\text{MSE} = \sum_{k=1}^{n} (Zs - Zo)^2 / n \qquad \ldots (8)$$

Average Relative Error (ARE) is expressed as:

$$\text{ARE} = 1/n \sum_{k=1}^{n} (Zs - Zo) / Zo^2 \qquad \ldots (9)$$

Average Relative Error (ARE) is expressed as:

$$\text{ARE} = 1/n \sum_{k=1}^{n} (Zs - Zo) / Zo^2 \qquad \ldots (9)$$

Where Zs is observed value, Zo is predicted value, n is number of samples. The model that gives the minimum ARE is recommended as the best one which can be used to predict the travel time in the future. Thus an adaptive network is constructed which is functionally equivalent to a Sugeno fuzzy model[5]. Note that the structure of this adaptive network is not unique, one can combine layer 3 and 4 to obtain an equivalent network with only four layers. The hybrid learning algorithms have been applied to identify ANFIS parameters.

Although ANN and fuzzy logic models are the basic areas of artificial intelligence concept, the ANFIS combines these two methods and uses the advantages of both methods. Since the ANFIS is an adaptive network which permits the usage of ANN topology together with fuzzy logic, it includes the characteristics of both methods and also eliminates some disadvantages of their lonely-used case. There-fore, this technique is capable of handling complex and nonlinear problems. Even if the targets are not given, the ANFIS may reach the optimum result rapidly. In addition, there is no vagueness in ANFIS as opposed to ANNs. Moreover, the learning duration of ANFIS is very short compared to ANN-based models. It implies that ANFIS may reach to the target faster than ANN [37]. Therefore, when a more sophisticated system with a high-dimensional data is implemented, the use of ANFIS instead of ANN would be more appropriate to faster overcome the complexity of the problem [36].

In the ANFIS structure, the implication of the errors is different from that of the ANN case. In order to find the optimal result, the epoch size is not limited [36]. In training high-dimensional data, the ANFIS can give results with the minimum total error compared to ANN and fuzzy logic methods [18] [19]. Moreover, fuzzy logic method seems to be the worst in contrast to others at a first look, since the rule size is limited and the number of membership functions of fuzzy sets was chosen according to the intuitions of the expert. However, if different types of membership functions and their combinations had been tested and more membership variables and more rules had been used to enhance the prediction performance of the proposed diagnosis system, better results could have been available.

IV. MODELING APPLICATIONS IN ENVIRONMENTAL ENGINEERING

In this section, recent applications of AI-based prediction models in the field of environmental engineering are examined in terms of solid waste management, water/wastewater treatment and air pollution related problems, and the important findings obtained in these studies are summarized.

A. Waste Management

Industrial solid waste management systems (ISWMS) require accurate prediction of waste generation for proper planning and design [19]. However, predicting the amount of generated waste is difficult because of various fluctuating parameters. In a study, the hybrid of wavelet transform-adaptive neuro-fuzzy inference system and wavelet transform-artificial neural network was used to predict the weekly generation of waste. In another study, Zade and Noori proposed an appropriate model for predicting the weight of waste generation in Mashhad with a feed-forward artificial neural network [26]. In a recent study, Jahandideh et al. used two predictor models, the ANN and multiple linear regression, to predict the total rate of medical waste generation and classify them as sharp, infectious, or general[27]. Srivastava and Nema used the fuzzy system to forecast the solid waste composition of Delhi [28], India between 2007 and 2024. Similar studies on waste management have been carried out in recent years.

V. INPUT PARAMETERS

The four input variables considered in the ANFIS model to predict ISW are 1. Population of DBTC, 2. ISW generated at DBTC, 3. Percentage of urban population of the nation and 4. GDP per capita of the nation.

