Desalination and Water Treatment
www.deswater.com
doi: 10.1080/19443994.2015.1111596

57 (2016) 21182–21188
September

Modeling of activated sludge process using artificial neuro-fuzzy-inference system (ANFIS)

R. Maachou[a], A. Lefkir[b,*], A. Khouider[a], A. Bermad[c]

[a]*Laboratory of Faculty of Chemistry, Electrochemistry-Corrosion, Metallurgy and Mineral Chemistry, USTHB, BP 32 El-Allia, PC 16111 Algiers, Algeria*
[b]*ENSTP, Laboratory of TPiTE, Algiers, Algeria, Tel. +213 21511261; email: a_lefkir06@yahoo.fr*
[c]*ENP, Ecole Nationale Polytechnique, URIE, B.P. 182-16200, El Harrach, Algiers, Algeria*

Received 4 June 2015; Accepted 18 October 2015

ABSTRACT

The paper describes the application of a neuro-fuzzy system in order to minimize the energy consumption on controlling the nitrate production in the wastewater treatment plant by activated sludge process. Neuro-fuzzy models are based on the extraction of knowledge from data collected upstream and downstream of a treatment plant. The historical values of the observed yields associated with the energy consumed during the study period enable the prediction of the energy needed for a validation period. The energy is controlled by the excess nitrates produced, which can be a symptom of over aeration. However, the simulation data are divided into two samples (data filtered and data unfiltered of nitrate). The input parameters used in this study includes the removal yields of organic pollutants parameters and energy consumption as a decision parameter with respect to the discharge standards. The predictive power of energy shows the feasibility and robustness of the simulation approach with a filtered data.

Keywords: Wastewater treatment; Biological nitrification; Biological treatment; Activated sludge; Fuzzy control

1. Introduction

Information and knowledge extraction techniques have rapidly evolved due to the development of computer tools, which help reducing the complexity of phenomena such as biological treatment [1,2]. The biological processes during wastewater treatment are complex and non-linear [3,4]. The randomness of the parameters surrounding the entrance of the reactor, specifically the inflow and polluted load, further exacerbate the difficulty of controlling these processes [5,6]. The models developed by biologists are empirical, often involving too many parameters for practical use [2]. Although deterministic models give a good insight into the mechanism, they require a lot of hard work before applying to a specific wastewater treatment plant. Because kinetic parameters and wastewater characteristics can show some fluctuations in different periods of time when the operating conditions are applied on a regional scale, calibration of these models are extremely time consuming, laborious, and needs extensive laboratory and computer work [7].

*Corresponding author.

Therefore, we propose using a "neuro-fuzzy" technique based on artificial intelligence to control these processes more effectively [8] by accounting for the data available upstream and the downstream from the treatment station. Developing tools based on fuzzy logic should ameliorate the difficulties posed by mathematical models and translate the behavior of a complex physical system [9].

The decision parameters of to the cleanup 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. These models include the following: (i) the amount of sludge to be recycled in the aeration tanks [10], (ii) the dose of oxygen to be injected in the aeration basins [5,6,10,11], and (iii) the energy needed to reach the treatment targets [12,13].

Therefore, this work focuses on diagnosing the operation of an activated sludge treatment plant to detect any problems and improve performance by reducing the energy consumption. However, a neuro-fuzzy model was constructed by accounting for the elimination of the pollution parameters and the energy consumed.

To select the parameters that dominate the model, a statistical analysis was performed to inventory the operation of the plant, surfacing in the output states, and the rate of elimination. The activated sludge process primarily enables the removal of organic matter with a high excess of nitrate [14,15]. This analysis allowed us to filter the training data for the neuro-fuzzy model related to the allowable nitrate thresholds downstream from the station. The satisfactory results obtained with this filter were compared to those without the filter to justify the adopted procedures describing the energy in a wastewater treatment plant.

2. Statistical study of the station

The Boumerdes treatment plant (located in Algeria) is within the "extended aeration activated sludge" category. This station has a processing capacity of 75,000 inhabitant equivalents with a low mass loading (of the order of 0.076 kg DBO/kg MVS/d). It is designed to treat domestic sewage, and the daily nominal flow is 15,000 m^3/d.

