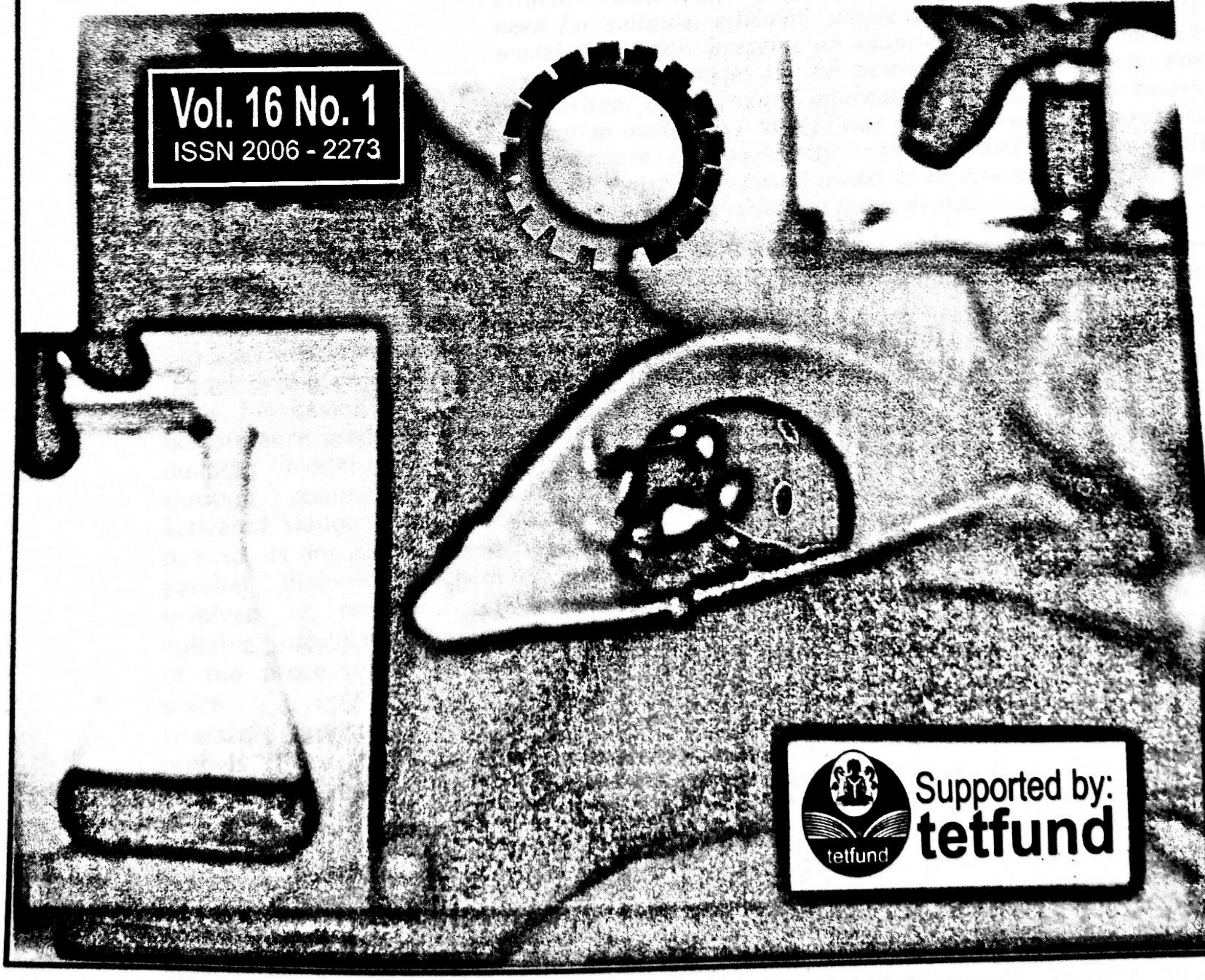
KANO UNIVERSITY OF SCIENCE AND TECHNOLOGY, WUDIL
LEARN WORK AND WORKSHOP

TECHNO SCIENCE
Africana Journal

TSAJ

TECHNO SCIENCE

Africana Journal



Vol. 16 No. 1
ISSN 2006 - 2273

Supported by:
tetfund

Techno Science Africana Journal

Journal homepage: www.technoscienceafricana.com

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM MODEL FOR MANAGEMENT OF AN ACTIVATED SLUDGE PROCESS IN WASTEWATER TREATMENT PROJECT

Aliyu Muhammad Kamilu

Dept. of Project Management Technology, School of Innovative Technology. Federal University of Technology, Minna.

ARTICLE INFO

Keywords: *Activated sludge process, modelling, BSM1 neuro-fuzzy, fuzzy inference system.*

*Correspondence author:
a.kamilu@futminna.edu.ng

ABSTRACT

The activated sludge process is the most versatile technological method used for urban wastewater treatment system. However, complex, non-linear and uncertain nature of the process has made building its model quite challenging. The existing models are highly complex to use for optimization, estimation and control purposes. Therefore, there is an urgent need for suitable, efficient, simple and easy to use process model. This paper presents an adaptive neuro-fuzzy inference system (ANFIS) model for an activated sludge process. For comparison, the standard international accepted benchmark simulation model no.1 (BSM1) was used. The promising results obtained are in conformity with the BSM1 results. This revealed that the proposed model is an efficient powerful tool for describing and predicting the activated sludge process.

