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Fuzzy and Neuro-Fuzzy Modelling for Prediction of Effluent COD for a Real Scale UASB Reactor Treating Distillery Wastewater

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Abstract: The high rate anaerobic processes are used for treatment of industrial wastewater. These processes are subjected to many disturbances due to variation in quantity and quality of wastewater. Neuro-fuzzy (ANFIS) and fuzzy models were developed for prediction of effluent COD for an UASB reactor treating distillery wastewater. Different combinations of input parameters were assessed to obtain the ANFIS model. A fuzzy rule based model was developed with same combination of input parameters as ANFIS model. Expert's knowledge, plant operator's opinion and trend of the data were considered during model development. Parameters required for daily monitoring and operation of the plant were used for model development. Statistical parameters like the correlation coefficient (*R*) and root mean square error (*RMSE*) were used to assess the performance of these models. The value of 0.8922 and 1334.69 for *R* and *RMSE* were observed with the ANFIS model whereas 0.8197 and 4208.34 were obtained with the fuzzy model respectively. These values indicate good agreement between the predicted and observed values of effluent COD and satisfactory performance of the models. The modelling approach discussed in this paper will be useful for assessment of performance of the real scale UASB reactor and to control the operation of the plant.

Key words: UASB reactor, spent wash, COD, fuzzy model, ANFIS model, biogas, pH.

Introduction

The high rate anaerobic treatment processes such as up-flow anaerobic sludge blanket (UASB) reactors are generally used for treatment of strong wastewater. Performance of these processes is measured in terms of biogas production, effluent chemical oxygen demand (COD), and effluent volatile suspended solids (VSS) and it varies with reactor configurations, influent characteristics and operational conditions (Carrasco et al., 2004; Cakmakci, 2007). Mathematical model of wastewater treatment systems can be developed to predict the performance, to simulate, control of system operation and to investigate certain engineering questions without time consuming and expensive laboratory test (Tay and Zhang, 1999). However to develop a mathematical model for UASB process is very difficult because the anaerobic treatment methods are very sensitive and complex in operation. It requires detailed process knowledge, determination of kinetics parameters and details of stoichiometric knowledge of microbial reactions occurring in the treatment process. Solution of these models is very complicated because many mathematical equations and parameters are involved.

The soft computing techniques such as artificial neural networks (ANN), fuzzy logic (FL) and hybrid systems are nowadays used for modelling and

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controlling the operations of the high rate anaerobic processes. The ANN models are black box in nature and its relationship between inputs and outputs are not easily interpreted (Huang et al., 2010). Fuzzy logic brings formalism with its own syntax and semantics capable of expressing qualitative knowledge about problem under study. Its excellence relies specially in the strength of its interpolative reasoning mechanism (Belanche et al., 1999). Fuzzy logic presents flexibility and tolerance with imprecise data. Fuzzy logic can be built on top of human experience, combining natural language in an easy to understand way and also being able to model complex nonlinear functions (Carrasco et al., 2004). There is increased trend of using hybrid system such as neuro-fuzzy for modelling of anaerobic processes (Cakmakci, 2007; Perendeci et al., 2008).

Literature Review

Fuzzy Modelling

The fuzzy rule based model consist of a set of Fuzzy IF THEN rules. Most commonly used fuzzy model for modelling and controlling operation of wastewater treatment systems are the Mamdani model and the Takagi-Sugino-Kang (TSK) model. The nature of rules used in Mamdani model is given below.

$$R_i\text{: IF } x_j \text{ is } A_{ij} \text{ AND } \ldots\ x_r \text{ is } A_{ir} \text{ THEN } y \text{ is } C_i$$

where x_j (j = 1, 2, 3 … r) are the input variables, y is the output variable and A_{ij} and C_i are fuzzy sets for x_j and y respectively. The TSK model is similar to Mamdani model except the consequent (THEN part) of the Mamdani model is replaced with a linear equation of the input variable. The generalized form of rules used in TSK model is as below.

$$\text{IF } x_1 \text{ is } A_{i1}.\ \ldots \text{ AND } x_r \text{ is } A_{ir} \text{ THEN } y = f_i\,(x_1, x_2, \ldots\ x_r) = b_{i0} + b_{i1}x_1 + \ldots + b_{ir}\,x_r$$

where f_i is the linear model and b_{ij} (j = 0, 1, 2, … r) are real valued parameters. Various steps involved in fuzzy modelling are: fuzzification of input and output parameters, construction of rule base, inference of various rules and aggregation to get the output. MIN operator (AND method) is used for inference of the rules. Mamdani model gives output in the form of fuzzy set which needs defuzzification to get crisp value whereas output of TSK model is crisp value.

The anaerobic treatment processes are difficult to operate due to complex nature of biochemical reactions and sensitivity to environmental conditions. Fuzzy logic is becoming very common for intelligent control of these processes (Manesis et al., 1997, Estaben et al., 1997, Punal et al., 2003; Garcia et al., 2007). Fuzzy rule based model was used for predicting the Coli form removal efficiency in a slow sand filter (Sadiq et al., 2004). The modelling provided a comprehensive approach for performing risk analysis and satisfactory prediction was obtained from the model. Fuzzy modelling offers a powerful tool to describe complex nonlinear biological processes (Tay and Zhang, 1999; Cakmakci, 2007). Polit et al. (2001) developed the fuzzy estimator based on Takagi-Sugeno model to determine total and partial alkalinity of the influent, substrate concentration at the input, and volatile fatty acid using online measurement of biogas flow rate, wastewater flow rate and pH. The predicted values of effluent partial and total alkalinity and VFA followed well with the measured values.