Activated sludge systems have been widely used during the treatment of municipal wastewater [8]. These systems are composed primarily of heterotrophic microorganisms that degrade organic matter [5,8]. The activated sludge treatment method is a biological treatment in a suspended culture; the necessary equipment includes a biological reactor where the wastewater is mixed with an aerated biomass and maintained in suspension. The substrate in the wastewater feeds the propagation and development of microorganisms contained in the biomass. Portions of the biomass are recycled in the reactor, while the other portions are separated by decantation. Excess biomass is extracted from the system and is called secondary sludge.

Database collection of the downstream and upstream from the station was conducted. The series of data was collected daily from January 2006 until March 2012. In addition, 185 daily data yields describing the pollution control were collected during a weekly measurement.

The magnitude of the organic pollutants parameters was more important than the nutrient pollutants, which influences the impact of the latter. Therefore, the raw variables were transformed such that the dimensionless variables representing percentages of excess were related to the standards.

Energy was treated as the maximal energy, and the flow is reported at the nominal rate (15,000 m^3/d); the removal efficiencies were selected to represent the pollution. The resulting values are normalized (between 0 and 1).

A graphical representation is illustrated in Fig. 1 showing the average drawdown of the organic (SS, BOD_5, and COD), nitrogenous (NH_4^+-N, NO_3^--N, NO_2^--N, (PO_4^{3-}-P) and TKN) and phosphorus pollutants in percentages of the requirements set by the discharge standards (AFNOR Standards).

The concentrations of PO_4^{3-}-P and TKN are insufficiently reduced. The activated sludge process is not sufficient, and an additional combination treatment is essential. The concentrations of NH_4^+-N and NO_2^--N increased, but the values are below the standard.

An excess drawdown of organic pollutants (SS, BOD, COD) was also present against an increased concentration of nitrate (NO_3^--N), which fell above the

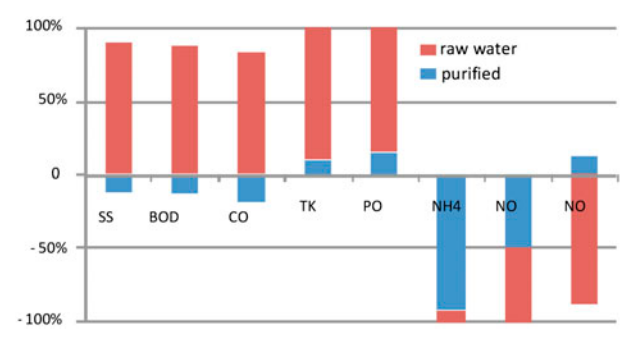

Fig. 1. Representation of the pollution parameters (input–output) relative to the AFNOR standard.

required standards. This behavior can be explained by over-aeration. Over aeration decreases the anaerobic zones and consumes energy. The energy consumption is primarily related to the amount of oxygen supplied to the aeration basins and the sequencing aeration periods; the latter is due to the variable NO_3^--N content, which represents the degree of de-nitrification that can occur at the aerators.

The performance of the purification process relative to energy consumption is related to the decrease in organic pollutants. However, this consumption can be controlled by the excess nitrates, which can be a symptom of over ventilation. To account for this relationship, the filtered database was reduced to 154 data points out of 185 relative to the required discharge standards downstream from the station.

3. Results and interpretations

3.1. Neuro-fuzzy modeling

In 1965, the concept of a fuzzy set was proposed by Zadeh [16], who has contributed to the shapes of fuzzy models; this research aimed to overcome the limitations posed by the uncertainties in the conventional models using differential equations. In 1973, Zadeh [16] proposed the application of fuzzy logic to control setting problems. In 1974, Mamdani [17] tested the theory proposed by Zadeh using a steam boiler; this equipment had a known complexity, enabling the introduction of a fuzzy controller during the control of an industrial process. In 1985, Sugneo [18] introduced fuzzy logic in Japan, leading to the first industrial products utilizing the principle of fuzzy logic to overcome regulation and control problems [3].

The key advantage of fuzzy logic methods is how they reflect the human mind in its remarkable ability to store and to process information that is consistently imprecise, uncertain, and resistant to classification [19]. The objective of the fuzzy modeling is to obtain a formal model that describes a natural, human, or industrial process to gain understanding based on the fuzzy rule. A fuzzy approach is more intuitive than traditional modeling approaches, both probabilistic (uncertain) or analytical (certain). The fuzzy approach can also represent a process studied using a natural language (imprecise) through the introduction of descriptors such as “low,” “high,” and “very high,” partially modeling the human approach to introduce an interpretable system.

