IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)
e-ISSN : 2278-1684, p-ISSN : 2320–334X
PP 71-79
www.iosrjournals.org

Review of Different Landfill Gas EstimationModels

Kshitija S. Tikhe[1], Dr. B. S. Balapgol[2], Dr. S. T. Mali [3]
[1](P.G. Student, Department of Civil Engineering, D Y Patil College of Engineering,Akurdi,Pune, India)
[2](Professor of Civil Engineering Department and Principal, D Y Patil College of Engineering,Akurdi,Pune , India)
[3](Professor and Head of Civil Engineering Department, Pimpri Chinchwad College of Engineering,Akurdi,Pune,India)

Abstract : *Municipal Solid waste (MSW) generated at different locations is collected by the authority for its further processing. A large amount of waste is deposited in the landfill site for its final disposal. This waste consisting of organic matter in higher extent decomposes in the presence of aerobic and anaerobic microorganisms and other favourable conditions and leads to the formation of the landfill gas (LFG). This gas is a major contributor to greenhouse effect. If estimated properly, this gas can be used as the source of the energy. A large amount of work has been carried out in estimation of the amount of LFG generated as well as its rate of generation. Present paper reviews various Hard Computing methods and the soft computing methods available for the landfill gas estimation.*
Keywords –*Hard Computing models, Landfill, LFG, MSW, soft computing models*.

I. Introduction

Municipal Solid Waste (MSW) is the type of waste generated from the refuse of the day to day items. This MSW generally consists of domestic waste, institutional waste, construction and demolition waste, etc. This waste is collected from different sources, transported and finally disposed off in open dumping or sanitary landfills. In the landfill due to the presence of organic matter and the different environmental conditions and presence of microbes a considerable amount of landfill gas is generated. LFG mainly consists of 50-60% of Methane (CH_4), 30-40% of Carbon Di Oxide (CO_2) by volume and oxygen(O_2) and other trace materials.(M. F. M. Abushamala,et al., 2015) These gases are required to be studied thoroughly as they contribute to the global warming phenomena which has an adverse effects on the environment. The potential of the CH_4 gas to global warming is about 20 times more than the CO_2. This LFG emission from the landfill is observed to increase continuously due to increase in the industrialisation, population and increase in the per capita waste generation rate (M. F. M. Abushamala,et al., 2015). So the LFG has to be estimated properly and well in advance so that any control measures required to be applied can be decided well in advance. Even though the LFG has higher threat to environment, if this gases are estimated properly and collected efficiently then they can be used as a source of energy by installing energy utilisation projects which includes either flaring of gas, its direct use or as a source of electricity generation.

Hence a detailed study on the LFG generation, different processes involved in its generation, factors affecting the generation and use of the gas is required to be done. However the rate of emission of the LFG is difficult to be studied as it depends on the number of factors. These factors involve the gas production rate, gas migration properties from lateral movement from waste layers, gas collection efficiency and the effect of atmospheric factors on the gas generation, oxidation of CH_4 in the presence of oxygen. (Mohammad F. M. Abushammala et al.,2009) Hence in the present paper a brief review of gas generation process, different methods of estimation of gas and the extent of work carried out for estimation of the gas generated from the landfill site or from the lab scale models of landfill.

II. Landfill Gas Generation Process

In the landfill gas generation process different aerobic, facultative and anaerobic bacteria's take part in degradation of the organic matter present in the waste. The gas generation process is divided into 5 stages as shown in Fig. 1.

In stage 1 which is generally termed as the initial adjustment stage, the waste dumped into the landfill consumes the moisture and oxygen and with the help of aerobic bacteria degrades the organic matter and produce the CO_2 and H_2O.This CO_2 may release or gets mixed with the H_2O to form Carbonic acid(H_2CO_3) which activates the leachate generation process.(Mohammad F. M. Abushammala et al.,2009) In stage 2 which is the Transition Stages the transition of aerobic condition to anaerobic condition takes place. Here the oxygen content starts reducing and the facultative bacteria's gets activated for further degradation.This bacteria's hydrolysis the carbohydrates, proteins and fatty acids to sugars. This sugar decomposes to carbon di oxide, hydrogen and ammonia. (Mohammad F. M. Abushammala et al.,2009)In stage 3 which is the acid formation stage, the acids generated into second stage gets further fermented into short chain compounds. In this stage Acetic Acid, Hydrogen and carbon di oxide are formed by the acetogenic microorganisms present in this stage along with the formation of the H_2S by the reduction of the Sulphate(SO_4^{-2}) compounds. In stage 4 which is Methane fermentation Stage, the Methanogenicmicroorganisms degrades the organic acids from the third stage to CH_4 and CO_2 in the anaerobic conditions. In the stage 5 i.e. Maturation stage, the gas formation reduces and in the aerobic conditions the CH_4 generated in the earlier stage is oxidised and converted into CO_2 and H_2O.

