Application of control strategies in wastewater treatment plants for effluent quality improvement, costs reduction and effluent limits violations removal

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PhD Thesis

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CERTIFIE

That the doctoral thesis entitled "**Application of control strategies in wastewater treatment plants for effluent quality improvement, costs reduction and effluent limits violations removal**" by Ignacio Santín López, presented in partial fulfillment of the requirements for the degree of PhD, has been developed and written under their supervision.

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Contents

List of Figures

List of Tables

Abbreviations

AE	Aeration Energy
ANN	Artificial Neural Network
ASM1	Activated Sludge Model No. 1
BOD$_5$	Biological Oxygen Demand
BSM1	Benchmark Simulation Model No. 1
BSM2	Benchmark Simulation Model No. 2
CL1	First control strategy of the finalisation of BSM2 plant layout in [1]
CL2	Second control strategy of the finalisation of BSM2 plant layout in [1]
COD	Chemical Oxygen Demand
defCL	Default control strategy of the original BSM2 definition in [2]
EC	Consumption of External Carbon source
EQI	Effluent Quality Index
FC	Fuzzy Controller
HE$_{net}$	Net Heating Energy
IAE	Integral of the Absolute Error
ISE	Integral of the Squared Error
K$_L$a	Oxygen transfer coefficient
m	Control horizon
$MaxIn$	Maximum value of the input variable of the fuzzifier
$MaxOut$	Maximum value of the output variable of the defuzzifier
ME	Mixing Energy
mean($\|e\|$)	Average of the absolute error
MET$_{prod}$	Methane production in the anaerobic digester
$MinIn$	Minimum value of the input variable of the fuzzifier
$MinOut$	Maximum value of the output variable of the defuzzifier

MPC	Model Predictive Control
MPC+FF	Model Predictive Control with feedforward compensation
OCI	Overall Cost Index
p	Prediction horizon
PE	Pumping Energy
PI	Proportional-Integral
Q	Flow rate
$\mathbf{q}_{EC}$	External carbon flow rate
$\mathbf{S}_{N_{tot,ep}}$	Prediction of the effluent total nitrogen concentration
$\mathbf{S}_{N_{tot}}$	Total nitrogen
$\mathbf{S}_{ND}$	Soluble biodegradable organic nitrogen
$\mathbf{S}_{NH,ep}$	Prediction of the effluent ammonium and ammonia nitrogen concentration
$\mathbf{S}_{NH}$	Ammonium and ammonia nitrogen concentration
$\mathbf{S}_{NO}$	Nitrate nitrogen concentration
$\mathbf{S}_{O}$	Dissolved oxygen
$\mathbf{S}_{S}$	Readily biodegradable substrate
SP	Sludge Production
$\mathbf{T}_{as}$	Temperature
TSS	Total Suspended Solids
WWTP	Wastewater Treatment Plants
$\mathbf{X}_{B,A}$	Active autotrophic biomass
$\mathbf{X}_{B,H}$	Active heterotrophic biomass

Chapter 1

Introduction

During the last decade the importance of integrated and plant-wide control has been emphasized by the research community and the wastewater industry is now starting to realise the benefits of such an approach. Biological wastewater treatment plants (WWTPs) are considered complex nonlinear systems and its control is very challenging, due to the complexity of the biological and biochemical processes that take place in the plant and the strong fluctuations of the influent flow rate. In addition, there are effluent requirements defined by the European Union (European Directive 91/271 Urban wastewater) with economic penalties, to upgrade existing wastewater treatment plants in order to comply with the effluent standards.

In this work the evaluation and comparison of the different control strategies is based on Benchmark Simulation Model No.1 (BSM1) and Benchmark Simulation Model No. 2 (BSM2), developed by the International Association on Water Pollution Research and Control. These benchmarks define a plant layout, influent loads, test procedures and evaluation criteria. They provide also a default control strategy. BSM1 corresponds to the secondary treatment of a WWTP, where the biological wastewater treatment is performed using activated sludge reactors. The evaluation is based on a week of simulation. BSM2 is extended to a complete simulation of a WWTP, including also a primary clarifier, anaerobic digesters, thickeners, dewatering systems and other sub-processes. In BSM2, a year of simulation is evaluated.

The application of different control strategies are focused on obtaining a plant performance improvement. In the literature there are many works that present different methods for controlling WWTPs. Most of the works use 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. 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 with the 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 ($S_{NO,2}$)), or propose hierarchical control structures that regulate the S_O set-points according with some states of the plant, usually ammonium and ammonia nitrogen concentration (S_{NH}) and S_{NO} values in any tank or in the influent or S_O in other tanks.

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, as the present work. 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 manipulating the wastage flow rate (Q_w).

The control objectives of previous works are usually based on achieving an improvement in the effluent quality and / or costs indices. However, it is of significant importance to avoid violations of pollution in the effluent, regarding the quality of the water from a legal point of view, and certainly in terms of cost, as these violations involve fines to be paid.

This thesis uses first BSM1, and secondly BSM2 as working scenarios to evaluate the applied control strategies. The goal of the presented work is to avoid S_{NH} in the effluent ($S_{NH,e}$) and total nitrogen ($S_{N_{tot}}$) in the effluent ($S_{N_{tot,e}}$) limits violations and, at the same time, to improve effluent quality and to reduce operational costs. The innovative proposed control strategies are based on Model Predictive Control (MPC), fuzzy controller (FC), functions that relate the input and manipulated variables and Artificial Neural Networks (ANN). The MPC controllers are implemented with the aim of improving the control tracking. The control strategies applied with FCs and the functions that relate the inputs with the manipulated variables are based on the processes that take place in the biological reactors. And the ANNs are applied to predict effluent concentrations by evaluating the influent at each sample time, in order to select the appropriate control strategy to be applied.

1.1 Publications

This work has resulted in the papers listed next:

- Journal Papers
  - I. Santín, C. Pedret, R. Vilanova, Applying variable dissolved oxygen set point in a two level hierarchical control structure to a wastewater treatment process. *Journal of Process Control* 28 (2015) 40–55.
  - I. Santín, C. Pedret, R. Vilanova, Fuzzy control and Model Predictive Control Configurations for Effluent Violations Removal in Wastewater Treatment Plants, *Industrial and Engineering Chemistry Research* 51 (2015) 2763–2775.
  - I. Santín, C. Pedret, R. Vilanova, M. Meneses, Removing violations of the effluent pollution in a wastewater treatment process *Chemical Engineering Journal* 279 (2015) 207-219.
  - I. Santín, C. Pedret, R. Vilanova, M. Meneses, Intelligent decision control system for effluent violations removal in wastewater treatment plants, *Control Engineering Practice* (Submitted).
- Conference Papers
  - I. Santín, C. Pedret, R. Vilanova. Model predictive control and fuzzy control in a hierarchical structure for wastewater treatment plants, *18th International Conference on System Theory, Control and Computing.* Sinaia, Romania, 17-19 October, 2014.
  - I. Santín, C. Pedret, R. Vilanova. Control strategies for ammonia violations removal in BSM1 for dry, rain and storm weather conditions, *23rd Mediterranean Conference on Control and Automation.* Torremolinos, Spain, 16-19 June, 2015.

– I. Santín, C. Pedret, M. Meneses, R. Vilanova. Process Based Control Architecture for avoiding effluent pollutants quality limits violations in wastewater treatment plants, *19th International Conference on System Theory, Control and Computing.* Cheile Gradistei - Fundata Resort, Romania, 14-16 October, 2015 (Submitted).

– I. Santín, C. Pedret, M. Meneses, R. Vilanova. Artifical Neural Network for Nitrogen and Ammonia effluent limits violations risk detection in Wastewater Treatment Plants, *19th International Conference on System Theory, Control and Computing.* Cheile Gradistei - Fundata Resort, Romania, 14-16 October, 2015 (Submitted).

1.2 Outline

The thesis is divided in eight chapters. In Chapter 2 a description of BSM1 and BSM2 benchmarks, as well as of the control approaches are done. After this, the thesis is divided in two parts:

The first part is focused in the objective of effluent quality improvement and costs reduction by the application of a hierarchical structure. Chapter 3 explains the implementation and design of the MPC with feedforward compensation (MPC+FF) controllers that compose the lower level of the hierarchical control structure. Here is also shown the control tracking improvement in comparison with the default control strategy and with the literature. Chapter 4 focuses on the higher level of the hierarchical control, choosing first, the controller alternatives for manipulating S_O in the fifth tank ($S_{O,5}$) and secondly, extending the higher level control by manipulating S_O of the three aerobic reactors.

The second part is related with the goal of effluent limits violations removal. In Chapter 5, the proposed control strategies for removing effluent pollutants are presented. Chapter 6 explains the implementation of the ANNs for the required effluent predictions using BSM2 as working scenario, in order to choose the suitable control strategy to be applied. Chapter 7 presents the control strategies applied with the intelligent decision control system, when there is a risk of violation and the rest of the time.

Chapter 2

Working scenarios and control approaches

2.1 Working Scenarios

2.1.1 Benchmark Simulation Model No. 1

This section provides a description of the BSM1 working scenario ([3]). This is a simulation environment defining a plant layout, a simulation model, the procedures for carrying out the tests, the criteria for evaluating the results and a default control stretegy.

2.1.1.1 Plant layout

The schematic representation of the WWTP is presented in Fig.2.1. The plant consists in five biological reactor tanks connected in series, followed by a secondary settler. The first two tanks have a volume of 1000 m^3 each and are anoxic and perfectly mixed. The rest three tanks have a volume of 1333 m^3 each and are aerated. The settler has a total volume of 6000 m^3 and is modeled in ten layers, being the 6th layer, counting from bottom to top, the feed layer. Two recycle flows, the first from the last tank and the second from the underflow of the settler, complete the system. The plant is designed for an average influent dry weather flow rate of 18446 m^3/d and an average biodegradable chemical oxygen demand (COD) in the influent of 300 g/m^3. Its hydraulic retention time, based on the average dry weather flow rate and the total tank and settler volume

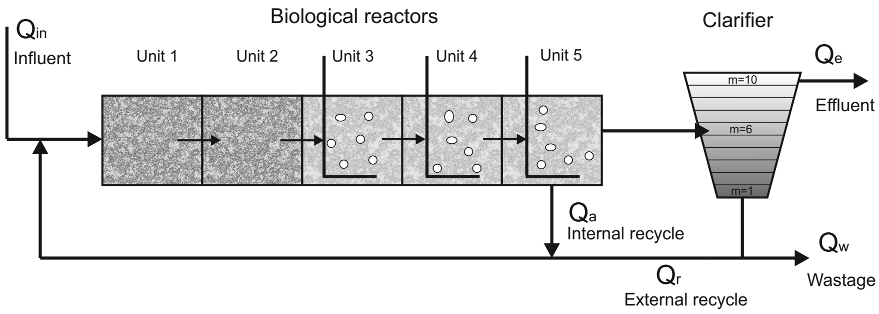


FIGURE 2.1: Benchmark Simulation Model 1

(12000 m^3), is 14.4 h. Q$_w$ is fixed to 385 m^3/d that determines, based on the total amount of biomass present in the system, a biomass sludge age of about 9 days. The nitrogen removal is achieved using a denitrification step performed in the anoxic tanks and a nitrification step carried out in the aerated tanks. The internal recycle is used to supply the denitrification step with S$_{NO}$.

