CONTROL OF RECYCLE SLUDGE IN ACTIVATED SLUDGE PROCESS USING ADAPTIVE NEURO-FUZZY LOGIC CONTROLLER (ANFIS)

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ABSTRACT

Activated sludge process is usually difficult to operate and control because of its complex operational behavior and of its complex nature. The optimization and further process development of this technology go the availability of fuzzy logic model, this model is powerful because it can learn to represent complicated data patterns or data relationships between input and output variables of the system being studied.

The objective of this study is to determine the amount of sludge necessary to be recycled in the aeration tanks to allow the attainment of a good quality of effluent wastewater and to minimise the excess sludge, a fuzzy control model of activated sludge process was developed. The detailed information on development of fuzzy model was addressed based on collecting and analyzing previous experimental data.

Neuro-fuzzy modeling should be able to determine the amount of recycle sludge necessary to treat an activated sludge treatment plant. The input parameters used in this study include the removal yields of organic pollution parameters such as COD and BOD, SS and recycle sludge as a decision parameter with respect to the discharge standards.

The historical values of the observed yields associated with the recycle sludge during the study learning period enable the prediction of the recycle sludge needed for a validation period.
Satisfactory results were obtained during the study and validation periods, revealing the advantages of fuzzy logic and justifying the predictive power of the model.

Keywords: activated sludge process, simulation fuzzy logic, recycles sludge.

1. Introduction

The dynamic behaviour of activated sludge processes is a result of many complex mechanisms (Zhua et al., 2010) due to the specific growth rate of bacteria in biological process which varies with time and is influenced by many factors such as the substrate concentration, temperature, pH, dissolved oxygen concentration, light intensity (Bououden et al., 2015), imprecision and uncertainty of several parameters which are difficult to identify and strong nonlinearities. Given all these factors, it is very difficult to construct a mathematical model for control of the process. In order to meet these demands, the use of advanced modeling methods by fuzzy logic model is required (Maachou et al., 2015). The basic components of fuzzy logic model and techniques that have been used for their development will be discussed in the following.

The decision parameters of the activated sludge process permit the evaluation of the performance of the treatment plant by using fuzzy logic models, which have been the subject of intense research activity. However, sludge recycling system is an important part of WWTP, which can ensure the required reactor sludge concentration, the maintenance of secondary sedimentation tank and the reactor, the dynamic balance between the amount of sludge, its wastewater treatment plant effluent quality, system stability operations and operating costs have a major impact (Wangyani., 2013).

The aim of this work is to controlling the quantity of sludge necessary to be recycling in reactor to maximize the conversion rates of parameters of organic matters (COD, BOD) and SS of the biological processes and minimize the excess sludge product.

2. Materials and methods

2.1. Activated Sludge Pilot

Activated sludge systems have been widely used during the treatment of municipal wastewater. In This process, microorganisms utilize carbon, phosphorus and nitrogen in the presence of oxygen for metabolism and growth (Maachou et al., 2015) under conditions that optimize the consumption of influent biodegradable organic matter (Belchiora et al., 2012). These systems involve inoculation with floc forming bacteria, which oxidize the organic matter, stabilizing the wastewater under aerobic conditions. A settling tank is used to separate the biomass constituents according to their settling abilities (Mafalda et al., 2009).

The clarifier is an integral part of the activated sludge system. It has two main functions: it separates the biomass from the water in order to produce a good quality effluent free from settleable solids and it also thickens the biomass. Part of the thickened biomass is then wasted as sludge and part of it is returned to the biological reactor (recycle sludge) to maintain an appropriate biomass concentration. Recycle sludge is a critical control variable as it redistributes the sludge between the secondary clarifier and the aeration tank, such that the healthy population of biomass is maintained in the aeration basin. Thus, the operator must maintain a continuous return of activated sludge to the aeration tank or the process will show drastic decrease in performance (Rustom at al., 2009).

To obtain the desired level of performance in an activated sludge system, a proper balance must be maintained between aeration (energy consumption) and the quantity of sludge recirculation (pumped from the secondary clarifier back to the aeration tank), and the amount of excess sludge withdrawn from the system (usually pumped from the secondary clarifier towards sludge treatment).

