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Effluent predictions in wastewater treatment plants for the control strategies selection

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Abstract

One of the main objectives of a wastewater treatment plant is to ensure that the concentrations of pollutants in the effluent are below the limits established. This is due to the consequent environmental effects and the economic penalties to be paid if these limits are violated. It is very likely that the plant is not designed to prevent these violations of pollutant concentrations in all cases due to the large variability of the influent. One of the possible methods of preventing violations is the adequate implementation of control strategies. However, these control strategies may result in an increase in operational costs, which is why it is convenient to apply them only when there is a risk of violation. If the risk detection is based on some states variables of the plant, in many cases there will not be enough time to prevent violations. Therefore, this work presents the prediction of the effluent in order to detect a risk of violation with enough time in advance to select the suitable control strategy. This prediction is carried out by Artificial Neural Networks that estimate the future effluent values, based on information of the entrance of the biological treatment. The prediction is applied to a controlled plant and it is shown how a logical signal can be generated at the instants where such a risk of violation is detected.

Keywords: Wastewater Treatment Process, BSM1 Benchmark, Artificial Neural Network, Control Strategies.

1 Introduction

The control of biological wastewater treatment plants (WWTPs) is very complex due to the following facts. The biological and biochemical processes that take place inside the plants are strongly interrelated and involve a great number of states variables and very different constant values. The flow rate and composition of the influent is very variable. There are legal requirements that penalize the violation of the pollution effluent limits. In addition, the improvement of water quality and the reduction of operational costs must be considered.

For the evaluation of control strategies in WWTPs, Benchmark Simulation Model No.1 (BSM1) was developed in [1]. This benchmark was extended in a new version, Benchmark Simulation Model No.2 (BSM2), in ([10]) which was updated in [13]. BSM2 includes the entire cycle of a WWTP, adding the sludge treatment. In addition, the simulation period is extended to one year assessment, rather than a week, as in BSM1. In this work, the simulations and evaluations of the control strategies have been carried out with the BSM2. It provides a default control strategy that applies a Proportional-Integral (PI) controller. PI and Proportional-Integrative-Derivative (PID) controllers have attracted the research interest for process control looking for good robustness/performance trade-off ([22]). However WWTPs exhibit high complex dynamics that demand for more advanced alternatives.

In the literature there are many works that present different methods for controlling WWTPs. Most of the works use the Benchmark Simulation Model No. 1 (BSM1) as working scenario. In some cases they put their focus on avoiding violations of the effluent limits by applying a direct control of the effluent variables, mainly ammonium and ammonia nitrogen (S_{NH}) and total nitrogen ($S_{N_{tot}}$) ([4, 18, 19]). Nevertheless, they need to fix the set-points of the controllers at lower levels to guarantee their objective, which implies a great increase of costs. Other works give a trade-off between operational costs and effluent quality, but they do not tackle effluent violations. They usually deal with the basic control strategy (control of dissolved oxygen (S_O) of the aerated tanks and nitrate nitrogen concentration (S_{NO}) of the second tank ($S_{NO,2}$)) ([9, 2]), or propose hierarchical control structures that regulate the S_O set-points according to some states of the plant, usually S_{NH} and S_{NO} values in any tank or in the influent ([23, 20, 21, 17]) or S_O in other tanks ([5]).

Other works in the literature use BSM2 as testing plant. Some of them are focused on the implementation of control strategies in the biological treatment. Specifically, they propose a multi-objective control strategy based on S_O control by manipulating oxygen transfer coefficient (K_La) of the aerated tanks, S_{NH} hierarchical control by manipulating the S_O set-points, $S_{NO,2}$ control by manipulating the internal recycle flow rate (Q_a) or total suspended solids (TSS) control by

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manipulating the wastage flow rate (Q_w) ([7, 3, 6, 12]). These referred works have different goals, but all of them obtain an improvement in effluent quality and/or a reduction of costs. However, none of them aims to avoid the limits violations of the effluent pollutants. Nevertheless, this issue is of significant importance because high concentrations of pollutants in the effluent can damage the environment and the health of the population. In addition, there are legal requirements penalized with fines, which result in an increment of costs.