INTRODUCTION

Successful operation of an activated sludge process relies on an effective and reliable model of the process. Models are valuable tools for design, process control, future performance prediction and safety analysis. Building model whether analytically or through computer simulation for an activated sludge process is quite complex due to its intricate, uncertain nature and parallel biological/biochemical reactions involved in the process. Nevertheless, suitable process model expounds intricacies of the process and the reactions taking place.

Literature survey has shown that numerous models have been developed for the activated sludge process such as the activated sludge model No.1 (ASM1), developed by the International Association on Water Quality (IAWQ) mainly for organic carbon and nitrogen removal, the model received international acceptability and served as a reference in the scientific research community and among practitioners. The later versions of activated sludge model families such as ASM2, its extension ASM2d and ASM3 as described in (Henze et al. 1987; Henze *et al.* 2000). Arguably, the models have contributed immensely in the field of modelling of urban wastewater treatment system and proven to be indispensable tools. However, these mathematical models are highly cumbersome, tough to handle for estimation/regulation purposes, require large experimental information and extensive knowledge of the process. Various approaches were proposed to reduce the complexity, especially of ASM1 and maintaining the non-linearity of the model, as suggested by (Jeppson and Olsson, 1993).From linearization view point, proposals by (Smets *et al.* 2003; Smets *et al.* 2006; Steffens *et al.* 1997; Torregrossa 2018) implemented linear model of ASM1 through linearization around one or more equilibrium point to obtain multiple-models, which significantly simplified ASM1. However, loss of vital information is the main disadvantageous feature of the methods.

To avoid the limitation of the aforementioned techniques (Nagy et al. 2010) suggested a purely analytical multi modelling approach in which the original non-linear ASM1 is transformed into multiple model by obtaining a set of sub-models with a simple linear structure and a set of suitable weighting functions, the final model is realized by combining the sub-models. The proposal conserved the non-linear structure of ASM1, but considered only pollution part of ASM1, requires rigorous computations and large amount of time before realizing the final model. Evidently, a robust and straightforward model capable of capturing complex and non-linear behaviour of the process is needed so that cost related to analysis, and experimentation may be reduced drastically. Soft-computing approach has proven to bean effective and powerful device for model development in many engineering problems.

One well-known soft-computing technique is the neuro-fuzzy method. The integration of a neural-network and fuzzy system can yield an efficient and reliable approach for system modeling. Accurate, speedy learning, flexibility, smoothness, ease of use, handling of a large amount of noisy data from complex dynamic and non-linear system made neuro-fuzzy technique to be a superior choice in various applications. Moreover, the main principle of neuro-fuzzy is the ability to endure imprecision, uncertainty and intricacy of a system under consideration with less computational cost.

Neuro-fuzzy have been applied to the activated sludge process as in (Civelekoglu et al. 2007; Perendeci et al. 2008; Pai et al. 2011; Szeląg et al. 2018; Newhart et al. 2020), however, the applications do not focus on simplifying the complex structure of the ASM1 (the state of art), so that the model can easily be used for control purposes and process optimization. Therefore, it is the objective of this paper to purvey a robust and straightforward model for the process and assess the performance relative to the standard international accepted model. The state and model equations for the system were discussed and the proposed approach is described.

MATERIALS AND METHODS

System description

Wastewater treatment system consists of many parallel processes occurring at a different rate. Typically, biological treatment method served as the commonly preferred wastewater treatment technique. The prime component of biological treatment is the activated sludge process. The success of the process lied on the mixing of influent wastewater with a consortium of microorganisms capable of degrading organic pollutants, and then the treated water is separated from sludge flocs in the settler. Based on the design and specific task, apart from removal of organic waste material from the wastewater, activated sludge process can achieve nitrogen and phosphorus removal from wastewater (Gernaey et al. 2004). The process has been utilized in its classical form and modernized form; all have the ability of producing a satisfactory treatment of wastewater.

Demands for high quality effluent coupled with operational difficulties significantly increases the use of system models, which in-turns led to the need for mathematical models capable of describing the dynamics of the system. An appropriate model helps not only in keeping the performance of the system close to optimal operating condition, but also better ways for system start-up (Makinia, 2010).

Activated Sludge Process Modelling

Here, the considered activated sludge process is shown in Fig. 1. The process consists of a biological reactor tank where a group of a microorganisms break down the pollutants and a settling unit in which the suspended solids are separated from the wastewater, small fraction of the sludge is removed as a waste while the larger part returned to the reactor tank to keep the microorganisms.

