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A DISTINCT INDICATOR TO PREDICT BIOGASIFICATION POTENTIAL OF URBAN WASTEWATER BY FUZZY COMPOSITE APPROACH

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Abstract

A novel blending of fuzzy, statistical and neural approach in prediction of biogas from urban wastewater treatment plants has been projected in this research work. Recently biogas has become a popular energy source due to its safe and affordable productivity. Municipal wastewater contains abundant organic load to yield biogas. Bearing in mind number of wastewater treatment plants across India, biogas from these plants will be an infinite, economic and consistent source. Variation in wastewater quality and quantity confines the biogas harvesting and prediction practices. Various prediction approaches deals with characterization of digester feedstock; whereas there are no such practices possible in routine. In present research work a most significant parameter affecting influent wastewater characteristics was identified statistically. A unique multi parameter aggregated index (MPAI) was obtained by fuzzification and mathematical aggregation of influent characteristics. This index was further correlated with most significant parameter and biogas. Multiparameter aggregated index for influent was found in the range of 0.40 to 0.70 and varying according to seasons. Suspended solids were found most significant parameter affecting biogasification. A neural network model was developed to predict biogas by monitoring suspended solids from influent only and using MPAI as cross reference.

***Keywords*:**biogas, fuzzy neural, multipramater aggregated index, suspended soilds, wastewater.

1 INTRODUCTION

Energy from renewable source is a prevalent approach and that of from biogas is the most, due to its affordability for production and safety in distribution. As biogas energy harvesting involves a very simple mechanism of anaerobic digestion and so adopted in rural globe. Excellent organic loading rates, limited sludge production rates and efficient energy generation are the advantages of anaerobic process. Worldwide practices and research works are going on to fetch maximum yield from biomass to biogas, (Zhang et al. 2016;Bharati Barua Kalamdhad B 2016;Yetilmezsoy et al. 2012;Mao et al. 2015; Budzianowski 2012). The process of biogasification predominantly involves anaerobic digestion. The anaerobic gas mixture called biogas having calorific value of 4 7.5 KwH/M3, [10] can be used as energy resource. Biogas is generated when organic material is broken down by microbial action. In municipal waste water treatment plants large amount of sludge is generated which is rich in organic content and can be digested anaerobically to get biogas which liberates from organic content exists in sludge (Parkin Owen 1987; Zhang et al. 2016). Municipal wastewater contains an organic loading which has the potential of energy recovery. The biomass in the form of organic component is rich in nutrients and hence responsible to generate energy.

Prediction of biogas is essentially carried out for simulation of anaerobic digestion to estimate energy potential. Various models developed in recent years which are bound in the assessment of biogasification with reference to the degradation rate of the feedstock, the biogas and methane yield, concentrations of organic acids and ammonium nitrogen etc. Buswell and Muellepi in 1952 stated equation to estimate the biogas considering 100% breakdown of material. [15][17]. In practice the model developed by International Water Association task group ADM1 [18] is considered as the well-defined and competent in prediction of biogas. Batstone et al. predicted all the key processes happening in anaerobic digestion system and could provide a benchmark for forecasting. The model is based on disintegration, hydrolysis, acidogenic, acetogenic and methanogenic stages and the kinetics involved therein, (Zhou et al. 2011; Mairet, Bernard, Ras, Lardon Steyer 2011; Yu et al. 2013). Kujawski; developed model based on mass balances of dry organic matter and nitrogen. The work also simplified kinetics of anaerobic degradation and process of ammonium production [22]. All these approaches were found theoretically precise but failed in case of biogas from municipal sludge due to complexity in application, frequent variation in wastewater characteristic and rainfall. Considering regular operations at urban wastewater treatment plants; some uncertainty about model working found as ADM 1 model deals only with biochemical kinetic matrix [24] which includes physical, chemical, and biological processes involved in anaerobic digestion, where in inlet and outlet characterization that of treatment plants are getting neglected (Curry Pillay 2012). A complex biogasification process results to develop a complicated nonlinear relation which causes failure of traditional data processing while solving problem. This can be overcome by using fuzzy logic approach in biogas modelling.