A fuzzy dynamic model was developed (Polit et al., 2002) to determine a fuzzy coefficient for various conditions of pH and temperature. The kinetic growth rate was modified by multiplying it with the fuzzy coefficient to determine substrate utilization rate and biogas production rate for an anaerobic digester. Tay and Zhang (2000) proposed a fuzzy stability index N to integrate the complex information contained in system parameters like effluent quality, gas production and composition subjected to disturbance such as overloading and toxic substances. The instability of a system subjected to a certain shock was correlated with variance of N. This approach was found to be more convenient compared with direct examination of the reactor's performance. Fuzzy logic is used for predicting state of the reactor, fault detection and isolation, diagnosis and control of operation (Estaben et al., 1997; Genovesi et al., 2000; Carrasco et al., 2004). Fuzzy modelling techniques are found to be suitable for modelling anaerobic treatment process.

Neuro-Fuzzy Modelling

The integration of fuzzy logic (FL) and neural network (NN) combine the merits of both systems and offer a powerful tool for modelling (Tay and Zhang, 1999). The neural fuzzy system is called as adaptive network based fuzzy inference system (ANFIS). The ANFIS was proposed by Jang (1993) and it was further developed by Jang and Sun (1995). The structure of the ANFIS for two inputs, two fuzzy rules and one output and other details can be found in Jang (1993). The ANFIS is based on Takagi Sugino fuzzy inference system. It is a fuzzy system that uses a learning algorithm derived from NN theory to determine its parameters (fuzzy memberships and fuzzy rules) by processing data. Many researchers (Tay and Zhang, 1999; Cakmakci, 2007; Perendeci et al., 2008; Tay and Zhang, 2000) used the ANFIS technique for modelling of wastewater treatment systems. Tay and Zhang (1999) developed an ANFIS model for a complex anaerobic system particularly UASBR and AFBR.

Volumetric methane production (VMP) and TOC concentration were predicted using the input parameters of organic loading rate (OLR), hydraulic loading rate (HLR) and alkalinity loading rate (ALR). The model had the advantage of adaptability to the variation of system configuration. A fast predicting neural fuzzy model was developed (Tay and Zhang, 2000) to predict the response of a high rate anaerobic system under different disturbances. The organic loading rate (OLR), hydraulic loading rate (HLR), and alkalinity loading rate (ALR) were used as input parameters for the model, to predict volumetric methane production (VMP), effluent TOC and total VFA concentration. The performance of a system at a time instant '*t*' is affected by the system inputs through a period '*T*' before the time instant '*t*'. The input and output of the system at n^{th} time instant was used as input parameters for the model to predict the output of the system at $(n + 1)^{th}$ time instant. The performance of the model was assessed by evaluating correlation coefficient (R) and root mean square error ($RMSE$).

Cakmakci (2007) used ANFIS for modelling of anaerobic digester to predict effluent volatile solids (VS) and methane yield in two stages with pH, VS concentration, and flow rate of pre-thickened sludge and temperature of the influent as input parameters. When effluent VS, the output of first stage model was used as an additional input parameter in the second stage model, the performance of the model was improved as indicated by drop in *RMSE* value. Perendeci et al. (2008) proposed an ANFIS model for a real scale anaerobic treatment plant to estimate effluent COD by using appropriate on line input variables. The operating data was obtained for 192 days for different stages of the plant operation for model development. The software MATLAB and the fuzzy logic toolbox were used to derive the models and the resulting model was verified by using a validation database.

The typical characteristic of distillery wastewater can be found in Tewari et al. (2007) and Sarayu et al. (2009). It is treated by the combination of anaerobic method consisting UASB reactors and aerobic processes such as composting (Sarayu et al., 2009). If any system disturbance like organic overload, fluctuations in input parameters occurs, it affects the performance of the reactor expressed in terms of the biogas production and effluent COD. Fuzzy logic is being used for modelling wastewater treatment plants (Manesis et al., 1997; Estaben et al., 1997; Polit et al., 2002; Punal et al., 2003; Carrasco et al., 2004; Traore et al., 2006). ANFIS is used for modelling anaerobic treatment systems (Tay and Zhang, 1999; Cakmakci, 2007; Traore et al., 2007; Perendeci et al., 2007; Lopez and Borzacconi, 2009) such as UASB reactor, anaerobic fluidized bed reactor (AFBR) and anaerobic expanded bed reactor (AEBR) treating different types of wastewater. Most of these attempts for developing the ANFIS model are for laboratory scale reactors; only Perendeci et al. (2008) and Cakmakci (2007) developed ANFIS model for modelling of real scale wastewater treatment plant. However no attempt of fuzzy and neuro-fuzzy modelling for a real scale UASB reactor treating distillery wastewater is reported.