A. Population of DBTC

The population data collected from DBTC as per census of India is shown below. As per the report of technical group on population projections constituted by the national commission on population to the office of the Registrar general & Census commissioner of India, May 2006 the population growth in India from 2001 to 2026 shall have a growth of 36% in 25 years at a rate of 1.2% of annum. This growth rate is considered in the ANFIS model from 2001 to 2026 to predict the ISW generation. The population of DBTC year wise from 1961 to 2001 is obtained from the best fit curve equation shown below in Fig.3 The empirical formula for population is [37]: $y = 742.79x^4-12218x^3+68264x^2-12793x+215787$ … (10)

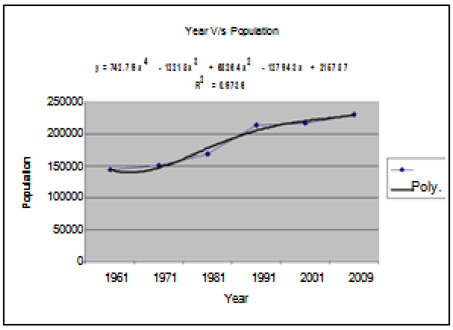

Fig.3, Best Fit Curve of Year V/S Population

B. Industrial Solid Waste in MT

The ISW data collected from DBTC as per the office records is shown below. It is estimated that the amount of waste generated in India will increase at a per capita rate of approximately 1.4% annually is considered for estimate of ISW from the year 2009 to 2026. The ISW of year wise from 1961 to 2009 is obtained from the best fit curve equation shown below in Fig.4.The empirical formula for ISW in MT is [37]:

$y = 32.5x^4-116.39x^3-256.67x^2+2917x+1405$ … (11)

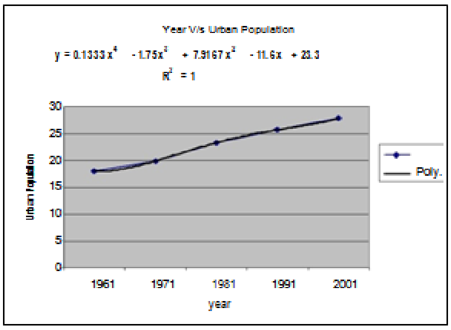

Fig.4, Best Fit Curve of Year V/S ISW

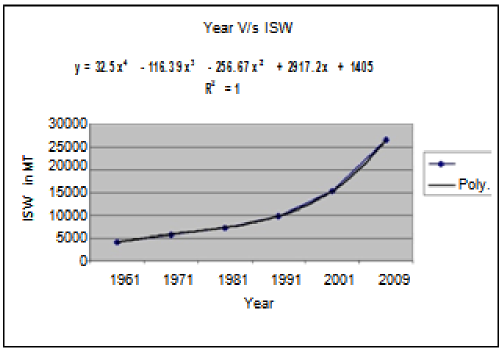

Fig.5. Best fit curve of year V/s urban population

C. Effect of Urban Population Growth on ISW Generation In India

India historically has been an agricultural economy, with the majority of people living in rural areas engaged in the agricultural sector. However, with an expanding service and manufacture driven economy, urban areas are seeing unprecedented growth. According to 2001 census, around 28% of India's population lives in urban areas.(census 2001) and the percentage of urban population of India is extracted from census India available online are shown below is used in the proposed ANFIS model to predict ISW. The % of urban population for India will increase to 40% by 2026 in 25 years. This growth rate is considered in the ANFIS model from 2001 to 2026 to predict the ISW generation [36][37]. The percentage of urban population year wise from 1961 to 2001 is obtained from the best fit curve equation shown below in Fig.5.

D. GDP Per Capita

The gross domestic product (GDP) or gross domestic income (GDI) is the market value of all final goods and services produced within a country in a given period of time. It is often positively correlated with the standard of living, alternative measures to GDP for that purpose.

Gross domestic product comes under the heading of national accounts, which is a subject in macroeconomics. The empirical formula for percentage urban population is [37]:

$$y = 0.1333x^4-1.75x^3+7.9167x^2-11.6x+23.3 \quad \ldots (12)$$

E. Standard of living and GDP

GDP per capita is not a measurement of the standard of living in an economy. However, it is often used as an indicator, on the rationale that all citizens would benefit from country's increased economic production. Similarly, GDP per capita is not a measure of personal income. GDP may increase while real incomes for the majority decline. The major advantage of GDP per capita as an indicator of standard of living is that it is measured frequently, widely, and consistently. It is measured frequently in a sense that most countries provide information on GDP on a quarterly basis, allowing trends to be seen quickly. It is measured widely because some measure of GDP is available for almost every country in the world, allowing inter-country comparisons [2][37]. It is measured consistently because the technical definition of GDP is relatively consistent among countries. The major disadvantage is that it is not a measure of standard of living. GDP is intended to be a measure of total national economic activity which is a separate concept. There is a direct link between GDP and ISW generation. A number of studies have found that the higher the household income and standard of living, the higher the amount of ISW generated. The World Bank study summarized the progression of ISWM practices in a country as its income increases. The GDP per capita of India at current prices is available on line from World Bank World development indicator. GDP per capita are shown below is used in the proposed ANFIS model to predict ISW [31][37]. The GDP per capita projection for India will increase at the rate of 5.5% in the coming years, is considered in ANFIS model for prediction of ISW in future.

The output data of predicted ISW at DBTC is obtained with the ANFIS Model on MAT LAB, Version: 7.8.0.347, 32-Bit (win32) as shown in Table1. Fig.6, illustrates the estimates of waste quantum for period from 2010 to 2026, shows that if the growth of population, Growth of percentage increase in per capita waste generation, growth of urban population and future estimate of GDP per capita are considered as per the nation projections [37], the ISW in the study area can be expected by ANFIS model around 40190.29984MT per year by 2026 in DBTC. Fig.7 shows the graph between % error between the ANFIS model and ISW generation in MT by extrapolation per year at DBTC.

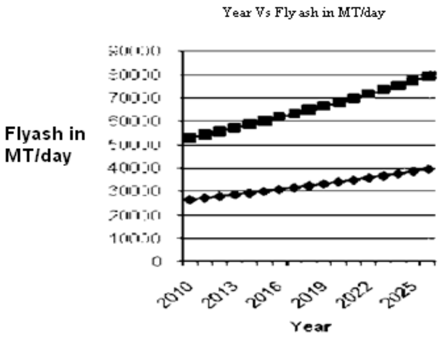

Fig. 6. Prediction of ISW at DBTC by ANFIS Model

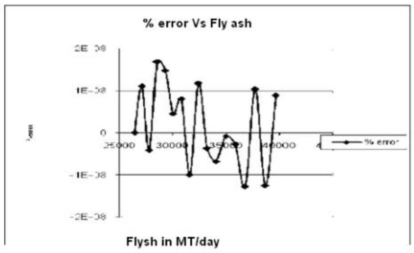

Fig.7. % of Error Vs ISW by ANFIS Mode

VI. RESULTS & DISCUSSION

It is important to mention here that the above projection of ISW is based on the national projections of data and the local Fig.7 on ISW also depend upon food habits of people and the degree of commercial and industrial activity in DBTC by 2026.

Table.1. Predicted ISW at DBTC Is Obtained With the ANFIS

Year	ISW projection by ANFIS model in MT	% Error
2010	27861.5	0
2011	27390.5618	-3.1E-06
2012	26837.05015	1.27E-06
2013	27851.41186	-4.6E-06
2014	28984.10531	-4.8E-06
2015	35535.60174	-1.42E-06
2016	31906.38319	-2.7E-06
2017	31666.94488	3.21E-06

2018	**32987.79328**	**-3.2E-06**
2019	**34339.45651**	**1.41E-06**
2020	**34762.45324**	**2.53E-06**
2021	**34777.33876**	**2.99E-07**
2022	**36564.68542**	**9.78E-07**
2023	**37885.11928**	**4.87E-06**
2024	**38929.12377**	**-3.94E-06**
2025	**39097.24944**	**4.86E-06**
2026	**40190.29984**	**-3.48E-06**

The Results of Calibrating and Testing Stage For ANFIS Model (Three Rules) are Presented in Table 2 and Fig. 8.

Table 2 Results of Calibrating and Testing Stages for Different Models

Model	Calibrating stage				Testing stage			
	R^2	RMSE	MSE	ARE	R^2	RMSE	MSE	ARE
ANN	0.49	2293	1843	3.81	0.33	3812	2798	5.87
ANFIS	0.49	2465	1867	3.99	0.41	2316	3096	5.87

Coefficient of determination (R^2)

The combination of results of these two models is the final output of ANFIS model. The optimal r_a for the models of approximation and detail coefficients achieved 0.91 and 0.66, respectively, and leads to produce ANFIS models with two rules for each sub cluster [36]. Results for calibrating and testing stages are shown in Table 2 and Fig. 8.