2.1.1.2 Models

The biological phenomena of the reactors are simulated by the Activated Sludge Model No. 1 (ASM1) [4] that considers eight different biological processes. The vertical transfers between layers in the settler are simulated by the double-exponential settling velocity model [5]. None biological reaction is considered in the settler. The two models are internationally accepted and include thirteen state variables. 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:

$$r_{NH} = -0.08\rho_1 - 0.08\rho_2 - \left(0.08 + \frac{1}{0.24}\right)\rho_3 + \rho_6 \tag{2.1}$$

$$r_{NO} = -0.1722\rho_2 + 4.1667\rho_3 \tag{2.2}$$

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 of soluble organic nitrogen (S$_{ND}$). They are defined below:

$$\rho_1 = 4\left(\frac{S_S}{10 + S_S}\right)\left(\frac{S_O}{0.2 + S_O}\right)X_{B,H} \tag{2.3}$$

$$\rho_2 = 4\left(\frac{S_S}{10+S_S}\right)\left(\frac{0.2}{0.2+S_O}\right)\left(\frac{S_{NO}}{0.5+S_{NO}}\right)0.8\cdot X_{B,H} \tag{2.4}$$

$$\rho_3 = 0.5\left(\frac{NH}{1+NH}\right)\left(\frac{S_O}{0.4+S_O}\right)X_{B,A} \tag{2.5}$$

$$\rho_6 = 0.05\cdot S_{ND}\cdot X_{B,H} \tag{2.6}$$

where S_S is the readily biodegradable substrate, $X_{B,H}$ the active heterotrophic biomass and $X_{B,A}$ the active autotrophic biomass. The biological parameter values used in the BSM1 correspond approximately to a temperature of 15 °C.

The general equations for mass balancing are as follows:

- For reactor 1:

$$\frac{dZ_1}{dt} = \frac{1}{V_1}(Q_a\cdot Z_a + Q_r\cdot Z_r + Q_{in}\cdot Z_{in} + r_{z,1}\cdot V_1 - Q_1\cdot Z_1) \tag{2.7}$$

- For reactor 2 to 5:

$$\frac{dZ_k}{dt} = \frac{1}{V_k}(Q_{k-1}\cdot Z_{k-1} + r_{z,k}\cdot V_k - Q_k\cdot Z_k) \tag{2.8}$$

  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_{in} is Z from the influent, V is the volume, V_1 is V in the first reactor, Q_r is the external recirculation flow rate, Q_{in} is the flow rate of the influent, Q_1 is the flow rate in the first tank and it is equal to the sum of Q_a, Q_r and Q_{in}, k is the number of reactor and Q_k is equal to Q_{k-1}

2.1.1.3 Test procedure

BSM1 defines four different influent data [6]: constant influent, dry weather, rain weather and storm weather. Each scenario contains 14 days of influent data with sampling intervals of 15 minutes. A simulation protocol is established to assure that results are got under the same conditions and can be compared. So first a 150 days period of stabilization in closed-loop using constant influent data has to be completed to drive the system to a steady-state, next a simulation with dry weather is run and finally the desired influent data (dry, rain or storm) is tested. Only the results of the last seven days are considered.

2.1.1.4 Evaluation criteria

In order to compare the different control strategies, different criteria are defined. 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. It is assessed by Integral of the Squared Error (ISE), Integral of the Absolute Error (IAE) and average of the absolute error (mean($|e|$)) criteria.

$$ISE = \int_{t=245days}^{t=609days} e_i^2 \cdot dt \tag{2.9}$$

$$IAE = \int_{t=7days}^{t=14days} |e_i| \cdot dt \tag{2.10}$$

$$mean\,(\,|\,e\,|\,) = \frac{1}{T\_s} \sum_{i=1}^{i=T\_s} |e_i| \tag{2.11}$$

where e_i is the error in each sample between the set-point and the measured value and T_s is the total number of samples.

The second level provides measures for the effect of the control strategy on plant performance. It includes effluent violations, Effluent Quality Index (EQI) and Overall Cost Index (OCI).

The evaluation must include the percentage of time that the effluent limits are not met. The effluent concentrations of $S_{N_{tot}}$, Total COD (COD_t), NH, TSS and Biological Oxygen Demand (BOD_5) should obey the limits given in Table 2.1.

$S_{N_{tot}}$ is calculated as the sum of S_{NO} and Kjeldahl nitrogen (NKj), being this the sum of organic nitrogen and S_{NH}.

EQI is defined to evaluate the quality of the effluent. It is related with the fines to be paid due to the discharge of pollution. EQI is averaged over a 7 days observation period

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

TABLE 2.1: Effluent quality limits

and it is calculated weighting the different compounds of the effluent loads.

$$EQI = \frac{1}{1000 \cdot T} \int_{t=7days}^{t=14days} (B_{TSS} \cdot TSS(t) + B_{COD} \cdot COD(t) + B_{NKj} \cdot NK_j(t) +$$

$$+ B_{S_{NO}} \cdot S_{NO}(t) + B_{BOD_5} \cdot BOD_5(t)) \cdot Q(t) \cdot dt \tag{2.12}$$

where B_i are weighting factors (Table 2.2) and T is the total time.

Factor	B_{TSS}	B_{COD}	B_{NKj}	$B_{S_{NO}}$	B_{BOD_5}
Value(g pollution unit g^{-1})	2	1	30	10	2

TABLE 2.2: B_i values

OCI is defined as:

$$OCI = AE + PE + 5 \cdot SP + 3 \cdot EC + ME \tag{2.13}$$

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 and ME is the mixing energy.

AE is calculated according to the following relation:

$$AE = \frac{S_o^{sat}}{T \cdot 1.8 \cdot 1000} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} V_i \cdot K_L a_i(t) \cdot dt \tag{2.14}$$

where i is the reactor number and S_o^{sat} is the saturation concentration for oxygen that is equal to 8 mg/l.

PE is calculated as:

$$PE = \frac{1}{T} \int_{7days}^{14days} (0.004 \cdot Q_{in}(t) + 0.008 \cdot Q_a(t) + 0.05 \cdot Q_w(t)) \cdot dt \qquad (2.15)$$

SP is calculated from the TSS in the flow wastage (TSS_w) and the solids accumulated in the system:

$$SP = \frac{1}{T} \cdot (TSS_a(14days) - TSS_a(7days) + TSS_s(14days) - TSS_s(7days) + \\ + \int_{t=7days}^{t=14days} TSS_w \cdot Q_w \cdot dt) \qquad (2.16)$$

where TSS_a is TSS in the reactors and TSS_s is TSS in the settler.

EC refers to the carbon that could be added to improve denitrification.

$$EC = \frac{COD_{EC}}{T \cdot 1000} \int_{t=7days}^{t=14days} \left(\sum_{i=1}^{i=n} q_{EC,i} \right) \cdot dt \qquad (2.17)$$

where $q_{EC,i}$ is external carbon flow rate (q_{EC}) added to compartment i, $COD_{EC} = 400\ gCOD.m^{-3}$ is the concentration of readily biodegradable substrate in the external carbon source.

ME is a function of the compartment volume:

$$ME = \frac{24}{T} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} \left[0.005 \cdot V_i\ if\ K_La_i(t) < 20d^{-1}\ otherwise\ 0 \right] \cdot dt \qquad (2.18)$$

2.1.1.5 Default control strategy

The original BSM1 definition includes the so called default control strategy that is commonly used as a reference. This strategy uses two Proportional-Integral (PI) control loops as shown in Fig. 2.2. The first one involves the control of $S_{O,5}$ by manipulating K_La in the fift tank (K_La_5). The set-point for $S_{O,5}$ is 2 mg/l. The second control loop has to maintain $S_{NO,2}$ at a set-point of 1 mg/l by manipulating Q_a.

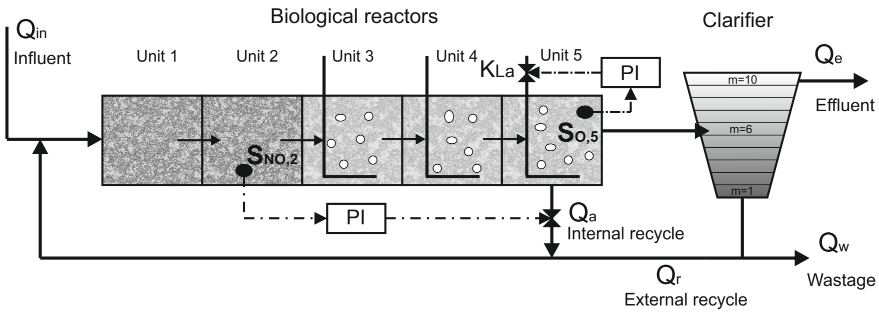


FIGURE 2.2: Default control strategy of BSM1

2.1.2 Benchmark Simulation Model No. 2

BSM1 was extended in a new version, BSM2, in [2] which was updated in [1]. BSM2 also defines a plant layout, a simulation model, a test procedure, evaluation criteria and default control strategies.

2.1.2.1 Plant layout

The finalized BSM2 layout (Fig. 2.3) 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 added. The liquids collected in the thickening and dewatering steps are recycled ahead of the primary settler.

2.1.2.2 Models

This work is based on the implementation of control strategies in the zone of biological treatment of BSM2. For this reason, the explanation of the simulation model is focused on the 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 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

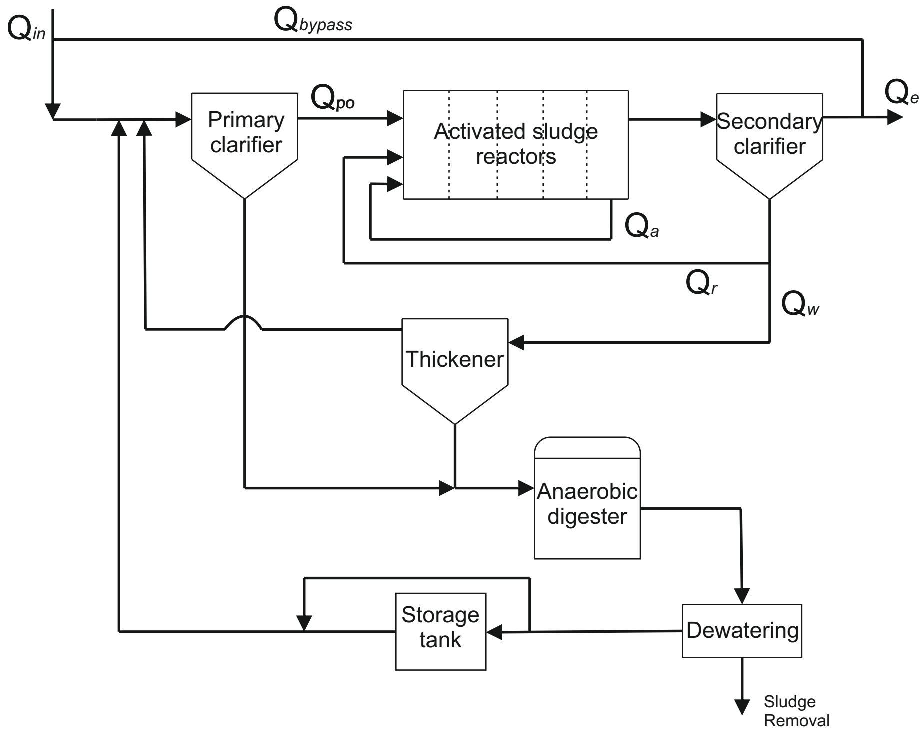


FIGURE 2.3: BSM2 plant with notation used for flow rates

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}.