The goal of the presented work is to gain a step forward in avoiding S_{NH} in the effluent ($S_{NH,e}$) or $S_{N_{tot}}$ in the effluent ($S_{N_{tot},e}$) limits violations. The paper uses BSM2 as working scenario and some of the control strategies are based on [15].In addition, it introduces a novel method to deal with the effluent violations: the situations of risk of effluent violations are predicted by forecasting the future output concentrations of pollutants based on the input variables. To detect such risky situations, ANNs are applied to predict the $S_{NH,e}$ and $S_{N_{tot},e}$ concentrations by evaluating the influent at each sample time.

2 Benchmark Simulation Model No. 2

The simulation and evaluation of the proposed control strategy is carried out with BSM2 ([10]) which was updated by [13].

The finalized BSM2 layout (Fig. 1) includes BSM1 for the biological treatment of the wastewater and the sludge treatment. A primary clarifier, a thickener for the sludge wasted from the clarifier of biological treatment, a digester for treatment of the solids wasted from the primary clarifier and the thickened secondary sludge, as well as a dewatering unit have been also added. The liquids collected in the thickening and dewatering steps are recycled ahead of the primary settler.

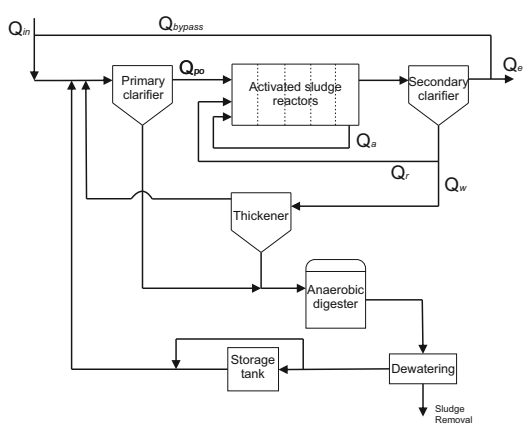

Figure 1: BSM2 plant with notation used for flow rates

The influent dynamics are defined for 609 days by means of a single file, which takes into account rainfall effect and temperature variations along the year. Following the simulation protocol, a 200-day period of stabilization in closed-loop using constant inputs with no noise on the measurements has to be completed before using the influent file (609 days). Only data from day 245 to day 609 are evaluated.

2.1 Activated sludge reactors

The activated sludge reactors consist in five biological reactor tanks connected in series. Q_a from the last tank complete the system. The plant is designed for an average influent dry weather flow rate of 20648.36 m^3/d and an average biodegradable chemical oxygen demand (COD) in the influent of 592.53 mg/l. The total volume of the bioreactor is 12000 m^3, 1500 m^3 each anoxic tank and 3000 m^3 each aerobic tank. Its hydraulic retention time, based on the average dry weather flow rate and the total tank volume, is 14 hours. The internal recycle is used to supply the denitrification step with S_{NO}.

The Activated Sludge Model No. 1 (ASM1) [8] describes the biological phenomena that take place in the biological reactors. They define the conversion rates of the different variables of the biological treatment. The proposed control strategies in this work are based on the conversion rates of S_{NH} (r_{NH}) and S_{NO} (r_{NO}). They are shown following:

$$r_{NH} = -0.08\rho_1 - 0.08\rho_2 - \left(0.08 + \frac{1}{0.24}\right)\rho_3 + \rho_6 \tag{1}$$

$$r_{NO} = -0.1722\rho_2 + 4.1667\rho_3 \tag{2}$$

where ρ_1, ρ_2, ρ_3, ρ_6 are four of the eight biological processes defined in ASM1. Specifically, ρ_1 is the aerobic growth of heterotrophs, ρ_2 is the anoxic growth of heterotrophs, ρ_3 is the aerobic growth of autotrophs and ρ_6 is the ammonification of soluble organic nitrogen. They are defined below:

$$\rho_1 = \mu_{HT}\left(\frac{S_S}{10+S_S}\right)\left(\frac{S_O}{0.2+S_O}\right)X_{B,H} \tag{3}$$

where S_S is the readily biodegradable substrate, $X_{B,H}$ the active heterotrophic biomass and μ_{HT} is:

$$\mu_{HT} = 4 \cdot exp\left(\left(\frac{Ln\left(\frac{4}{3}\right)}{5}\right)\cdot(T_{as}-15)\right) \tag{4}$$

$$\rho_2 = \mu_{HT}\left(\frac{S_S}{10+S_S}\right)\left(\frac{0.2}{0.2+S_O}\right)\left(\frac{S_{NO}}{0.5+S_{NO}}\right)0.8\cdot X_{B,H} \tag{5}$$

$$\rho_3 = \mu_{AT}\left(\frac{S_{NH}}{1+S_{NH}}\right)\left(\frac{S_O}{0.4+S_O}\right)X_{B,A} \tag{6}$$

where T_{as} is the temperature, $X_{B,A}$ is the active autotrophic biomass and μ_{AT} is:

$$\mu_{AT} = 0.5 \cdot exp\left(\left(\frac{Ln\left(\frac{0.5}{0.3}\right)}{5}\right) \cdot (T_{as} - 15)\right) \quad (7)$$

$$\rho_6 = k_{aT} \cdot S_{ND} \cdot X_{B,H} \quad (8)$$

where S_{ND} is the soluble biodegradable organic nitrogen and k_{aT} is:

$$k_{aT} = 0.05 \cdot exp\left(\left(\frac{Ln\left(\frac{0.05}{0.04}\right)}{5}\right) \cdot (T_{as} - 15)\right) \quad (9)$$

The general equations for mass balancing are as follows:

- For reactor 1:

$$\frac{dZ_1}{dt} = \frac{1}{V_1}(Q_a \cdot Z_a + Q_r \cdot Z_r +$$
$$+ Q_{po} \cdot Z_{po} + r_{z,1} \cdot V_1 - Q_1 \cdot Z_1) \quad (10)$$

  where Z is any concentration of the process, Z_1 is Z in the first reactor, Z_a is Z in the internal recirculation, Z_r is Z in the external recirculation, Z_{po} is Z from the primary clarifier, V is the volume, V_1 is V in the first reactor, Q_{po} is the overflow of the primary clarifier and Q_1 is the flow rate in the first tank and it is equal to the sum of Q_a, Q_r and Q_{po}.

- For reactor 2 to 5:

$$\frac{dZ_k}{dt} = \frac{1}{V_k}(Q_{k-1} \cdot Z_{k-1} + r_{z,k} \cdot V_k - Q_k \cdot Z_k) \quad (11)$$

  where k is the number of reactor and Q_k is equal to Q_{k-1}

2.2 Evaluation criteria

The performance assessment is made at two levels. The first level concerns the control. Basically, this serves as a proof that the proposed control strategy has been applied properly. The second level measures the effect of the control strategy on plant performance. It includes the percentage of time that the effluent limits are not met, the Effluent Quality Index (EQI) and the Overall Cost Index (OCI) explained below. The effluent concentrations of N_{tot}, total COD (COD_t), S_{NH}, TSS and Biological Oxygen Demand (BOD_5) should obey the limits given in Table 1. $S_{N_{tot}}$ is calculated as the sum of S_{NO} and Kjeldahl nitrogen (S_{NKj}), being this the sum of organic nitrogen and S_{NH}.

EQI is defined to evaluate the quality of the effluent. EQI is averaged over a 364 days observation period and it is calculated weighting the different compounds of the effluent loads.