After standardization of input variables and change of neuron numbers in a hidden layer, different prediction models are produced. In this study, model with five neurons at a hidden layer was selected as the best model for WG forecasting [36]. Results of calibrating and testing stages of the model are shown in Table 2 and Fig. 9.

Approximation and detail coefficients of input variables have been obtained and for each group of coefficients a suitable ANN model was constructed by change of neuron numbers in a hidden layer. The combination of results of these two models is the final output of ANN model [36]. Obtained results for model calibrating and testing stages are illustrated in Table 2 and Fig. 9.

A. Determination of the best model

According to Table 2, the results of ANFIS are better than a ANN model. It shows that the input variables have a positive effect in the operation of ANFIS model than ANN model [36]. For the better evaluation of the results, distribution of the prediction errors for ANFIS and ANN is plotted (Fig. 10). For example, this figure shows that ARE for 50% prediction of testing stage in ANN is 2.7%. This value (ARE) is 1.6% in ANN. However, 90% of prediction of the testing stage in ANN and ANFIS models have ARE equal to 7.7% and 3.9%, respectively [36]. Generally, it can be observed from Fig.10 and Table 2 that ANFIS model has better result than the ANN model.

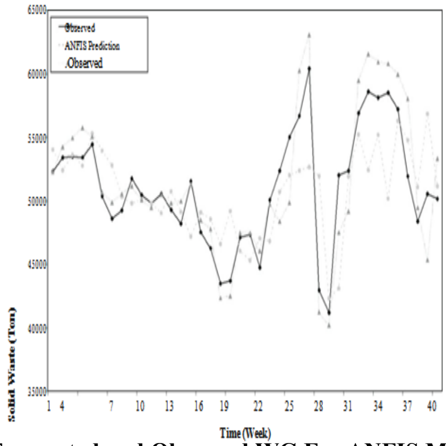

Fig.8. Forecasted and Observed WG For ANFIS Model in Testing Stage.

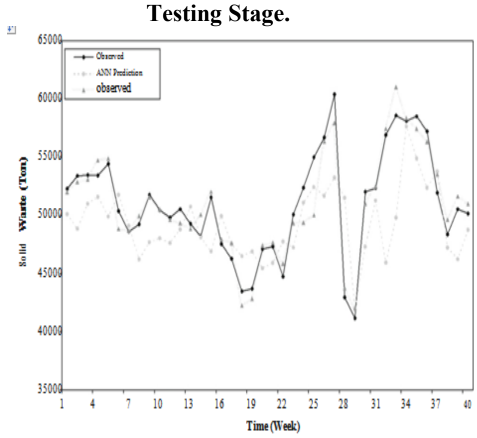

Fig 9. Forecasted and Observed WG For ANN Model in Testing Stage.

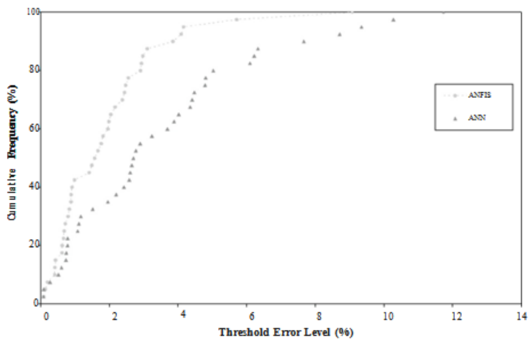

Fig. 10. Distribution of Forecast Error for ANFIS and ANN Models in Testing Stage.

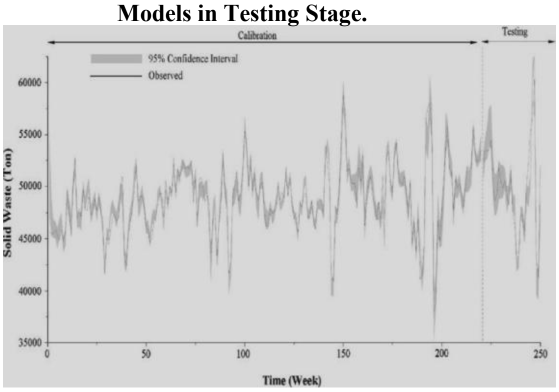

Fig. 11. Confidence Intervals (95%) For The Estimates Of Weekly WG Values During The Calibrating and Testing Stages By ANFIS Model.

