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A SIMPLIFIED MODEL STRUCTURE FOR AN ACTIVATED SLUDGE SYSTEM

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Abstract- Activated sludge system is the essential technology in use for municipal wastewater treatment plant. The system design for pollutants removal, safety analysis and experimentation relied upon an effective, straightforward and reliable model. However, most of the available models are too complex to use for control purposes either practically or via simulation. Therefore, vehement need for a simplistic

and efficient model could not be avoided. This paper presents a simplified model structure for an activated sludge system using neuro-fuzzy system. Efficiency, ease of use, effectiveness and fast convergence are some of the alluring qualities of neuro-fuzzy technique. Building a reliable and flexible model requires validation with full scale or experimental data. Therefore, with the use of the full-scale data from the domestic wastewater treatment plant in Malaysia, the validation was achieved. For comparison, auto regressive with exogenous input (ARX) model was used. Simulation studies showed that the proposed method produced promising results, thus revealing the technique is effective and robust in modelling the activated sludge system.

Index terms: Model, pollutants, neuro-fuzzy, anfis, parameters.

I. INTRODUCTION

Activated sludge systems are characterized by their complexity and non-linearity. Efficient system design, operation, analysis and control relied solidly upon an accurate model capable of describing the activities taking place in the system. Models are crucial for improving performance of the system which in turn reduced the operational and maintenance costs drastically. The activities responsible for pollutants removal from wastewater are highly intricate and involve large biological interactions. However, effective organic pollutants removal from wastewater is essential not only to minimize the impact on subsequent processes in the system but to our health and the environment, also to produce an effluent that could meet the recommended standard quality at low cost.

The current modelling tools in use consists of activated sludge models built by international association on water quality (IAWQ) such as activated sludge model no. 1 (ASM1) and its families [1-4]. These mathematical models are powerful tools that have been in use in wastewater treatment industries, particularly the ASM1 which serves as a state-of-art model [5]. However, complex architecture of the ASM1 and large parameters associated with the model contributed to the difficulties in utilizing the model for control or optimization purpose [6-8]. Literature revealed that several studies were proposed to simplify the complexity of ASM1 so that applications leading to minimizing the operational and maintenance costs could be easily achieved. From linearization perspective, suggestion by [9] linearized based on the reaction rate through linear combination of states to realized locally equivalent to the ASM1 model. The linear rates are substituted in the dynamic equation of ASM1. The linearized model significantly tracks much closely the ASM1 responses. The proposal by [10] uses linearization around one or more operating point to obtain a multi-model, the global model is realized by combining the valid local multi-model. Another linearized model based on Taylor's series linearization principle was proposed [11], the approach significantly reduced the computational time. However, loss of information is the main disadvantage of the aforementioned methods.

Also, [12] proposed statistical models whereby the original non-linear model was linearized using Taylor's series principle to obtain a linearized continuous model and then discretize the continuous linear model through approximations of derivatives. The parameters are estimated using recursive identification method. The technique shows severe reduction of computational time for model parameters' estimation. Despite the large amount of computations and time required to obtain the statistical model, there are drifts and the behaviour of the system was not well captured. Another proposal, [13] suggested a systematic analytical approach in order to avoid loss of information, the nonlinear model is transformed into a multiple model which constitutes a set of sub models with a simple linear architecture and suitable weighting functions, the combination of these sub models realized the global model. The approach requires rigorous computation and significant amount of time before realizing the final model. Vehement need for simple and efficient modelling approach capable of conserving the intricate nature of the original carbon removal model could not be avoided. Neuro-fuzzy technique is a good and promising candidate for this challenge. Neuro-fuzzy has proven to be a powerful, robust and efficient tool for solving many complex scientific and engineering problems.

Neuro-fuzzy approach evolved from integration of neural network and fuzzy system, which creates an effective tool for real-world application. Adaptability, fast learning abilities, accuracy and less computational cost contributed to the success of the approach. Apparently, the neuro-fuzzy method has become the preferred choice than conventional techniques due to its ability to endure uncertainties in a system. Neuro fuzzy techniques have been implemented to activated sludge system [14-16], however, the implementation do not focused on simplifying the complex structure of the state of art model (ASM1), particularly conserving the original ASM1 nature and the states biological interpretation. As mostly control strategies and optimization techniques requires straightforward model and easy to use.