Variable	Value
$S_{N_{tot}}$	< 18 g N.m^{-3}
COD_t	< 100 g COD.m^{-3}
S_{NH}	< 4 g N.m^{-3}
TSS	< 30 g SS.m^{-3}
BOD_5	< 10 g BOD.m^{-3}

Table 1: Effluent quality limits

$$EQI = \frac{1}{1000 \cdot T} \int_{t=245days}^{t=609days} (2 \cdot TSS(t) + 1 \cdot COD(t) +$$

$$+ 30 \cdot S_{NKj}(t) + 10 \cdot S_{NO}(t) + 2 \cdot BOD_5(t)) \cdot Q(t) \cdot dt \quad (12)$$

OCI is defined to evaluate the operational cost as:

$$OCI = AE + PE + 3 \cdot SP + 3 \cdot EC + ME - 6 \cdot MET_{prod} + HE_{net} \quad (13)$$

where AE is the aeration energy, PE is the pumping energy, SP is the sludge production to be disposed, EC is the consumption of external carbon source, ME is the mixing energy, MET_{prod} is the methane production in the anaerobic digester and HE_{net} is the net heating energy.

3 Controlled Plant scenario

The setup for the training and effluent limit violation risk detection by using ANN consists of a controlled WWTP. The scenario is that of a WWTP, represented here by the BSM2 where a series of local and higher level controllers are in place, therefore defining an hierarchical control structure. The control configuration is the one proposed in [15] and is based on MPC+FF and fuzzy control. MPC+FF controllers are used in order to keep the $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ at the given setpoint. Fuzzy control is applied as higher level controller in a hierarchical structure to vary the S_O references to be tracked by the MPC controllers. The application of FCs are based on the biological processes, but without the goal of keeping the controlled variable at a set-point, either fixed or variable. In this case, the control objectives are: the improvement of OCI and EQI. The resulting controlled plant is shown in figure

ANNs are proposed to generate models to predict the $S_{N_{tot,e}}$ and $S_{NH,e}$ values based on some inputs variables, in order to detect a risk of violation. On a future step, this detection could be used as a flag to choose the best control strategy to be applied .

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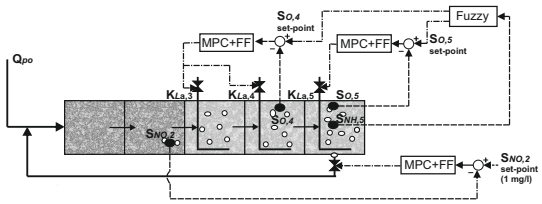


Figure 2: BSM2 Hierarchical control for ANN training and risk prediction

4 Artificial Neural Network

ANNs are inspired by the structure and function of nervous systems, where the neuron is the fundamental element ([25]). ANNs are composed of simple elements, called neurons, operating in parallel. ANNs have proved to be effective for many complex functions, as pattern recognition, system identification, classification, speech vision, and control systems ([24, 14]). ANNs are frequently used for nonlinear system identification, to model complex relationships between the inputs and the outputs of a system, as it is the case of WWTPs.

An artificial neuron is a device that generates a single output y from a set of inputs x_i (i = 1 ... n). This artificial neuron consists of the following elements:

- Set of x_i inputs with n components
- Set of weights w_{ij} that represent the interaction between the neuron j and neuron i.
- Propagation rule, a weighted sum of the scalar product of the input vector and the weight vector: $h_i(t) = \sum w_{ij} \cdot x_j$.
- Activation function provides the state of the neuron based on of the previous state and the propagation rule (i.e. threshold, piecewise linear, sigmoid, Gaussian): $a_i(t) = f(a_i(t-1), h_i(t))$:.
- The output $y(t)$ that depends on the activation state.

The architecture of an ANN is the structure of network connections. The connections between neurons are directional and the information is transmitted only in one direction. In general, neurons are usually grouped into structural units called layers. Within a layer, the neurons are usually of the same type. Figure 3 shows the typical network architecture with three layers: input layer, hidden layer (processing neurons between the input and the output) and output layer.