ASM1 describes the biological phenomena that take place in the biological reactors. They define the conversion rates of the different variables of the biological treatment. Unlike BSM1, the temperature is considered in the BSM2. The proposed control strategies in this work are based on r_{NH} and r_{NO}. They are shown following:

$$r_{NH} = -0.08\rho_1 - 0.08\rho_2 - \left(0.08 + \frac{1}{0.24}\right)\rho_3 + \rho_6 \tag{2.19}$$

$$r_{NO} = -0.1722\rho_2 + 4.1667\rho_3 \tag{2.20}$$

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 S_{ND}. They are defined below:

$$\rho_1 = \mu_{HT}\left(\frac{S_S}{10 + S_S}\right)\left(\frac{S_O}{0.2 + S_O}\right)X_{B,H} \tag{2.21}$$

where μ_{HT} is:

$$\mu_{HT} = 4 \cdot exp\left(\left(\frac{Ln\left(\frac{4}{3}\right)}{5}\right) \cdot (T_{as} - 15)\right) \tag{2.22}$$

where T_{as} is the temperature

$$\rho_2 = \mu_{HT}\left(\frac{S_S}{10 + S_S}\right)\left(\frac{0.2}{0.2 + S_O}\right)\left(\frac{S_{NO}}{0.5 + S_{NO}}\right)0.8 \cdot X_{B,H} \tag{2.23}$$

$$\rho_3 = \mu_{AT}\left(\frac{S_{NH}}{1 + S_{NH}}\right)\left(\frac{S_O}{0.4 + S_O}\right)X_{B,A} \tag{2.24}$$

where μ_{AT} is:

$$\mu_{AT} = 0.5 \cdot exp\left(\left(\frac{Ln\left(\frac{0.5}{0.3}\right)}{5}\right) \cdot (T_{as} - 15)\right) \tag{2.25}$$

$$\rho_6 = k_{aT} \cdot S_{ND} \cdot X_{B,H} \tag{2.26}$$

where k_{aT} is:

$$k_{aT} = 0.05 \cdot exp\left(\left(\frac{Ln\left(\frac{0.05}{0.04}\right)}{5}\right) \cdot (T_{as} - 15)\right) \tag{2.27}$$

The general equations for mass balancing are as follows:

- For reactor 1:

$$\frac{dZ_1}{dt} = \frac{1}{V_1}(Q_a \cdot Z_a + Q_r \cdot Z_r + Q_{po} \cdot Z_{po} + r_{z,1} \cdot V_1 - Q_1 \cdot Z_1) \tag{2.28}$$

  where Q_{po} is the Q from the primary clarifier and Z_{po} is Z from the primary clarifier.

- For reactor 2 to 5:

$$\frac{dZ_k}{dt} = \frac{1}{V_k}(Q_{k-1} \cdot Z_{k-1} + r_{z,k} \cdot V_k - Q_k \cdot Z_k) \tag{2.29}$$

2.1.2.3 Test procedure

The influent dynamics are defined for 609 days by means of a single file, which takes into account rainfall effect and temperature. 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). Nevertheless, only the data generated during the final 364 days of the dynamic simulation are used for plant performance evaluation.

2.1.2.4 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. It is assessed by ISE and IAE criteria.

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, EQI and OCI. The effluent concentrations of $S_{N_{tot}}$, COD_t, S_{NH}, TSS and BOD_5 should obey the limits given in Table 2.1.

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.

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

$$+ B_{NO} \cdot S_{NO}(t) + B_{BOD_5} \cdot BOD_5(t)) \cdot Q(t) \cdot dt \qquad (2.30)$$

where B_i are weighting factors (Table 2.2).

OCI is defined to evaluate the operational cost as:

$$OCI = AE + PE + 3 \cdot SP + 3 \cdot EC + ME - 6 \cdot MET_{prod} + HE_{net} \qquad (2.31)$$

where MET_{prod} is the methane production in the anaerobic digester and HE_{net} is the net heating energy.

AE is calculated according to the following relation:

$$AE = \frac{8}{T \cdot 1.8 \cdot 1000} \int_{t=245days}^{t=609days} \sum_{i=1}^{5} V_i \cdot K_L a_i(t) \cdot dt \qquad (2.32)$$

PE is calculated as:

$$PE = \frac{1}{T} \int_{245days}^{609days} (0.004 \cdot Q_{in}(t) + 0.008 \cdot Q_a(t) + 0.06 \cdot Q_w(t)) + 0.06 \cdot Q_{to}(t)) + 0.004 \cdot Q_{du}(t)) \cdot dt \tag{2.33}$$

where Q_{to} is the overflow rate from the thickener and Q_{du} is the underflow rate.

SP is calculated as:

$$SP = \frac{1}{T} \cdot (TSS_a(609days) - TSS_a(245days) + TSS_s(609days) - TSS_s(245days) +$$

$$+ 0.75 \cdot \int_{t=245days}^{t=609days} TSS_w \cdot Q_w \cdot dt) \tag{2.34}$$

EC is defined as:

$$EC = \frac{COD_{EC}}{T \cdot 1000} \int_{t=245days}^{t=609days} \left(\sum_{i=1}^{i=n} q_{EC,i} \right) \cdot dt \tag{2.35}$$

ME is defined as:

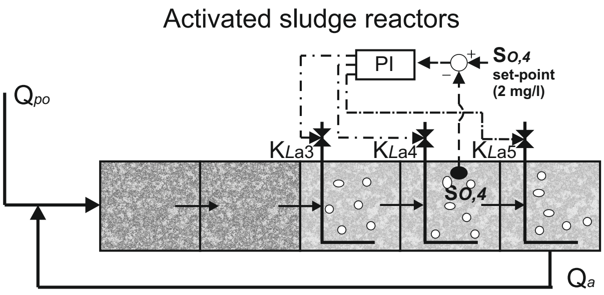
$$ME = \frac{24}{T} \int_{t=245days}^{t=609days} \sum_{i=1}^{5} \left[0.005 \cdot V_i \ if \ K_L a_i(t) < 20d^{-1} \ otherwise \ 0 \right] \cdot dt \tag{2.36}$$

2.1.2.5 Default control strategies

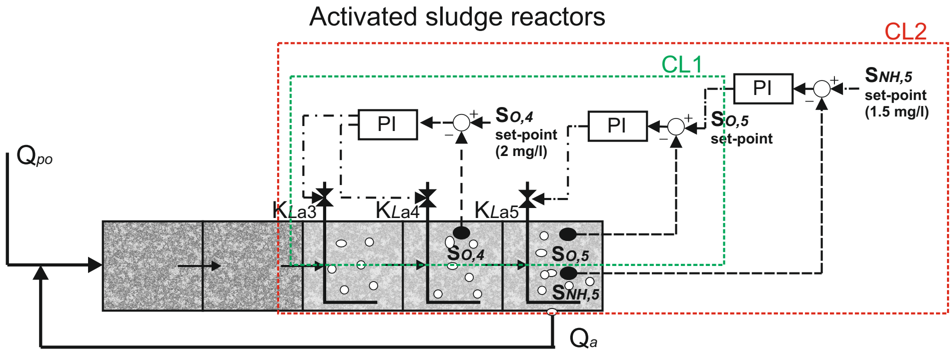
The original BSM2 definition ([2]) proposes a PI control strategy (defCL). The closed-loop control configuration consists of a PI that controls S_O in the fourth tank ($S_{O,4}$) at a set-point of 2 mg/l by manipulating K_La in the third tank (K_La_3), K_La in the fourth tank (K_La_4) and K_La_5, with K_La_5 set to the half value of K_La_3 and K_La_4. q_{EC} in the first reactor ($q_{EC,1}$) is added at a constant flow rate of 2 m^3/d. Two different Q_w values are imposed dependent on time of the year: from 0 to 180 days and from 364 to 454 days Q_w is set to 300 m^3/d; and for the remaining time periods Q_w is set to 450 m^3/d.

The finalisation of BSM2 plant layout is reported by [1], in which two new control strategies are proposed. The first control strategy (CL1) is based on modifying the defCL, controlling the $S_{O,4}$ set-point at 2 mg/l, by manipulating K_La_3 and K_La_4, and adding another loop to control $S_{O,5}$ by manipulating K_La_5. PI controllers are applied for both control loops. The second control strategy (CL2) adds a hierarchical control to CL1. Therefore, a PI controller is applied to control S_{NH} in the fifth tank ($S_{NH,5}$) at a set-point of 1.5 mg/l by manipulating $S_{O,5}$ set-point. In the case of CL2, $q_{EC,1}$ is added at a constant value of 1 m^3/d.

Fig. 2.4 shows the three explained control strategies.



(a) defCL control strategy



(b) CL1 and CL2 control strategies

Figure 2.4: Default control strategies of BSM2

2.2 Control Approaches

The control strategies applied in this thesis are based on MPC controllers, FCs and ANNs. They are implemented using Matlab® for the simulation and on-line control. Specifically, MPC controllers have been designed with MPC toolbox, FCs with FIS editor and ANNs with Neural Network Fitting toolbox. The prediciton models of MPC controllers have been identified with System Identification toolbox. To solve the quadratic objective of MPC in equation (2.39), the Quadratic Dynamic Matrix Control solver ([7]) with hard linear constraints in the inputs provided by Matlab® MPC toolbox has been used.

2.2.1 Model Predictive Control

The basis of MPC is the use of an optimization algorithm to solve the control problem and the use of a model of the plant to make predictions of the output variables ([8]). At each control interval, $\triangle t$, for a prediction horizon, p, and a control horizon, m, $(m < p)$, the MPC algorithm computes the sequences of control moves over the horizon m:

$$\triangle u(k), \triangle u(k+1), ..., \triangle u(k+m-1) \tag{2.37}$$

makes predictions of the outputs variables over a future horizon p (see Fig. 2.5):

$$\hat{y}(k+1|k), \hat{y}(k+2|k), ..., \hat{y}(k+p|k) \tag{2.38}$$

and selects the sequence of control moves that minimizes a quadratic objective of the form:

$$J = \sum_{l=1}^{p} ||\Gamma_y[y(k+l|k) - r(k+l)]||^2 + \sum_{l=1}^{m} ||\Gamma_{\triangle u}[\triangle u(k+l-1)]||^2 \tag{2.39}$$

where the output prediction $y(k+l|k)$ means a predicted controlled output for the future sampling instant $k+1$, performed at the current instant k, and Γ_y and $\Gamma_{\triangle u}$ are the output weight and input rate weight respectively, which penalize the residual between the future reference and the output variable prediction, and the control moves.

The MPC algorithm requires a state-space linear model to foresee how the plant outputs, $y(k)$, react to the possible variations of the control variables, $u(k)$, and to compute the control moves at each $\triangle t$. WWTPs are nonlinear systems, but their operation can be approximated in the vicinity of a working point by a discrete-time state-space model as:

$$x(k+1) = Ax(k) + Bu(k)$$

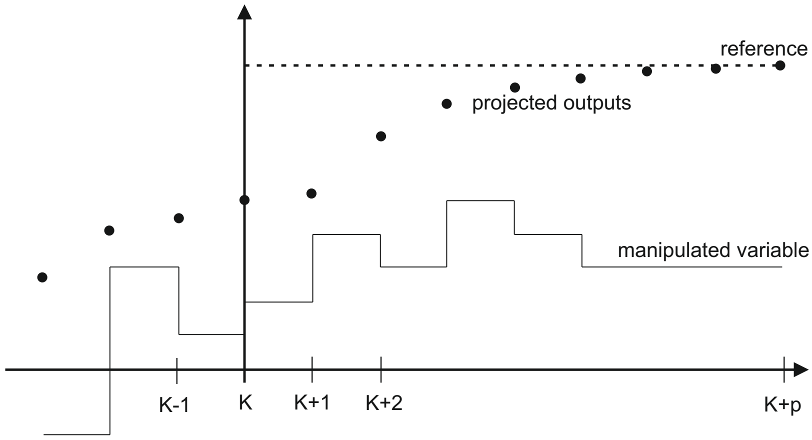


FIGURE 2.5: Model Predictive Control performance

$$y(k) = Cx(k) + Du(k) \tag{2.40}$$

where $x(k)$ is the state vector, and A, B, C and D are the state-space matrices.

Due to the presence of strong disturbances on WWTPs, MPC has difficulties in keeping the controlled variables at their reference level. To compensate the disturbances, a feed-forward control action is added, as in [9], [10], [11] and [12]. MPC provides feedforward compensation for the measured disturbances as they occur to minimize their impact on the output. The combination of feedforward plus feedback control can significantly improve the performance over simple feedback control whenever there is a major disturbance that can be measured before it affects the process output. The idea of the feedforward control is to act on the process when the disturbances appear and before they cause deterioration in the effluent quality.