During our work, we focused only on the model proposed by Sugeno (Takagi-Sugeno-Kang). In this context, we note that several methods have been developed to identify the parameters of these models. Sugeno’s model established a relationship that connects the analytical inputs to the output of the modeled system. The model parameters are estimated by introducing optimization methods that minimize a specific criterion.

Two types of parameters are identified: input and output parameters. The input parameters include the membership functions in the partitions of the input space. Each of these membership functions can be described by parameters (p), where p depends on the shape of the selected function. For Gaussian functions, p equals two parameters (mean and standard deviation). The output parameters are those appearing during the conclusions of the rules.

3.2. Artificial neuro-fuzzy-inference system (ANFIS) approach

A general fuzzy system has basically four components [20]: fuzzification, fuzzy rule base, fuzzy inference, and defuzzification

(1) The fuzzification transforms the modeled fuzzy variable into a fuzzy part. The fuzzification is used to model the inputs of a system as curves called membership functions. These curves define the fuzzy sets and represent the degree of membership for a value in a given state; they can also have different shapes (triangle, trapezoid, etc.).
(2) Fuzzy rule base contains rules that include all possible fuzzy relations between inputs and outputs.
(3) The fuzzy inference produces an image of the fuzzy part through the fuzzification constructed from the fuzzy rules. When each entry is presented based on the fuzzy inference rules, the degree of membership for a given subset is determined. Fuzzy inference systems (FIS) are used to model most applications as a continuous n-dimensional space in ($\Re$). Unlike mathematical or black box models, the representation is made in natural language as If … Then rules, enabling an immediate interpretation that can be exploited in two ways: a priori, which gives a value that might be approximate for the different parameters of the FIS, and a posteriori, which allows the knowledge extracted during the optimization to be examined (we also speak of learning).
(4) The defuzzification portion converts the fuzzy inference result to a digital output value.

3.3. Neural learning fuzzy models (models ANFIS)

To approximate the function between the input and the output of the system, the learning (supervised) process must define the basis of the fuzzy rules; their number, premises, and conclusion minimize the gap between the desired outputs and those inferred by the fuzzy set.

The problems with fuzzy modeling can be observed when identifying a fuzzy system. Conceptually, a fuzzy inference system can be identified in two phases: identifying the model structure and estimating the model parameters from a data-set.

3.4. Simulation and discussion

Modeling is a valuable tool in both design and operation and can be used for process optimization and testing of control strategies in order to meet effluent quality requirements at a reasonable cost. Neuro-fuzzy modeling is performed to simulate the energy consumption. The data (filtered and unfiltered) were separated into two subsamples: the learning of the model parameters and data validation. These subsamples were selected from the filtered data and the crimping parameters that describe the organic matter, which does not exceed the standards.

The input parameters, including the yield, SS, BOD, COD, and flow, are reported as named and calibrated with the output parameter (energy). The performance of the model is tested during validation to assess its predictive abilities.

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

(1) The 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:

$$\mathrm{RMSE} = \sqrt{\left(\frac{1}{n_{\mathrm{obs}}}\sum_{i=1}^{n_{\mathrm{obs}}}\left(Y_{\mathrm{imod}} - Y_{\mathrm{iobs}}\right)^2\right)} \tag{1}$$

(2) The correlation coefficient is expressed as follows:

$$R = \sqrt{\frac{\sum_{i=1}^{n}\left(\left(Y_{\mathrm{iobs}} - \bar{Y}_{\mathrm{obs}}\right) \times \left(Y_{\mathrm{imod}} - \bar{Y}_{\mathrm{mod}}\right)\right)}{\sum_{i=1}^{n}\left(Y_{\mathrm{iobs}} - \bar{Y}_{\mathrm{obs}}\right)^2 \times \sum_{i=1}^{n}\left(Y_{\mathrm{imod}} - \bar{Y}_{\mathrm{mod}}\right)^2}} \tag{2}$$

The criteria used to validate the model during the learning and validation periods are shown in Table 1.

The best results with respect to the RMSE criterion are obtained with filters for the learning (12.7) and validation periods (9.7). The filters reduce the distortions between the simulated and observed values. A better measurement of the energy is obtained when the nitrate discharge standards are met.

The correlation coefficient of the learning period for the first variant (filtered) (67%) is slightly lower than the second variant (unfiltered) (70%) because the data-set was small (185 measures). However, during validation, the correlation coefficient for the filter with variations (88.6%) is significantly higher than that of the second variant (52.6%).