ARX is a black box modelling approach based on input, output and transfer characteristics without detailed knowledge of internal operation and structure of the system under consideration. It is powerful and provides unique solution that satisfies the global minimum of the loss function. ARX has being widely used in many scientific and engineering problems [17]. The main objective is to provide a simple, reliable and easy to use model capable of effectively describing/predicting the activated sludge system. The system and the proposed technique are described; comparisons were made with ARX model.

II. ACTIVATED SLUDGE SYSTEM

The existing mathematical model is valuable in describing the activities taking place in an activated sludge system. The model serves as the basis for implementing control strategies and optimizing the performance of the system. The Fig. 1 shows the schematic of the most commonly used activated sludge system for carbon removal (aerobic process) which consists of a biological reactor and a settler. In the biological reactor, a favourable condition is provided to keep microorganisms responsible for oxidizing most of the suspended and dissolved organic pollutants from the wastewater. The settler performs the separation of activated sludge from the treated wastewater by gravity sedimentation. Part of the activated sludge is returned to the biological reactor.

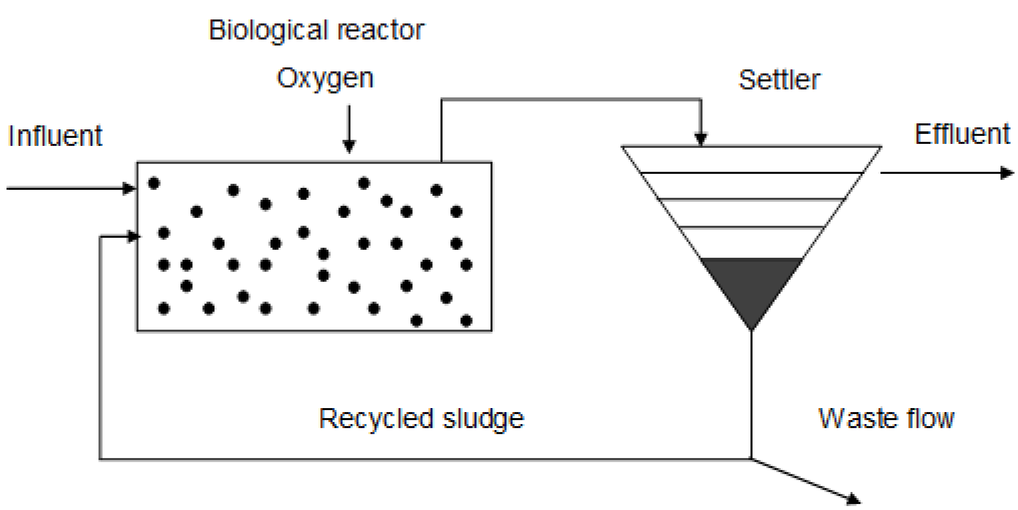

Figure 1. A schematic of an activated sludge system

Mostly the settler is assumed to be perfect, no dynamics and no biomass in the effluent [18]. The applying mass balance around the biological reactor [19] the dynamics of the system (aerobic process) can be described by the following nonlinear differential equations:

$$\left.\begin{aligned}
\frac{dS_S}{dt} &= -\frac{1}{Y}\mu X_B + \frac{Q_{in}}{V}S_{S,in} - \frac{Q_o}{V}S_S \\
\frac{dX_B}{dt} &= \mu X_B + \frac{Q_{in}}{V}X_{B,in} - \frac{Q_o}{V}X_B - bX_B \\
\frac{dS_O}{dt} &= -\frac{1-Y}{Y}\mu X_B + \frac{Q_{in}}{V}S_{O,in} - \frac{Q_o}{V}S_O + K_L a\ \ S_{O,sat} - S_O
\end{aligned}\right\} \tag{1}$$

where S_S is the substrate concentration, S_O is the dissolved oxygen concentration, X_B is the biomass concentration, μ is the biomass growth rate, b is the decay rate, Y is the yield coefficient, $S_{O,sat}$ is the saturated dissolved oxygen concentration, Q_{in} is the inlet flow rate and Q_o refers to the outlet flow rate. The biomass growth rate μ depends on soluble substrate and dissolved oxygen concentration as given by:

$$\mu = \mu_m \frac{S_S}{K_S + S_S} * \frac{S_O}{K_{O,H} + S_O} \tag{2}$$

where μ_m is the maximum specific biomass growth rate, K_S and $K_{O,H}$ are constant and have dimension of a concentration, they indicate for substrate and dissolved oxygen respectively.