2.2.2 Fuzzy Control

Fuzzy logic is described as an interpretative system in which objects or elements are related with borders not clearly defined, granting them a relative membership degree and not strict, as it is customary in traditional logic. The typical architecture of a FC, shown in Fig. 2.6, consists of: a fuzzifier, a fuzzy rule base, an inference engine and a defuzzifier ([13, 14]).

Fuzzy control is defined as a control based on human expertise, determined by words instead of numbers and sentences instead of equations ([13, 14]). In fact this does not

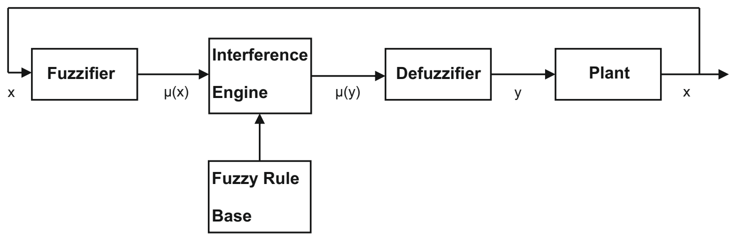


Figure 2.6: Architecture of a FC

mean at all that a knowledge of the process dynamics is not needed. Good knowledge of the dynamic behavior of the controlled plant is to be available to the designer. However, process variables are measured in numbers instead of words. For this reason, the fuzzifier adapts the input variables into suitable linguistic values by membership functions. There are different forms of membership functions, e.g. triangular, trapezoidal or gaussian, and they are chosen according to the user's experience. Range of membership functions values are also set: minimum value of the input variable ($MinIn$), maximum value of the input variable ($MaxIn$), minimum value of the output variable ($MinOut$), maximum value of the output variable ($MaxOut$). The fuzzy rule base is a set of *if-then* rules that store the empirical knowledge of the experts about the operation of the process. First the fuzzy logic computes the grade of membership of each condition of a rule, and then aggregates the partial results of each condition using fuzzy set operator. The inference engine combines the results of the different rules to determine the actions to be carried out, and the defuzzifier converts the control actions of the inference engine into numerical variables, determining the final control action that is applied to the plant. There are two different methods to operate these modules: Mamdani ([15]) and Sugeno ([16]). Mamdani system aggregates the area determined by each rule and the output is determined by the center of gravity of that area. In a Sugeno system the results of the $if - then$ rules are already numbers determined by numerical functions of the input variables and therefore no deffuzifier is necessary. The output is determined weighting the results given by each rule with the values given by the if conditions.

For example, Fig. 2.7 shows three triangular membership functions ($mf1$, $mf2$ and $mf3$) with $MinIn = 0$ and $MaxIn = 5$. Thus, an input of 1.5 can be transformed into fuzzy expressions as 0.25 of $mf1$ and simultaneously 0.5 of $mf2$. Fig. 2.8 shows the three membership functions ($mf4$, $mf5$, $mf6$) of the Mamdani defuzzifier with $MinOut$ $= 0$ and $MaxOut = 5$. The $if - then$ rules implemented are:

if $(Input$ is $mf1)$ **then** $(Output$ is $mf4)$
if $(Input$ is $mf2)$ **then** $(Output$ is $mf5)$
if $(Input$ is $mf3)$ **then** $(Output$ is $mf6)$

The output is the result of the aggregation of two rules, one that gives 0.25 of $mf4$ and other that gives 0.5 of $mf5$.

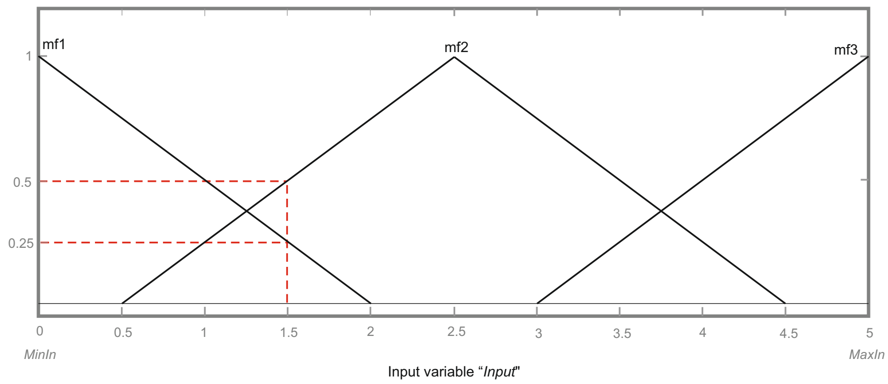


Figure 2.7: Example of membership functions of fuzzifier

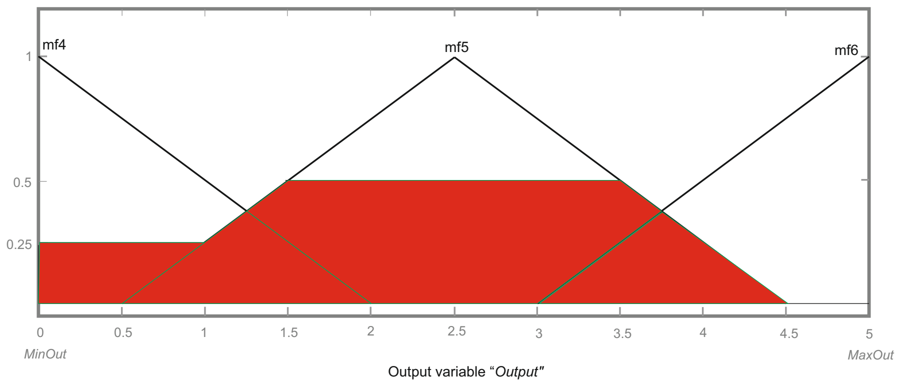


Figure 2.8: Example of membership functions of defuzzifier

2.2.3 Artificial Neural Network

ANNs are inspired by the structure and function of nervous systems, where the neuron is the fundamental element ([17]). 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 ([18, 19]). 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 2.9 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 is needed to design an ANN, and the input 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.

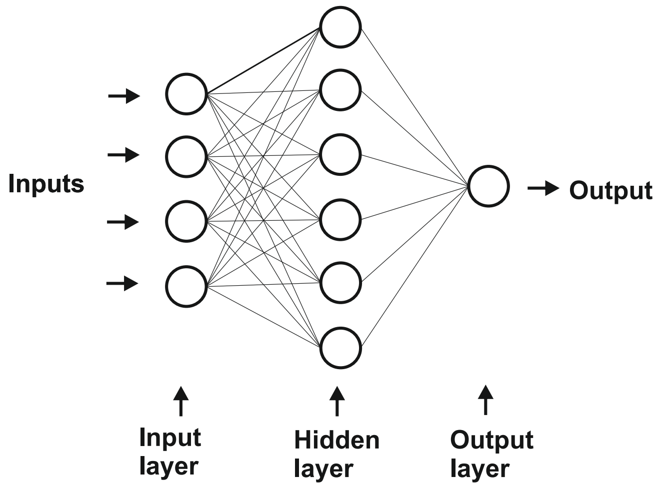


FIGURE 2.9: Structure of Artificial Neural Network layers

The number of input nodes, output nodes and the nodes in the hidden layer depend 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 ([20]).

Part I

Effluent quality improvement and costs reduction

Chapter 3

Lower level control: tracking improvement

This chapter presents the lower level control of a hierarchical structure using BSM1 as working scenario. This level is based on the default control strategy, $S_{O,5}$ and $S_{NO,2}$ control by manipulating K_La_5 and Q_a respectively. Next, the S_O control is extended to the third and fourth tanks by manipulating K_La_3 and K_La_4.

Other works dealt with the default control strategy applying different controllers, as PI/PID ([21, 22]), fuzzy ([23]) or MPC ([12, 24, 25]). In this work, MPC+FF has been proposed with the objective of improving the S_O and $S_{NO,2}$ tracking in comparison with the default control strategy and with the literature.

3.1 MPC+FF configuration

The two PI controllers of the default BSM1 control strategy are replaced by an MPC+FF with two inputs ($S_{O,5}$ and $S_{NO,2}$) and two outputs (K_La_5 and Q_a), in order to improve the tracking of $S_{O,5}$ and $S_{NO,2}$ set-points, whose results are evaluated by the ISE criterion. Some studies deal with this basic control strategy (S_O of the aerated tanks and S_{NO} of the last anoxic tank), but testing with different controllers such MPC and FC ([12, 21–25]).

In addition, two MPC+FF controllers are added to control S_O in the third tank ($S_{O,3}$) and $S_{O,4}$ by manipulating K_La_3 and K_La_4 respectively (see Fig. 3.1).

Different variables have been considered for the feedforward action in the literature, but in our case Q_{in} has been selected for its better results. Any change in Q_{in} affects directly the flow rates of all the tanks, modifying their hydraulic retention time. Therefore, it is necessary to adjust the manipulated variables immediately to compensate the Q_{in} disturbances.

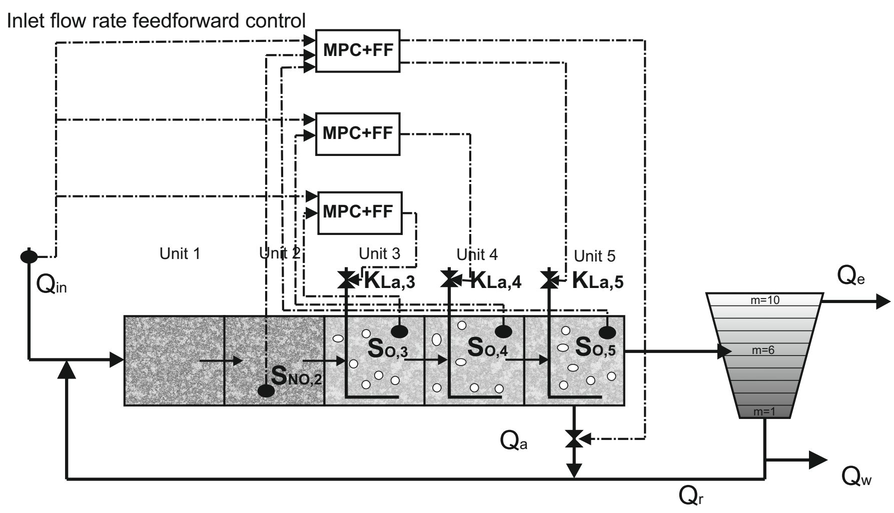


FIGURE 3.1: BSM1 with MPC+FF for the control of $S_{NO,2}$ and S_O in the three aerobic tanks

The variables of the state-space model (2.40) for the three MPC controllers are described following: $u_1(k)$ is Q_a, $u_2(k)$ is K_La_5, $u_3(k)$ is Q_{in} and $y_1(k)$ is $S_{NO,2}$ and $y_2(k)$ is $S_{O,5}$ in the controller of $S_{O,5}$ and $S_{NO,2}$; $u_1(k)$ is K_La_4, $u_2(k)$ is Q_{in} and $y_1(k)$ is $S_{O,4}$ in the controller of $S_{O,4}$ and $u_1(k)$ is K_La_3, $u_2(k)$ is Q_{in} and $y_1(k)$ is $S_{O,3}$ in the controller of $S_{O,3}$.