The activated sludge treatment plant of Boumerdes is within the “extended aeration activated sludge” category. This site has a processing capacity of 75,000 inhabitant equivalents with a low mass loading (of the order of 76 kg DBO / kg MVS / day). It is designed to treat domestic sewage, and the daily nominal flow is 15000 m3 / day. 281 daily data describing the pollution control during a weekly measurement at upstream and downstream from May 2007 until December 2013 were collected (Lefkir et al., 2015).

2.2. Description of Fuzzy Logic

The theory of fuzzy sets, firstly published by Zadeh (1965), presents a useful way of representing the uncertainty and imprecision in data without the need of complex mathematical relationships. These models have the advantages of being able to model non-linear functions in an easy and understandable way by explaining the reasoning linguistically rather than with numerical quantities. They provide a useful way of representing human knowledge in a readable way in the form of fuzzy rules (Rustum et al., 2009). This fuzzy logic technique uses non-conventional membership functions that are different from the classical membership functions that take only two values: one, when an element belongs to the set; and zero, when it does not. Whereas, in fuzzy logic the degree to which an element belongs to a subset may be any value in the interval [0, 1] (Center et al., 1998).

Fuzzy logic has successfully been used in the environmental field to deal with uncertain data. There exist different procedures to implement the fuzzy principles. The most used nowadays are the Artificial Neuro Fuzzy Inference System (ANFIS) which are capable to assign output variables to input variables using fuzzy logic.

2.3. ANFIS modeling strategy

The fuzzy logic analysis is proposed to obtain the optimal combination of elimination yields of Y_{BOD}, Y_{COD}, Y_{SS} to obtain the optimal recycle sludge quantity. A fuzzy system is a static nonlinear mapping between its inputs and output on the basis of membership functions and fuzzy rules.

Adaptive-Network-based Fuzzy Inference System (ANFIS) is a multi-layer feedforward network in which each node performs a particular function on incoming signals. The parameters associated with these nodes are updated according to a given training data and a gradient based learning procedure in order to achieve a desired input-output mapping. ANFIS can be used to optimize membership functions and has the advantage of being able to construct fuzzy IF-THEN rules representing these optimized membership functions (Rustum et al, 2009).
The membership functions as well as their degree of overlapping can be customized by the user according to the configuration and characteristics of the simulated activated sludge plant.

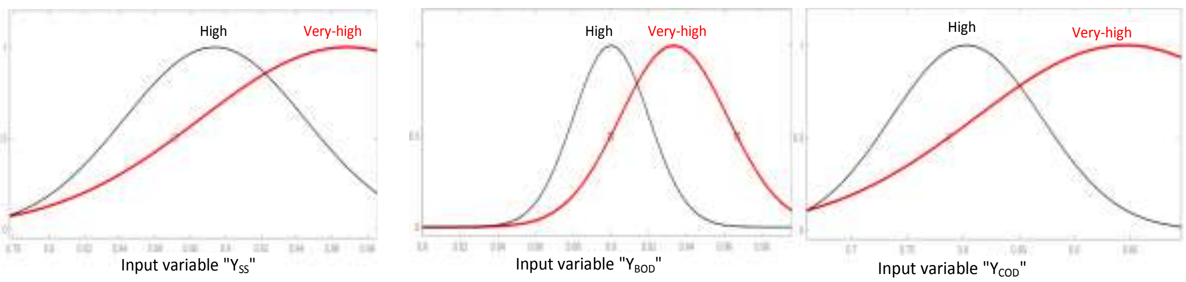


Figure 1: Example of membership functions for the input and output variables

The membership function is used to fuzzify the input variables into assigned fuzzy sets. In membership functions, crisp input values are interpreted into the linguistic fuzzy sets according to membership grades. When the membership grade equals to 1, the value absolutely belongs to the fuzzy set. When the grade is 0, the value is not included into the fuzzy set. In between, the element is assigned to the fuzzy set to some extent (Zhai et al., 2012).

The three steps in the ANFIS are: the fuzzification, Fuzzy inference, Defuzzification shown in Figure 2.