Therefore, a larger database that measures the standards for the nitrate discharge will improve our knowledge and, consequently, the model results.

Straight correlations are shown in both learning (Fig. 2) and validation periods (Fig. 3).

In Fig. 2(a), which corresponds to the filtered variant, the distortions are decreased compared to the second variant 2b, but the correlation coefficients are similar.

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. However, the filter model performs better during the learning period compared to the unfiltered model when accounting for the relatively low RMSE values and the similar correlation coefficients (approximately 70%).

Fig. 3(a) is compared to Fig. 3(b) to display the clear improvement of both validation criteria with the filter model. The extra observations that fall short of the standards for nitrates discharge in the unfiltered variant only disrupt the reasoning model during validation because the data validation meets these standards.

The differences between the observed and simulated energy function during the accumulated learning period, which is during the neuro-fuzzy model validation, are illustrated in Figs. 4 and 5, respectively.

In all of the figures showing a relatively accurate reproduction of the energy values and peaks, a better reproduction is obtained with the filter, as shown in Figs. 4(a) and 5(a).

Fig. 5(b) shows that the simulated energy is higher than when the data are not filtered. In Fig. 5(a), the data are filtered, and the simulated energy is similar to the observed energy.

Table 1
Validation criteria for the learning and validation periods

	Validation criterion	Filtered NO_3^--N	Unfiltered NO_3^--N
Learning period	RMSE	12.7	14.0
	R (%)	67.0	70.2
Validation period	RMSE	9.7	22.0
	R (%)	88.6	52.6

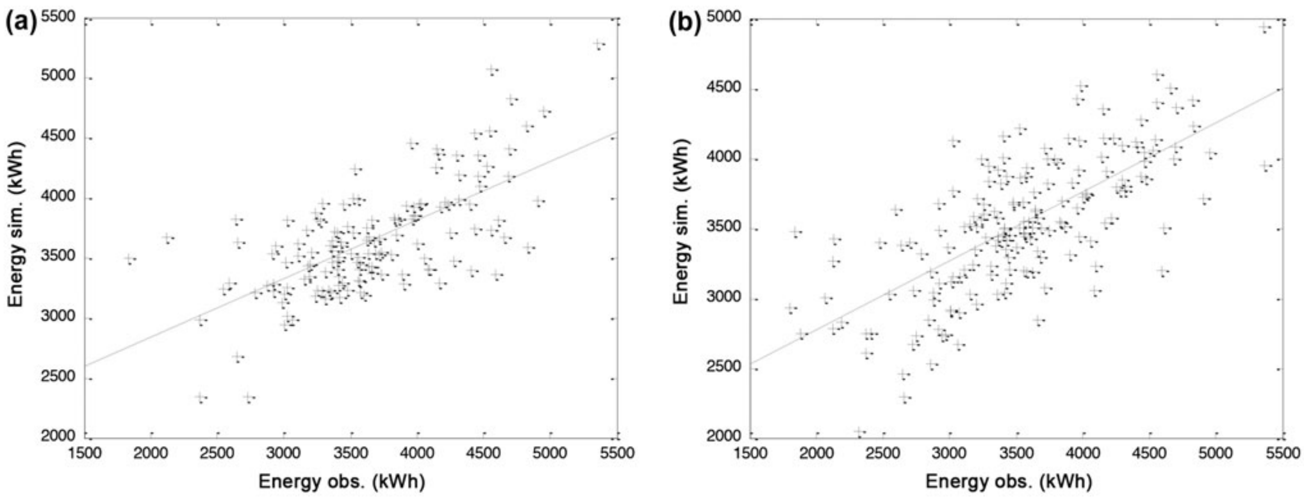

Fig. 2. Simulated energy correlations in the energy functions observed during learning (a) filtered NO_3^--N and (b) unfiltered NO_3^--N.