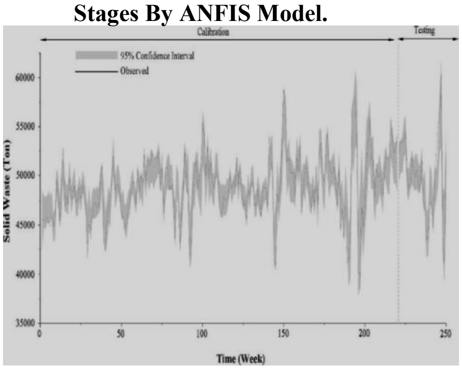

Fig. 12. Confidence Intervals (95%) For The Estimates of Weekly WG Values during the Calibrating and Testing Stages by ANN Model

B. Determination of ANFIS and ANN uncertainty

For calculating the uncertainty of ANFIS and ANN models in this research during the network calibration, prediction models were generated from historical data. The uncertainty in the estimates of the observed and predicted weekly WG during the calibrating and testing stages has been quantified by estimating the confidence intervals of the simulation results. The 95% confidence intervals are determined by finding the 2.5th and 97.5th percentiles of the associated distribution of the simulation results [36]. The plot of the range of 95% confidence intervals for the estimates of weekly WG values during the calibrating and testing stages for ANFIS and ANN are shown in Figs. 11 and 12. The results are discussed below. As displayed in Figs. 6 and 7, it was obvious that during the calibration stage [36] [37], both the models consistently predict well the trend of decrease and increase of WG along with time. A similar trend was also found at the testing stage (Figs. 11 and 12), although the magnitude of uncertainty in the testing stage was lower than that of the calibration stage and the magnitudes of lower and upper bound of WG are estimated closer to the observed data in the calibration stage. As shown in Figs. 6 and 7, outputs of ANN (Fig. 12) had more uncertainty at all prediction times than those of ANFIS (Fig. 11), whereas with regard to noticeable in-crease in wide of 95PPU bond, observed data numbers placed on the bond increased slightly in comparison with ANFIS.

VII. CONCLUSION

In the absence of adequate past data on waste generation rates, it is extremely difficult to decide upon the methodology to make any kind of projections for the future. Hardly any primary survey studies have been made in the study area, which could indicate the actual waste quantum generated. As a result, except for data points from 1961 to 2001 population based on census , Industrial solid waste generated at DBTC from 1961 to 2001 and 2009 based on the data collected from the DBTC, urban population percentage in the total population as per census for the above period based on national scenario and the year wise data of GDP per capita on the national scenario, there is no data available on this basis . The population of year wise from 1961 to 2001 is obtained from the best fit curve equation. It is estimated that the amount of waste generated in India will increase at a per capita rate of approximately 1.33% annually is considered in the ANFIS model from 2010 to 2026 to predict the future generation of ISW. The ISW of year wise from 1961 to 2009 is obtained from the best fit curve equation. The % of urban population for India will increase to 40% by 2026 in 25 years. This growth rate is considered in the ANFIS model from 2001 to 2026 to predict the ISW generation. The % of urban population year wise from 1961 to 2001 is obtained from the best fit curve equation. The GDP per capita projections for India estimate an increase at the rate of 5.5% in the coming years is considered in ANFIS model for prediction of ISW in future. The Industrial organizations being the responsible authority in India for ISW management, in addition to a wide range of responsibilities related to health and sanitization have not been very effective as far as ISW services are concerned and DBTC is not an exception to this scenario. The central idea in this work is to utilize radial basis function approach of ANFIS model so as to minimize the discrepancy between the predicted values and observed values of ISW. A case study of future solid waste generation in DBTC demonstrates the application potential of such an approach. Due to important role of WG prediction in ISWMS, a proper model was developed using ANN and ANFIS models. In this study, first WG in DBTC was predicted using ANN and ANFIS models. Also, uncertainty analysis was used to determine the uncertainty of two hybrid models. The following conclusions could be drawn from the present study:

1. Input variables preprocessing was improved for WG prediction of both models.
2. ANFIS gave better results than ANN.
3. Although, ANFIS gave better results than ANN based on the studied criteria of model evaluation, but uncertainty analysis showed that ANN had more uncertainty than ANFIS.
4. Due to a smaller uncertainty of ANFIS than ANN, the output stability of ANFIS is suitable, and this model was selected as the optimum model for WG forecasting in DBTC. However, ANN presented weak results than ANFIS with respect to statistical criteria.
5. The presented methodology of this study is general and if it is the available data with high range periods, the methodology can be used for the prediction of longer time in the future (for example, one or more months).