There are certain factors which influence the LFG emission rate such as Oxygen, Hydrogen, ph, Sulphate, inhibitors, nutrient, temperature, water content, waste composition, sewage sludge addition, buffer addition, compaction, soil cover, leachate recirculation, precompostingetc (Mohammed F. M. Abushammala et al., 2009)

III. Models of landfill gas estimation

The above mentioned process takes place at the landfill site or at the simulated reactor and with the passage of time CH_4 is generated. In order to estimate the generated gas, various hard and soft computing methods are used.

Hard computing or conventional computing methods require a precisely stated analytical model and often a lot of computation time. Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, partial truth, and approximation. In effect, the role model for soft computing is the human mind.

Hard computing is deterministic whereas soft computing incorporates stochasticity. Hard computing requires exact input data; soft computing can deal with ambiguous and noisy data. Hard computing methods are very easy to use and anybody can apply them provided complete dataset is available. On the other hand application of Soft computing methods requires special training.

Following are some of the Hard and soft computing methods applied for LFG estimation.

3.1 Hard Computing Methods

3.1.1 Default Methodology

This model is based on the Mass Balance Concept. This model can be used for any region of the country. This method was firstly introduced byBingemer and Crutzen and later it was revised in IPCC. This model depends upon the estimation of the Degradable Organic Carbon Content present in the solid waste and depending upon that calculates the amount of Methane that will be generated from the waste. (Mohammad F.M. Abushammala et al.,2009) In this method, number of constants are involved and they vary depending upon the composition of waste,depth of waste,etc.(Mali S. T. et al.,2011) The equation for the calculation of Methane Generation is as follows:

$$Emission = \left(MSW_T\ X\ MSW_F\ X\ MCF\ X\ DOC\ X\ DOC_F\ X\ F\ X\ {}^{16}/_{12} - R\right) X\ (1 - OX) \quad (1)$$

where,MSW_T is the total MSW generated,MSW_F is the fraction of MSW disposed off to landfill site,MCF is the CH_4 generation factor while DOC is the degradable organic carbon fraction based on the waste composition.DOC_F is the dissimilated organic fraction which means the portion of DOC that is converted to LFG,F is the fraction of CH_4 in LFG with 0.5 default Factor is the value of CH_4 recovered and OX is the oxidation factor fraction with default value equal to zero.

3.1.2 First Order Decay Model (FOD)

In this method, the Landfill gas isestimated in two phases. In the first phase the gas generation keeps on increasing till the peak is not reached and then it starts decreasing till the material gets stabilised. The formula for estimation is as follows:

$$\alpha_t = \xi 1.87 AC_{OK1e^{-k1^t}} \quad (2)$$

where αt is the landfill gas formation at a certain time , ζ is the formation fraction,k1 is the degradation rate constant , A is the amount of waste deposited, Co is the amount of degradable organic carbon in the waste at the time of deposition. This method doesnot take into consideration the age of the waste.

3.3 Triangular Method

Triangular method is a slight modification of the FOD.In this method, the amount of LFG generated corresponds to the area of triangle for a particular period of time. In this method it is assumed that the gas generation takes place since first year and increases till a peak is reached and then declines and becomes zero at the end of sixteenth year. Fig 2 gives the information of the amount of gas generation (Sunil kumar et al.,2004).

3.1.4 Modified Triangular Method

This method is the slight modification to the triangular method. This method is used when the detailed data from the landfill is not available. In this method ,it is assumed that the total gas generated is equal to the gas estimated in the Default Methodology method and the corresponding gas generation is calculated using the triangular area and the corresponding heights.(Mali S. T. et al.,2011)

3.2 Soft Computing Methods

3.2.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are biologically inspired parallel computational models. They consists of simple highly inter connected processing elements which processes the input similar to human brain. ANN’s acquires, represent and compute mapping from one multivariate space to another using self-learning. ANN is used in almost all the fields of Civil Engineering. ANN’s developed in recent years, can handle nonlinear systems and have been used to model LFG estimation with promising results. This is regarded as an intelligent, cost-effective approach and has received much attention in Environmental Engineering.