The mathematical model equation (1) describes carbon removal in the activated sludge process. However, in practice, the nature and strength of wastewater are measured based on parameters such as biological oxygen demand (BOD), chemical oxygen demand (COD) and suspended solids (SS). The COD consists of substrate (S) and the active biomass (X_B). The substrate is further subdivided into biodegradable and non-biodegradable. Moreover, the biomass is often expressed in terms of suspended solids (SS), since the biomass comprises of solids that are suspended in the biological reactor tank [20]. Therefore, the typical state variables for carbon removal practically include chemical oxygen demand (COD), suspended solids (SS) and dissolved oxygen (S_O) [18]. The treatment efficiency of the plant is determined based on these variables. Therefore, this paper considered these variables.

III. NEURO-FUZZY SYSTEM

Neural network and fuzzy system are robust tools capable of estimating functions without any mathematical representation. However, the weakness of the individual technique serves as an impetus of creating a hybrid structure where the two methods (neural network and fuzzy system) are combined to overcome the limitations of individual approach. This hybrid system is powerful and flexible enough to deal with large system involving ill-defined behaviour. The system determines its parameters by learning algorithm and has a neural network structure constructed from fuzzy reasoning [21-22]. The learning is used to update the rules in the rule base and optimize the membership functions of a fuzzy system. There are several neuro-fuzzy systems, but here an adaptive neuro-fuzzy inference system (ANFIS) is considered.

ANFIS is an adaptive network trained using a hybrid learning algorithm [Jang, 1993]. The algorithm uses the least square estimation and gradient descent to adapt the parameters in the network. The architecture of the ANFIS is shown in Fig. 2 comprising of five layers with output node in each layer. For illustration, suppose that the fuzzy inference system (FIS) has two inputs (x and y) and one output (z). For the first order Sugeno fuzzy system, a distinctive rule set with two fuzzy "if-then rules" can be given as:

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2 x + q_2 y + r_2$

The round nodes are fixed whereas the square nodes have parameters in them. The layers could be described as;

Layer 1: This layer creates the membership grades

$$O_{1,i} = \mu_{A_i}(x) \qquad i = 1,2 \tag{3}$$

Or

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad i = 3,4 \tag{4}$$

The membership functions could be bell-shaped or triangular or Gaussian. Here Gaussian membership function is used.

$$\mu_A(x) = \exp\left\{ -\left(\frac{x - c_i}{a_i} \right)^2 \right\} \tag{5}$$

where a_i, c_i are premise parameters

Layer 2: The output of this layer is the product of all incoming signals

$$O_{2,i} = \mu_{A_i}(x).\mu_{B_i}(y) \qquad i = 1,2 \tag{6}$$

Layer 3: Every node in this layer is fixed and computes the ratio of firing strength of the rules

$$O_{3,i} = \overline{W} = \frac{W_i}{W_1 + W_2} \tag{7}$$

Layer 4: This layer contain adaptive nodes with a node function

$$O_{4,i} = \overline{W} f_i = \overline{W} \quad p_i x + q_i y + r_i \tag{8}$$

where these parameters p_i, q_i, r_i are called consequent parameters.

Layer 5: In this layer, the single node calculates the overall output

$$O_{5,i} = \sum_i W_i f_i = \frac{\sum_i W_i f}{\sum_i W_i} \tag{9}$$

The premise and consequent parameters are estimated using the hybrid learning algorithm. The ANFIS uses forward pass and backward pass. In the forward pass, the node outputs go forward until layer 4, the consequent parameters are identified using the least square techniques and then the error measure is calculated. As the values of the premise parameters are fixed, the overall output can be expressed as linear combinations of consequent parameters.

$$\begin{aligned} f &= \frac{W_1}{W_1 + W_2} f_1 + \frac{W_2}{W_1 + W_2} f_2 \\ &= \overline{W_1} f_1 + \overline{W_2} f_2 \\ &= \overline{W_1}x \;\; p_1 + \overline{W_1}y \;\; q_1 + \overline{W_1} \;\; r_1 + \overline{W_2}x \;\; p_2 + \overline{W_2}y \;\; q_2 + \overline{W_2} \;\; r_2 \end{aligned} \tag{10}$$

which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2.

