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A Fast Predictive of Sludge Age in Five Step SBRs Using FLC Model

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Abstract: Removal efficiency of COD, NH_4-N and PO_4-P and NO_3-N in five step SBR processes is widely influenced by mean cell residence time of Five step sequencing batch reactor whereas the sludge age is influence directly on removal efficiency of this system therefore the operator of this system cannot control on this system without experience or a control model. The major objective of this study is develop a control model (Fuzzy Logic Control Model) based on fuzzy logic rule to predict the maximum removal efficiency of COD, NH_4-N, PO_4-P and NO_3-N and minimize mean cell residence time of SBR process where the controlled variables was the sludge age in the five step system and the output variables was the COD, NH_4-N, PO_4-P and NO_3-N removal efficiency (or release rate when negative value) at constant ratio of C/N/P and hydraulic retention time. In order to improve the network performance, fuzzy subtractive clustering was used to identify model architecture, extract and optimize fuzzy rule of the model. As a results the study shows that Adaptive Neural Fuzzy model provide a suitable tool for control and fast predict of mean cell residence time (sludge age) effects on biological nutrient removal efficiency in five-step sequencing batch reactor.

Keywords: Activated sludge and SBR, fuzzy model, MCRT

INTRODUCTION

Conventional control methods are powerful when good analytical mathematical models are available to support their development and operation. This situation is uncommon in real processes. Particularly, the real-time control of Waste Water Treatment Plants (WWTP) is a difficult but essential task, due to the lack of accurate dynamical models describing the process (Olsson and Newell, 1999). However, WWTP can be properly operated by specialized people, having knowledge about the process, though in practice, this know-how is essentially qualitative, empirical and incomplete. The operation of a WWTP represents therefore a knowledge intensive task. In this regard, a system capable of giving all the possible information about the state of the process must be available in order to establish the basis of a diagnosis system integrating all the possible knowledge. This requirement is an important step to have successful control decisions (Patry and Chapman, 1989). Applications of knowledge-based systems to activated sludge processes are being widely studied (Cakmakci *et al*., 2008; Barnett *et al*., 1992). Most of systems are Knowledge-Based Expert Systems (KBES) mainly diagnostic and advising tools to help process Operators. An activated sludge wastewater treatment plant can be classified as a complex system due to its nonlinear dynamics, large uncertainty in uncontrolled inputs and in the model parameters and structure, multiple time scale of the dynamics and multi input-output structure. Many researchers have studied the Operation characteristics and parameters of step feeding process by theoretical analysis and computer simulation (Fujii, 1996; Larrea *et al*., 2001; Zhu and Peng, 2006). Some practical experiences were also drawn from extended; renewed or retrofitted Conventional activated sludge process, (Fillos *et al*., 1996; Schlegel 1992; Gorgun *et al*., 1996; Wang *et al*., 2006). During the last two decades, there were a variety of applications of fuzzy logic control in wastewater treatment plants to optimize operation and performance of bioprocesses. Fuzzy logic provides a language with a syntax and semantics to translate qualitative knowledge into numerical reasoning. In most engineering problems, information about the probabilities of various risk items is only vaguely known. The term computing with words has been introduced by Zadeh (1996) to explain the notion of reasoning linguistically rather than with numerical quantities. Fuzzy rule-based modeling is one of techniques that make use of human knowledge and deductive processes where the experience of operator is assisted to manage and operate biological wastewater treatment plant satisfactorily using operational observations. It is important to develop Computer operational decision support systems that are able to play a similar role to the expert in daily operation in minimizing cost and increase performance of wastewater