In the anaerobic digestion of wastewater sludge, chemical oxygen demand (COD), which is the oxygen present along with sugar as a substrate; gets consumed to liberate carbon dioxide which in further complex reaction results to generate about 72% of the methane and 28% of carbon dioxide which is biogas. Thus COD of feedstock is the indicative characteristic to assess the biogas productivity [26], [27].

In the present research work researcher adopted a novel composite approach using suspended solid concentration of influent as an indicative characteristic to predict biogasification potential of urban waste water. In recent days, determination of suspended solid has become very fast process using electronic devices. Hence this will help to reduce limitations those were there in case of COD. The laboratory scale setup was designed and operated on real feedstock sludge collected from wastewater treatment plant. Two separate multi parameter aggregated indices (MPAI) for influent wastewater and inlet sludge were calculated by fuzzy approach. The model was developed using fuzzy neural approach where suspended solids concentration will be the input and biogas will be predicted.

2 METHODOLOGY

A typical municipal wastewater treatment plant maintains the organic mass balance at various levels of treatment starting from primary treatment to sludge generation. The sludge is allowed for biogasification after necessary pretreatments mostly dewatering. In the present work a laboratory scale anaerobic digester was designed and developed for simulation. A retention time for design is considered to be 21 days (Muller et al. 1995; Karlsson et al. 2014; Okonkwo C P et al. 2013). Design temperature is considered to be room temperature normally in the range of 230C to 300C. Factors affecting biogasification were monitored and regulated. The waste audit was carried out for entire year and accordingly the capacity was suggested. The size of the reactor was calculated by a modified version of the organic loading rate equation suggested by Curry et al; [25]. Wastewater characteristics are assumed to be uniform throughout the span of year. An arrangement was made to collect supernatant and biogas. Mixing within the digester helps to maintain the uniform temperature within the digester. For thorough mixing a magnetic stirrer was introduced and to maintain temperature in winter and monsoon season the hot water bath assembly was provided to reactor.

$$Volume(Cum) = \frac{FlowRate\frac{Cum}{day} \times VolatileSolidConcentrations(\frac{Kgs}{Cum})}{OrganicLoadingRate\frac{Kg}{Cum}/day} \quad (1)$$

As per design calculation and relevance to field observations and expert directions; the reactor of capacity 3000 ml was designed as shown in Fig 1; with 2000 ml of feedstock capacity, 400 ml sludge zone and 600 ml gas collection zone. Every day 200 ml of real feedstock collected from municipal wastewater treatment plant was added to reactor so that around 200 ml supernatant was collected which was analysed regularly on the basis of pH, COD, BOD, volatile fatty acids and suspended solids. The digester assembly as shown in Fig 1 was maintained in operation for a span of a year so as to study seasonal effect on biogas generation. Sampling, handling, transportation and preservation of samples was carried as per standard guidelines. The characterization of inlet was carried out on the basis of pH, TDS, SS, BOD5, and COD. Similarly characterization of sludge which is digester input; was performed on the basis of TDS, SS, BOD, COD, COD of supernatant, volatile fatty acids, mixed liquor suspended solids and alkalinity. Wastewater plant influent characteristics are tabulated in table 1 of result section. The environmental index is

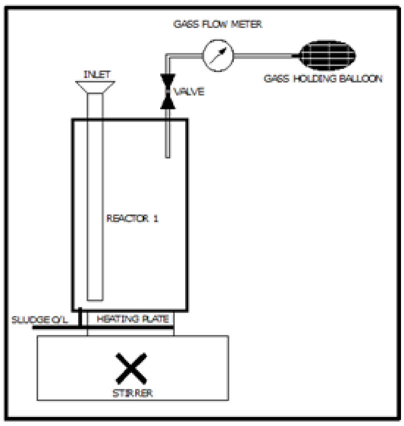

Figure 1: Laboratory setup - line diagram

a unitless number ranging from 1 to 100; a higher number is indicative of better quality. In case of present experimental work an attempt has been done to calculate MPAI which could define characteristic of digester feedstock and influent as well. Steps involved in MPAI calculation for MWWTP as well as digester inlet are formulated as in Fig.2 [32].