In the backward pass, the error signal propagates backward and the set of premise parameters are updated by gradient descent method. Typically, once the training data (input-output data) is made available, this is how ANFIS model is realized.

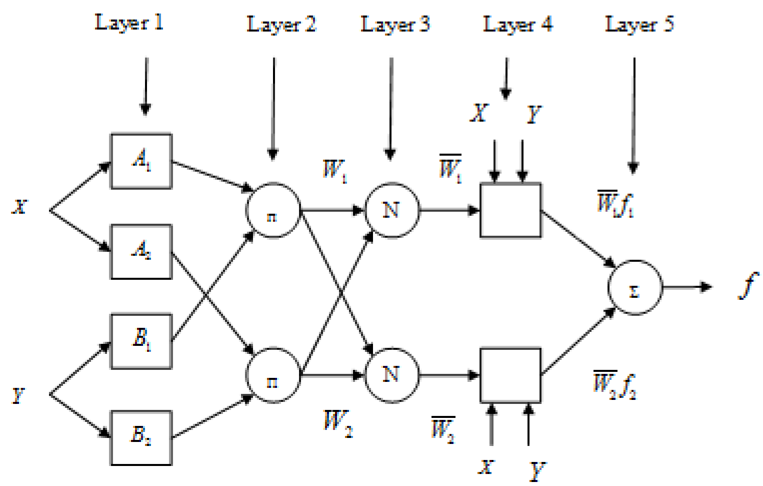

Figure 2. The ANFIS architecture

Sufficient training data which comprises of high and low values of the system are required to build the model. In order to avoid inaccuracies the data set need to be within the training data range and converted into trainable form. The data was normalized between zero (0) and one (1).The normalized full-scale data set of 170 days was divided into 127 days data for training and 43 days data for validation. The selections of the data were done arbitrarily. ANFIS model is implemented using the available fuzzy toolbox in Matlab 7.1. The function “genfis 1” was used to generate the fuzzy inference system (FIS) based on grid partition on the data set. Four (4) Gaussian membership functions were assigned to each input variable. As the FIS structure is made available, the hybrid learning algorithm is utilized to train the parameters of the FIS by learning from the data to realize the desired model.

IV. RESULTS AND DISCUSSION

Simulation offers a better means of evaluating the performance of different models in predicting the process under consideration. The accuracies of prediction of the models were determining using the root mean square error (RMSE) and mean absolute percentage deviation (MAPD) given by the following expressions:

$$RMSE=\sqrt{\frac{\Sigma\ x_i-y_i\ ^{2}}{N}} \qquad (11)$$

$$MAPD=\frac{\Sigma\,|\,x_i-y_i\,|}{|\,x_i\,|} \qquad (12)$$

where x_i is the measured value, y_i is the predicted value and N is the number of samples. The concentration level of dissolved oxygen is nil at the inlet of the plant. The influent concentrations for the COD and SS are shown in Fig 3.