ANN is a universal approximator which does not need any priori knowledge about the system to be analyzed. ANN’s have ability of adaptive learning and can recognize the patterns but are tolerant to the data. As the performance of ANN models entirely depend on the quality and the quantity of the data, they are considered as black box. Deciding ANN architecture is a complex process which demands the skill of the programmer as there is no fixed rule to decide the data division and the number of neurons in the hidden layer. Sometimes ANN models may suffer from over fitting due to addition of too many hidden neurons or executing large number of iterations. Despite of many advantages, some researchers have found that ANN’s are insufficient to predict extreme events (Londhe 2008).

3.2.1.1Types of Neural Networks

ANN’s are broadly classified as non-recurrent (feed forward) neural networks and recurrent neural networks.

a)Non recurrent (feed forward) networks**-** Network has generally three layers namely input, output and hidden layer. No of layers are controlled by training algorithm. Input layer receives the input variables for the problem. Output layer consists of values predicted by the network. Number of neurons in the hidden layer is decided by trial and error method. Network has subgroup of processing elements which makes independent computations based on a weighted sum of its inputs. Following fig no. 3 illustrate feed forward network.

b) Recurrent networks-

Recurrent networks have feedback path as shown in fig no. 4 which makes it sequential rather than combinatorial .Once cyclic connections are included, network becomes a non linear dynamic system.

All training algorithms are basically aimed at reducing the global error, E, between the network output and the actual observation, as defined below:

$$E = \sum (O_n - O_t)^2 \qquad (3)$$

Where O_n is the network output at a given output node and O_t is the target output at the same node. The summation is carried out over all output nodes for a given training pattern and then over all training patterns.

3.2.2 Fuzzy Logic

Fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based.The idea of fuzzy logic was first advanced by Dr.LotfiZadeh of the University of California at Berkeley in the 1960s. Dr.Zadeh was working on the problem of computer understanding of natural language. Natural language (like most other activities in life and indeed the universe) is not easily translated into the absolute terms of 0 and 1. (Whether everything is ultimately describable in binary terms is a philosophical question worth pursuing, but in practice much data we might want to feed a computer is in some state in between and so, frequently, are the results of computing.)

Fuzzy logic includes 0 and 1 as extreme cases of truth (or "the state of matters" or "fact") but also includes the various states of truth in between so that, for example, the result of a comparison between two things could be not "tall" or "short" but ".38 of tallness ". Fuzzy logic seems closer to the way our brains work. We aggregate data and form a number of partial truths which we aggregate further into higher truths which in turn, when certain thresholds are exceeded, cause certain further results such as motor reaction. A similar kind of process is used in artificial computer neural network and expert systems.

Various mathematical models for simulating landfill gas are presented in the literature .However, the uncertainties of solid waste characteristics, as well as the complex physical, chemical, and biological processes taking place within the landfill ecosystem, motivated use of advanced modeling techniques such as ANN and fuzzy logic systems.

IV. Findings from the available literature

According to the research carried out by **Mohamed Abdallah et al., 2011**, on lab scale model, Experimental data were compiled from the work byS., Rendra as a part of PhD work which involved 8 liters lab-scale landfill cells containing a total mass and density of waste of 2.50 kg/reactor and 350 kg/m3, respectively. Major components of the waste were paper (36.6%), food (36.2%), and yard trimmings (27.2%). The cells were recirculated with different rates of leachate and sludge that remained unchanged along the experiment. Experimental measurements included temporal biogas generation rate as well as supplemental addition rates.The input variables included time (or operating phase), leachate recirculation, and sludge addition.

It was found that ANFIS could model the LFG estimation process well but the performance depends on the quality and the quantity of the data and no. of training epochs. Overfitting problems may cause unexpected model distortion. On condition of proper training process, this technique can present a prospective alternative methodology in the modeling of landfill processes.