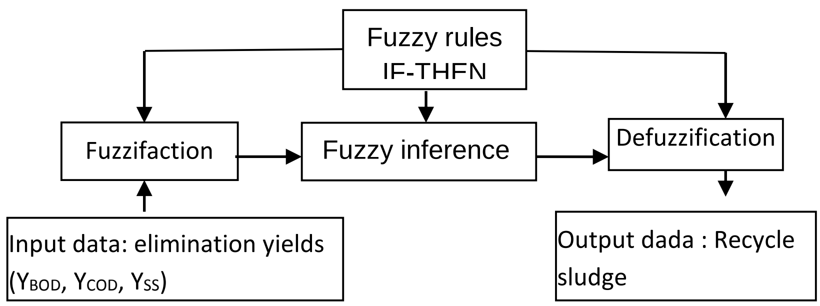


Figure 2: Model structure of the ANFIS for modeling RS in activated sludge process

A general fuzzy system has basically three components: fuzzification, fuzzy inference and defuzzification

i) Fuzzification, where the crisp values of numerical data are converted into linguistic/qualitative descriptors or input fuzzy sets (i.e. low, middle, high, very high...) by means of corresponding membership functions (Comas et al., 2008). Membership functions are defined by elimination yields of Y_{SS}, Y_{BOD}, Y_{SS}. Gauss functions are used as membership functions (figure 1).
ii) Fuzzy inference of recycle sludge through a Sugeno (1985) approach, generate a fuzzy output from the corresponding input fuzzy sets based on implications contained in the fuzzy rule base implemented as folowing :

if *((Y_{BOD}* ***is*** *high)* **and** *(Y_{COD}* ***is*** *high)* **and** *(Y_{SS}* ***is*** *high))* **then** *(RS* ***is*** *high)*

(iii) Defuzzification of the output variable, where the linguistic fuzzy output has to be translated into a numerical value such as the necessary recycle sludge.

2.4. Validation of the model ANFIS

In order to evaluate the predicting performance of ANFIS, the Root Mean Square Error criterion is used to calculate the difference between the simulated and observed values. The RMSE criterion will be low over the gap between the values and will be limited. RMSE is expressed as follows:

$$RMSE = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}\left(Y_{ipre} - Y_{iobs}\right)^2\right)} \tag{1}$$

- The correlation coefficient R is expressed as follows:

$$R = \sqrt{\frac{\sum_{i=1}^{n}\left(\left(Y_{iobs} - \overline{Y}_{obs}\right)\times\left(Y_{ipre} - \overline{Y}_{pre}\right)\right)}{\sum_{i=1}^{n}\left(Y_{iobs} - \overline{Y}_{obs}\right)^2 \times \sum_{i=1}^{n}\left(Y_{ipre} - \overline{Y}_{pre}\right)^2}} \tag{2}$$

Where Y_{ipre} is the prediction value, Y_{iobs} is the observed value, $\overline{Y}_{obs}$ and $\overline{Y}_{pre}$ are the average values of observed and prediction values, respectively.

3. Results and discussion

Neuro-fuzzy modeling is performed to simulate the recycle sludge. The data were separated into two sub-samples: the learning of the model parameters and data validation. These sub-samples were selected from the parameters that describe the organic matter and SS. The input parameters, including the elimination yields of SS, BOD and COD, are reported as named and calibrated with the output parameter including recycle sludge.

Sample size of data learning must be larger than sample size of data Validation. In the learning phase the model must scanning the possible cases of process.

The performance of the model is tested during validation to assess its predictive abilities. To evaluate the model, its output is compared with additional data (test data) collected from the system. It is important that the test data is not used in the construction of the model, so that the predictive capability of the model can be objectively assessed (Center et al., 1998).

During any modeling, simulated results must be validated relative to the observed data. The Two criteria were calculated during this study.

In this study, a collection of data upstream and downstream of the station was made. It has a series of daily data dating from January 2006 until March 2012. It has 185 daily data yields pollution control due to a weekly measurement.

The simulation results are shown in the following table:

Table 1: Validation criteria of learning and validation periods.