The identification of the linear predictive models of the MPC controllers was performed using Matlab® System Identification Tool. The data of the output variables ($S_{O,3}$, $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$) are obtained by making changes to the input variables (K_La_3, K_La_4, K_La_5 and Q_a) with a maximum variation of 10% regarding its operating point, which is the value of K_La necessary to obtain 2 mg/l of S_O and the value of Q_a necessary to obtain 1 mg/l of $S_{NO,2}$. Specifically, the working points are 264.09 day $^{-1}$, 209.23 day $^{-1}$, 131.65 day $^{-1}$ and 16486 m^3/day for K_La_3, K_La_4, K_La_5 and Q_a respectively. Different sources were tested to modify the input variables as random, sinusoidal or step, and finally the best fit was obtained with random source. These input variations are performed every 2.4h, sufficient time to ensure the effect of these variations on the output signals. Furthermore, for the feedforward compensation, a step to Q_{in} of +10% is added over 18446 m^3/day, which is the average value during the stabilization period. Two methods were tested for determining the model with the obtained data, prediction error method (PEM) ([26]) and subspace state spacesystem identification (N4SID) ([27]). Finally PEM were selected because it fits better with the real response of the plant. The order of the models was chosen from a trade-off between the best fit and the lowest order. Therefore the following third order state-space models are obtained:

- $S_{O,5}$ and $S_{NO,2}$ control

$$\begin{aligned}
A &= \begin{bmatrix} 0.8748 & 0.04463 & 0.1314 \\ 0.04091 & 0.7331 & 0.1796 \\ 0.2617 & -0.1318 & 0.3007 \end{bmatrix} \\
B &= \begin{bmatrix} 7.641 \cdot 10^{-6} & 0.004551 & -2.749 \cdot 10^{-5} \\ -2.631 \cdot 10^{-5} & 0.006562 & -4.551 \cdot 10^{-6} \\ -9.63 \cdot 10^{-6} & -0.02161 & 2.447 \cdot 10^{-5} \end{bmatrix} \\
C &= \begin{bmatrix} 0.8812 & -0.5948 & 0.02114 \\ 1.187 & 0.9893 & -0.3754 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\end{aligned} \tag{3.1}$$

- $S_{O,3}$ control

$$\begin{aligned}
A &= \begin{bmatrix} 0.7859 & 0.4576 & -0.131 \\ 0.3334 & 0.2599 & 0.2718 \\ -0.003132 & 0.03235 & -1.003 \end{bmatrix} \\
B &= \begin{bmatrix} 0.009308 & -2.285 \cdot 10^{-5} \\ -0.01546 & 3.503 \cdot 10^{-6} \\ 0.003654 & -1.987 \cdot 10^{-5} \end{bmatrix} \\
C &= \begin{bmatrix} 0.6376 & -0.4621 & 0.03698 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned} \tag{3.2}$$

- $S_{O,4}$ control

$$
\begin{aligned}
A &= \begin{bmatrix} 0.8201 & 0.371 & -0.1016 \\ 0.3054 & 0.307 & 0.2544 \\ -0.003381 & 0.03144 & -0.9993 \end{bmatrix} \\
B &= \begin{bmatrix} 0.007712 & -4.65 \cdot 10^{-5} \\ -0.0148 & 8.164 \cdot 10^{-6} \\ 0.004523 & -2.526 \cdot 10^{-5} \end{bmatrix} \\
C &= \begin{bmatrix} 0.947 & -0.496 & 0.02472 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned}
\tag{3.3}
$$

Data acquisition for the model identification is based on simulations, as this work is a first step to be subsequently tested in a pilot plant and finally in a real plant. In order to predict the possible application in a real plant, the data acquisition for the identification is performed while the plant is kept at a certain desired operating point, whose values are considered suitable for the biological wastewater treatment of this plant. Therefore, what the identification needs is only the possibility of adding some incremental changes to those operating conditions. As mentioned before, the inputs used for identification purposes represent a maximum variation of 10%. Therefore they will not disturb the actual plant operation. The generated outputs will reflect the effect of such input variables manipulation. Data for identification have been generated simulating one week. However, in the case of the real plant, the identification could be carried out in different periods and not necessarily in consecutive days. Plants operator knowledge can in addition be used to know the more appropriate days to perform the experiment.

With regard to the tuning of the MPC controllers, the parameters are: $\triangle t$, m, p, $\Gamma_{\triangle u}$, Γ_y and the overall estimator gain.

- $\triangle t$ has a significant effect on the effectiveness of the controller. High $\triangle t$ can give less controller performance, mainly when there are important input disturbances, and low $\triangle t$ can produce changes too quickly in the actuators and also high energy consumption.

- Lower $\Gamma_{\triangle u}$ or higher Γ_y give better performance of the controlled variable that could otherwise produce strong oscillations in the actuators that must be avoided.

- m and p should be adjusted depending on system control in each case. However values that are too high can increase the computational time in excess, and on the other hand, values that are too small may result in oscillatory responses or may not work at all.
- At each $\triangle t$ the controller compares the true value of the outputs with the expected values. The difference can be due to noise, to measurements errors and to unmeasured disturbances. With the overall estimator gain parameter, it is determined the percentage of this difference that is attributed to unmeasured disturbances and the calculation matrix is consequently adjusted. Higher overall estimator gains improve the results, but too high values can make the controller unfeasible.

The selected values to tune the MPC controllers are $m = 5$, $p = 20$, $\triangle t = 0.00025$ d (21.6 s), $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 0.01$ for $S_{O,3}$, $S_{O,4}$ and $S_{O,5}$ control and $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 0.0001$ for $S_{NO,2}$ control and overall estimator gain = 0.8. It should be noted that the values of m and p are not critical and they can be slightly changed with similar results.

3.2 Simulations Results

3.2.1 $S_{O,5}$ and $S_{NO,2}$ control

Fig. 3.2 shows $S_{O,5}$ and $S_{NO,2}$ for the dry weather case compared with the default PI control. Table 3.1 shows that MPC+FF reduces ISE of $S_{NO,2}$ control more than 99% and ISE of $S_{O,5}$ control more than 97% in comparison with the default PI controllers. This control performance improvement results in a 1.1% of EQI reduction, keeping a similar OCI (increase of 0.0063%).

This comparison is also done for the rain (see Fig. 3.3 and Table 3.1) and storm influents (see Fig. 3.4 and Table 3.1), obtaining similar percentages of improvement: ISE 99.6% (rain) and 99.5% (storm) for $S_{NO,2}$ control and 92.02% (rain) and 90.8% (storm) for $S_{O,5}$ control, and reducing EQI with MPC+FF 1.03% for rain and 1.09% for storm. OCI is similar, increasing a 0.037% for rain and 0.044% for storm; nevertheless this difference is not significant.

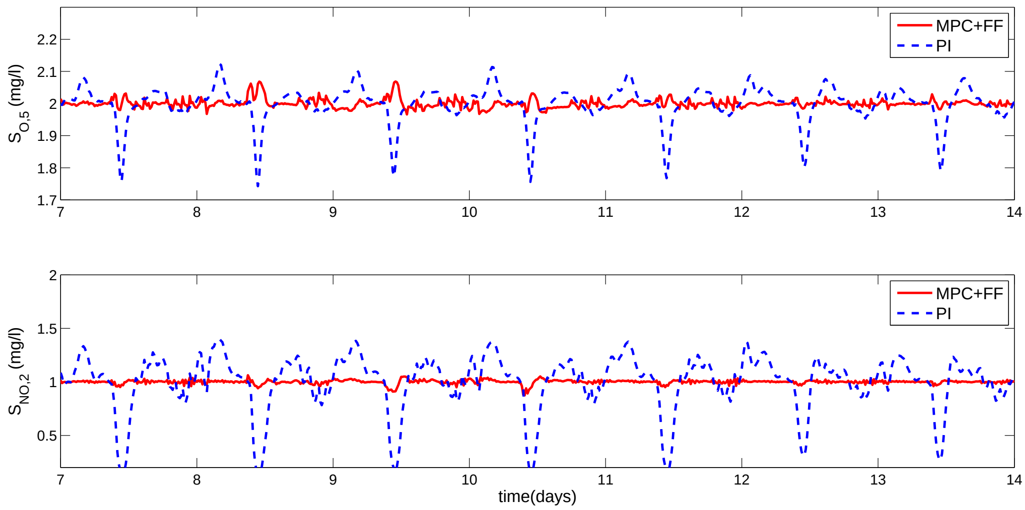


FIGURE 3.2: Dry influent: Control performance of $S_{O,5}$ and $S_{NO,2}$ with default PI controllers and with MPC+FF

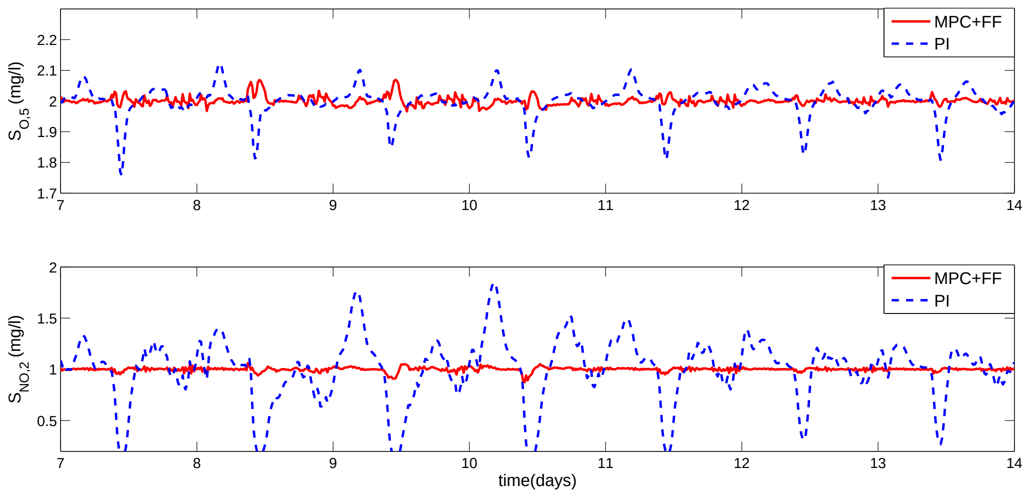


FIGURE 3.3: Rain influent: Control performance of $S_{O,5}$ and $S_{NO,2}$ with default PI controllers and with MPC+FF

For a more comprehensive comparison, the results of the referenced papers which provide indicators of the control performance have been added and compared with the proposed MPC+FF for dry influent in Table 3.2. To ensure a fair comparison, it is done with the referenced papers, which control $S_{O,5}$ at the set-point of 2 mg/l and/or $S_{NO,2}$ at the set-point of 1 mg/l and use the original version of BSM1. To allow the comparison with the greatest possible number of papers, two control performance criteria have been added to the usual ISE: IAE and mean($|e|$).