Sunil Kumar et al., 2004 has carried out study on national level methane emission from solid waste disposal sites using the default methodology Considering the triangular pattern of gas generation indicates that the methane emissions vary between 119.01Gg in 1980 and 400.66 Gg in 1999.However, there are certain limitations in the inventory estimation of methane emission estimated for the years 1980–1999 in India. The inventory estimation has been made mostly on the basis of published documents and a little on the data generated. Mostly, the default values suggested by IPCC have been used in estimation, as guided by IPCC based on the studies made in other situations. For realistic values for Indian condition, detailed study is required to arrive at appropriate factors. Similarly, in data collection also several constraints have been observed. Most of the municipalities do not maintain the solid waste data due to lack of awareness, small financial budget and low priority.

M. F. M. Abushamalla et al; 2015 have proposed ANN to predict CH_4 oxidation in a sandy landfill cover soil. The result indicated small MSE (0.001475) and high R^2 (0.9) between the predicted and the measured values. However the model is applicable only for that site.

V. Case Study

Combining Fuzzy Logic and Neural Networks in Modeling Landfill Gas Production

Authors-Mohamed Abdallah, MostafaWarith, Roberto Narbaitz, Emil Petriu, and Kevin Kennedy
Published in World Academy of Science, Engineering and Technology Vol:5 2011-06-25

The study proposes the integration of fuzzy logic and ANN for modelling of the Landfill gas production. It combines the merits of both systems, and is a more powerful modelling tool. The basic idea of incorporating both systems is to design an architecture that uses a FL system to represent knowledge in an interpretable manner and implements the learning algorithms of ANN to optimize its parameters. Hence, the drawbacks of both systems, such as the black box behavior of ANN and the problems of tuning the membership values in FL systems, could be avoided.

5.1 Experimental data-

The experimental data consists of 8 liters lab-scale landfill cells containing a total mass and density of waste of 2.50 kg/reactor and 350 kg/m3, respectively. Major components of the waste were paper (36.6%), food (36.2%), and yard trimmings (27.2%). The cells were recirculated with different rates of leachate and sludge that remained unchanged along the experiment.Experimental measurements included temporal biogas generation rate as well as supplemental addition rates.

Fuzzy Logic controller

The components of fuzzy logic controller structure include: (1) inputs, (2) fuzzifier unit, (3) data base, (4) rule base, (5) fuzzy inference engine, (6) defuzzifier unit, and (7) outputs.

5.2 Fuzzy Inference System

The present study applies the Takagi-Sugeno method for the fuzzy inference system. The Sugeno output membership functions are either linear or constant making them compact and computationally efficient and compatible to the use of adaptive techniques such as ANN. The ANFIS model was built and trained using Fuzzy Logic toolbox of MATLAB. The process starts by loading the training and checking datasets which include input and output data vectors. Each input/output pair contains three inputs (time, sludge addition rate, and leachate recirculation rate) and one output (biogas generation rate). An error tolerance (ET) value is defined for the maximum acceptable difference between the actual and simulated output. The model starts the training process with the initial parameters of the membership functions, and the error for each data pair is calculated. If this error is larger than the ET value, the membership parameters are adjusted through an optimization step. Simultaneously, the error of checking dataset is calculated. Typically, it decreases down to a certain point, and then increases. This overturn represents the point of model overfitting. The program chooses the model parameters associated with the minimum checking error. Finally, the model is validated against independent testing dataset.

1. Model Validation

Model validation is used to examine the potential of the ANFIS model under untrained range of operating conditions. Commonly, the main concern in model validation is selecting a data set that is both representative of the data via which the model was developed, yet sufficiently distinct from it otherwise the validation process becomes meaningless. It was found that the model predictions were in excellent agreement with the training datasets (average correlation coefficient of 0.98).

Performance of the developed models was evaluated using P, SB, NU, LC, MSE, RMSE and N-RMSE.There was not much difference between the performances of ANFIS sub-models; all sub-models achieved high correlation with their training datasets. The best fit was achieved by M-300, the most trained model, whereas the least trained model, M-50, scored the lowest fit. During validation stage, the most distorted sub-models were M-50 and M-100. Statistically, the number of training vectors highly affected the performance of ANFIS to a certain point. Starting from M-150, a great enhancement was observed in terms of all statistical measures. However, beyond M-150, the model did not show significant improvement in response to a larger training dataset.