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treatment processes. The control objective and parameters ranged from aeration (Ferrer *et al*., 1998; Kalker *et al*., 1999; Fiter *et al*., 2005). Effluent suspended solid (Tsai *et al*., 1996) external carbon addition (Yong *et al*., 2006) and loading rate (Murnleitner *et al*., 2002) to nitrification in Sequencing Batch Reactor (SBR) process (Peng *et al*., 2003). And dissolved oxygen concentration (Traoré *et al*., 2005). A fuzzy control strategy was applied by Meyer and Pöpel (2003) for the control of aeration in wastewater treatment plants with pre-denitrfication. The implementation of expert systems based on fuzzy logic rules are described elsewhere (Carrasco *et al*., 2002; Puñal *et al*., 2002). Recently, especially attention to the expert supervision and control of anaerobic digestion processes is reported (Flores *et al*., 2000; Polit *et al*., 2002). Fuzzy control algorithms have been widely applied to pursue better effluent quality and higher economic efficiency on aerobic biological treatment processes (Irene *et al*., 2008; Wu *et al*., 2007; Murnleitner *et al*., 2002). Marsili-Libelli (2006) developed fuzzy pattern recognition to control SBR switching. The switching strategy was from the indirect observation of process state through simple physicochemical measurements and the use of an inferential engine to determine the most appropriate switching schedule. In this study, fuzzy rule based model is developed to predict the maximum removal efficiency of COD, NH_4-N, PO_4-P and NO_3-N and minimize mean cell residence time of SBR system whereas the sludge age have direct influence on energy and operation cost of wastewater treatment plant. The fuzzy model is built based on if-then rules for mean cell residence time and removal efficiency of COD, NH_4-N, PO_4-P and NO_3-N based on experimental data in each step of SBR System.

MATERIALS AND METHODS

Experimental setup: The experimental set up was fermenter (Bioflo IIC, New Brunswick) with a 5 Lworking volume was used as the SBR. The fermenter was microprocessor controlled for aeration, agitation, pH and Dissolved Oxygen (DO). Aeration was provided by using an air pump and a sparger. Agitation speed was varied between 25 and 300 rpm. The fermenter was used to investigated the effectiveness of mean cell residence time on the removal efficiency of COD, NH4-N, PO4-P and NO_3-N. The effect of mean cell residence time on removal efficiency at constant Hydraulic retention time (10.5 days) whereas the hydraulic retention time was 2 h for anaerobic tank, 1 h for anoxic tank no. 1, 4.5 h for oxic tank no. 1, 1.5 h for Anoxic tank no. 2 and 1.5 h for Oxic tank no. 2.

Model architecture and model components: The schematic architecture of the neural fuzzy model is depicted in Fig. 1. It consists of the five key components:

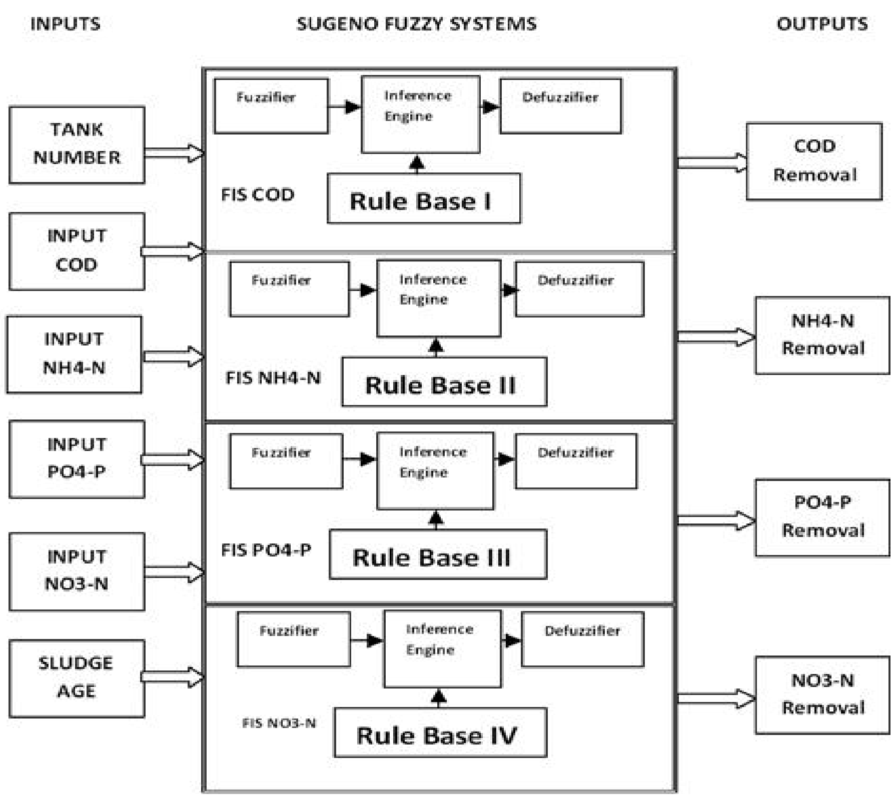

Fig. 1: Architectural of the neural fuzzy model for five step sequencing batch reactor