ANNs are subjected to a learning process also called training. Typically, a large data set of inputs and outputs sets is needed to design an ANN, and the input

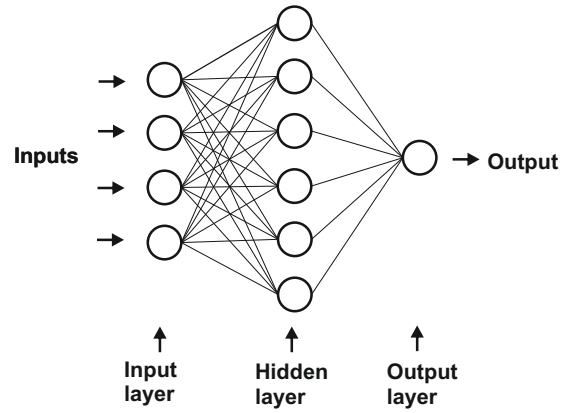


Figure 3: Structure of Artificial Neural Network layers

and output data are divided into a set used for training the ANN and the rest for testing the results of the ANN. The network learns the connection weights from available training patterns. Performance is improved by updating iteratively the weights in the network. When the training is over, the ANN performance is validated, and depending on the difference between the outcome and the actual outputs, the ANN has to be trained again or can be implemented.

The number of input nodes, output nodes and the nodes in the hidden layer depends upon the problem being studied. If the number of nodes in the hidden layer is small, the network may not have sufficient degrees of freedom to learn the process correctly, and if the number is too high, the training will take a long time and the network may sometimes over-fit the data ([11]).

5 Effluent violations risk detection

For an efficient elimination of effluent violations, a prognostication of the situations of risk is essential to react as soon as possible and to apply immediately the necessary preventive actions to the plant; otherwise most violations cannot be avoided. This prediction is carried out by ANNs that estimate the future effluent values, based on information of the entrance of the biological treatment.

Specifically, two ANNs are proposed in this paper. One ANN predicts the value of $S_{NH,e}$ ($S_{NH,ep}$) and the other ANN predicts the value of $S_{N_{tot},e}$ ($S_{N_{tot},ep}$). When a risk of violation of $S_{N_{tot},e}$ or $S_{NH,e}$ is foreseen, special control strategies could be applied to avoid them. However this is not conducted here.

An accurate prediction of $S_{NH,e}$ and $S_{N_{tot},e}$ is not possible due to the fact that ANNs use only influent variables as inputs, while the effluent concentrations also depend on other variables of the process. Those variables can not be taken into account because it is nec-

essary to predict the risk of effluent violations with enough time in advance. Moreover, all data used to predict the risk has to be easily measurable. However, as we will see, with an adequate choice of the input variables of ANNs, it is possible to achieve an adequate approximation in order to detect a risk of violation for applying the suitable control strategy.

Therefore, the inputs of ANNs have been determined according to the mass balance equations (10 and 11) explained in Section 2.1. The variables used to perform the prediction for both ANNs are Q_{po}, Z_{po} and T_{as}. The variable Q_a has also been used as an input for the ANN that predicts $S_{N_{tot,e}}$, but it is not used to predict $S_{NH,e}$ because it is a manipulated variable in the control strategy applied to remove $S_{NH,e}$ violations. Specifically, S_{NH} from the primary clarifier ($S_{NH,po}$) is the pollutant concentration chosen as a predictor for both ANNs. On one hand, S_{NH} and S_{NO} are the pollutants with higher influence in $S_{N_{tot,e}}$, but $S_{NO,po}$ is very low and it is not taken in account. On the other hand, $S_{NH,po}$ not only affects largely $S_{NH,e}$, but also affects the nitrification process, the consequent S_{NO} production and therefore the resulting $S_{N_{tot,e}}$.

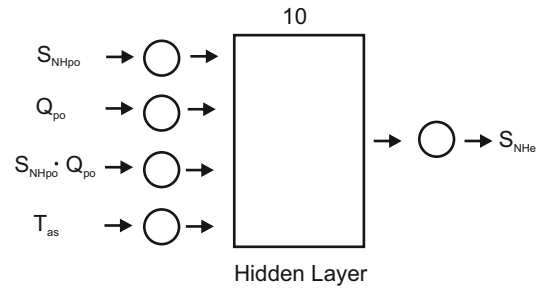
T_{as} is also added as a predictor variable due to its influence in the nitrification and denitrification processes (5 and 6). $S_{NH,e}$ and $S_{N_{tot,e}}$ values are inversely proportional to the T_{as} values.