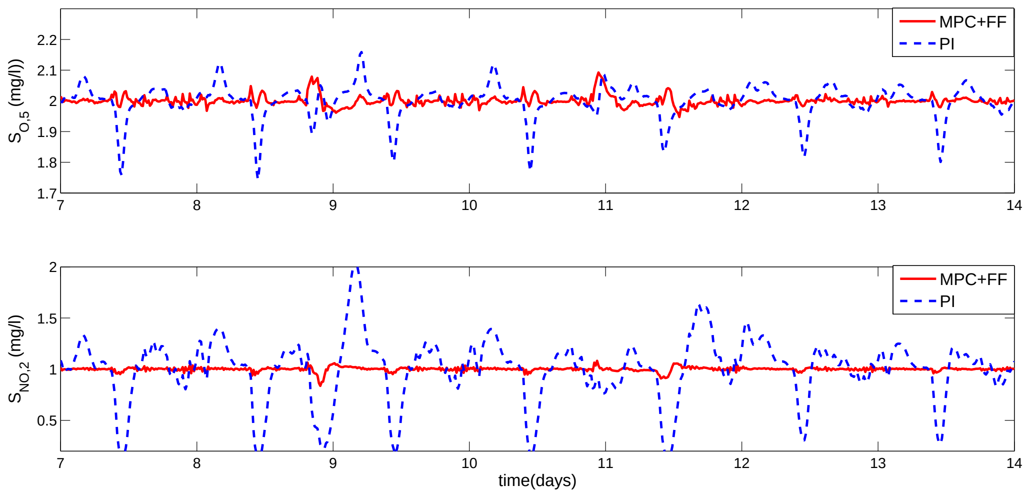


FIGURE 3.4: Storm influent: Control performance of $S_{O,5}$ and $S_{NO,2}$ with default PI controllers and with MPC+FF

Dry weather			
	PI	MPC+FF	%
ISE ($S_{NO,2}$ control)	0.47	0.0013	-99.7%
ISE ($S_{O,5}$ control)	0.022	0.00067	-96.9%
EQI (kg pollutants/d)	6115.63	6048.25	-1.1%
OCI	16381.93	16382.97	+0.0063%
Rain weather			
	PI	MPC+FF	%
ISE ($S_{NO,2}$ control)	0.69	0.0028	-99.6%
ISE ($S_{O,5}$ control)	0.016	0.0013	-92.02%
EQI (kg pollutants/d)	8174.98	8090.29	-1.03%
OCI	15984.85	15990.85	+0.037%
Storm weather			
	PI	MPC+FF	%
ISE ($S_{NO,2}$ control)	0.69	0.0032	-99.5%
ISE ($S_{O,5}$ control)	0.020	0.0018	-90.8%
EQI (kg pollutants/d)	7211.48	7132.60	-1.09%
OCI	17253.75	17261.39	+0.044%

TABLE 3.1: ISE, EQI and OCI results using default PI controllers and MPC+FF for dry, rain and storm influents

	$S_{O,5}$ control			$S_{NO,2}$ control			$S_{O,5}$ and $S_{NO,2}$ control
	ISE	IAE	mean(|e|)	ISE	IAE	mean(|e|)	mean(|e|)
Proposed MPC+FF	0.00067	0.047	0.0068	0.0013	0.067	0.0096	0.0082
[25]	-	-	-	-	-	-	0.024
[21]	-	-	0.9	-	-	-	-
[24]	0.0026	0.0892	-	-	-	-	-
[23]	0.0012	0.0792	-	-	-	-	-
[22]	0.00092	0.049	-	0.408	1.21	-	-

TABLE 3.2: Comparison of the performance of $S_{O,5}$ and $S_{NO,2}$ control between MPC+FF and the referenced works

The improvement of $S_{NO,2}$ and $S_{O,5}$ tracking as a result of applying MPC+FF compared to the rest of the referenced papers is shown.

3.2.2 $S_{O,3}$ and $S_{O,4}$ control

It is also important to obtain a good $S_{O,3}$ and $S_{O,4}$ tracking, because the variation of the S_O set-point is applied to the three aerobic reactors, as shown in the next chapter. Fig. 3.5 and Fig, Fig. 3.6 and Fig. 3.7 show $S_{O,3}$ and $S_{O,4}$ evolution applying MPC+FF controllers for the dry, rain and storm influents. Table 3.3 shows satisfactory results of $S_{O,3}$ and $S_{O,4}$ control with the MPC+FF controllers. Comparison of the results has been accomplished only with [21] for dry weather, due to it is the only referred work that provides results of $S_{O,3}$ and $S_{O,4}$ control. However, it can be seen that the control performance results are similar to those obtained with $S_{O,5}$, and even better in the case of $S_{O,3}$, as it is shown in Table 3.2 and Table 3.1 of previous section.

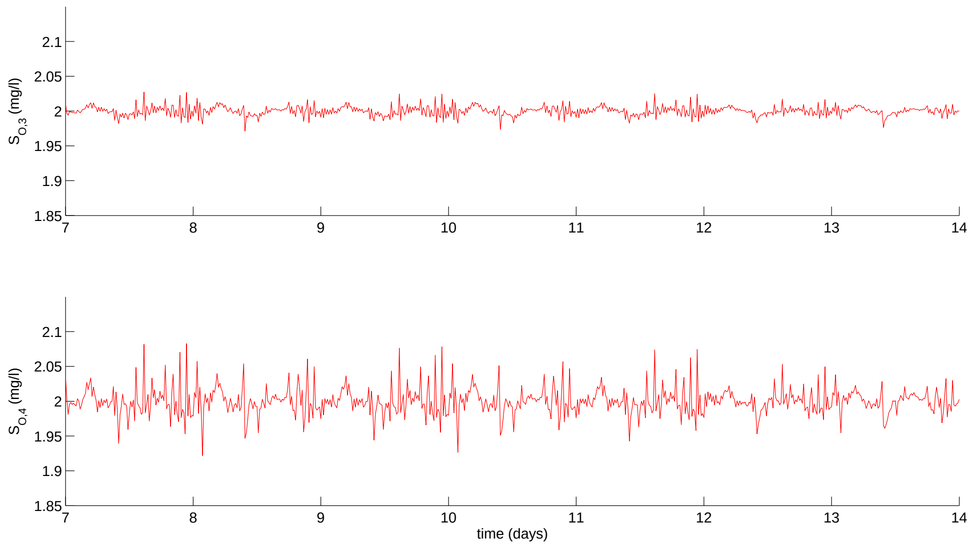


FIGURE 3.5: Dry influent: Control performance of $S_{O,3}$ and $S_{O,4}$ with MPC+FF

	Dry weather					
	$S_{O,3}$ control			$S_{O,4}$ control		
	ISE	IAE	mean(|e|)	ISE	IAE	mean(|e|)
MPC+FF	0.00037	0.038	0.0054	0.0027	0.096	0.014
[21]	-	-	1.5	-	-	2.7
	Rain weather					
	$S_{O,3}$ control			$S_{O,4}$ control		
	ISE	IAE	mean(|e|)	ISE	IAE	mean(|e|)
MPC+FF	0.0004	0.039	0.0055	0.0027	0.094	0.013
	Storm weather					
	$S_{O,3}$ control			$S_{O,4}$ control		
	ISE	IAE	mean(|e|)	ISE	IAE	mean(|e|)
MPC+FF	0.00056	0.043	0.0062	0.004	0.11	0.015

TABLE 3.3: Results of $S_{O,3}$ and $S_{O,4}$ control with MPC+FF controllers for dry, rain and storm weather conditions

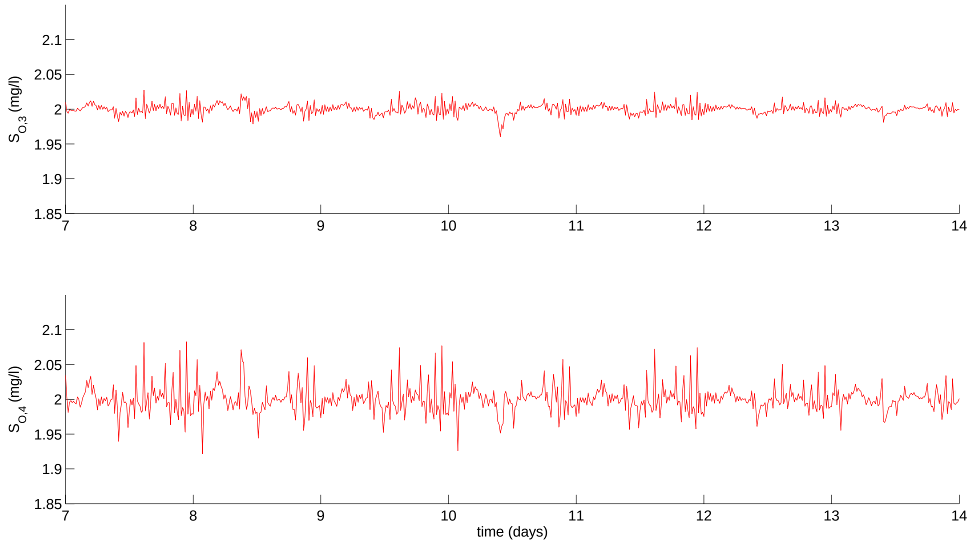


FIGURE 3.6: Rain influent: Control performance of $S_{O,3}$ and $S_{O,4}$ with MPC+FF

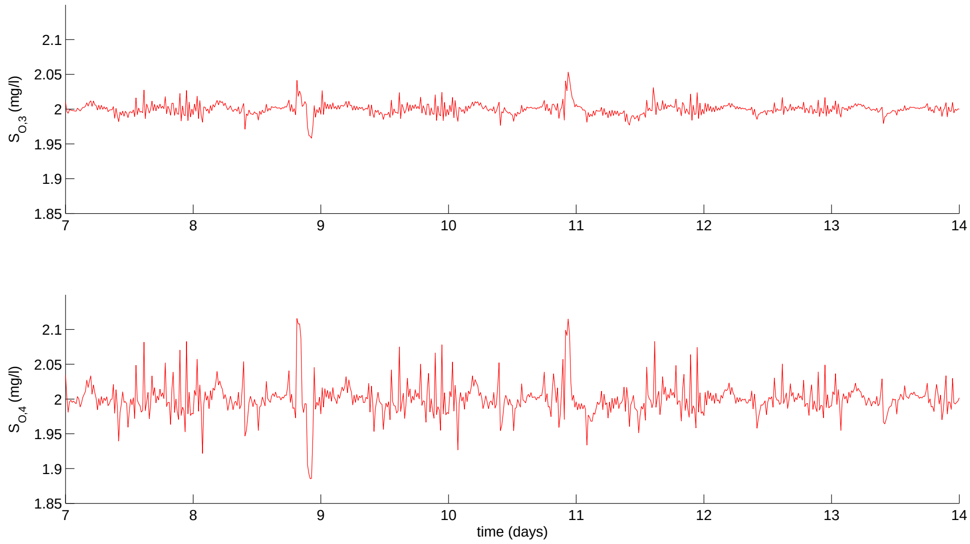


FIGURE 3.7: Storm influent: Control performance of $S_{O,3}$ and $S_{O,4}$ with MPC+FF

3.3 Summary

In this chapter, the lower level of a hierarchical control structure has been implemented using BSM1 as working scenario. This is based on $S_{O,3}$, $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ control by manipulating K_La_3, K_La_4, K_La_5, Q_a respectively.

First, the default control strategy is evaluated. Next, a MPC+FF controller tracks S_O5 and $S_{NO,2}$, improving the control performance with an ISE reduction of more than 90%

compared to the default PI controllers for the three influents. The control performance of the MPC+FF controllers has been also compared to the referenced papers, showing the improvement of the proposed method and thus the successful tracking. Next, the S_O control is extended to the third and fourth tanks. Thus, two MPC+FF controllers are added to control $S_{O,3}$ and $S_{O,4}$ by manipulating K_La_3 and K_La_4 respectively, obtaining similar control performance results as in $S_{O,5}$ control.

The tracking improvement of $S_{O,5}$ and $S_{NO,2}$ using MPC+FF controllers result in a EQI reduction of around 1% with a similar OCI, in comparison with the default PI controllers. In addition, the importance of the satisfactory S_O tracking achieved in the three aerobic tanks is remarkable, especially for the implementation of the hierarchical control structure explained in next chapter, to ensure that the value of S_O is as close as possible to the set-point provided by the higher level.

Chapter 4

Higher level control: manipulation of dissolved oxygen set-points

In this chapter the higher level control of a two-level hierarchical structure is proposed using BSM1 as testing plant. The lower level is composed of the MPC+FF controllers described in the previous chapter. The higher level controller has to manipulate S_O set-points of the lower level controllers according to $S_{NH,5}$ (see Fig. 4.1). The biological treatment of S_{NH} and S_{NO} is the result of various processes given by ASM1. When S_{NH} increases, more S_O is needed for nitrification (2.1, 2.5). On the contrary, when S_{NH} decreases, less S_O is required, producing less S_{NO} (2.2, 2.5).

Some investigations propose a hierarchical control that regulates the DO set-points, depending on some states of the plant, usually S_{NH} and S_{NO} concentration values in any tank or in the influent ([22, 28–31]) or DO in other tanks ([32]). Nevertheless, these investigations use PI controllers or MPC as higher level control, trying to keep the controlled variable at a fixed set-point, but with a large resulting error. In this work, three alternatives are tested for the higher level: An MPC, an affine function and a FC. For each of these alternatives a range of tuning parameters are proposed. The control alternatives have been tested only by controlling the fifth reactor.