Materials and Methods

Fuzzy and ANFIS models are developed for prediction of effluent COD for an UASB reactor treating distillery wastewater. The operational data of the UASB reactor of a distillery located near Nashik is used for development of the models. The type and number of membership functions, and number of rules are automatically determined by ANFIS. Performance of the ANFIS model depends on quality of the training data used for model development. Number of trials was conducted with different combinations of input parameters to obtain optimum ANFIS model. Same combination of input/output parameters was used to develop fuzzy model considering expert knowledge, plant operator's opinion and local operating conditions. In case of fuzzy modelling, it is convenient to incorporate expert knowledge in model development (Estaben et al., 1997; Garcia et al., 2007).

Description of Wastewater Treatment Plant

The treatment plant consists of a buffer tank, two UASB reactors working in parallel, gas holder and various pumps. The treatment flow sheet is shown in Figure 1. During the treatment, pH of spent wash increases; therefore portion of treated effluent is recycled and mixed along with raw spent wash in the buffer tank to neutralize the pH and dilution of raw spent wash. The recirculation ratio varies from 2 to 3 and it depends on the pH and temperature of influent spent wash. The diluted spent wash is then fed to the reactor.

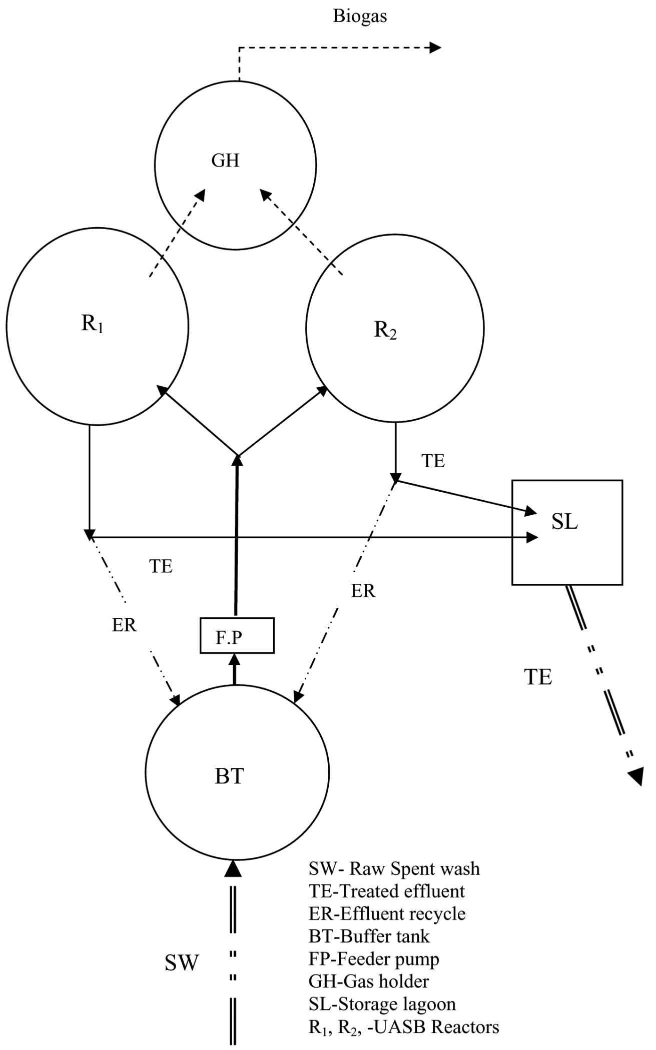

Figure 1: Layout of treatment plant consisting of UASB reactor.

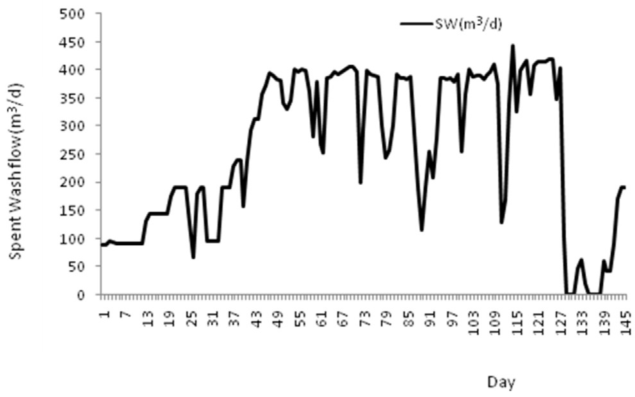

Figure 2: Variation in raw spent wash flow (m^3/d).

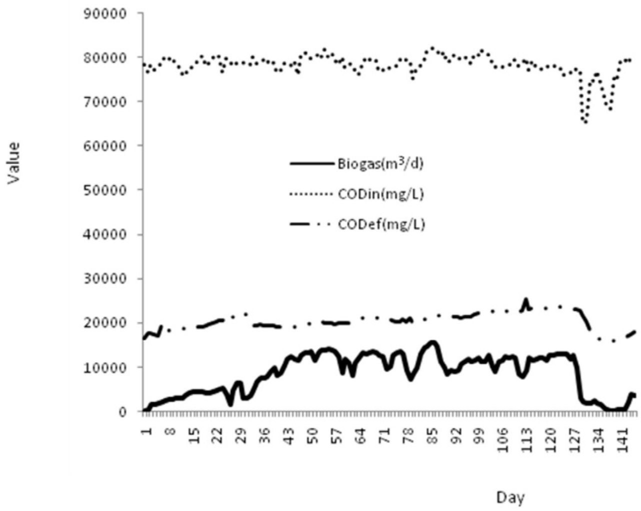

Figure 3: Variation influent COD, effluent COD in mg/L and biogas production (m^3/d).