From the results it can be seen that the ANFIS model could map the LGF generation process. The authors concluded that,

The model achieved acceptable statistical measures in terms of linear regression, F test and mean square error. On the other hand, the discussion revealed some limitations in the neural fuzzy model. First, its performance is highly dependent on the quality and quantity oftraining data as well as the number of training epochs. Besides, the over fitting problem may cause unexpected model distortion. On condition of proper training process, this technique can present a prospective alternative methodology in the modelling of landfill processes.

VI. Summary

i. Study of landfill is the most important task to be performed as the quantity of solid waste generation goes on increasing day by day due to increase in population, development in industrialization.
ii. The by-products of landfill viz. landfill gas is required to be taken into consideration as the landfill gas mainly consists of methane, carbon di oxide and other trace materials out of which methane is the principal component of greenhouse gases.
iii. If this estimation of gas is done in advance to its generation then proper arrangement for its disposal as well as its use in energy recovery can be done.
iv. There is a need for use of soft computing approach towards the estimation of landfill gas as the characteristics of gas generation and process of generation is very complex and non linear in nature which can be identified and processed using soft computing techniques as they are the proven tools for modelling highly non-linear systems.

FIGURES AND TABLES

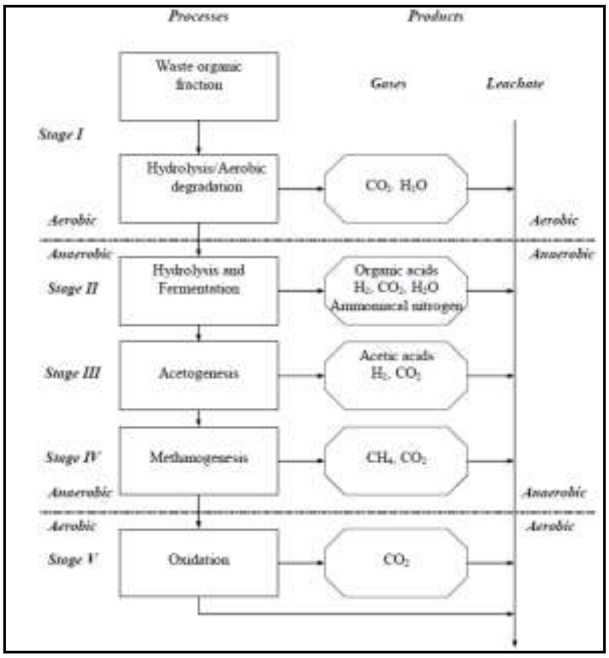

Fig 1 Stages of Waste Degradation and Gas Generation
(Source: Mohammed F. M. Abushammala et al., 2009)

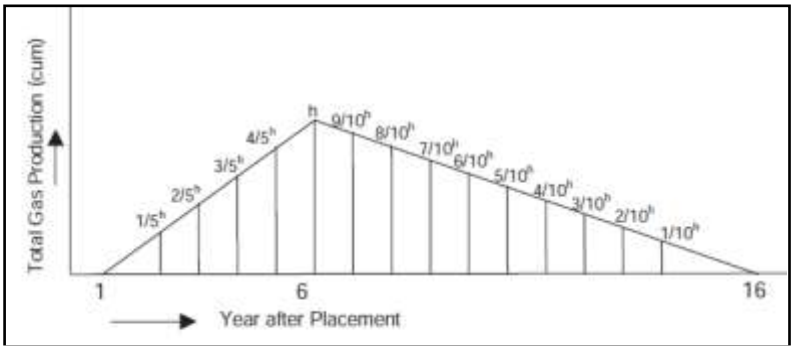

Fig 2 Triangular Method of Estimation (Source: Sunil kumar et al.,2004)

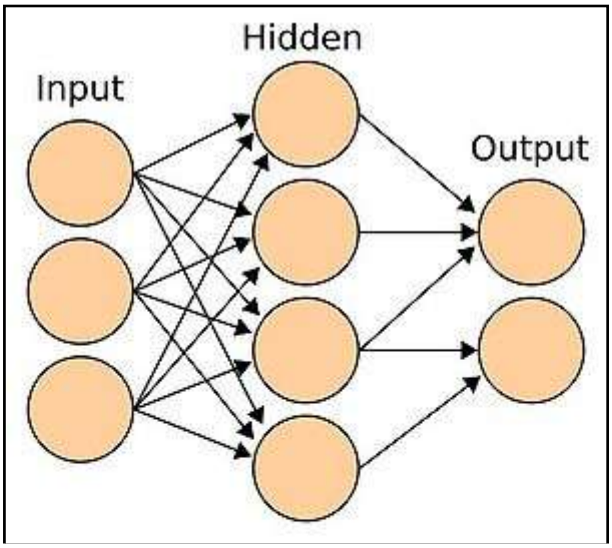

Fig.3 Feed forward networks (Source : ASCE Task Committee,2000)