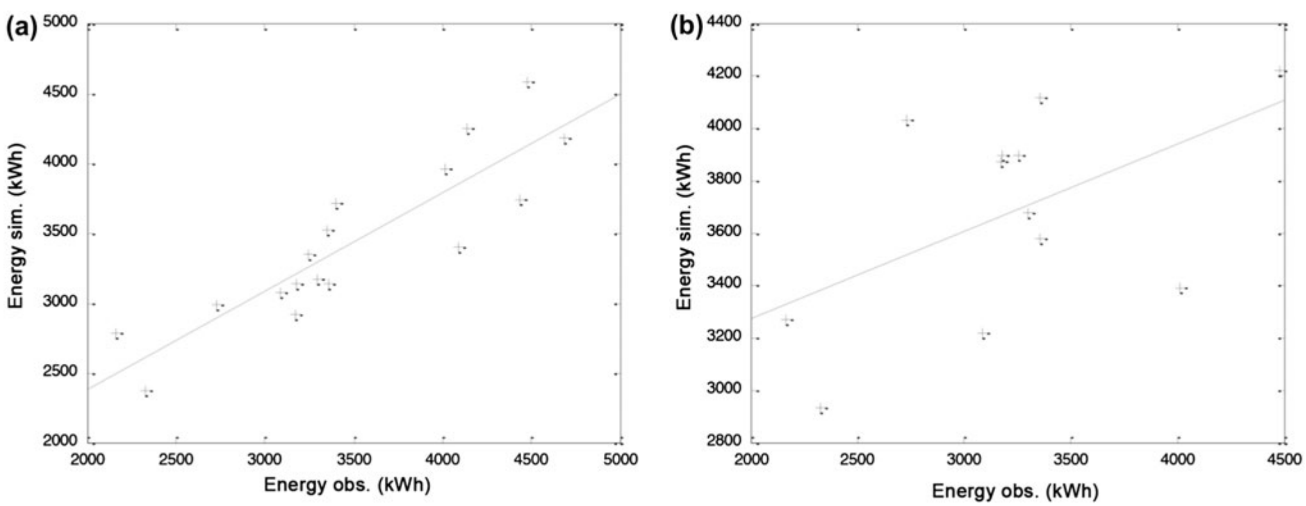

Fig. 3. Simulated energy correlations in energy observed during validation period (a) filtered NO_3^--N and (b) unfiltered NO_3^--N.

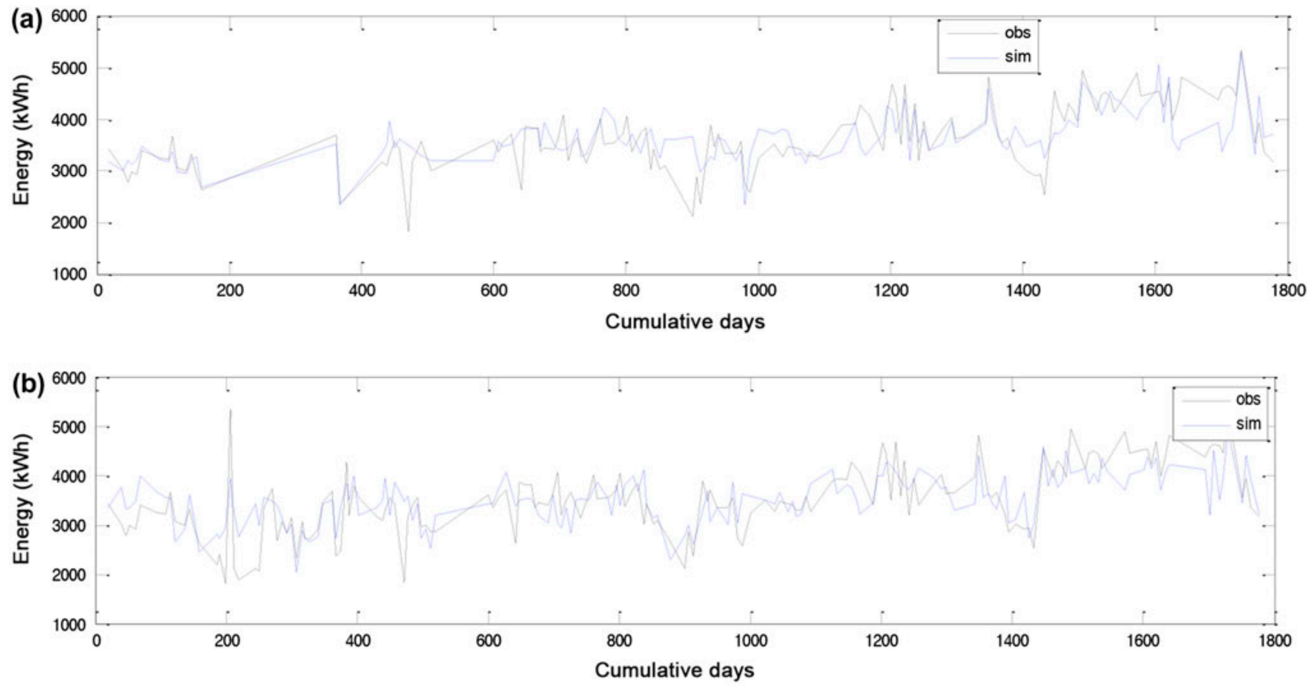

Fig. 4. Energy variations observed over cumulative days during the learning period (a) filtered NO_3^--N and (b) unfiltered NO_3^--N.