Finally, due to the mentioned reasons, the inputs for the ANNs are:

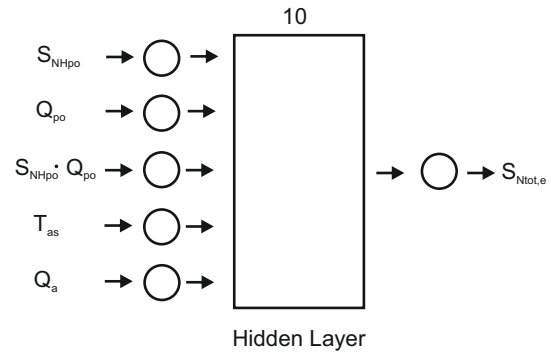
- Inputs of ANN for $S_{NH,e}$ model prediction: Q_{po}, $S_{NH,po}$, $Q_{po} \cdot S_{NH,po}$, T_{as}.
- Inputs of ANN for $S_{N_{tot,e}}$ model prediction: Q_{po}, $S_{NH,po}$, $Q_{po} \cdot S_{NH,po}$, T_{as}, Q_a.

To train and validate ANNs, a collection of input and output data is necessary. The variations in the inputs affect the outputs with a variable delay that depends on the hydraulic retention time. Due to this fact and, in order to simplify the data collection process, for the ANNs inputs and outputs only the maximum and minimum values of each day have been selected. Except for T_{as}, where the daily average value has been considered. As it is necessary a large number of data to generate a satisfactory model for an ANN, the data are obtained in a one year simulation period with the plant working with the presented hierarchical control in place. Therefore, as no special experiments are needed, in a real plant, the stored historical data could be used for this purpose. The number of hidden layers for both ANNs is 10. The structures are shown in Fig.4.

For the training of the ANN the MATLAB© NNToolbox has been used. As already mentioned, recorded data corresponding to one year of running the plant with the hierarchical control in place has been used.



(a) ANN for $S_{NH,e}$ prediction



(b) ANN for $S_{N_{tot,e}}$ prediction

Figure 4: Structures of the proposed ANNs

The data is partitioned in different sets that are used for training (70% of data), another one to validate the network is generalizing and to stop training before overfitting (15% of data). The rest of the data (the remaining 15%) is used as a completely independent test of network generalization. The training results are evaluated by means of error histogram. Figure (5) shows the error histograms corresponding to both ANN. The blue bars represent training data, the green bars represent validation data, and the red bars represent testing data. As it can be seen, the ANN for $S_{N_{tot,e}}$ prediction is more difficult to train. Even this, there are practically no significant outliers and, if any, their magnitude is really small. It remains a subject of further exploration about the suitability of more complex network structures if precise effluent following is needed.

As a result, figure 6 show the effluent concentrations of $S_{NH,e}$ and $S_{N_{tot,e}}$ predicted by the trained ANN. As it can be seen, the prediction does not follow with high precision the real effluent profile. Instead, the ANN have been trained to generate the peaks that are of interest, those that are significant for $N_{tot,e}$ and NH_e limit violation. The idea is not to predict the whole effluent profile with precision but to detect where possibly high values will occur.

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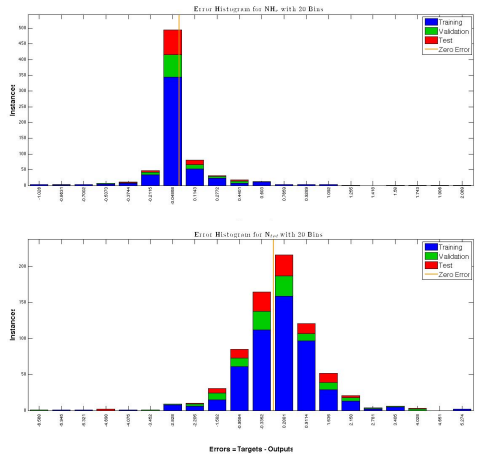

Figure 5: ANN training error histograms.