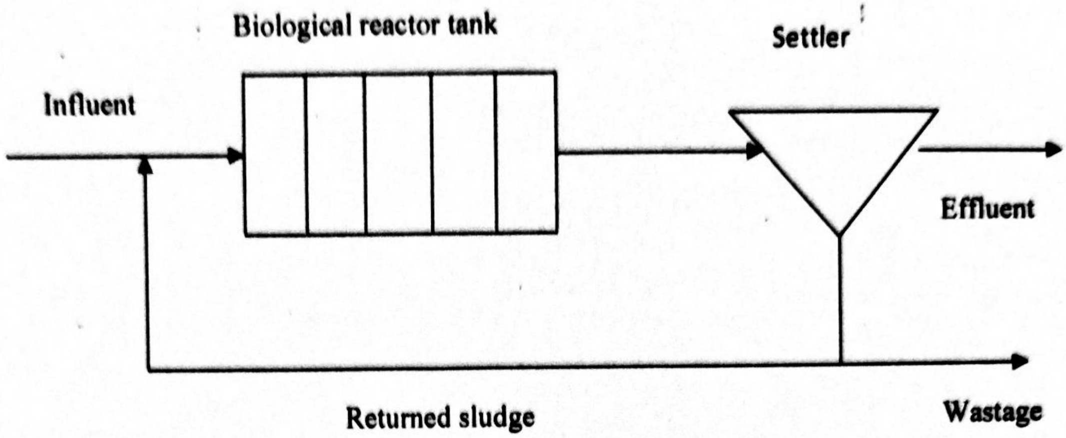


Fig. 1 The schematic of the activated sludge process

The process under study considered ASM1 model biological reactor tank. The model helps greatly in describing biological/chemical interactions occurring in the process and has being used by researchers and practitioners. ASM1 consists of 13different components and eight (8) separate processes (Alex et al. 2008). Each of the components is described by non-linear differential equation obtained from applying material balance around completely mixed biological reactor tank.

$$\frac{d\psi_K}{dt} = \frac{Q}{V}\left(\psi_{K,in} - \psi_K\right) + r_K \quad 1$$

where Q denotes influent flow rate, V denotes volume of the reactor, r_K denotes reaction of the k^{th} component, $\psi_{K,in}$ is the inlet concentration of k^{th} component and ψ_K is the outlet concentration. The reactions are as the results of biochemical transformation among the processes which include:

Growth of heterotrophic bacteria under aerobic condition

$$\Gamma_1 = \mu_H \left(\frac{S_S}{K_S + S_S}\right)\left(\frac{S_O}{K_{O,H} + S_O}\right) X_{B,H} \quad 2$$

Growth of heterotrophic bacteria under anoxic condition

$$\Gamma_2 = \mu_H \left(\frac{S_S}{K_S + S_S}\right)\left(\frac{K_{O,H}}{K_{O,H} + S_O}\right)\left(\frac{S_{NO}}{K_{NO} + S_{NO}}\right) \eta_g X_{B,H} \quad 3$$

Growth of autotrophic bacteria under aerobic condition

$$\Gamma_3 = \mu_A \left(\frac{S_{NH}}{K_{NH} + S_{NH}}\right)\left(\frac{S_O}{K_{O,A} + S_O}\right) X_{B,A} \quad 4$$

Decay of heterotrophic bacteria

$$\Gamma_4 = b_H X_{B,H} \quad 5$$

Decay of autotrophic bacteria

$$\Gamma_5 = b_A X_{B,A} \quad 6$$

Ammonification of soluble organic nitrogen

$$\Gamma_6 = k_a S_{ND} X_{B,H} \quad 7$$

Hydrolysis of entrapped organics

$$\Gamma_7 = k_h \frac{X_S / X_{B,H}}{K_x + \left(X_S / X_{B,H}\right)} \left[\left(\frac{S_O}{K_{O,H} + S_O}\right) + \eta_h \left(\frac{K_{O,H}}{K_{O,H} + S_O}\right)\left(\frac{S_{NO}}{K_{NO} + S_{NO}}\right)\right] X_{B,H} \quad 8$$

Hydrolysis of entrapped organic nitrogen

$$\Gamma_8 = k_h \frac{X_S / X_{B,H}}{K_X + \left(X_S / X_{B,H} \right)} \left[\left(\frac{S_O}{K_{O,H} + S_O} \right) + \eta_h \left(\frac{K_{O,H}}{K_{O,H} + S_O} \right) \left(\frac{S_{NO}}{K_{NO} + S_{NO}} \right) \right] X_{B,H} \left(X_{ND} / X_S \right) \quad 9$$

For detailed description and more information regarding ASM1 model, (1) should be referred. The optimal operation of the process demands for removal of the sludge from treated wastewater in the settling unit before being released.

Settler performs two independent functions-separation of solids from the water by gravity and thickening of sludge to be returned to the reactor tank. Due to complexity associated with the settler and its relevance in successful operation of the process, different models were proposed (Olsson and Newell, 2010; Takac's et al. 1991). The considered settler model is the traditional one-dimensional model with ten layers in which the mixed liquor from the biological reactor tank enters through the feed layer (m). The model is based on solid flux principle, and the flux in each layer is restricted by the adjacent layer. The solids flux as the result of bulk flow of liquid in each layer can be either above or below the feed layer (v_{up} or v_{dn}). Assuming completely mixed settler, applying solids mass balance yields

For bottom layer (m=1)

$$\frac{dX_1}{dt} = \frac{v_{dn}(X_2 - X_1) + \min(\varphi_{S,2} - \varphi_{S,1})}{h_1} \quad 10$$

For layers below feed layer (m=2 to 5)

$$\frac{dX_m}{dt} = \frac{v_{dn}(X_{m+1} - X_m) + \min(\varphi_{S,m} - \varphi_{S,m+1}) - \min(\varphi_{S,m} - \varphi_{S,m-1})}{h_m} \quad 11$$

For the top layer (m=10)

$$\frac{dX_{10}}{dt} = \frac{v_{up}(X_9 - X_{10}) - \varphi_{clar,10}}{h_{10}} \quad 12$$