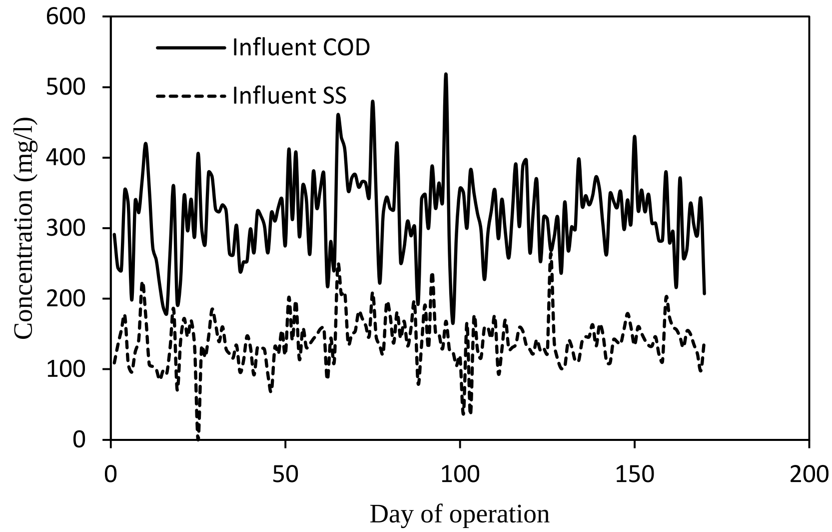

Figure 3. The influent concentration

The performance of the models in predicting the variables are presented in table 1. Minimal RMSE and smaller MAPD signify how well a model predicts the measured value. The accuracy in prediction can easily be obtained using these measures. The model predictions of the validation pattern are illustrated in Fig. 4, 5 and 6.

Table 1: Model prediction performance

Variable	Model	Training		Validation	
		RMSE	MAPD (%)	RMSE	MAPD (%)
COD	ANFIS	0.00148	0.51	0.04623	8.79
	ARX	0.05494	37.14	0.05713	39.19
SS	ANFIS	0.00050	0.35	0.01308	7.78
	ARX	0.05989	38.79	0.06054	45.12
S_O	ANFIS	0.00428	2.20	0.04751	3.45
	ARX	0.03499	12.64	0.3278	14.93

For all the variables in the both training and validation the MAPD for ANFIS model were below 10%, this demonstrated that the ANFIS model has accurately predicted the measured values.

From the Fig. 4 the ANFIS model was able to follow the measured COD as compared to the ARX model.

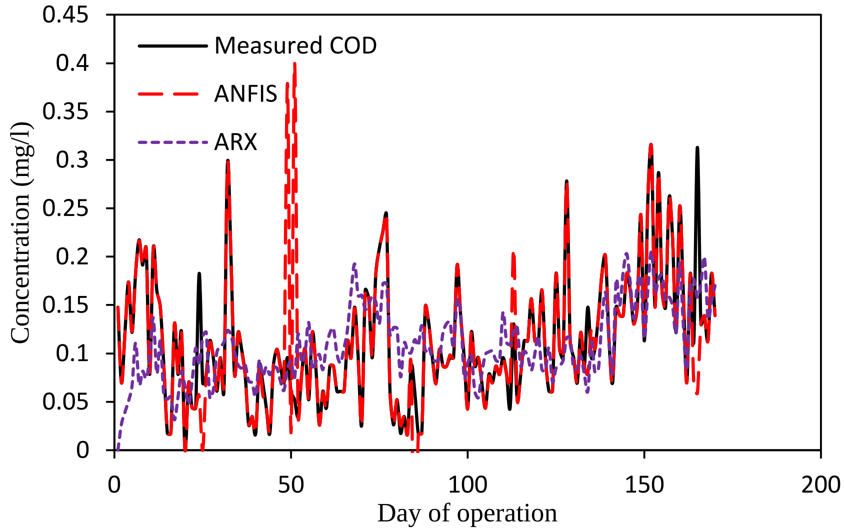

Figure 4. The validation of models for COD variable

As illustrated in Fig. 5 the prediction errors in ANFIS model were quite small, which resulted in having the MAPD of 7.78%. The model demonstrated good capability in estimating the suspended solids (SS). The MAPD for ARX model in both training and validation were high, which indicate the model do not well predicted the measured values.