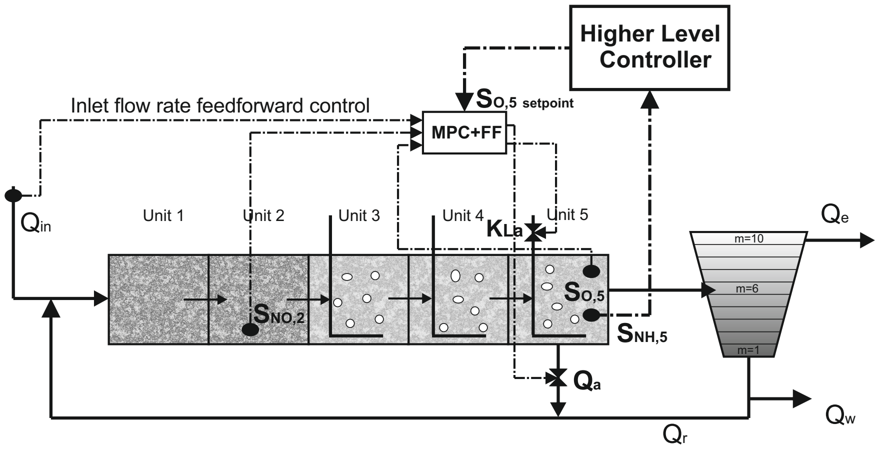


FIGURE 4.1: BSM1 with MPC+FF and Hierarchical control

4.1 Testing alternatives for the higher level control

4.1.1 Proposed alternatives

First, a MPC is proposed for the higher level control, with the aim of keeping $S_{NH,5}$ at a fixed set-point by manipulating $S_{O,5}$.

Next, an affine function is applied based on the biological processes. The nitrification process is performed by the autotrophic bacteria whose growth is obtained by ρ_3 (2.5). As it can be observed, higher S_{NH} and S_O produce a greater S_{NH} removal. However, increasing the S_O value also increases S_{NO} and operational costs, as it can be observed in equations 2.2 and 2.13. For this reason it is important to increase S_O when S_{NH} increases to reduce S_{NH} peaks, and decrease S_O when S_{NH} decreases, producing less S_{NO} and reducing costs. Unlike MPC, the affine function regulates $S_{O,5}$ set-point based on $S_{NH,5}$, to obtain the $S_{O,5}$ value, but without having the aim of keeping $S_{NH,5}$ at a reference level. Thus the following affine function is proposed:

$$S_{O,5}\, set-point(t) = S_{NH,5}(t) - k \tag{4.1}$$

where k is a constant. $S_{O,5}$ value obtained is directly proportional to $S_{NH,5}$, subtracting the k value. Also, a constraint of a maximum value of $S_{O,5}$ has been added to improve the EQI and OCI trade-off. Values of k and $S_{O,5}$ maximum are considered tuning parameters.

Finally, a higher level FC is also implemented, with the same idea of the higher level affine function. Thus, the higher level FC modifies $S_{O,5}$ based on $S_{NH,5}$, but does not try to keep $S_{NH,5}$ at a given set-point. However, the methodology to obtain the $S_{O,5}$ set-point is modified, using fuzzy logic in this case.

4.1.2 Controllers tuning

Higher level MPC: As it has been done with lower level MPC in the previous chapter, a linear model (2.40) of the plant is needed to compute predictions of the output variables of the MPC. In this case, the plant model has one input and one output. Concretely, $u(t)$ is the set-point value of $S_{O,5}$ and $y(t)$ is $S_{NH,5}$.

In order to identify the linear model, $S_{NH,5}$ has been determined by varying $S_{O,5}$ set-point around 2 mg/l, with maximum values of ±10%.

By using a prediction error method, a second order state-space model (2.40) is obtained, as:

$$
\begin{aligned}
A &= \begin{bmatrix} 0.2531 & 0.3691 \\ 0.2781 & -0.2695 \end{bmatrix} \qquad B = \begin{bmatrix} -0.4507 \\ -0.1712 \end{bmatrix} \\
C &= \begin{bmatrix} 0.08655 & -0.01681 \end{bmatrix} \qquad D = \begin{bmatrix} 0 \end{bmatrix}
\end{aligned}
\tag{4.2}
$$

The following tuning parameters have been selected: $\triangle t$=0.035 days (50.4 minutes), m=2, p=10. To determine $\Gamma_{\triangle u}$ and $S_{NH,5}$ set-point values, a trade-off representation for OCI and EQI is provided and showed in Fig. 4.2. Every line corresponds to the results obtained for different $\Gamma_{\triangle u}$ (0.1, 0.05, 0.01 and 0.001), and the points marked with crosses are the results for a range of $S_{NH,5}$ set-point values, from 0.5 to 6.5 with increments of 0.25.

The results with MPC+FF alone and with default PI controllers alone are also represented. Fig. 4.2 shows an area in which results obtained with higher level MPC controller improve simultaneously OCI and EQI in comparison with MPC+FF and with default PI controllers alone. This is the proposed tuning region.

The OCI and EQI trade-off representation has also been done for rain and storm influents (Fig. 4.3 and Fig. 4.4 respectively), obtaining also the corresponding tuning regions. However, they are smaller than the one obtained for the dry influent.

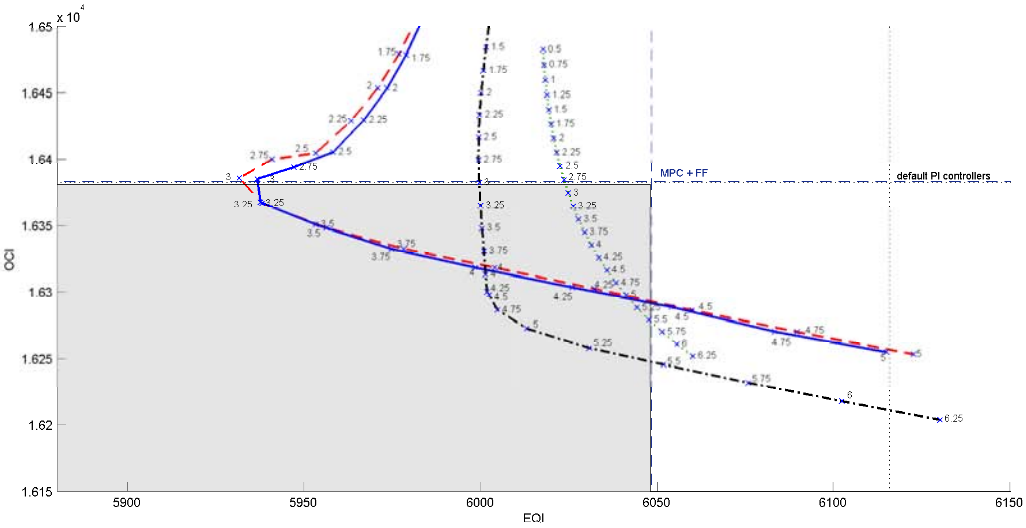


FIGURE 4.2: Dry influent: OCI and EQI trade-off with higher level MPC for a range of $S_{NH,5}$ values (points marked with crosses) and $\Gamma_{\triangle u} = 0.001$ (dashed line), 0.01 (solid line), 0.05 (dash-dotted line) and 0.1 (dotted line)

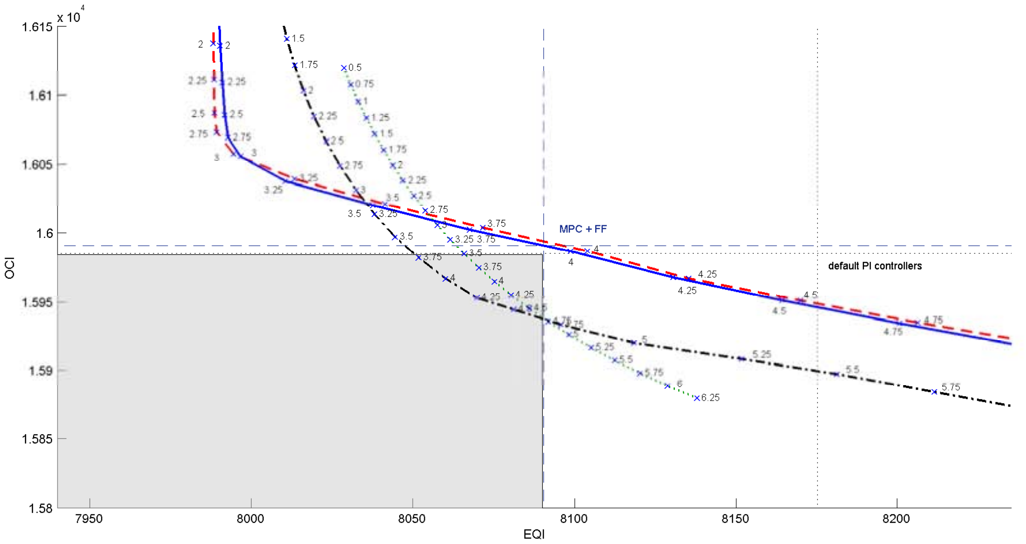


FIGURE 4.3: Rain influent: OCI and EQI trade-off with higher level MPC for a range of $S_{NH,5}$ values (points marked with crosses) and $\Gamma_{\triangle u} = 0.001$ (dashed line), 0.01 (solid line), 0.05 (dash-dotted line) and 0.1 (dotted line)

Taking into account the OCI and EQI trade-off representations for dry, rain and storm influents (Fig. 4.2, 4.3 and Fig. 4.4 respectively), $\Gamma_{\triangle u}$ and $S_{NH,5}$ set-points have been selected for the cases of lowest EQI without increasing OCI and the lowest OCI without worsening EQI for every influent in comparison with MPC+FF alone (Table 4.1).

Higher level affine function: For the affine function, k values and maximum

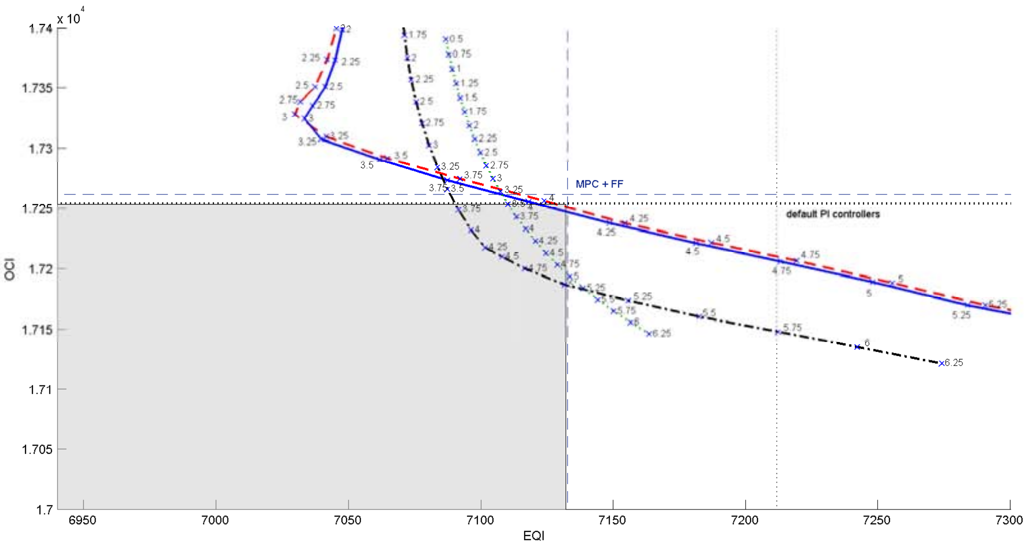


FIGURE 4.4: Storm influent: OCI and EQI trade-off with higher level MPC for a range of $S_{NH,5}$ values (points marked with crosses) and $\Gamma_{\triangle u} = 0.001$ (dashed line), 0.01 (solid line), 0.05 (dash-dotted line) and 0.1 (dotted line)

	dry		rain		storm	
	lowest EQI	lowest OCI	lowest EQI	lowest OCI	lowest EQI	lowest OCI
$\Gamma_{\triangle u}$	0.001	0.05	0.05	0.05	0.05	0.05
$S_{NH,5}$ set-point	3.1	5.4	3.75	4.6	3.7	5

TABLE 4.1: Higher level MPC tuning: $\Gamma_{\triangle u}$ and $S_{NH,5}$ set-point

values of $S_{O,5}$ have been selected for the OCI and EQI trade-off representation showed in Fig. 4.5. In this case, each line corresponds to the results obtained with different $S_{O,5}$ maximum values (2.5-k; 3-k; 3.5-k; 4-k and 4.5-k), while each one of the points marked with crosses are the results obtained for different values of k (from 0.3 to 1.6 with increments of 0.1). In the same way, the results obtained with MPC+FF alone and with PI default controllers alone are also shown.