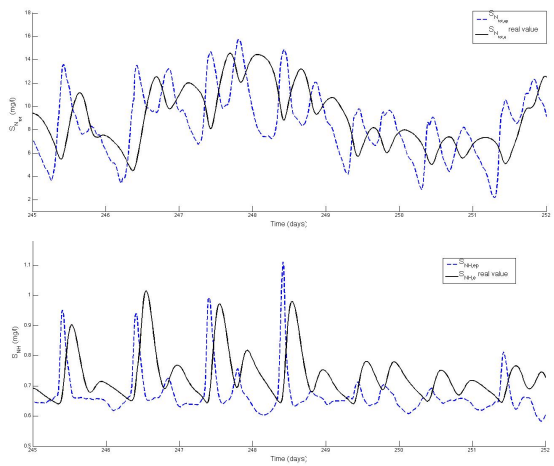

Figure 6: ANN Effluent prediction for $S_{NH,e}$ and $S_{N_{tot},e}$

6 Control strategies for avoiding violations

Once a risk of violation of $S_{N_{tot},e}$ and / or $S_{NH,e}$ has been identified, it is necessary to apply the adequate control strategy to avoid exceeding the limits establish. One possibility is to apply the proposed control strategies in [15] and [16]. These studies show control strategies using fuzzy controllers ([15]) and by functions ([16]) in order to eliminate violations of $S_{N_{tot},e}$ or $S_{NH,e}$. Both works use BSM1 as working scenario, but these control strategies could be tested in BSM2.

Regarding $S_{N_{tot},e}$ violations, according to the biological processes of ASM1, an increase of substrate produces a growth of heterotrophic bacteria and therefore the denitrification process and the consequently reduction of S_{NO} are improved. Therefore, $S_{N_{tot},e}$ is reduced with the dosage of EC in the first tank (EC1). However dosing EC1 results in an increase of operational costs, so it is important to dosage EC1 only when a violation of $S_{N_{tot},e}$ could take place. Consequently, the control strategy is based on the manipulation of EC flow rate (q_{EC}) in the first reactor($q_{EC,1}$) according to S_{NH} in the fifth reactor ($S_{NH,5}$) plus S_{NO} in the fifth reactor ($S_{NO,5}$) (see Fig. 7).

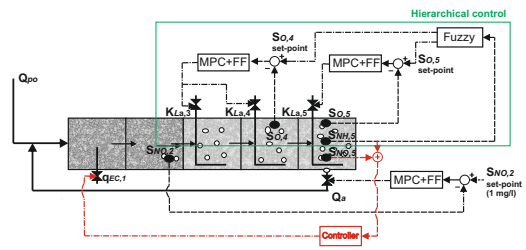

Figure 7: Proposed control strategies for $S_{N_{tot},e}$ violations removal

With the goal of removing $S_{NH,e}$ violations, Q_a is manipulated based on $S_{NH,5}$ (see Fig. 8). When a peak of pollution enters in the reactors, it is propagated through them with a delay determined by the retention time. Thus, any change in Q_{po} or in the Q_a directly affects the propagation of the peaks of pollution inside the tanks. On the contrary, the peaks of flow rate are transmitted to all the plant immediately, because the system is always full and any variation in the influent causes an identical variation in the effluent and inside the system. Thus, according to the mass balance equation (10) in the first reactor, when $S_{NH,po}$ increases, Q_a is incremented to reduce the rise of S_{NH} in the first tank ($S_{NH,1}$), and when the increase of S_{NH} arrives to the fifth tank, Q_a is reduced to increase the retention time and so to improve de nitrification process.

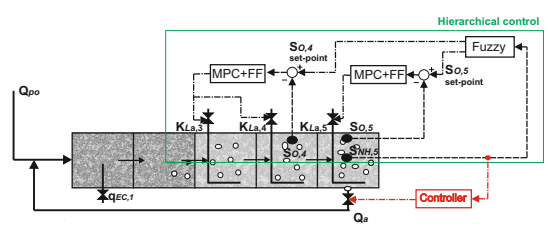

Figure 8: Proposed control strategies for $S_{NH,e}$ violations removal

7 Simulation Results

In this section the BSM2 benchmark scenario under the hierarchical control presented above is shown. As it can be seen, the control scheme is quite efficient as it is able to minimize the effluent violations substantially. However there are still moments where the high disturbances coming from the influent make plant operation very difficult. Therefore, the ANN prediction will show the potential risk of effluent limit violation.