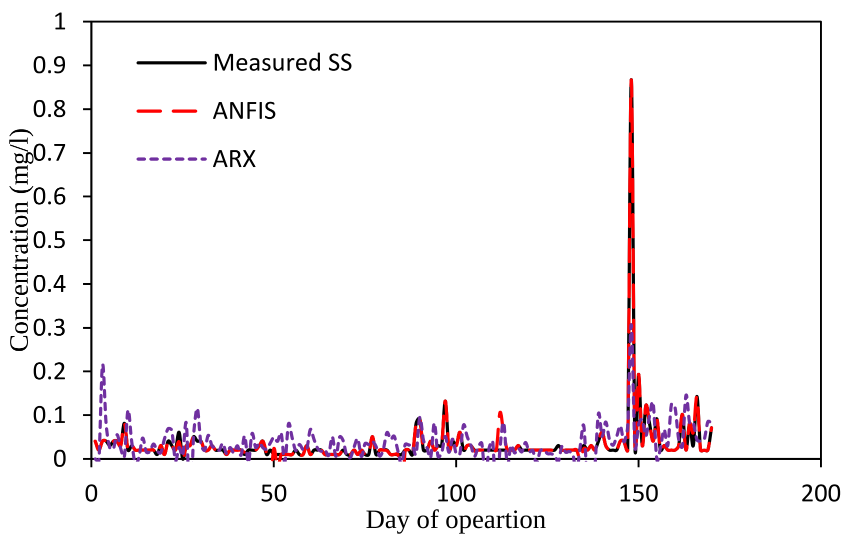

Figure 5. The validation of models for SS variable

Although, there are some drifts, but both the models show good agreement with the measured So, as shown in Fig. 6. The RMSE for ANFIS is slightly smaller than that of ARX model, which means ANFIS model has better prediction.

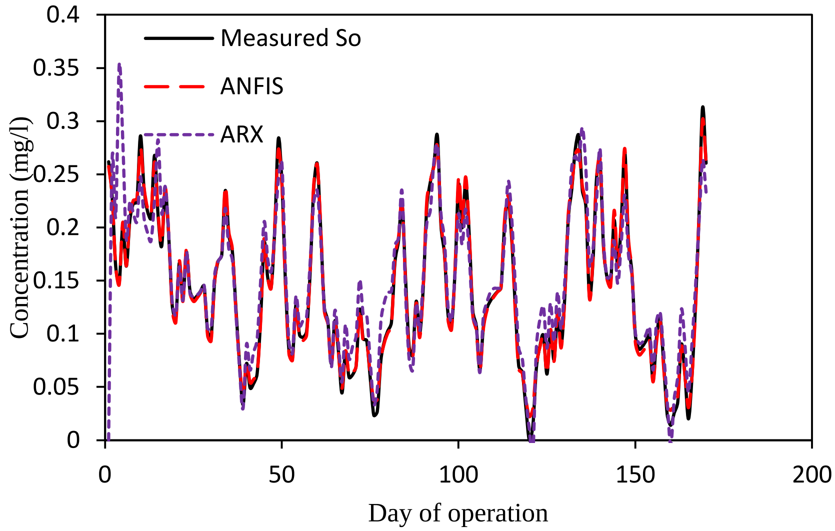

Figure 6. The validation of models for S_O variable

V. CONCLUSIONS

In this paper a simplified model structure for an activated sludge system has been presented. The proposed technique performed remarkably, which could be connected to its flexibility and adaptability in handling complex noisy data. The results demonstrate the robustness and effectiveness of the method in modelling this uncertain system, there are significant reduction in the error and good MAPD percentages compared to the ARX model. The proposed method is quite meaningful in simplifying the complexity of the most widely use model especially for control and optimization of the system. The approach is valuable and powerful tool for the wastewater treatment industry.

VI. ACKNOWLEDGEMENT

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REFERENCES

[1] W. Gujer, "Activated Sludge Modelling: Past, Present and Future", Water Science and Technology, Vol. 53, 2006, pp.111-119.

[2] M.Henze, W.Gujer, T.Mino, T.Matsuo, M.C.Wentzel , G.V.R.Marais and M.C.M. Loosdrecht , "Activated Sludge Model No.2D, ASM2D",Water Science and Technology, Vol. 39, 1999, pp.165–182.

[3] K.V.Gernaey, M.C.M.Loosderecht, M.Henze, M.Lind and B.Jorgensen, "Activated Sludge Wastewater Treatment Plant Modelling and Simulation: State of the Art", Environmental Modelling Software, Vol. 19,2004, pp. 763-783.

[4] A.Nuhoglu, B.Keskinler and E.Yildiz, "Mathematical Modelling of the Activated Sludge Process—the Erzincan Case", Process Biochemistry, Vol. 40, 2005, pp. 2467-2473.

[5] I.Y.Smets, J.V.Haegebaert, R.Carrette and J.F.V.Impe, "Linearization of the Activated Sludge Model ASM1 for Fast and Reliable Predictions", Water Research, Vol. 37, 2003, pp. 1831-1851.