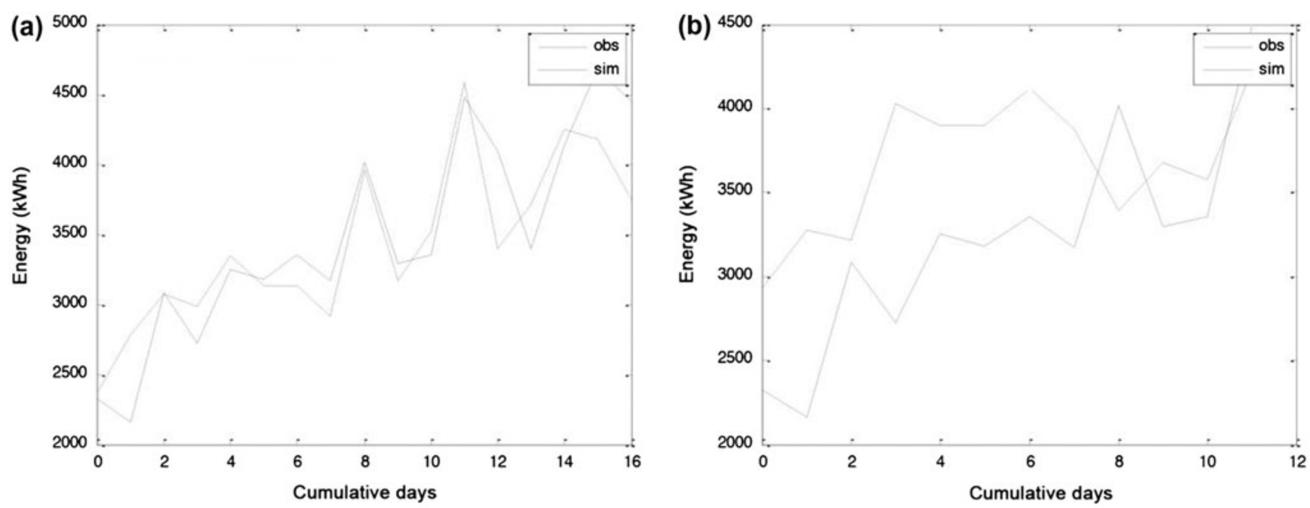

Fig. 5. Energy variations observed over cumulative days during the validation period (a) filtered NO_3^--N and (b) unfiltered NO_3^--N.

When the nitrate concentration exceeds the threshold limit, it disrupts the fuzzy reasoning. The simulated energy is higher than the energy observed, indicating that the energy consumption is overestimated when the data are not filtered, but the simulated energy is similar to the observed energy when using the filtered data.

4. Conclusions

The purpose of a treatment plant is to protect and to preserve the environment before by treating discharges. We found a significant removal of organic pollution, revealing that the plant station was running smoothly. Indeed, a statistical analysis of the data demonstrated that the parameters for the organic pollutants of purified water are satisfactory and meet the objectives of the station relative to the discharge standards. However, the parameters for the dissolved pollution (nitrogen and phosphorus), which do not meet the standards, constitute a major problem for all of the activated sludge processes. The energy consumption was detected using the excess removal efficiencies of the organic pollutants parameters and the excess nitrate concentration.

To determine the amount of energy necessary to achieve treatment purposes, the most efficient methods were modeled to describe the complex and evolving phenomena. However, a neuro-fuzzy model was developed that accounted for the allowable threshold nitrate concentrations at the outlet of the filter station; this model used the learning data and the yields of eliminated organic matter as input variables for the model.

This model, which was based on neural learning, must use some information from the knowledge base to recognize specific situations and act on the process. The historical values of the observed parameters for organic pollution relative to energy consumption during the learning period enable predictions of the energy consumption during the validation yields. Satisfactory results were obtained with the nitrate filter compared with the results without the filter; the learning and validation periods revealed the homogeneity of the fuzzy reasoning in the first case compared to the disruptions in the second case. Therefore, when the nitrate concentration exceeds the permissible threshold, the rate of organic matter removal no longer justifies the energy consumption.