Data Collection

Measurement of flow rate, temperature, pH, COD of raw spent wash and temperature, pH, COD, VFA and alkalinity for treated spent wash is carried out during daily monitoring. The parameters pH, temperature and spent wash flow rate and biogas production rate are measured online and remaining parameters are measured off line. The pH and temperature of the diluted spent wash in the buffer tank is also recorded daily. The daily variation in spent wash flow, influent COD, biogas production rate and effluent COD observed during data collection is shown in Figures 2 and 3 respectively. The operating data of UASB reactor was collected for 220 days and divided randomly into three parts, viz., training, testing and checking and used for model development.

ANFIS Model

Selection of Input Parameters

The input and output parameters for the ANFIS model are selected from the routine parameters used for daily monitoring and controlling operation of the UASB reactor. Some parameters useful in describing working of the plant and useful for modelling were calculated from the basic data. These parameters are given below.

(i) $t\text{CODL} = Q \times \text{COD}_{in}$

(ii) TA/VA = total alkalinity in the reactor/volatile fatty acids in the reactor

(iii) Rcr = Qr/Q

where *t*CODL = total COD load (kgCOD/d) applied to the reactor, *Q* = raw spent wash flow rate (m^3/d), *Qr* = recycled treated effluent flow (m^3/d) and COD_{in} = influent COD in kg/m^3.

The data was arranged in matrix form in excels with all possible inputs consisting basic parameters and some derived parameters with output parameter as last column. This data was imported in MATLAB work space for model construction. Fuzzy Logic toolbox of MATLAB software is used for model development. ANFIS modelling depends on the data used for modelling; model construction and testing can be performed quickly. Number of trials were taken for ANFIS modelling for different combination of input parameters by dropping or adding a parameter in the input matrix. For each trial of the model, performance was assessed using *R* and *RMSE*. The parameters producing negative effects on the model performance were eliminated from the input matrix. The parameters leading to improvement in the performance were retained as the input parameters for the model. Accordingly the influent and effluent temperatures were eliminated due to small variation and less influence on the model performance.

If history of the reactor in the form of input parameters applied earlier and some output parameter of the reactor are included as the input parameters for the model, it improves the performance of the model (Cakmekci, 2007; Tay and Zang, 2000). Thus after inclusion of parameters *t*CODL2, *t*CODL1, CODe2 and CODe1, the performance of the model was improved. The parameters *t*CODL2, *t*CODL1 and *t*CODL are total COD loading applied to the reactor two days, one day before and on the current day. The parameters CODe2, CODe1 and CODe indicate the effluent COD concentration observed on two days, one day before and on the current day. The parameters *t*CODL2, *t*CODL1, CODe2 and CODe1 provided back history of the reactor in the form of loading applied and the performance of the reactor.

Optimum performance to predict effluent COD for the ANFIS model was obtained with input parameters of *t*CODL2, CODe2, *t*CODL1, CODe1, *t*CODL, pH_{in}, $pH_{ef,}$ TA/VA ratio and Recirculation (Rcr) ratio.

Structure of Model

The ANFIS model has nine input parameters and one output. A view of FIS editor and model structure is shown in Figures 4 and 5. There are two methods of ANFIS model, grid partition and subtractive clustering. Grid partition method produces large number of rules and expert knowledge is required (Perendeci et al., 2008) to eliminate some of the ineffective rules. The subtractive clustering method has four algorithm