For the layers above feed layer (m=7 to 9)

$$\frac{dX_m}{dt} = \frac{v_{up}(X_{m-1} - X_m) + \varphi_{clar,m+1} - \varphi_{clar,m}}{h_m} \quad 13$$

$$\varphi_{clar,j} = \begin{cases} \min\left(v_{S,j}X_j, v_{S,j-1}X_{j-1}\right) \text{if} X_{j-1} \succ X_t \\ v_{S,j}X_j \text{if} X_{j-1} \le X_t \end{cases} \quad 14$$

where X_t is the threshold solids concentration and v_S is the settling velocity function(Takac's et al. 1991) given as

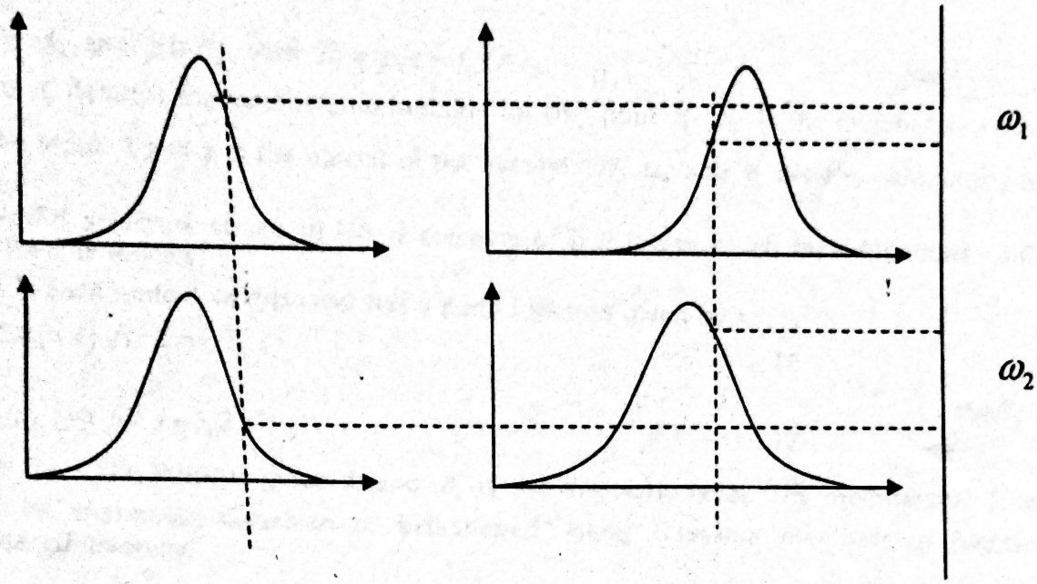
$$v_S(X) = \max\left[0, \min\left\{v_0', v_0\left(e^{-r_h(X - X_{min})} - e^{-r_p(X - X_{min})}\right)\right\}\right] \quad 15$$

The report of the implementation of the complete process model with different software packages could be found (11).Considering the complexity of the process model and cost of experimentation and analysis, neuro-fuzzy approach could be a better choice to model the process.

ANFIS Modelling

Neuro-fuzzy modelling involves building of a model from input-output data representing dynamic nature of a system. From the considered data, ANFIS generates a fuzzy inference system whose membership function parameters are adjusted using a back propagation algorithm alone or in conjunction with a least squares estimation, this enables the ANFIS learn the rules and membership function from the data set. ANFIS is an adaptive network consisting of layers and nodes. Each node does a certain function according to a signal entering and parameters related to the node (Jang, 1993; Jang et al. 1997; Cruz and Figueroa, 2009). The circular nodes are fixed while the square nodes have parameters to be learnt, the links only indicates the direction of signal flow.

The desired input-output mapping is achieved through adjusting of these parameters based on the considered training data and a gradient based learning algorithm. In ANFIS the objective is to optimize the parameters of the FIS which is achieved via minimizing error between simulated (desired) output and real output.



$$f_1 = p_1x + q_1y + r_1$$

$$f_2 = p_2x + q_2y + r_2$$

$$\Longrightarrow \quad f = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2}$$