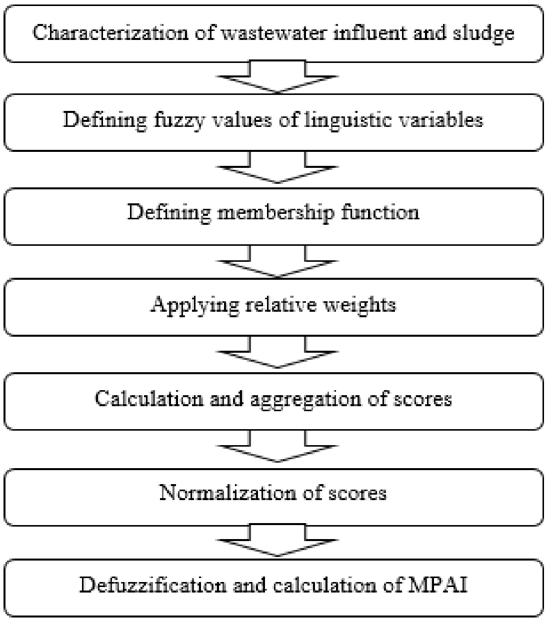

Figure 2: MPAI calculation process

The weights were calculated for nine parameters of wastewater for both raw wastewater and digester inlet. On the basis of opinions received from various environmental the experts the criterions were defined in terms of linguistic variable, a fuzzy decision matrix for the wastewater parameters was computed. Weights were evaluated using the equation (ii).

$$aij = \frac{xij}{\sqrt{\sum_{j=1}^{n} x_{i,j}^2}} \qquad (2)$$

Where aij is the normalized crisp value, i = 1, 2, ., m; j = 1, 2, , n. The normalized value vij is calculated by applying weight, as; ij

= qij . aij, Where qi is the weight of ith criterion, i = 1, 2,, m; j = 1, 2, , n. The average fuzzy numbers for all the environmental experts opinion are expressed as in equation (ii) bellow.

$$a_{ij}^{k} = (1/\rho)(a_{i1}^{k} + a_{i2}^{k} + a_{i3}^{k} + ... + a_{p}^{k}) \quad (3)$$

Where a_{ij}^{k} be the fuzzy number which is a relative importance or weight assigned to an alternative a_i by decision maker (one); DMi for Ck - the decision criteria and p is number of experts involved in the evaluation process. Experts from academics, consultants, plant operation, chemists, research scholars etc. were provided with question sets to invite opinions regarding importance of parameter and its significance. The linguistic variables as assigned by the experts are converted to fuzzy numbers used in the above expressions through figure. At last the parametric values of raw and treated wastewater are converted into the fuzzy numbers (membership functions) based on the specified statutory norms. MPAI for waste water inlet is calculated by aggregation of all membership grades of corresponding characteristics, as in equation (iii).

$$MPAI_{inlet} = \sum_{i=1}^{n} s_{i1} + s_{i2} + ... + s_{in} \quad (4)$$

For precise predictive tool neural network tool was diployed. Out of 380 data 70% was utillised for training, 15% for testing and 15% for validating. The ANN tested were all of feed- forward backpropagation type. Static networks such adopted are simple and easy to train. In case of nonlinear process modeling ANN was trained by providing MPAI and suspended solids concentration as an input to predict biogas.

3 RESULTS AND DISCUSSIONS

The average characteristics of inlet waste water is tabulated bellow. Statistically obtained correlation provided the suspended solids concentration as a most significant parameter which gets affected according to monsoon and influence the production of biogas. At higher suspended solids concentrations due to lower water content biogas production increases.

Table 1: Average yearly characteristics of influent wastewater

Temp.	**TDS**	**SS**	**BOD**	**COD**	**Phosphate**	**Nitrogen**	**Cl-**	**pH**
°C	mg/l	mg/l	mg/l	mg/l	mg/l	mg/l	mg/l	-
26.9	574	144	132	403	5.8	42.3	307.9	7.7

In evidence of uncertainty fuzzy logical approach is superior in decision making process. Thus MPAI was calculated in range so as to get appropriate buffer in determination of index. Accordingly the MPAI for influent was obtained in the range of 0.40 to 0.70.MPAI, being a wholesome number indicating overall characteristic. The relation of influent MPAI with suspended solids is as shown in Fig 3. A very significant relation found with suspended solid and MPAI of influent with statistical R-squre value of 0.91; where as the relation between MPAI of influent and biogas generated is represented in Fig. 4. Suspended soilds being a major contributor in influent characteristics as per mass balance it also affects biogas production (Bodk et al. 2011; Markis et al. 2014). COD is another parameter which regulates biogas.