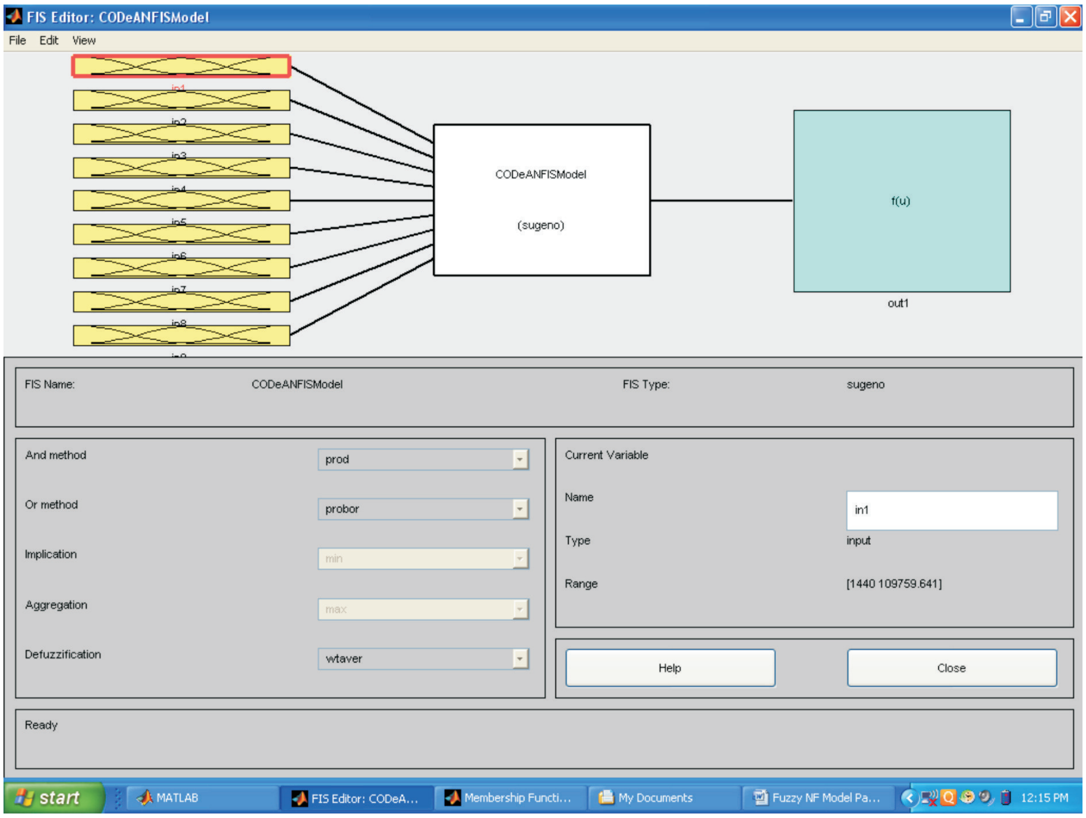

Figure 4: FIS editor of the CODeANFIS model.

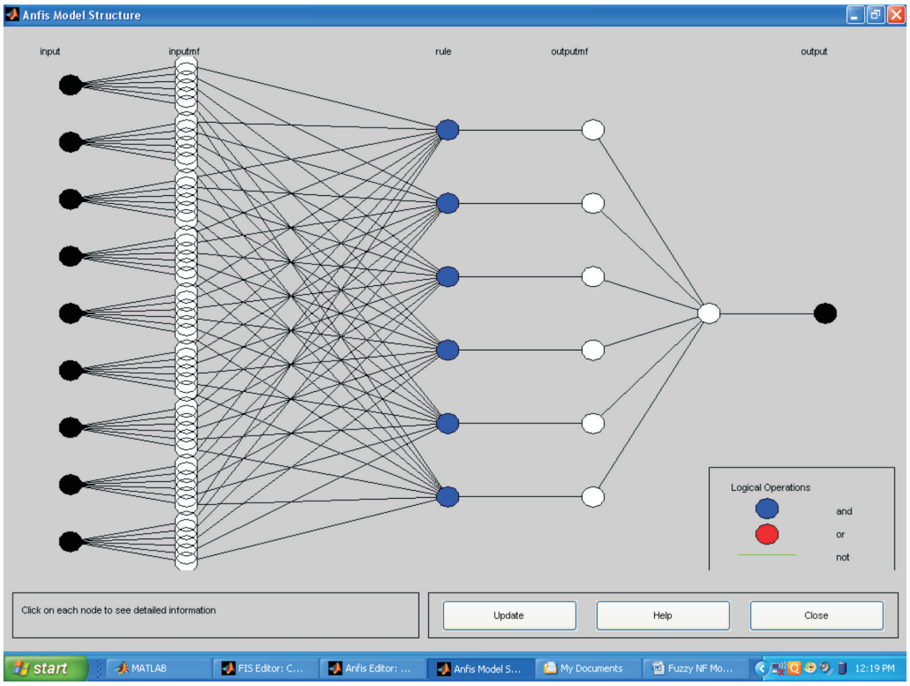

Figure 5: ANFIS model structure.

parameters: range of influence, squash factor, accept ratio and reject ratio. The subtractive clustering method with the default values of these parameters—0.5, 1.25, 0.5 and 0.15 respectively—is used here for ANFIS model development.

Testing of the Model

The model was tested with testing data set collected for different time period. Figure 6 shows the time series plot between observed and predicted values of effluent COD. The performance of the model was assessed with statistical parameters (Tay and Zhang, 2000; Cakmakci, 2007) like *R* and *RMSE*. The value of *R* and *RMSE* was found to be 0.8922 and 1334.698 respectively. These values indicate satisfactory prediction of effluent COD.

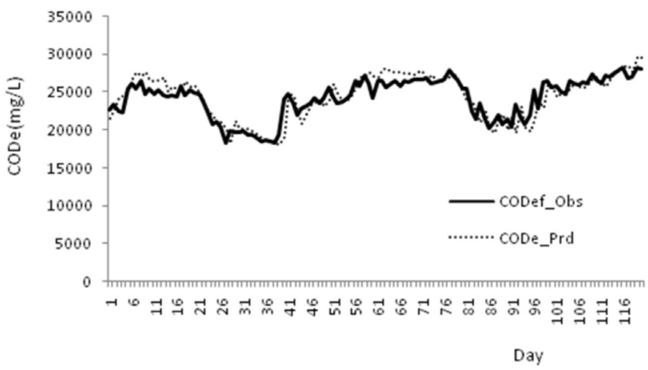

Figure 6: Time series plot between observed and prediction values of effluent COD for ANFIS model.