The BSM2 is now simulated by applying the same

hierarchical control scheme. In parallel, the influent data feeds both ANN and output pollutant concentrations are predicted. As mentioned when describing the BSM2 scenario, the assessment period is extended to one year instead of one week. In figure 9 show, as an example, the simulation results for $S_{NH,e}$ risk detection for a time window of 150 days. It can be seen that the hierarchical, two-level control system, operates the plant quite well, so there are practically no limit violations. Two risk situations are detected. Therefore it is on such time instants when supplementary control actions will be needed.

In order to better show how risk detection works, figures 10 and 11 show the risk detection for both output concentrations $S_{NH,e}$ and $S_{N_{tot},e}$ in an enlarged time window. As it can be observed, the way ANN have been trained allows for a real effluent pollutants prediction. This allows for an early detection of the possible limit violation. A flag signal is activated during 6h. For future use, this boolean signal could be used to activate a decision system that signals for appropriate corrective actions regarding these violations.

On the other hand, in figure 11, we can see there is a mismatch between the number of real limit violations and the times the risk signal is activated. This is because of the three maximums the effluent do has during the violation period. In any case, the fact that during one day the signal is activated three times, corresponds to a really dangerous sittuation.

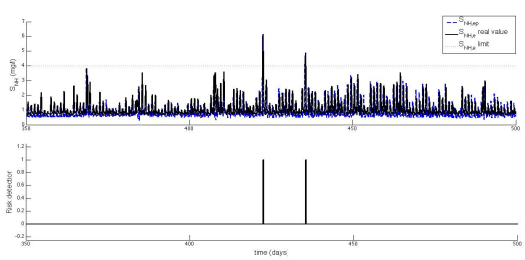

Figure 9: $S_{NH,e}$ limit violation risk detection. Long time window.

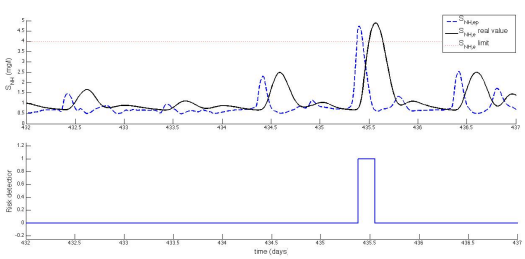

Figure 10: $S_{NH,e}$ limit violation risk detection

8 Conclusions

This paper has presented an effluent pollutants prediction on the basis of Artificial Neural Networks. Predictions are performed with the purpose of detection of the $N_{tot,e}$ and NH_e limit violations risk. Based on the BSM2 scenario, a two-layer hierarchical control architecture has been used as the controlled plant for generating the training data. This way, the data is according to data that is usually recorded on WWTPs. No need for specific experiments.

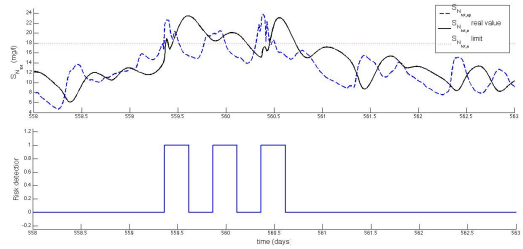

Figure 11: $S_{N_{tot},e}$ limit violation risk detection

The trained ANN show the ability to predict the peak values of $N_{tot,e}$ and NH_e. The idea is not to predict the whole effluent profile with precision but to detect where possibly high values will occur. Simulation results show this is accomplished. Also when running the ANN over the controlled plant, effluent limit violations are detected and appropriately signaled. From this point, next step will be to build up appropriate control strategies that can react to these signals.

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