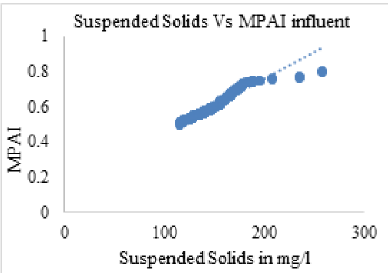

Figure 3: Relating influent MPAI and suspended solids

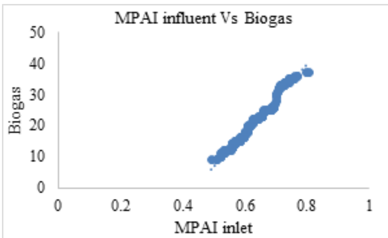

Figure 4: Relating Biogas and MPAI influent

In prediction neural network is an advanced tool to achieve single output from multiple uncertain inputs (Bashiri et al. 2015; Nair et al. 2016; Pakrou et al. 2014). In case of neural network model developed the biogas prediction was found precise, with influent MPAI and suspended solid as input. The performance was found best at 19th epoch and is shown in Fig. 6.

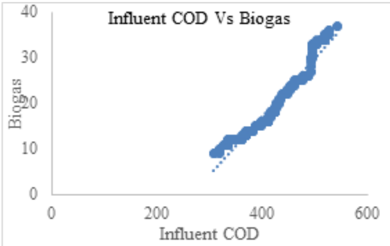

Figure 5: Relating Influent COD and Biogas

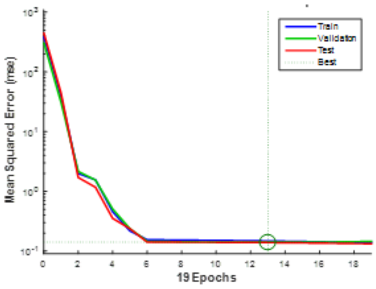

Figure 6: Performance of ANN Model

4 CONCLUSIONS

MPAI variation found due to rainfall and hence indicating effect of season on influent characteristics. Definitely this MPAI can be utilised further for plant optimization.The Buswels equation stated relation of feedstock COD and biogas as discussed in earlier section. But through MPAI; influent COD and suspnded solids found regulatory parameters for biogas too. This is the most demarkable conclusion of this study. Fig. 7 elaborates the predicted biogas with referance to actual measured biogas. The model was validated for 15% data. The present research work emphsized that along with feedstock COD, suspended solid is the significant parameter which influence the biogas generation. In case of municipal wastewater treatment the biogas from sludge will be the need of time. The prediction of biogas will be essentialy carried out for maximum yield. Prediction from feedstock characteristic is common but labourious and dificult in situ. The present novel prediction aproach deals with opearation with suspended solid concentration which is now a days being measured by electronnic, portable and handy devices. The present approach has been validated in situ and found very easy to adopt by layman working at plant and hence is recommended.