$$= \overline{\omega}_1 f + \overline{\omega}_2 f_2$$

Fig.2 Illustrate fuzzy reasoning

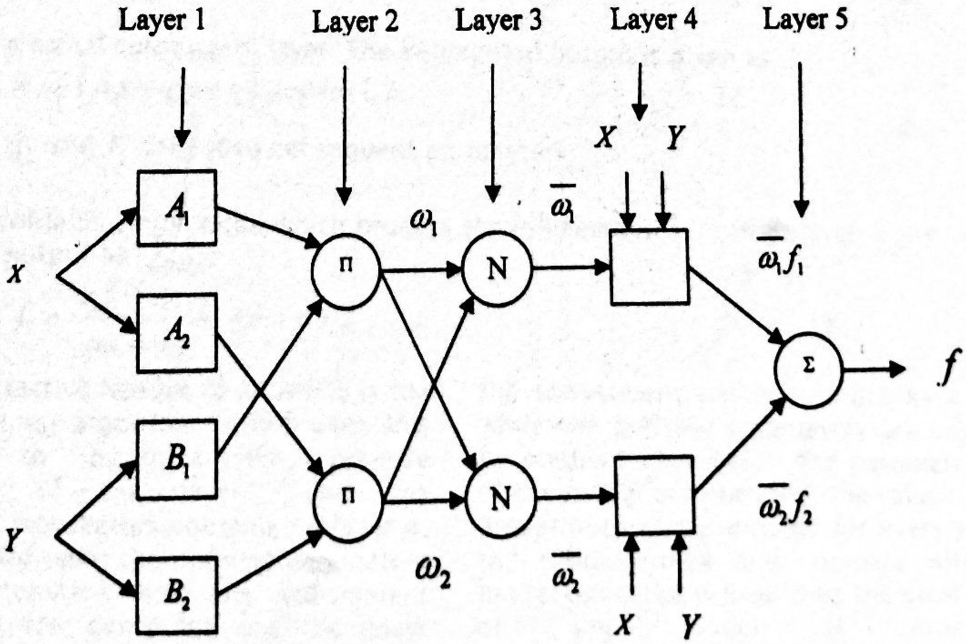


Fig.3 the ANFIS structure

The Fig.2 depicts fuzzy reasoning while Fig. 3 illustrates structure of ANFIS which consists of two inputs (x and y) and one output z. Since the FIS has two inputs and one output, a first order Sugeno fuzzy model has rules of the following form:

Rule 1

If x is A_1 and y is B_2, then $Z_1 = p_1x + q_1y + r_1$

Rule 2

If x is A_2 and y is B_2, then $Z_2 = p_2x + q_2y + r_2$

where A_i denotes the membership function for the input x, B_i is the membership function for the input y and z is the output of the system, p_i, q_i and r_i are the parameters of the output.

The ANFIS structure shown in Fig. 3 consists of five layers which their functions could be described as follows:

Layer 1: Each node i in this layer has a node function given by

$$O_{1,i} = \mu_{A_i}(x) \ for \ i = 1,2 \qquad 16$$

Or

$$O_{1,i} = \mu_{B_i}(y) \ for \ i = 1,2 \qquad 17$$

where x is the input to node i and A_i is the linguistic label. The membership function could be triangular, Gaussian or bell-shaped. Here, Gaussian membership function is considered given by

$$\mu_{A_i}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)^2} \qquad 18$$

where c_i and σ_i are the parameters. As their values changes, the Gaussian membership function changes accordingly. These parameters are referred as premise parameters.

Layer 2:

The information sent from layer 1 is processed in this layer, multiplications of incoming signals are performed and a rule firing strength is computed as:

$$O_{2,i} = \mu_{A_i}(x)\mu_{B_i}(y) = \omega_i \ for \ i = 1,2 \qquad 19$$

Layer 3:

The nodes in this layer are circular, the nodes normalize the weight functions obtained from the layer 2.

$$O_{3,i} = \omega_i^n = \frac{\omega_i}{\omega_1 + \omega_2} \ for \ i = 1,2 \qquad 20$$

Layer 4:

This layer is called consequent layer. The defuzzified output is given as

$$O_{4,i} = \omega_i^n f_i = \omega_i^n (p_i x + q_i y + r_i) \ for \ i = 1,2 \qquad 21$$

where p_i, q_i and r_i are called consequent parameters

Layer 5:

This layer contains single node which process the information sent from layer 4 and returns the overall output as

$$O_{5,i} = \sum_{i=1}^{2} \omega_i^n f_i = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2} \ for \ i = 1,2 \qquad 22$$

Another attractive feature of an ANFIS is the hybrid learning algorithm. ANFIS uses this algorithm to optimize the premise parameters of the layer1, and the consequent parameters contained inlayer 4. In the forward pass, the premise parameters are held constant and the consequent parameters are computed by the least square estimation. In the backward pass, the consequent parameters are kept fixed while the premise parameters are adjusted by gradient descent. As the parameter sets of the model are obtained, the values of the model output is computed for every pair of the training data and compare with the model expected values, thus the error value of the model is evaluated.

The training of the network is stopped based on considering properminimal error value, and the final model is realized. The ANFIS technique employs a hybrid learning optimization method to update the parameters of the FIS through learning from the data set to match the predicted output to the target output. The optimal structure of the ANFIS is established by trial and error.

RESULTS AND DISCUSSION

Simulation provides a better approach of validating model and effectively reveals authentic information of a system under various operating conditions. Real influent disturbance data files of BSM1 are used, which contained the influent flow and concentration. Each of the files consists of 14days influent data sampled at an interval of 15minutes. Here, dry influent data file which illustrates the diurnal variations in flow and COD load is considered. The data are set as:

$t\ S_I\ S_S\ X_I\ X_S\ X_{B,H}\ X_{B,A}\ X_P\ S_O\ S_{NO}\ S_{NH}$

$S_{ND}\ X_{ND}\ S_{ALK}\ Q_0$

With the following influents S_O, $X_{B,A}$, S_{NO}, X_P are assumed to be zero and $S_{ALK} = 7mg/l$. Fig.4 depicts the dry influent (a) flow rate (b) the soluble component (c) the solid components) which is the input to the wastewater treatment plant. For the ANFIS, the technique described above is utilized to model the training data. Sufficient data is intensely required, which comprises of high and low values of the state variables that an accurate model can be realized. Mostly training error become stool large when the input-output data are outside the training data range. In each case, the variable under study is considered as the output while the remaining variables are inputs to the system. Two Gaussian membership functions for each of the inputs of a variable were used to train the data for ten epochs with an exception of X_I where four Gaussian membership functions for each of the inputs are used. A sequential simulation is performed using the dry influent data file.