Table 1: Ranges of input variables

Input variable	Range
Tank number	1-5
Chemical Oxygen Demand (COD)	856-1120 mg/L
NH4-N	41.2-58.4 mg/L
PO4-P	10.8-13.6 mg/L
NO3-N	0.9-3.9 mg/L
Sludge ageay	5-30 ay

inputs and outputs database and preprocessor, a fuzzy system generator, a fuzzy inference system and, an adaptive neural network representing the fuzzy system. The input and output parameters are selected or generated from the major parameter that is influence on removal efficiency. Table 1 showed the range of each input that is used in this study.

MODELING RESULTS AND DISCUSSION

The network was trained by hybrid algorithm whereas the Membership functions of the variables were drawn after the premise parameter was obtained. Figure 2 shows the FIS editor screen in which the input and output variables can be seen. In addition to that after the model was trained, the inference was performed in accordance with 13 fuzzy linguistic rules as shown in Fig. 3. Those rules were obtained after the network was

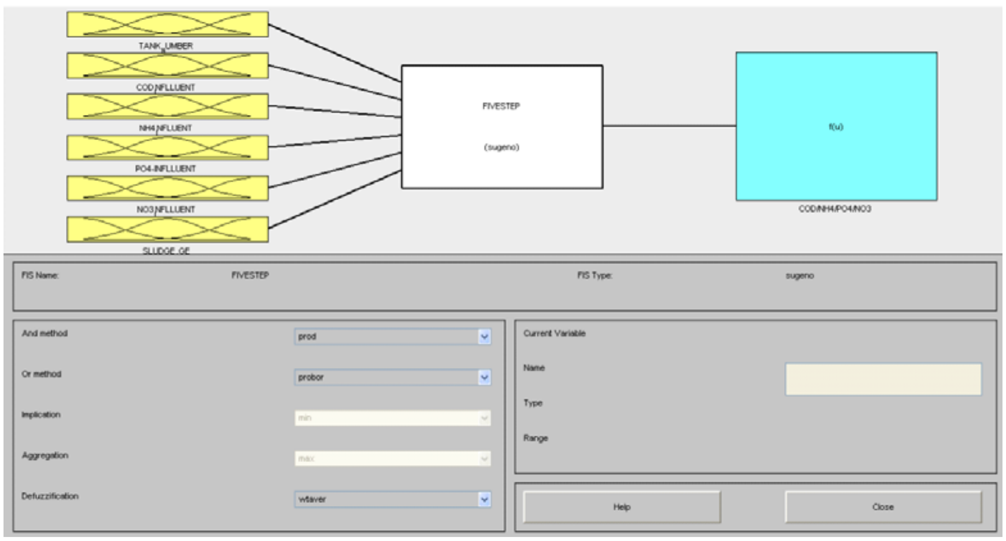

Fig. 2: FIS editor screen box

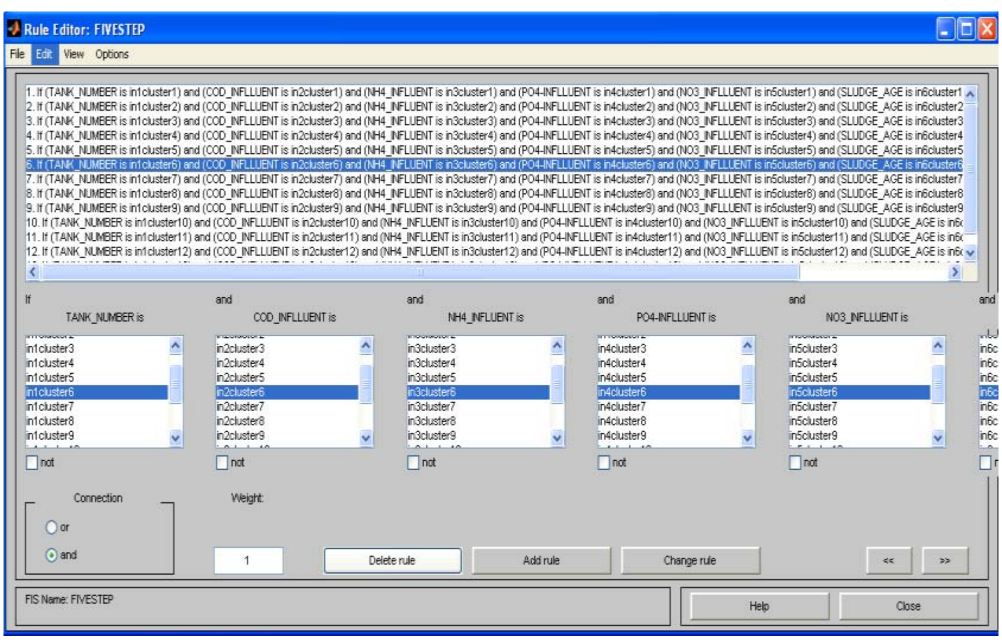

Fig. 3: Rule editor of fuzzy logic control tool box

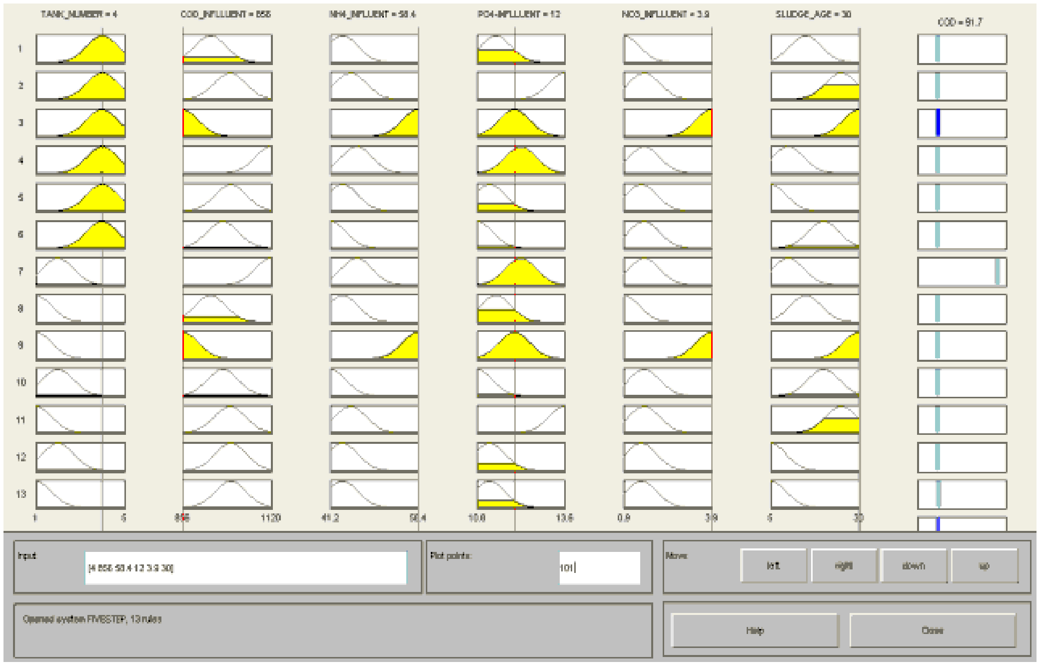

Fig. 4: Rule viewer screen to obtain COD defuzzified results

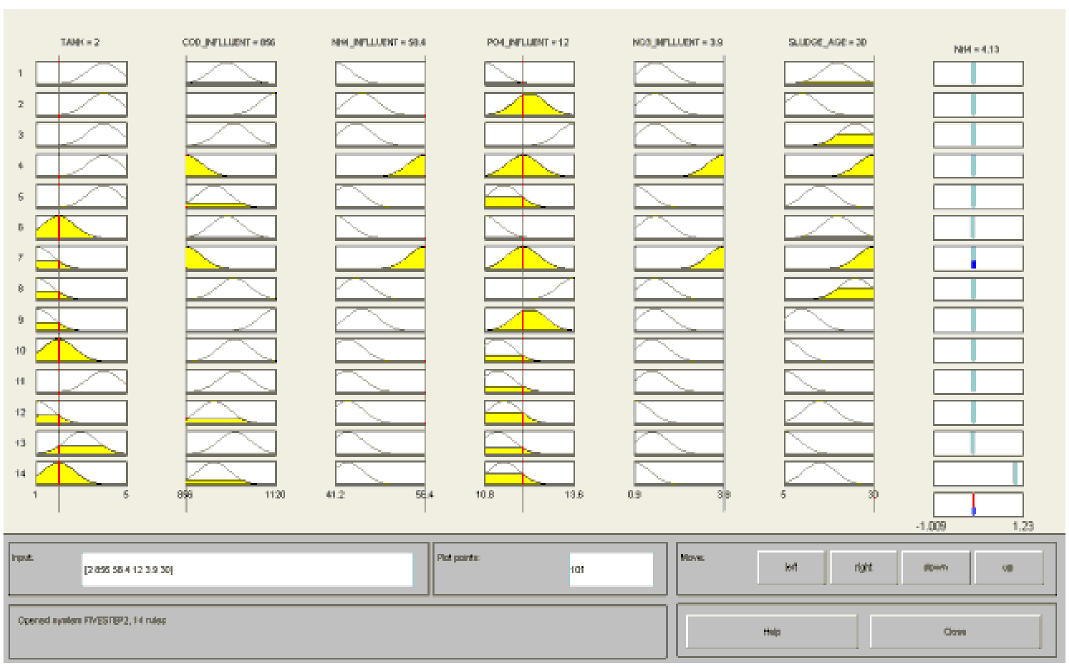

Fig. 5: Rule viewer screen to obtain NH4-N defuzzified results

trained. Some other rules were also included heuristically in terms of comparing output values in accordance with input values. These rules are applied with deferent boundary condition to predict nutrient removal efficiency.

Figure 4 to 7 shows the results of applied rules and their corresponding outputs according to the mass center of variables. Using the interface, defuzzified values for output variables can be derived changing input values manually. Different output values can be obtained through the rule viewer according to the given input values. It is not flexible to get deffuzzified output values for all the real input values using interface. For that reason the