REFERENCES

[1] Erdogmus D and Principe j.6. "Generalized information potential criterion for Adaptive system Training" IEEE Trans on Neural networks vol. 13, no5,pp 1035-1044, 2002.

[2] Hojati M Gazor S "Hybrid Adaptive fuzzy Identification and control in Nonlinear systems" IEEE Trans on fussy systems, vol10, No2 pp198-210, 2002.

[3] Park BJ Pedrycz Wad oh S.K. "Fussy Polynomial Neural Networks: Hybrid Architectures of Fussy modeling" IEEE Trans on Fussy systems, vol.10, No5, pp 607-621, 2002.

[4] Cheol W. Lee and Yang C. Shin "Construction of Fussy systems using least squares method and genetic algorithm" Elsevier science direct, pp 297-323, 2003.

[5] Z hang B and Govidaraju RS "Prediction of water shed runoff using Bayesian concepts and modular neural networks" Water Resources Research Vol. 56, No.3 P753-762, 2000.

[6] Roger tang, Chuen TS and Mizutani E "Neuro-fuzzy and soft computing A computational Approach to learning and machine Intelligence" Prentice Hall of India, New Delhi, P335-368, 2004.

[7] World Bank. 1999. What a Waste – Solid Waste Management in Asia, Urban Development Sector Unit, East Asia and Pacific Region, May 1999.

[8] Ministry of Urban Development. 2000, Government of India, Solid Waste Management Manual.

[9] Eduard V, My T, Levin A, Bulato Rudolfo A. Bos. World Population Projections, 1992–1993Edition: Estimates and Projections with Related Demographic Statistics. The World Bank: John Hopkins, 1993.

[10] Leung M T, Chen A S, Daouk H, Forecasting exchange rates using general regression neural networks, Computers & Operation Research,27 (4), pp1093-1110, 2000.

[11] Cao L, Gu Q, Dynamic support vector machines for non stationary time series forecasting, Intell Data Anal 6, pp.67–83, 2002.

[12] Cao LJ, Tay Francis EH, Financial forecasting using support vector machines, Neural Computing & applications, 10(2), pp.184-192, 2001.

[13] Virili F, Freisleben B, Neural network model selection for financial time series prediction, Compute Stat,16(3), pp.451-463 ,2001.

[14] Qai M, GP Zhang, An investigation of model selection criteria for neural network time series forecasting, European Journal of Operational Research 132, pp. 188-102, 2001.

[15] A.Sfetsos, C.Siriopoulos, Combinatorial time series forecasting based on clustering algorithms and neural networks, Neural Compute & Applic,, pp.56-64, 2004.

[16] Liu,Z. F., X. p., Wang, S. W., & Liu, G. F. Recycling strategy and a recyclability assessment model based on an artificial neural network, Journal of materials processing technology, 129, pp500-506, 2002..

[17] Nie, X. H., Huang, G. H., Li, Y. P., &Liu, L.IFRP: A hybrid interval parameter fuzzy robust programming approach for waste management planning under uncertainty, Journal of environmental management, 84, pp1-11, 2007.

[18] Chi, Y., Wen, J. M., Zhang, D. P., Yan, J.H., Ni, M. J., &Cen, K. F,HCL emission characteristics and BP neural networks prediction in MSW/coal co-fired fluidized beds. Journal of environmental science,17, pp699-704, 2005.

[19] Shu, H. Y., Lu, H. C., Fan, H. J., Chang, M. c., & Chen, J.C., Prediction for energy content of Taiwan municipal solid waste using multilayer perception neural networks. Journal of air and waste management association, 56, pp852-858, 2006.