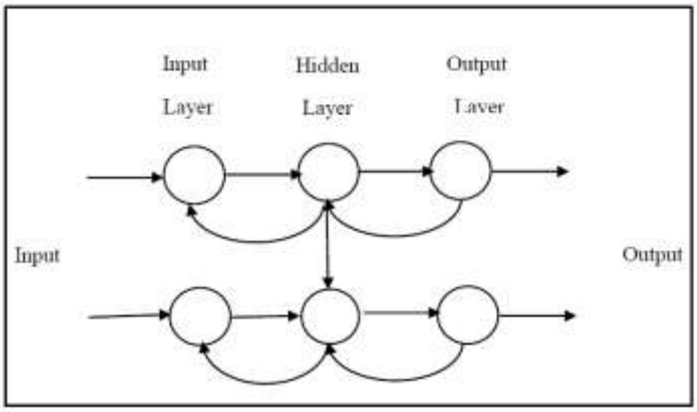

Fig.4. The Recurrent Network (Source : ASCE Task Committee,2000)

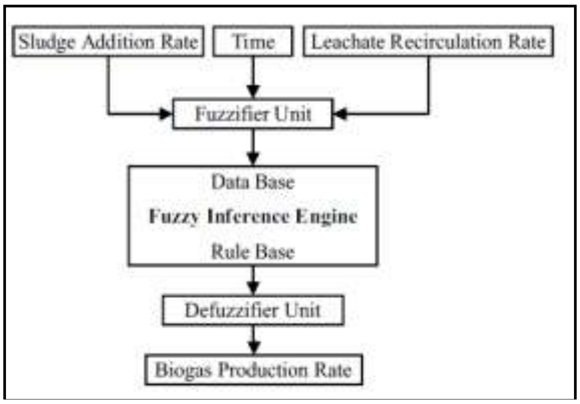

Fig. 5 Typical structure of a fuzzy logic controller

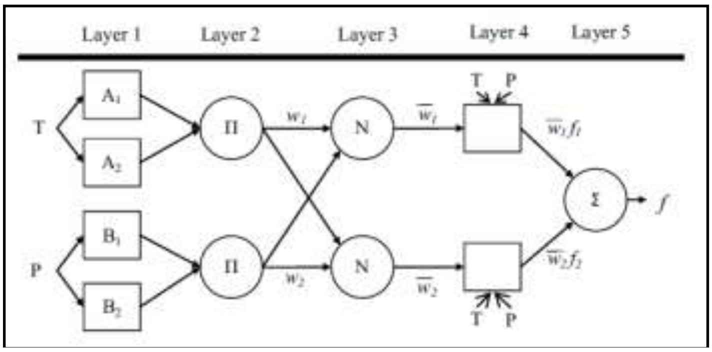

Fig. 6 ANFIS Architecture

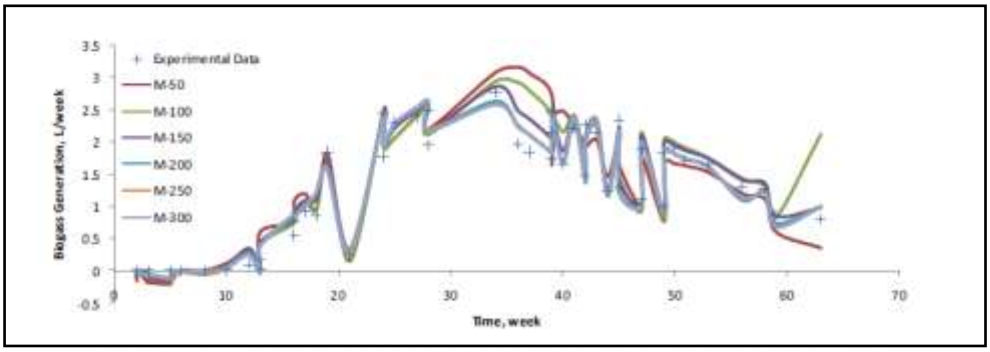

Fig 7 Actual and Simulated Biogas Generation rate for the ANFIS sub model with time