[6] U.Jeppson and G.Olsson, "Reduced Order Models for On-line Parameter Identification of the Activated Sludge Process", Water Science and Technology, Vol. 28, 1993, pp. 173-183.

[7] N.Abdulwahab, M.R.Katebi and J.Balderud, "Multivariable PID Tuning of Activated Sludge Process with Nitrification and Denitrification. Biochemical Engineering Journal, Vol. 42, 2009, pp. 239-248.

[8] B.Boulkroune, M.Darouch, M.Zasadzanski, S.Gille and D.Fiorelli, "A Non-linear Observer Design for an Activated Sludge Wastewater Treatment Process", Journal of Process Control, Vol. 19, 2009, pp. 1558-1565.

[9] A.Benhalla, M.Houssou and M.Charif, "A Linearization of Full Activated Sludge Model no.1 for Interaction Analysis", Bioprocess Biosystem Engineering, Vol. 33, 2010, pp. 759-771.

[10] I.Smets, L.Verdict and J.V Impe, "A Linear ASM1 Based Multi-Model for Activated Sludge Systems", Mathematical and Computer Modelling of Dynamical Systems, Vol. 12, 2006, pp. 489-503.

[11] J.Derco, M.Kralik, P.Gubova and I.Bodik, "Dynamic Modelling of Activated Sludge Process II. Linearized Kinetic Model", Chemical Papers, Vol. 44, 1990, pp. 659-668.

[12] M.Kralik, J.Derco, J.Farkas and P.Gubova, "Dynamic Modelling of Activated Sludge Process III. Statistical Model", Chemical Papers, Vol. 44, 1991, pp. 313-320.

[13] A.Nagy, G.Mourot, B.Marx, G.Schutz and J.Ragot, Systematic Multi-modelling Methodology Applied to an Activated Sludge Reactor Model. Industrial and Engineering Chemistry Research, Vol. 49, 2010, pp. 2790-2799.

[14] T. Y. Pai, P. Y. Yang, S. C. Wang, M. H. Lo, C. F. Chiang, J. L. Kuo, H. H. Chu, H. C. Su, L. F. Yu, H. C. Hu, Y. H. Chang, "Predicting Effluent from the Wastewater Treatment Plant of Industrial Park based on Fuzzy Network and Influent Quality", Applied Mathematical Modelling, Vol. 35, 2011, pp. 3674-3684.

[15] A.Perendeci, S.Arslan, S.S.Celebi and A.Tanyolac, " Prediction of Effluent Quality of an Anaerobic Treatment Plant under Unsteady state through ANFIS Modeling with On-line Input Variables", Chemical Engineering Journal, Vol. 45, 2008, pp. 78-85.

[16] M.Huang, Y.Ma, J.Wan, H.Zhang and Y.Wang, "Modelling a Paper Making Wsatewater Treatment Process by means of an Adaptive Network –based Fuzzy Inference System and Pricipal Component Analysis", Industrial and Engineering Chemistry Research, Vol. 51, 2012, pp. 6166-6174.

[17] O. Nelles, Nonlinear System Identification: From Classical Approach to Neural network and Fuzzy models, Springer, Germany, 2001, p.461-466.

[18] G. Olsson, B. Newell, "Wastewater Treatment Systems, Modelling, Diagnosis and Control", IWA Publishing, UK, 2010, p.655-658.

[19] F.Nejjari, B.Dahhou, A.Benhammou and G.Roux, "Non-linear Multivariable Adaptive Control of an Activated Sludge Treatment Process", International Journal of Adaptive Control and Signal Processing, Vol. 13, 1999, pp. 347-365.

[20] M. V. Sperling, Basic principles of wastewater treatment, IWA Publishing, London, UK, 2007, p.

[21] J. Jang, "ANFIS: adaptive-network-based fuzzy inference system", IEEE Transactions on Systems, Man and Cybernetics, vol.23, No.3 , 1993, pp. 665–685.

[22] J. Jang, C. Sun, E. Mizutani, Neuro-Fuzzy and Soft Computing, Prentice Hall, New Jersey,1997, p. 335-340.