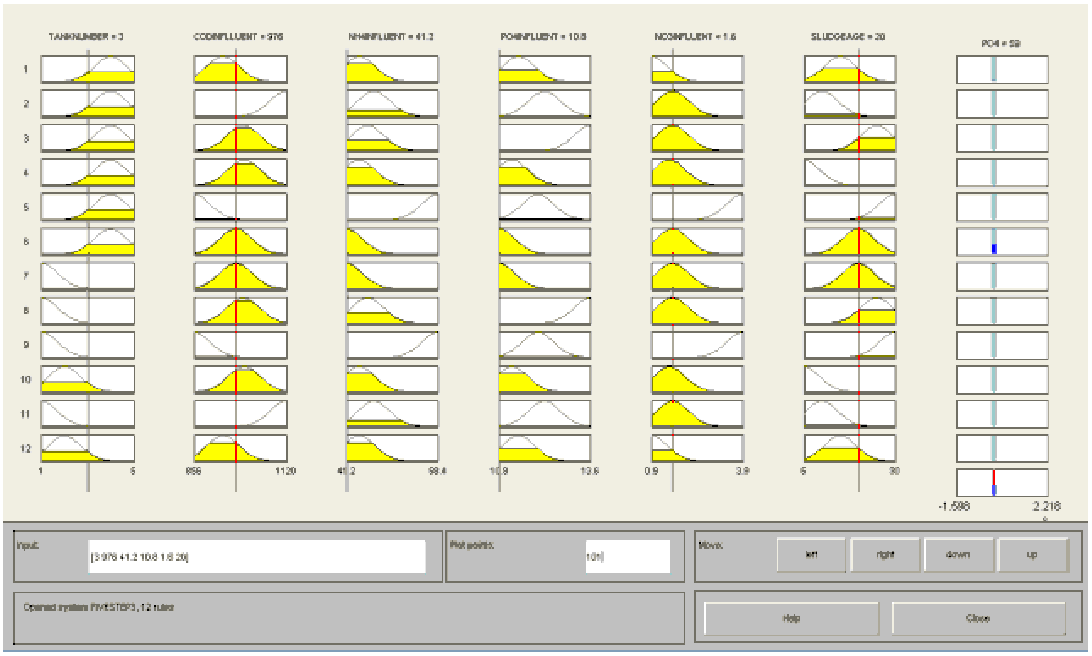

Fig. 6: Rule viewer screen to obtain PO4-P defuzzified results

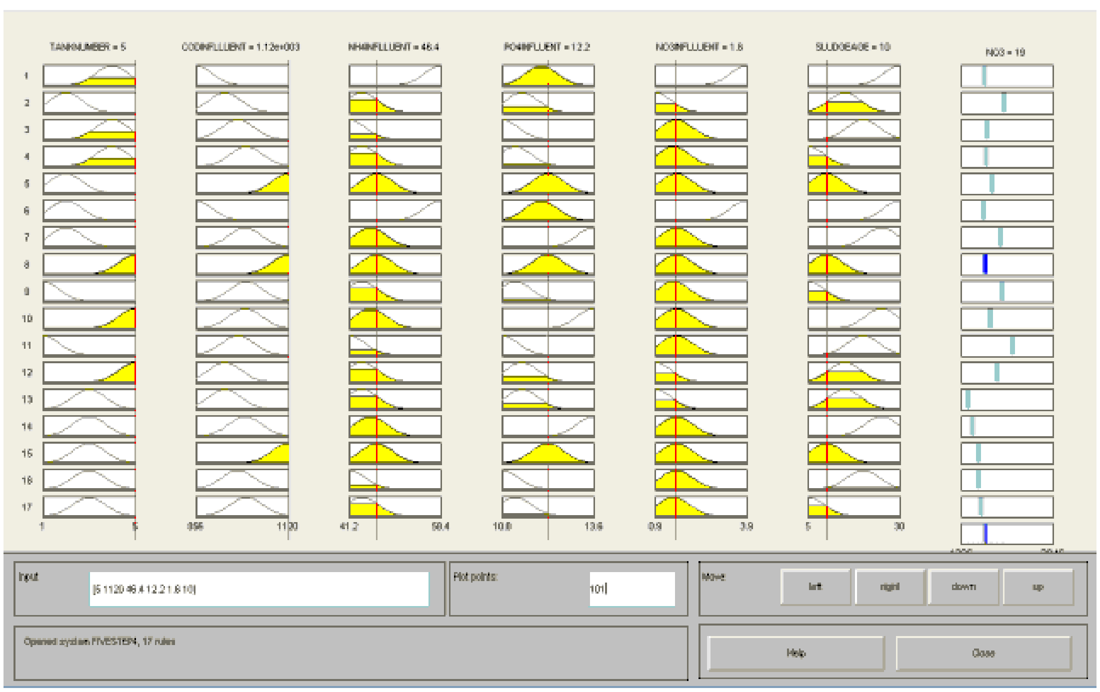

Fig. 7: Rule viewer screen to obtain NO3-N defuzzified results

program is written using Matlab codes to drive defuzzified output results in accordance with real input values.