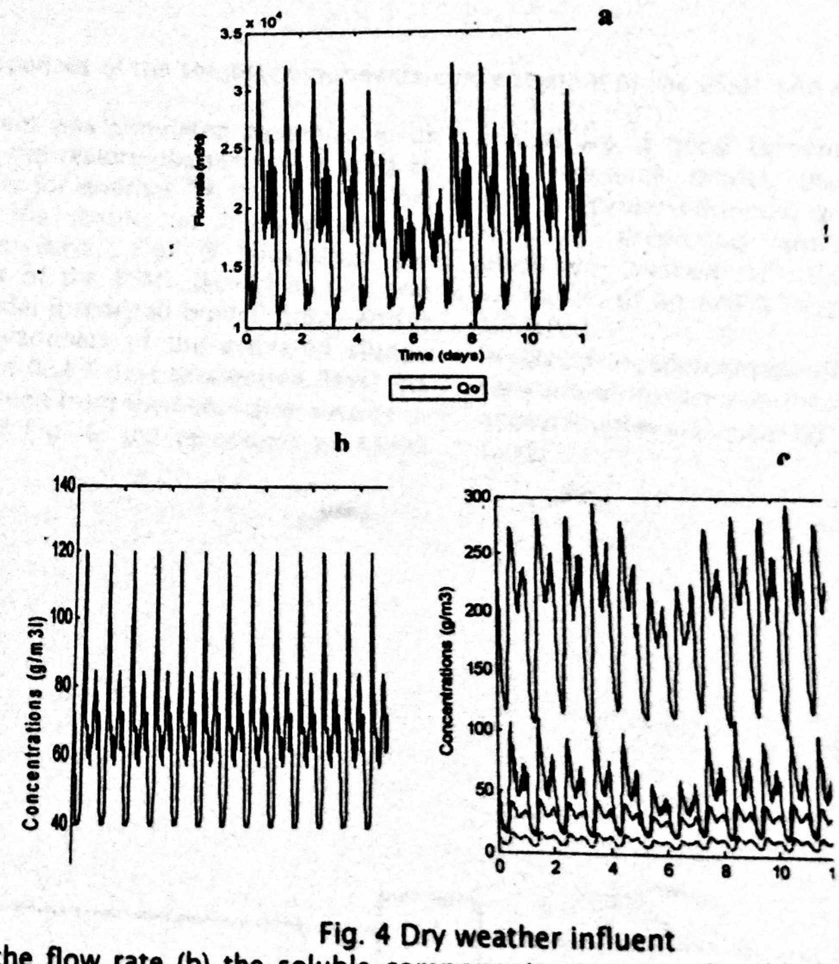


Fig. 4 Dry weather influent
(a) the flow rate (b) the soluble components concentration (c) the solids components concentration.

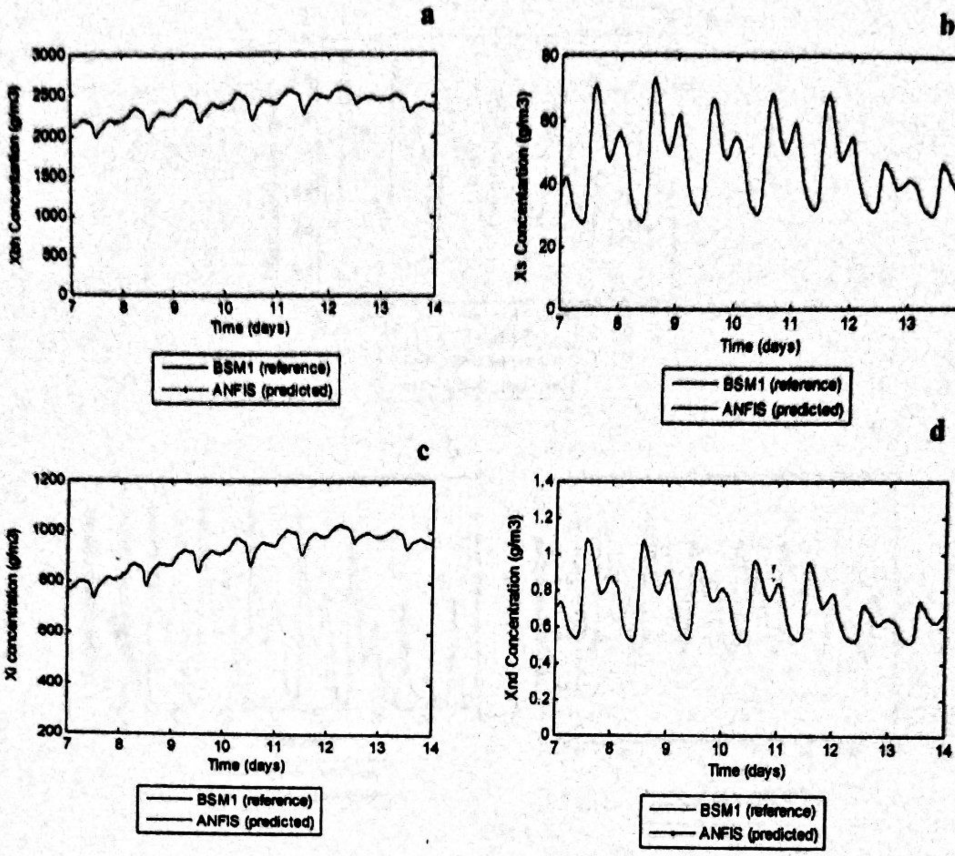


Fig. 5Responses of the soluble components concentration of the BSM1 and ANFIS model.