In summary, to optimize the energetic advantages, the amount of recirculated sludge and the amount of oxygen dissolved must be predicted as output parameters in the model, in addition to the energy consumption.

References

[1] Y.G. Du, R.D. Tyagi, R. Bhamidimarri, Use of fuzzy neural-net model for rule generation of activated sludge process, Process Biochem. 35 (1999) 77–83.
[2] A. Holmberg, Modelling of the activated sludge process for microprocessor-based state estimation and control, Water Res. 16 (1982) 1233–1246.
[3] Y. Tsai, C.F. Ouyang, W.L. Chiang, M.Y. Wu, Construction of an on-line fuzzy controller for the dynamic activated sludge process, Water Res. 28 (1994) 913–921.
[4] Wangyani, Control of sludge recycle flow in wastewater treatment plants using fuzzy logic controller, AISC 180 (2013) 313–318.
[5] B.A. Coelho, R. Araujoa, A. Matos, A. Jorge, C. Landeck, Dissolved oxygen control of the activated sludge wastewater treatment process using stable adaptive fuzzy control, Comput. Chem. Eng. 37 (2012) 152–162.
[6] D. Couillard, S. Zhu, Control strategy for the activated sludge process under shock loading, Water Res. 26 (1992) 649–655.
[7] K. Yetilmezsoy, Z. Sapci-Zengin, Stochastic modeling applications for the prediction of COD removal efficiency of UASB reactors treating diluted real cotton textile wastewater, Stoch. Environ. Res. Risk Assess. 23 (2009) 13–26.
[8] S. Tomida, T. Hanai, N. Ueda, H. Honda, T. Kobayashi, Construction of COD simulation model for activated sludge process by fuzzy neural network, J. Biosci. Bioeng. 88 (1999) 215–220.
[9] F. Chunsheng, M. Poch, Fuzzy model and decision of COD control for an activated sludge process, Fuzzy Sets Syst. 93 (1998) 281–292.
[10] H. Mingzhi, W. Jinquan, M. Yongwen, W. Yan, L. Weijiang, S. Xiaofei, Control rules of aeration in a submerged biofilm wastewater treatment process using fuzzy neural networks, Expert Syst. Appl. 36 (2009) 10428–10437.
[11] F.N. Koumboulis, N.D. Kouvakas, R.E. King, A. Stathaki, Two-stage robust control of substrate concentration for an activated sludge process, ISA Trans. 47 (2008) 267–278.
[12] M. Galluzzo, R. Ducato, V. Bartolozzi, A. Picciotto, Expert control of DO in the aerobic reactor of an activated sludge process, Computers, Chem. Eng. 25 (2001) 619–625.
[13] J. Alex, U. Jumar, R. Tschepetzki, A Fuzzy Controller for Activated Sludge Waste Water Plants., Artificial Intelligence in Real Time, Control, Valencia, Spain, 1994.
[14] M. Haubjerg, N. Nils, Nitrification–denitrification dynamics and community structure of ammonia oxidizing bacteria in a high yield irrigated Philippine rice field FEMS, Microbiol. Ecol. 49 (2004) 359–369.
[15] D. Patureau, E. Helloin, E. Rustrian, T. Bouchez, J.P. Delgenes, R. Moletta, Combined phosphate and nitrogen removal in a sequencing batch reactor using the aerobic denitrifier, *Microvirgula aerodenitrificans*, Water Res. 35 (2001) 189–197.
[16] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (1965) 338–353.
[17] E.H. Mamdani, Application of fuzzy algorithms for control of a simple dynamic plant, Proc. Control Sci. 12 (1974) 1585–1588.
[18] M. Sugeno, Industrial Applications of Fuzzy Control, Elsevier Sciences Publications, New York, NY, 1985.
[19] J. Cabanillas, A. Ginebreda, Fuzzy logic based risk assessment of effluents from waste-water treatment plants, Sci. Total Environ. 439 (2012) 202–210.
[20] K. Yetilmezsoy, Fuzzy-logic modeling of Fenton's oxidation of anaerobically pretreated poultry manure wastewater, Environ. Sci. Pollut. Res. 19 (2012) 2227–2237.