Figure 8 to 12 represents the validation results of the proposed fuzzy neural network model whereas it can be seen that the predicted values are able to follow the real values in all tanks of five steps systems. The removal efficiency is represented whole removal efficiency according to the tank number whereas Fig. 8 is represented the removal efficiency just in Anaerobic tank

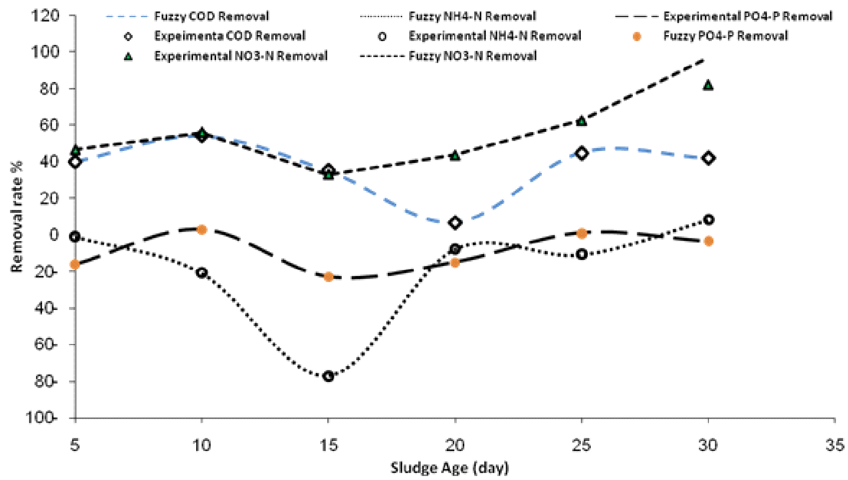

Fig. 8: Effect of mean cell residence time on nutrient removal efficiency in anaerobic tank

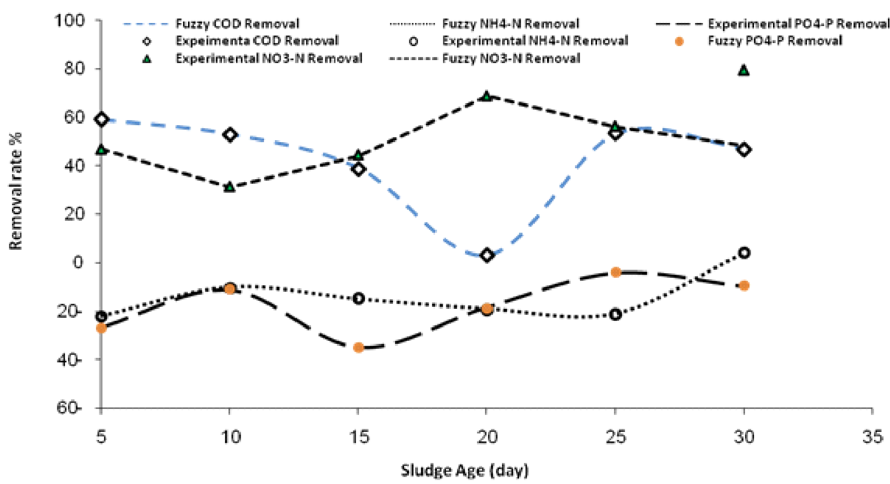

Fig. 9: Effect of mean cell residence time on nutrient removal efficiency in anaerobic/ Anoxic tanks

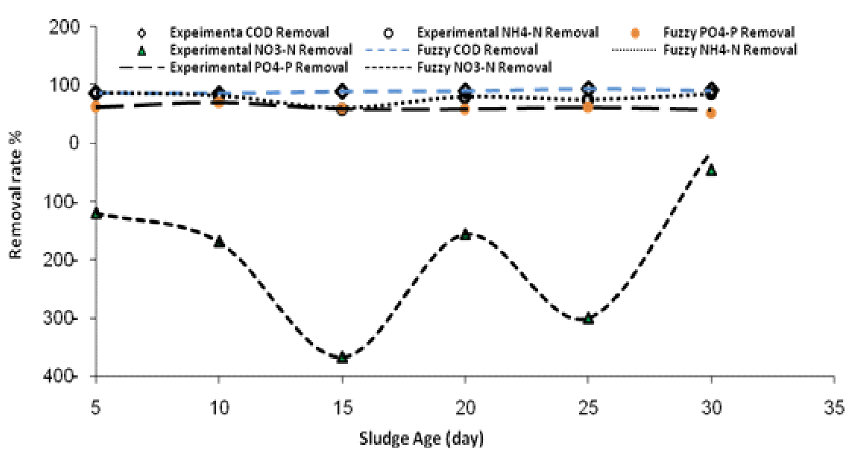

Fig. 10: Effect of mean cell residence time on nutrient removal efficiency in anaerobic/anoxic/oxic tanks