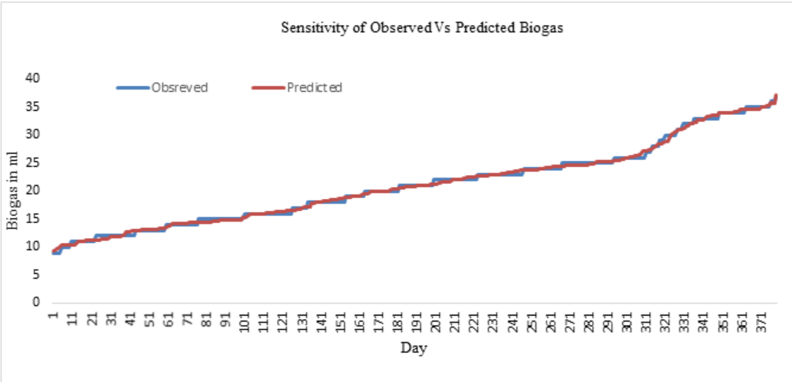

Figure 7: MPAI calculation process

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References

[1] D. P. Chynoweth, J. M. Owens, en R. Legrand, Renewable methane from anaerobic digestion of biomass, Renew. Energy, 2000.
[2] Q. Zhang, J. Hu, en D. J. Lee, Biogas from anaerobic digestion processes: Research updates, Renew. Energy, vol 98, bll 108119, 2016.
[3] J. Bjrklund, U. Geber, en T. Rydberg, Emergy analysis of municipal wastewater treatment and generation of electricity by digestion of sewage sludge, Resour. Conserv. Recycl., 2001.
[4] V. A. Bharati Barua en A. S. Kalamdhad B, Water Hyacinth To Biogas: a Review, Poll Res, vol 35, no 3, bll 491501, 2016.
[5] P. Weiland, Biogas production: Current state and perspectives, Appl. Microbiol. Biotechnol., vol 85, no 4, bll 849860, 2010.
[6] K. Yetilmezsoy, F. I. Turkdogan, en I. Temizel,

International Journal of Green Energy Development of Ann-Based Models to Predict Biogas and Methane Productions in Anaerobic Treatment of Molasses Wastewater, no July 2013, bll 3741, 2012.
[7] A. de Alwis, Biogas - a review of Sri Lankas performance with a renewable energy technology, Energy Sustain. Dev., vol 6, no 1, bll 3037, 2002.
[8] J.-F. . Akinbami, M. . Ilori, T. . Oyebisi, I. . Akinwumi, en O. Adeoti, Biogas energy use in Nigeria: current status, future prospects and policy implications, Renew. Sustain. Energy Rev., vol 5, no 1, bll 97112, 2001.
[9] C. Mao, Y. Feng, X. Wang, en G. Ren, Review on research achievements of biogas from anaerobic digestion, Renewable and Sustainable Energy Reviews, vol 45. Elsevier Ltd, bll 540555, 2015.
[10] T. Bond en M. R. Templeton, History and future of domestic biogas plants in the developing world, Energy Sustain. Dev., vol 15, no 4, bll 347354, 2011.
[11] W. M. Budzianowski, Sustainable biogas energy in Poland: Prospects and challenges, Renew. Sustain. Energy Rev., vol 16, no 1, bll 342349, 2012.
[12] G. F. Parkin en W. F. Owen, FUNDAMENTALS OF ANAEROBIC DIGESTION OF WASTEWATER SLUDGES, J. Environ. Eng., vol 112, no 5, bll 867920, 1987.
[13] S. Kalloum, H. Bouabdessalem, A. Touzi, A. Iddou, en M. S. Ouali, Biogas production from the sludge of the municipal wastewater treatment plant of Adrar city (southwest of Algeria), Biomass and Bioenergy, 2011.
[14] K. Kanger, C. Ebner, en H. Nlvak, BIOGAS PRODUCTION UNDER CO-DIGESTION OF FOOD WASTE WITH SEWAGE SLUDGE, UNIVERSITY OF TARTU, 2013.
[15] L. Hellgren, Energy Management in Wastewater Treatment Systems: Biogas Energy Recovery Management Application, 2015. [16] C. Banks, Anaerobic digestion and energy, 2011.
[17] C. fang Liu, X. zhong Yuan, G. ming Zeng, W. wei Li, en J. Li, Prediction of methane yield at optimum pH for anaerobic digestion of organic fraction