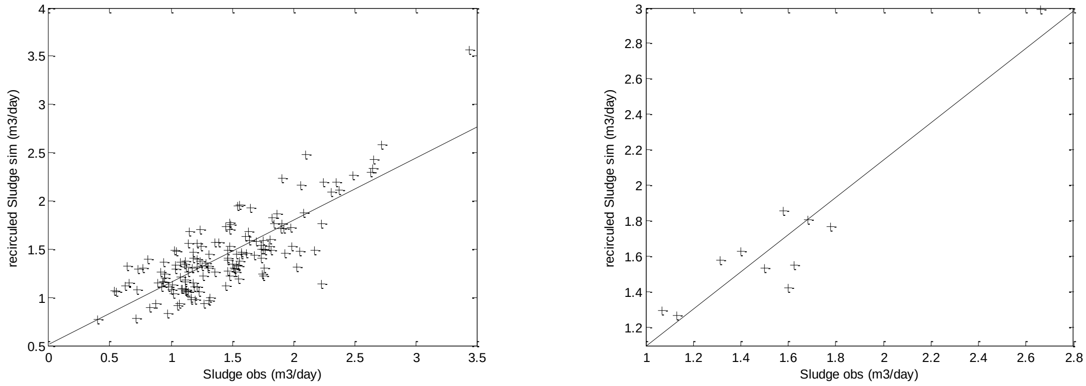
	validation criteria	
learning period	RMSE	20.7
	R(%)	80.3
validation period	RMSE	12.6
	R(%)	93.94

The best results with respect to the RMSE criteria are obtained for the validation period (12.6) compared to the learning period (20.7). The coefficient of correlation of learning period (80.3%)

is slightly lower compared to the validation period (93.94%). A better appreciation of the recirculated sludge is obtained with the ANFIS Model in the two cases learning and validation period.

RMSE and R vary with the sample size n; ie sample of data learning period is higher than sample of data validation period that caused the biggest mistakes which resulted in difference values of RMSE and R.

The correlation lines of learning and validation period are shown in figure 3. This figure shows that the distortions are reduced in validation period compared to the learning ones.



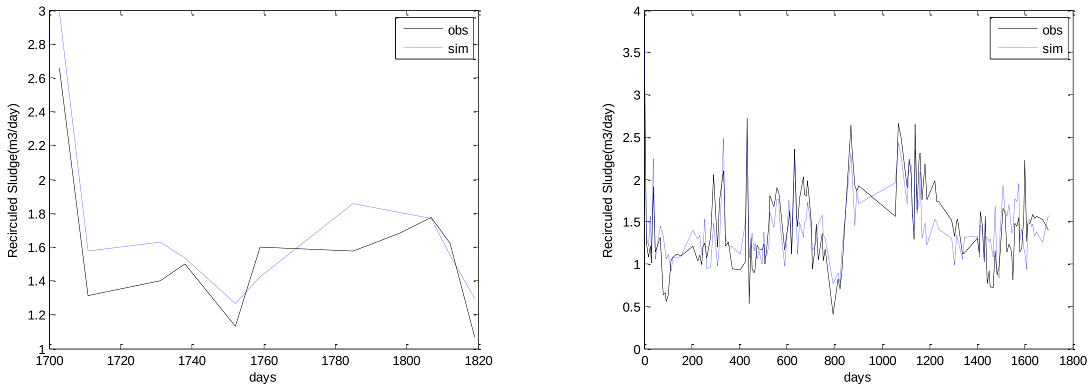
(a) learning period (b) validation period

Figure 3: Simulated recirculated sludge correlations in recirculated sludge function observed during learning (3.a) and validation period (3.b).

The correlation coefficient assesses the relationship, while the RMSE criterion is used to measure the distortion between the observed and simulated values. The two criteria must be coupled in a proper assessment model.

The variation of the observed and simulated recirculated slugde function in accumulated learning period and validation period by the neuro-fuzzy model is illustrated in Figure 4.

For all of the figures, a relatively accurate reproduction of the values of recirculated sludge and a relatively accurate reproduction of peaks, better reproduction is obtained with validation period shown in Figure (4. a).



(c) (d)

Figure 4: Recirculated sludge variation observed over cumulative days during the learning (4.a) and validation period (4. b).

4. Conclusion

The present study concludes that the application of ANFIS can improve Sludge recycling system, providing the optimal yields. ANFIS indicates the high ability of modeling a more complicated process such as the activated sludge processes, for improving the performance of wastewater treatment plant and can lead to a better understanding of the system. However, the complexity and uncertainty in the process make the task somewhat complicated using traditional deterministic models.

ANFIS model has been proposed and applied to simulate recirculated sludge in activated sludge process in objective to optimize the elimination yields of parameters COD, BOD and SS. Simulation and prediction have shown that the resulting model can adequately predict the process with a satisfactory results. These last were obtained during the learning and validation periods, revealing the advantages of fuzzy reasoning and justifying the predictive power of the model developed to simulate the amount of the recycle sludge in activated sludge process.

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