[20] Turkdogan-Aydinol F. I., Yetilmezsoy K.: A fuzzy logic-based model to predict biogas and methane production rates in a pilot-scale mesophilic UASB reactor treating molasses wastewater. J. Hazard. Mater.182, pp. 460-471, 2010.

[21] Yetilmezsoy K.: Modeling studies for the determination of completely mixed activated sludge reactor volume: Steady-state, empirical and ANN applications. Neural Network World, 20pp. 559-589, 2010.

[22] Murnleitner E., Becker T. M., Delgado A.: State detection and control of overloads in the anaerobic wastewater treatment using fuzzy logic. Water Res., 36, pp. 201-211, 2002.

[23] Domnanovich A. M., Strik D. P., Zani L., Pfei®er B., Karlovits M., Braun R., Holubar P.: A fuzzy logic approach to control anaerobic digestion. Commun. Agric. Appl. Biol. Sci., 68, pp. 215-218, 2003.

[24] Cakmakci M.: Adaptive neuro-fuzzy modeling of anaerobic digestion of primary sedimentation sludge. Bioproc. Biosyst. Eng., 30, pp. 349-357, 2007.

[25] Garcia C., Molina F., Roca E., Lema J. M.: Fuzzy-based control of an anaerobic reactor treating wastewaters containing ethanol and carbohydrates. Ind. Eng. Chem. Res., 46, pp. 6707-6715, 2007.

[26] Zade J. G., Noori R.: Prediction of municipal solid waste generation by use of artificial neural network: A case study of Mashhad. Inter. J. Environ. Res., 2, pp. 13-22, 2008.

[27] Jahandideh S., Jahandideh S., Asadabadi E. B., Askarian M., Movahedi M., Mehdi M., Hos-seini S., Jahandideh M.: The use of arti¯cial neural networks and multiple linear regression to predict rate of medical waste generation. Waste Manag., 29, pp. 2874-2879, 2009.

[28] Srivastava A. K., Nema A. K.: Forecasting of solid waste composition using fuzzy regression approach: a case of Delhi. Inter. J. Environ. Waste Manag., 2, pp. 65-74, 2008.

[29] Dong C., Jin B., Li D.: Predicting the heating value of MSW with a feed-forward neural network. Waste Manag., 23, pp. 103-106, 2003.

[30] Chen L. J., Cui L. Y., Xing L., Han L.J.: Prediction of the nutrient content in dairy manure using arti¯cial neural network modeling. J. Dairy Sci., 91, pp. 4822-4829, 2008.

[31] Bayar S., Demir I., Onkal Engin G.: Modeling leaching behavior of solidified wastes using back-propagation neural networks. Ecotoxic. Environ. Safety, 72, pp. 843-850, 2009.

[32] Onkal-Engin G., Demir I., Engin S. N.: Determination of the relationship between sewage odour and BOD by neural networks. Environ. Model. Soft., 20, pp. 843-850, 2005.

[33] Karaca F., Ozkaya B.: NN-LEAP: A neural network-based model for controlling leachate low-rate in a municipal solid waste landfill site. Environ. Model. Soft., 21, pp. 1190-1197, 2006.

[34] Al-Mutairi N., Kartam N., Koushki P., Al-Mutairi M.: Modeling and predicting biological performance of contact stabilization process using artificial neural networks. J. Comput. Civ. Eng., 18, pp. 341-349, 2004.

[35] Ozkaya B., Demir A., Bilgili M. S.: Neural network prediction model for the methane fraction in biogas from field-scale landfill bioreactors. Environ. Model. Soft. 22, pp. 815-822, 2007.

[36] Roohollah Noori , Mohammad Ali Abdoli , Ashkan Farokhnia , Maryam Abbasi” Results uncertainty of solid waste generation forecasting by hybrid of wavelet transform-ANFIS and wavelet transform-neural network” Expert Systems with Applications 36, 9991–9999, 2009.

[37] J. Sudhir Kumar, K. Venkata Subbaiah, and P. V. V.Prasada Rao” Prediction of Municipal Solid Waste with RBF NetWork- A Case Study of Eluru, A.P, India “Intern. Journal of Innovation, Management and Technology, Vol. 2, No. 3, June 2011.