Fuzzy Model

Selection of Input parameters

The set of input parameters for fuzzy model was determined using ANFIS modelling. Fuzzy rule based model is developed for same combination of input output parameters as for ANFIS model. Good quality of data is necessary to develop ANFIS model and there is little scope to change the rules and the membership function. However, expert's knowledge, plant operator's opinion, process theory and the field conditions are important factors for operation of a real scale anaerobic treatment plant. These conditions can be used in developing the fuzzy rule based model by properly designing membership function for input/output parameters and the fuzzy rule base.

Thus the parameters, *t*CODL2, COD2, *t*CODL1, CODe1, *t*CODL, pH_{in}, pH_{ef}, TA/VA ratio and Recirculation (Rcr) ratio, are used as the input parameters for fuzzy model.

Fuzzification of Input Parameters

All parameters except pH are fuzzified in five fuzzy subsets and designated by linguistic variables: very low (VL), low (L), medium (M), high (H) and very high (VH). Three subsets as Low (L), Medium (M) and High (H) are used for fuzzification of pH_{in} and pH_{ef}. Fuzzification of the input/output parameters is carried out using trapezoidal membership function. The trapezoidal membership function is shown in Figure 7. The trapezoidal membership function is defined by the equations given below.

$$\mu_A(x) = 0;\ x \le a;$$
$$= \frac{(x-a)}{(b-a)};a \le x \le b$$
$$= 1;\ b \le x \le c;$$
$$= \frac{(d-x)}{(d-c)};c \le x \le d;$$
$$= 0;\ d \le x$$

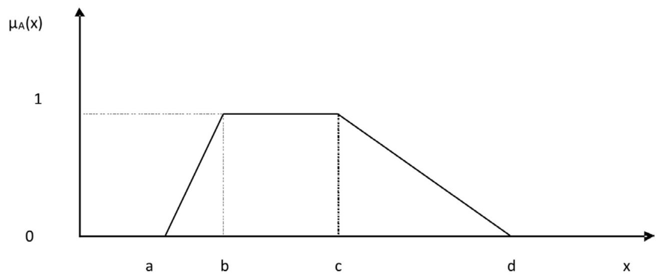

Figure 7: Trapezoidal membership function.

The range of each membership function for the input and output parameters is decided on the basis of domain of data, expert's knowledge and plant operator's opinion (Belanche et al., 1999; Manesis et al., 1998; Polit et al., 2001). Range of membership functions for the input and output parameters is given in Table 1.

Structure of the Fuzzy Model

The fuzzy model consists of nine inputs and one output. The structure of the model is shown in Figure 8. Fuzzy logic tool box of MATLAB 7.0 with Mamdani's model was used for designing rule base. The performance of the model depends on the number of fuzzy rules, number and type of membership function. The maximum number of fuzzy rules theoretically required to describe a biological process are n^x, where 'n' is number of membership function in each variable and 'x' is the number of variables in the system, which is very large and practically unmanageable (Manesis et al., 1997). However, less than 80 rules are sufficient for description and modelling of a biological wastewater treatment process.

Table 1: Range of membership functions for various input and output parameters

Parameter	*Fuzzy subset*	*Trapezoidal membership function parameters*			
		a	*b*	*c*	*d*
*t*CODL2, *t*CODL1 & *t*CODL	VL	0	0	5000	20000
(Range: *x* = 0-110000 kg/d)	L	5000	20000	25000	40000
	M	25000	40000	45000	70000
	H	45000	70000	75000	100000
	VH	75000	100000	110000	110000
CODe2,CODe1 & COD	L	0	0	5000	27500
(Range: *x* = 0-50000 mg/L)	M	5000	27500	32500	45000
	H	32500	45000	50000	50000
pH_{in}	L	2.5	2.5	3	3.5
(Range: *x* = 2.5-5.0)	M	3	3.5	3.75	4.5
	H	3.75	4.5	5	5
pH_{ef}	L	5	5	5.5	6.5
(Range: 5.0-8.0)	M	5.5	6.5	6.75	7.5
	H	6.75	7.5	8	8
TA/VA ratio	VL	0	0	1	2.5
(Range: *x* = 0-10)	L	1	2.5	3	4.5
	M	3	4.5	5	6.5
	H	5	6.5	7	8.5
	VH	7	8.5	10	10
Recirculation ratio (Rcr)	VL	0	0	1	2.5
(Range: *x* = 0-10)	L	1	2.5	3	4.5
	M	3	4.5	5	6.5
	H	5	6.5	7	8.5
	VH	7	8.5	10	10