The system was simulated dynamically for 14 days; the results obtained were used as the initials for another 14 days simulation, however the results of interest are the evaluation days. Fig. 5 illustrates the responses of the BSM1 (actual model) and ANFIS model (predicted model) obtained for different variables of the activated sludge process for last 7 days (evaluation days). As it can be seen from the simulation results in Fig. 5 and Fig. 6, the responses of ANFIS model are in good agreement with that of the reference model, thus demonstrates that the proposed model is an indispensable tool in predicting and describing an uncertain system of this nature. The validation of an ANFIS model could also be achieved bycalculatingapercentageofbestfitandrootmeansquareerrorbetweenthereferencemodelandpredictedmodel (ANFIS) as indicated in Table I.

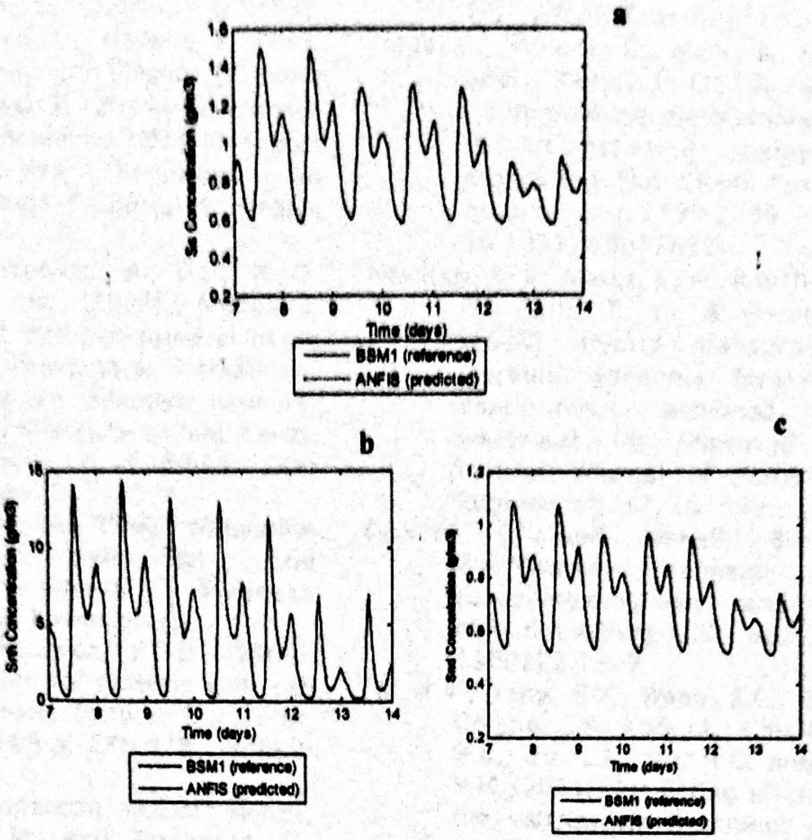


Fig. 6 the responses of soluble components concentration of the BSM1 and ANFIS model

Table 1. The model validation via training

Variables	Root Mean Square Error	Percentage of Best-fit (%)
[redacted]		
S_{NH}	0.0017	97.5
[redacted]		
X_{BH}	0.001	97.6
[redacted]		
X_I	0.09	96.4
[redacted]		

As shown in Fig. 5, the results for the variables indicate that the ANFIS model (predicted model) results are in total conformity with that of the BSM1 (reference model). Although for variable XI due to enormous error, two more membership functions were added to each input, and the addition resulted indrastic error reduction. Minimal error signifies how well the ANFIS model estimates the system behaviour in spite of all the non-linearity and large disturbances. From Table I, the root means square error (RMSE) for each of the variables is minimum, thus proven there liability of the ANFIS model. As in the table I, the best-fit percentages obtained for the different variables indicates the performance of the ANFIS modelling the process.

CONCLUSION

In this paper, ANFIS model for an activated sludge process has been presented. The developed models show an accuracy of more than 96% in all the scenarios. The promising results obtained proved the efficiency and robustness of the proposed approach in modelling the activated sludge process regardless of the influent disturbances. The proposed model could be easy to use for control and optimization of the process, requires less experimentation and computational cost. The ANFIS model is a valuable tool for predicting activated sludge process.

REFERENCES

Alex, J.; Benedetti, L.; Copp, J.; Gernaey, K.V.; Jeppson, U.; Nopens, I.; Pons, M.N.; Rosen, C.; Steyer, J.P. and Vanrolleghem, P. (2008). Benchmark simulation model no.1(BSM1), Report by the IWA Taskgroup on Benchmarking of Control Strategies for WWTPs.

Civelekoglu, G.; Perendeci, A.; Yigit, N. O. and Kitis, M. (2007). Modelling carbon and nitrogen removal in an industrial wastewater treatment plant using an adaptive network-based fuzzy inference system. Clean, vol. 35, no:6, p. 617-625. DOI: 10.1002/clen.200700076.

Copp, J.B. (2002). The COST simulation benchmark: description and simualtor manual, European Communities Luxembourg.