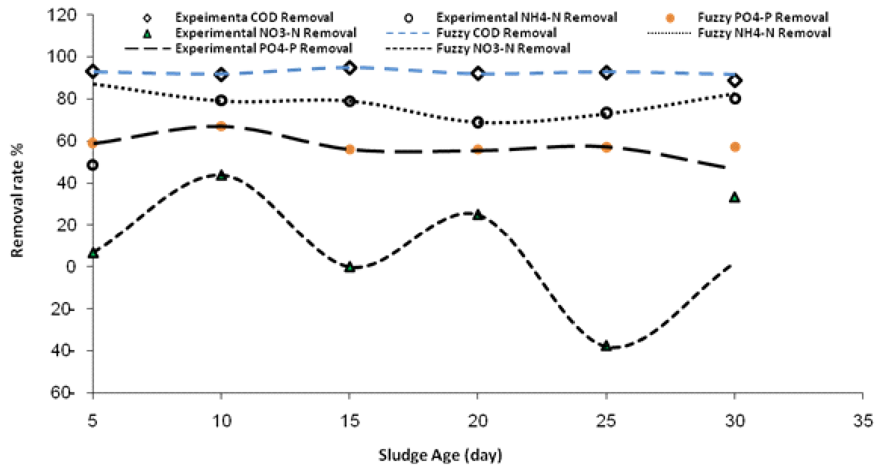

Fig. 11: Effect of mean cell residence time on nutrient removal efficiency in Anaerobic/Anoxic/oxic/Anoxic tanks

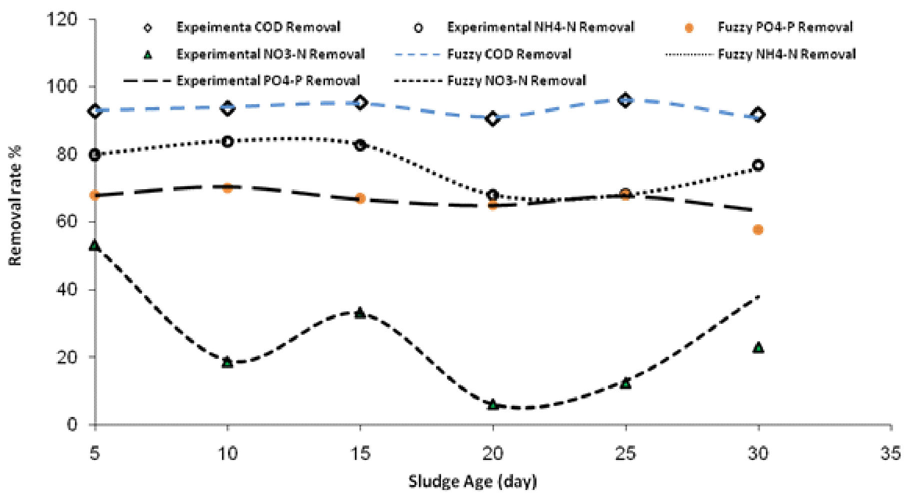

Fig. 12: Effect of mean cell residence time on nutrient removal efficiency in Anaerobic/Anoxic/oxic/Anoxic /Oxic tanks

while Fig. 12 represents the removal efficiency in the system as whole.

CONCLUSION

Fuzzy logic model was built based on if-then rules (from collection data) for COD, NH4-Nand PO4-P and NO_3-N removal efficiency and mean cell residence time of five step SBR process. A control law based on fuzzy logic features was developed and validated for sludge age of SBR wastewater process. The controlled variables was the tank number , input COD concentration mg/L, input NH_4-N concentration mg/L, input PO_4-P concentration mg/L, input NO_3-N concentration mg/L and sludge age (day) and the output variables was the COD, NH_4-N, PO_4-P and NO_3-N removal efficiency (or release rate when negative value) in each tank of five steps system. The model provide a new and good tool for control mean cell residence time effects on biological nutrient removal efficiency in five-step sequencing batch reactor.

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