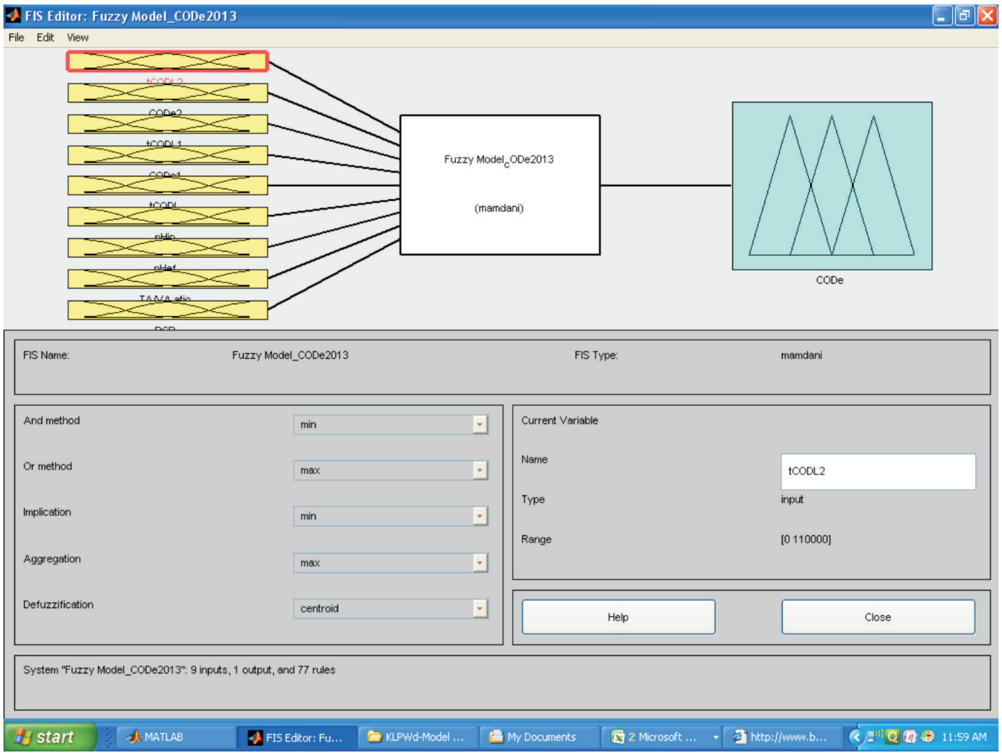

Figure 8: Structure of fuzzy rule based model.

Fuzzy rule base consisting of IF THEN rules was designed considering expert's knowledge, opinion of plant operator and the trend of the data. The optimum number of fuzzy rules was obtained by trial and error. Optimum performance for the model to predict the effluent COD was obtained with 77 IF THEN rules. The nature of fuzzy rules used in the model is given below.

If tCODL2 is *Medium* And CODe2 is *Medium* AND tCODL1 is *High* And CODe1 is *Medium* AND tCODL is *Medium* AND pH_{in} is *Medium* AND pH_{ef} is *Medium* AND TA/VA ratio is *Medium* AND RCR ratio is *High* THEN CODe is *Medium.*

The fuzzy toolbox uses MIN operator (AND method) for inference of a fuzzy rule. The final output of all rules is a fuzzy set obtained by MAX operator. The centroidal method with following equation is used for defuzzification of the output.

$$x^* = \frac{\sum_{i=1}^{n} x_i \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)}$$

Testing of the Fuzzy Model

Separate data set collected on different time period was used for model validation. Figure 9 shows the plot between the actual values and predicted values of effluent COD. The performance of the model was evaluated using statistical parameters. The correlation coefficient of 0.8197 and *RMSE* of 4208.34 was obtained between observed and predicted values of effluent COD which indicates good agreement between the predicted and observed values of effluent COD. The correlation coefficient of 0.8 and above (Cakmakci, 2007) is considered to be satisfactory. The *RMSE* values appears to be higher; however it is less than 14% of maximum value of effluent COD observed in the data

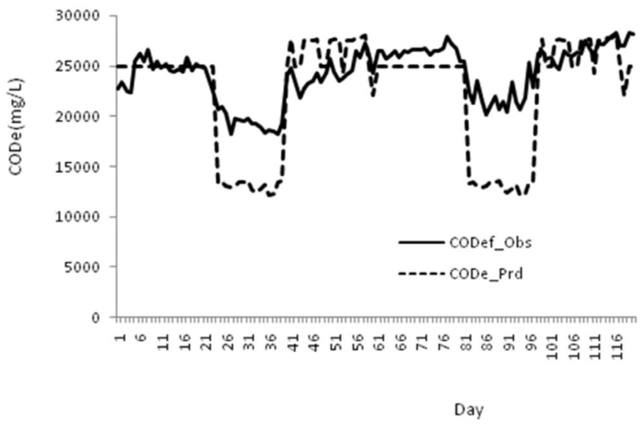

Figure 9: Time series plot between observed and predicted values of effluent COD.

set used for testing for a real scale UASB reactor, and is considered satisfactory.

Conclusions

ANFIS modelling technique is found to be useful for prediction of effluent COD. The ANFIS model can be used for other similar plant after training for data of that plant. ANFIS modelling gives best combination of input parameters required for prediction of effluent COD. From the ANFIS model, it is observed that data for three days consisting previous two days and the current day is required for satisfactory prediction of effluent COD. The methodology of ANFIS modelling for a real scale UASB reactor and developing fuzzy model with the input parameters given by ANFIS model is found to be practicable. Fuzzy model is more useful as it considers the field conditions, expert's knowledge and plant operator's opinion for model development.