of municipal solid waste, Bioresour. Technol., 2008.
[18] D. J. Batstone, J. Keller, en I. Angelidaki, Anaerobic digestion model no. 1, vol 1, no 1, 2002.
[19] H. Zhou, D. Lffler, en M. Kranert, Model-based predictions of anaerobic digestion of agricultural substrates for biogas. production, Bioresour. Technol., vol 102, no 23, bll 1081910828, 2011.
[20] F. Mairet, O. Bernard, M. Ras, L. Lardon, en J. P. Steyer, Modeling anaerobic digestion of microalgae using ADM1, Bioresour. Technol., vol 102, no 13, bll 68236829, 2011.
[21] F. Mairet, O. Bernard, M. Ras, L. Lardon, J. Steyer, en J.-P. S. Francis Mairet, Olivier Bernard, Monique Ras, Laurent Lardon, Testing the ability of ADM1 to represent the anaerobic digestion of microalgae. 2011.
[22] O. Kujawski en H. Steinmetz, Anaerobic Digestion Model based on Mass Balances. Development, Implementation and Validation. 2009, bll 14.
[23] L. Yu, P. Wensel, J. Ma, S. Chen, en Yu, Mathematical Modeling in Anaerobic Digestion (AD), J Bioremed Biodeg, vol S4, no 3, bl 12, 2013.
[24] S. Achinas en G. J. W. Euverink, Theoretical analysis of biogas potential prediction from agricultural waste, Resour. Technol., vol 2, no 3, bll 143147, 2016.
[25] N. Curry en P. Pillay, Biogas prediction and design of a food waste to energy system for the urban environment, Renew. Energy, vol 41, bll 200209, 2012.
[26] E. M. Contreras, N. C. Bertola, L. Giannuzzi, en N. E. Zaritzky, A modified method to determine biomass concentration as COD in pure cultures and in activated sludge systems, Water SA, 2002.
[27] G. Gngr-Demirci en G. N. Demirer, Effect of initial COD concentration, nutrient addition, temperature and microbial acclimation on anaerobic treatability of broiler and cattle manure, Bioresour. Technol., vol 93, no 2, bll 109117, 2004.
[28] E. B. Muller, A. H. Stouthamer, H. W. van Verseveld, en D. H. Eikelboom, Aerobic domestic waste water treatment in a pilot plant with complete sludge retention by cross-flow filtration, Water Res., 1995.
[29] P. Elefsiniotis en W. K. Oldham, Anaerobic

acidogenesis of primary sludge: The role of solids retention time, Biotechnol. Bioeng., vol 44, no 1, bll 713, 1994.
[30] A. Karlsson, A. Bjrn, S. S. Yekta, en B. H. Svensson, IMPROVEMENT OF THE BIOGAS, 2014.
[31] Okonkwo C P, A. B. O, en O. C. S, Factors Affecting Biogas Production during Anaerobic Decomposition of Brewery effluent-wastewater in a Fluidized Bed Digester, J. Environ. Earth Sci., vol 3, no 8, 2013.
[32] M. A. K. Khambete en R. A. Christian, Ranking Sewage Treatment Plants with the Application of Fuzzy Composite Programming, Int. J. Sci. Eng. Technol., vol 3, no 2, bll 116120, 2014.
[33] I. Bodk, S. Sedlek, M. Kubask, en M. Hutan, Biogas Production in Municipal Wastewater Treatment Plants Current Status in EU with a Focus on the Slovak Republic, 2011.
[34] F. Markis, J. C. Baudez, R. Parthasarathy, P. Slatter, en N. Eshtiaghi, Rheological characterisation of primary and secondary sludge: Impact of solids concentration, Chem. Eng. J., vol 253, bll 526537, 2014.
[35] C. F. Forster, The rheological and physico-chemical characteristics of sewage sludges, Enzyme Microb. Technol., vol 30, no 3, bll 340345, 2002.
[36] M. Bashiri, H. R. Rezaei, A. Farshbaf Geranmayeh, en F. Ghobadi, A Comparison of Regression and Neural Network Based for Multiple Response Optimization in a Real Case Study of Gasoline Production Process, J. Ind. Syst. Eng., vol 8, no 3, bll 7794, 2015.
[37] M. M. Hamed, M. G. Khalafallah, en E. A. Hassanien, Prediction of wastewater treatment plant performance using artificial neural networks, Environ. Model. Softw., vol 19, bll 919928, 2004.
[38] V. V. Nair, H. Dhar, S. Kumar, A. K. Thalla, S. Mukherjee, en J. W. C. Wong, Artificial neural network based modeling to evaluate methane yield from biogas in a laboratory-scale anaerobic bioreactor, Bioresour. Technol., 2016.
[39] S. Pakrou, N. Mehrdadi, en A. Baghvand, ARTIFICIAL NEURAL NETWORKS MODELING FOR PREDICTING

TREATMENT EFFICIENCY AND CONSIDERING EFFECTS OF INPUT PARAMETERS IN PREDICTION ACCURACY: A CASE STUDY IN TABRIZ TREATMENT PLANT, Indian J. Fundam. Appl. Life Sci., vol 4, bll 22316345, 2014.