STATISTICAL TESTING OF THE ANFIS MODEL AT DIFFERENT TRAINING SIZES

Model	*F*-test			Mean Square Error					
	$F_{calculated}$	$F_{critical}$	P	SB	NU	LC	MSE	RMSE	N-RMSE
M-50	1.069	1.607	0.409	0.001	0.000	0.026	0.027	0.166	14.423
M-100	1.018	1.394	0.465	0.001	0.000	0.020	0.022	0.147	11.236
M-150	1.021	1.310	0.451	0.001	0.000	0.021	0.022	0.149	11.846
M-200	1.051	1.263	0.364	0.001	0.001	0.019	0.021	0.145	12.290
M-250	1.052	1.232	0.346	0.001	0.001	0.017	0.019	0.138	11.790
M-300	1.049	1.210	0.341	0.001	0.001	0.015	0.017	0.132	11.380

P, probability; SB, squared bias; NU, non-unity slope; LC, lack of correlation; MSE: mean square error; RMSE: root mean square error; N-RMSE: normalized root mean square error (in percent).

Table 1 Statistics Testing of the ANFIS Model at different Training Sizes

STATISTICAL TESTING OF THE ANFIS MODEL FOR THE TESTING DATASET

Model	F-test		Linear Regression			Mean Square Error		
	$F_{calculated}$	$F_{critical}$	a	b	R^2	MSE	RMSE	N-RMSE
M-50	1.249	1.607	0.016	1.040	0.865	0.141	0.375	29.193
M-100	1.169	1.607	0.083	1.024	0.898	0.109	0.33	25.661
M-150	1.072	1.607	0.048	1.020	0.970	0.032	0.178	13.829
M-200	1.012	1.607	0.033	0.979	0.971	0.023	0.152	11.852
M-250	1.005	1.607	0.030	0.983	0.972	0.023	0.151	11.75
M-300	1.001	1.607	0.030	0.986	0.972	0.023	0.152	11.848

a, intercept of regression line; b, slope of regression line; R^2, coefficient of determination.

Table 2 Statistics Testing of the ANFIS Model at Different Testing Datasets

REFERENCES

[1] M. F. M. Abushamala,N.E.A. Basri and M. K. Younges.Landfill Methane Oxidation: Predictive Model Development,Journal of Applied sciences,volume 15,issue 2,2015,283-288.
[2] Ubavin D.,Madous N.,Milovanovic D.,stege G. A. and Leatherwood C ,Preliminary Estimate of Methane Production at Belgrade MSW Landfill “vinca”,The 6th PSU-UNS International Conference on Engineering and Technology,paper no. T 7-2.5,2013, 1-3.
[3] Mohammed F. M. Abushammala,Noor Ezlin Ahmad Basri,Abdul Amir H. Kadhum,Review on Landfill Gas Emission on Atmosphere,European Journal of Scientific Research,Vol.30 No.3,2009,427-436.
[4] Mali Sandip T., KhareKanchan C. and Biradar Ashok H.,Estimation Of Methane Gas Emission From Municipal Solid Waste Landfill:Pune City, India, EVRJ volume 6,2012,1-11.
[5] Sunil Kumar, S.A. Gaikwad, A.V. Shekdar, P.S. Kshirsagar, R.N. Singh,Estimation method for national methane emission fromsolid waste landfills,Atmospheric Environment 38,2004,3481-3487.
[6] Mohamed Abdallah, MostafaWarith, Roberto Narbaitz, Emil Petriu, and Kevin Kennedy ,Combining Fuzzy Logic and Neural Networks in Modeling Landfill Gas Production,World Academy of Science, Engineering and Technology Vol:5,2011,445-451.
[7] Londhe,Soft computing approach for real-time estimation of missing wave heights,Ocean Engineering 35,2008,1080-1089.
[8] ASCE Task Committee on Application of Artificial Neural Networks in Hydrology,Artificial Neural Networks in Hydrology.I: Preliminary Concepts, J. Hydrol. Eng., 5(2),2000, 115–123.