References

Belanche, L.A., Vades, J.J., Comas, J., Roda, I.R. and M. Poch (1999). Towards a model of input-output behavior of wastewater treatment plants using soft computing techniques. *Environmental Modelling & Software*, **14:** 409-419.

Cakmakci, M. (2007). Adaptive neuro-fuzzy modeling of anaerobic digestion of primary sedimentation sludge. Springer. *Bioprocess Biosyst Engineering*, **30:** 349-357.

Carrasco, E.F., Rodriguez, J., Punal, A., Roca, E. and J.M. Lema (2004). Diagnosis of acidification states in an anaerobic wastewater treatment plant using a fuzzy-based expert system. *Control Engineering Practice*, **12:** 59-64.

Estaben, M., Polit, M. and J.P. Steyer (1997). Fuzzy control for an anaerobic digester. *Control Eng. Practice*, **5(98):** 1303-1310.

Garcia, C., Molina, F., Roca, E. and J.M. Lema (2007). Fuzzy-based Control of an Anaerobic Reactor Treating Wastewaters containing Ethanol and Carbohydrates. *Industrial Engineering Chemical Research*, **46:** 6707-6715.

Genovesi, A., Armand, J. and J.P. Steyer (2000). Integrated Fault Detection and Isolation: Application to a Winery's Wastewater Treatment Plant. *Applied Intelligence*, **13:** 59-76.

Huang, M., Wan, J., Ma, Y., Li, W., Sun, X. and Y. Wan (2010). A fast predicting neural fuzzy model for on-line estimation of nutrients dynamics in anoxic/oxic processes. *Bioresource Technology*, **101(6):** 1642-1651.

Jang, J.S.R. (1993). ANFIS: Adaptive-Network based Fuzzy Inference System. *IEEE 9. Transactions on System, Man and Cybernetics*, **23(3)**.

Jang, J.S.R. and C.T. Sun (1995). Neuro-Fuzzy Modeling and Control. Proceedings of IEEE, March 1995.

Lopez, I. and L. Borzacconi (2009). Modeling a full scale UASB reactor using a COD global balance approach and state observers. *Chemical Engineering Journal*, **146(1):** 1-5.

Manesis, S.A., Sapidis, D.J. and R.E. King (1997). Intelligent control of wastewater treatment plants. *Artificial Intelligence in Engineering*, **12:** 275-281.

Perendeci, A., Arsan, S., Tanyolac, A. and S.S. Celebi (2007). Evaluation of Input Variables in Adaptive–Network-Based Fuzzy Inference System Modeling for an Anaerobic Wastewater Treatment Plant under unsteady state. *ASCE, Journal of Environmental Engineering*, **133(7):** 765-771.

Perendeci, A., Arsan, S., Celebi, S.S. and A. Tanyolac (2008). Prediction of an anaerobic treatment plant under unsteady state through ANFIS modeling with on-line input variables. *Chemical Engineering Journal*, **145(1):** 78-85.

Polit, M., Genovesi, A. and B. Claudet (2001). Fuzzy logic observers for a biological wastewater treatment process. *Applied Numerical Mathematics*, **39:** 173-180.

Polit, M., Estaben, M. and P. Labat (2002). A fuzzy model for an anaerobic digester, comparison with experimental results. Pergamon, *Artificial Intelligence*, **15:** 385-390.

Punal, A., Palazzotto, L., Bouvier, J.C., Conte, T. and I.P. Steyer (2003). Automatic control of volatile fatty acids in anaerobic digestion using a fuzzy logic based approach. *Water Science and Technology*, **48(6):** 103-110.

Sadiq, R., Al-Zahrani, M.A., Shaikh, A.K., Husain, T. and S. Farooq (2004). Performance evaluation of slow sand filters using fuzzy rule-based modeling. *Environmental Modeling & Software*, **19:** 507-515.

Sarayu Mohana, Acharya, B.K. and D. Madamwar (2009). Distillery Spent wash: Treatment technologies and potential applications. *Journal of Hazardous Materials*, **163(1):** 12-25.

Tewari, P.K., Batra, V.S. and M. Balkrishnan (2007). Water management initiatives in sugarcane molasses based distilleries in India. *Resources, Conservation & Recycling*, **52:** 351-367.

Tay, J.H. and X. Zhang (1999). Neural Fuzzy Modeling of anaerobic biological wastewater treatment system. *Journal of Environmental Engineering*, **125(12):** 1149-1159.

Tay, J.H. and X. Zhang (2000). Stability of high rate anaerobic systems. II: Fuzzy Stability Index. *Journal of Environmental Engineering*, **126(8):** 726-731.

Tay, J.H. and X. Zhang (2000). A fast predicting Neural Fuzzy model for high rate anaerobic wastewater treatment systems. *Water Research*, **34(11):** 2849-2860.

Traore, A., Grieu, S., Thiery, F., Polit, M. and J. Colprim (2006). Control of sludge height in a secondary settler using fuzzy algorithms. *Computers and Chemical Engineering*, **30:** 1235-1242.

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