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, multiparameter aggregated index, suspended solids, 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 4.75 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.

\[
Volume(Cum) = \frac{FlowRate_{Cum\ day} \times VolatileSolidConcentrations(Kgs\ Cum)}{OrganicLoadingRate\ Kg_{Cum}/day}
\]  

(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].

![Diagram](image)

**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 experts, the criteria were defined in terms of linguistic variables, a fuzzy decision matrix for the wastewater parameters was computed. Weights were evaluated using the equation (ii).

\[
aij = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{i,j}^2}}
\]  

(2)

Where \(aij\) is the normalized crisp value, \(i = 1, 2, \ldots, m; \ j = 1, 2, \ldots, n\). The normalized value \(v_{ij}\) is calculated by applying weight, as; \(ij\)
where \( q_{ij} \) is the weight of the \( i \)th criterion, \( i = 1, 2, ..., m \); \( j = 1, 2, ..., n \). The average fuzzy numbers for all the environmental experts' opinions are expressed as in equation (ii) below.

\[
a_{ij}^k = \frac{1}{\rho} (a_{i1}^k + a_{i2}^k + a_{i3}^k + ... + a_{ip}^k)
\]

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); \( \text{DMi} \) for \( C_k \) - the decision criteria and \( p \) is the 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 the importance of parameters and their significance. The linguistic variables as assigned by the experts were converted to fuzzy numbers used in the above expressions through a 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).

\[
MPAI_{inlet} = \sum_{i=1}^{n} s_{i1} + s_{i2} + ... + s_{in}
\]

For precise predictive tool, neural network tool was deployed. Out of 380 data, 70% was utilised 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 the input to predict biogas.

3 RESULTS AND DISCUSSIONS

The average characteristics of inlet waste water is tabulated below. 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

<table>
<thead>
<tr>
<th>Temp. °C</th>
<th>TDS mg/l</th>
<th>SS mg/l</th>
<th>BOD mg/l</th>
<th>COD mg/l</th>
<th>Phosphate mg/l</th>
<th>Nitrogen mg/l</th>
<th>Cl- mg/l</th>
<th>pH</th>
</tr>
</thead>
<tbody>
<tr>
<td>26.9</td>
<td>574</td>
<td>144</td>
<td>132</td>
<td>403</td>
<td>5.8</td>
<td>42.3</td>
<td>307.9</td>
<td>7.7</td>
</tr>
</tbody>
</table>

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-squared value of 0.91; where as the relation between MPAI of influent and biogas generated is represented in Fig. 4. Suspended solids 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.

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.
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 suspended solids found regulatory parameters for biogas too. This is the most demarkable conclusion of this study. Fig. 7 elaborates the predicted biogas with reference to actual measured biogas. The model was validated for 15% data. The present research work emphasized 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 essentially carried out for maximum yield. Prediction from feedstock characteristic is common but labourious and difficult in situ. The present novel prediction approach deals with operation with suspended solid concentration which is now a days being measured by electronic, 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.
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