Cruz, P.P. and Figueroa, F.D.R. (2009). Intelligent control systems with Lab VIEW. Springer, London Dordrecht, New York. 106 p. ISBN 978-1-84882-683-0

Gernaey, K.V.; Loosderecht, M.C.M.; Henze, M.; Lind, M. and Jorgensen, B. (2004). Activated sludge wastewater treatment plant modelling and simulation: state of the art. Environ. Mod. Soft., vol. 19, no. 9., p. 763-783. DOI: 10.1016/j.envsoft.2003.03.005

Henze, M.; C. G. Jr, Gujer,W.;Marais, G.v.R. and Matsuo, T. (1987).Activated sludge model no.1. IAWQ Scientific and Technical Report No.1.London, UK.

Henze, M.;Gujer, W.; Loosdretch, M.v. and Mino, T. (2000)Activated sludge models,asm1,asm2,asm2d and asm3, IAWQ Scientific and Technical Report No.9. London, UK.

Jang, J., Sun, C., and Mizutani, E.(1997).Neuro-Fuzzy and Soft Computing. Prentice Hall, New Jersey. 335 p. ISBN:0-13-261066-3.

Jang, J.S.R. (1993). ANFIS: adaptive - network-based fuzzy inference system. IEEE Trans. on systems, man and cybernetics, vol. 23, no. 3, p. 665-685. DOI:10.1109/21.256541

Makinia, J. (2010). Mathematical modelling and computer simulation of activated sludge systems. IWA Publishing, (2010).

Jeppsson, U. and Olsson, G. (1993). Reduced order models for on-line parameter identification of the activated sludge process. Wat. Sci. Tech., vol. 28,no.11, p. 173-183. DOI: wst/028/wst028110173.

Nagy, A.; Mourot, G.; Marx, B.; Schutz, G. and Ragot, J. (2010). Systematic multimodeling methodology applied to an activated sludge reactor model. Ind. Eng. Chem. Res., vol. 49, no.6, p.2790-2799. DOI: 10.1021/ie8017687.

Newhart, K. B., Marks, C. A., Rauch-Williams, T., Cath, T. Y., & Hering, A. S. (2020). Hybrid statistical-machine learning ammonia forecasting in continuous activated sludge treatment for improved process control. Journal of Water Process Engineering, 37, 101389.

Olsson, G. and Newell, B. (2010). Wastewater treatment systems: modelling,diagnosis and control. IWA Publishing, UK. 665 p. ISBN 1900222-15- 9.

Pai, T.Y.; Yang, P.Y.; Wang, S.C.; Lo, M.H.; Chiang, C.F.; Kuo, J.L.; Chu, H.H.; Su, H.C.; Yu, L.F.; Hu, H.C. and Chang, Y.H. (2011). Predicting effluent from the wastewater treatment plant of industrial park based on fuzzy network and influent quality. Applied mathematical modelling, vol. 35, no.8, p. 3674-3684. DOI: 10.1016/j.apm.2011.01.019.

Perendeci, G.; Arslan, S.; Celebi, S.S. and Tanyolic, A. (2008). Prediction of effluent quality of an anaerobic treatment plant under unsteady state through ANFIS modelling with on-line input variables. Chem. Eng. Journal, vol.45, no. 1, p. 78-85. DOI: 10.1016/j.cej.2008.03.008.

Smets, L.Y.; Haegebaert, J.V.; Carrette, R. and Impe, J.F.V. (2003). Linearization of the activated sludge model ASM1 for fast and reliable predictions. Wat. Res., vol.37, no.8, p. 1831-1851. DOI:10.1016/S0043-1354(02)00580-8

Smet, I.; Verdickt, L. and Impe, J.V. (2006). A linear ASM1 based on multi-model for activated sludge systems. Mathematical and computer modelling of dynamical systems, vol 12,no. 5, p. 489-503. DOI:10.1080/13873950600723467

Steffens, M.A.; Lant, P.A and Newell, R.B. (1997). A systematic approach for reducing the complex biological wastewater treatment model. Water Research, vol. 31, no., p. 590-606. DOI:10.1016/S0043-1354(96)00273-4

Szeląg, B., Barbusiński, K., & Studziński, J. (2018). Activated sludge process modelling using selected machine learning techniques. Desalination and Water Treatment, 117, 78-87.

Takacs, I.; Patry, G.G., and Nolasco, D. (1991). A dynamic model of the clarification-thickening process. Water Research,vol. 25, no., p. 1263-1271. DOI:10.1016/0043-1354(91)90066-Y

Torregrossa, D., Leopold, U., Hernández-Sancho, F., & Hansen, J. (2018). Machine learning for energy cost modelling in wastewater treatment plants. Journal of environmental management, 223, 1061-1067.

Appendix

List of ASM1 Variables

S_I Soluble inert organic matter
S_S Soluble substrate
X_I Particulate inert organic matter
X_S Slowly biodegradable substrate
X_{BH} Heterotrophic biomass
X_{BA} Autotrophic biomass
X_P Particulate product arising from biomass decay
S_O Dissolved oxygen
S_{NO} Soluble nitrate nitrogen
S_{NH} Soluble ammonium nitrogen
S_{ND} Soluble biodegradable organic nitrogen
X_{ND} Particulate biodegradable organic nitrogen
S_{ALK} Alkalinity