The same range of k and $S_{O,5}$ maximum values have been tested for rain and storms influents, obtaining also the trade-off representations (Fig. 4.6 and Fig. 4.7 respectively).

The areas of the tuning regions, which result in a simultaneous improvement of OCI and EQI in comparison with MPC+FF alone and with default PI controllers alone, are larger than those obtained with higher level MPC.

Taking into account the trade-off representations (see Fig. 4.5, Fig. 4.6, and Fig. 4.7), Table 4.2 shows $S_{O,5}$ maximum and k values for the extreme cases of lowest EQI without increasing OCI and the lowest OCI without worsening EQI in comparison with

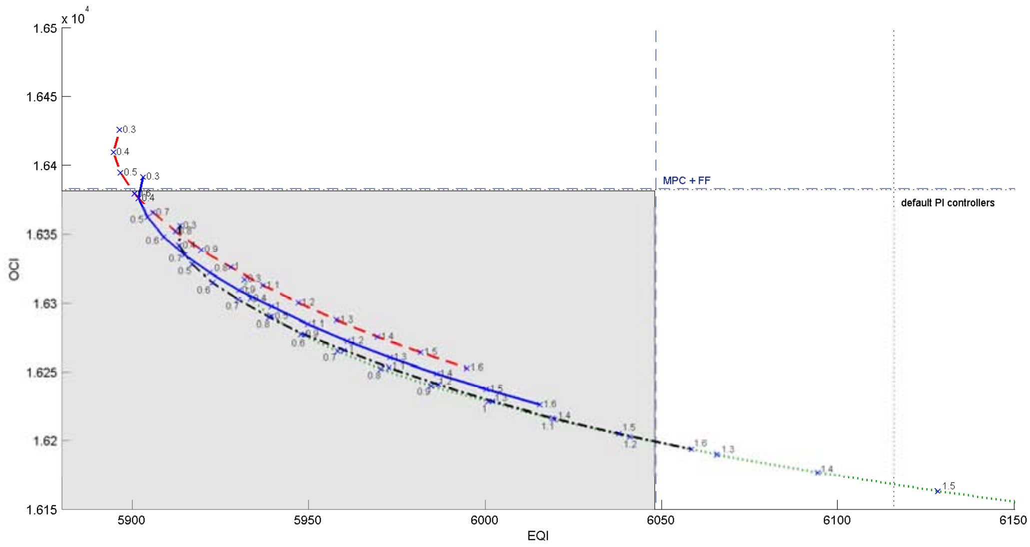


Figure 4.5: Dry influent: OCI and EQI trade-off with higher level affine function for a range of k values (points marked with crosses) and $S_{O,5}$ maximum = 4 (dashed line), 3.5 (solid line), 3 (dash-dotted line), 2.5 (dotted line)

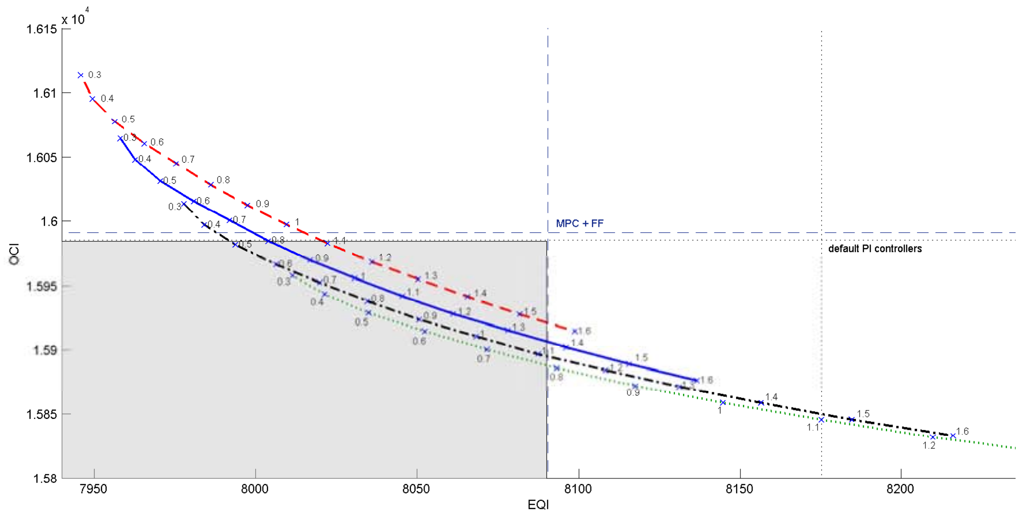


Figure 4.6: Rain influent: OCI and EQI trade-off with higher level affine function for a range of k values (points marked with crosses) and $S_{O,5}$ maximum = 4 (dashed line), 3.5 (solid line), 3 (dash-dotted line), 2.5 (dotted line)

MPC+FF alone and default PI controllers alone.

Higher level Fuzzy Controller: The implementation of the proposed FC was based on the observation of the simulations results obtained by operating the plant with the default control of BSM1.

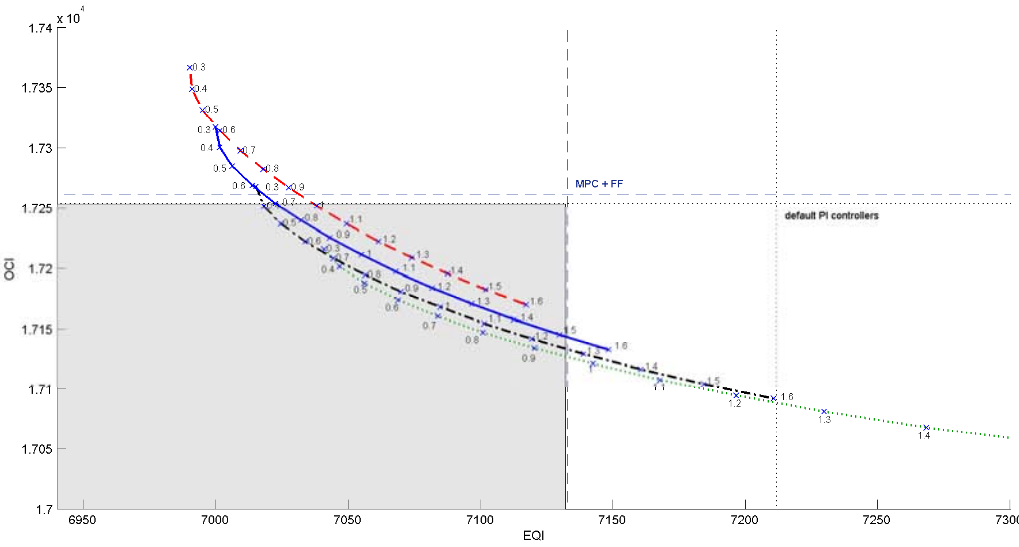


FIGURE 4.7: Storm influent: OCI and EQI trade-off with higher level affine function for a range of k values (points marked with crosses) and $S_{O,5}$ maximum = 4 (dashed line), 3.5 (solid line), 3 (dash-dotted line), 2.5 (dotted line)

	dry		rain		storm	
	lowest EQI	lowest OCI	lowest EQI	lowest OCI	lowest EQI	lowest OCI
k	0.59	1.23	0.48	0.79	0.39	0.96
$S_{O,5}$ maximum	3.41	1.27	2.52	1.71	2.61	1.54

TABLE 4.2: Higher level affine function tuning: k and $S_{O,5}$ maximum values

The input of the FC is $S_{NH,5}$. Three triangular membership functions are applied to the input to fuzzyfy. The following fuzzy sets have been used: *low*, *medium* and *high*.

The output is the $S_{O,5}$ set-point of the lower level control. Also three triangular membership functions have been applied to the output with the same fuzzy sets: *low*, *medium* and *high*.

The if-then fuzzy rules that relate the input and output are:

if ($S_{NH,5}$ is *low*) **then** ($S_{O,5}$ is *low*)
if ($S_{NH,5}$ is *medium*) **then** ($S_{O,5}$ is *medium*)
if ($S_{NH,5}$ is *high*) **then** ($S_{O,5}$ is *high*)

The Mamdani method has been chosen to defuzzify the results of the above if-then fuzzy rules and thereby to obtain a single value of the $S_{O,5}$ set-point based on the value of $S_{NH,5}$.

Values of $MinIn$ and $MinOut$ are both fixed to 0.1. Several OCI and EQI results have been obtained for different values of $MaxIn$ (3, 4, 5 and 7) and $MaxOut$ (2, 2.5, 3, 3.5, 4, 4.5, 5 and 5.5). With these results, trade-off representations of EQI and OCI for the three influents (dry, rain and storm) are made (Fig. 4.8, Fig. 4.9, and Fig. 4.10), obtaining a tuning area where both OCI and EQI are improved in comparison with MPC+FF alone and with the default PI controllers.

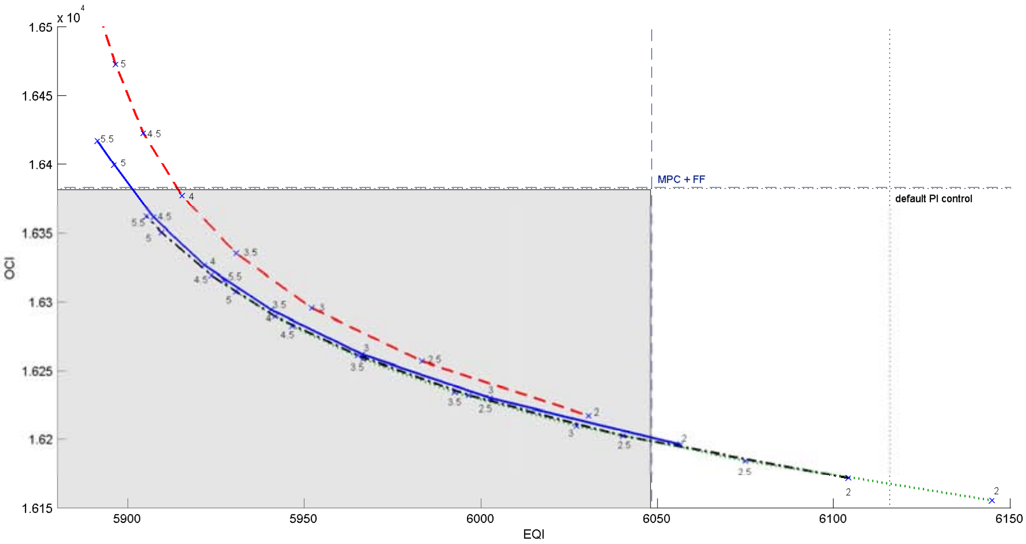


FIGURE 4.8: Dry influent: OCI and EQI trade-off with higher level FC for a range of $MaxOut$ values (points marked with crosses) and $MaxIn = 3$ (dashed line), 5 (solid line), 7 (dash-dotted line) and 9 (dotted line)

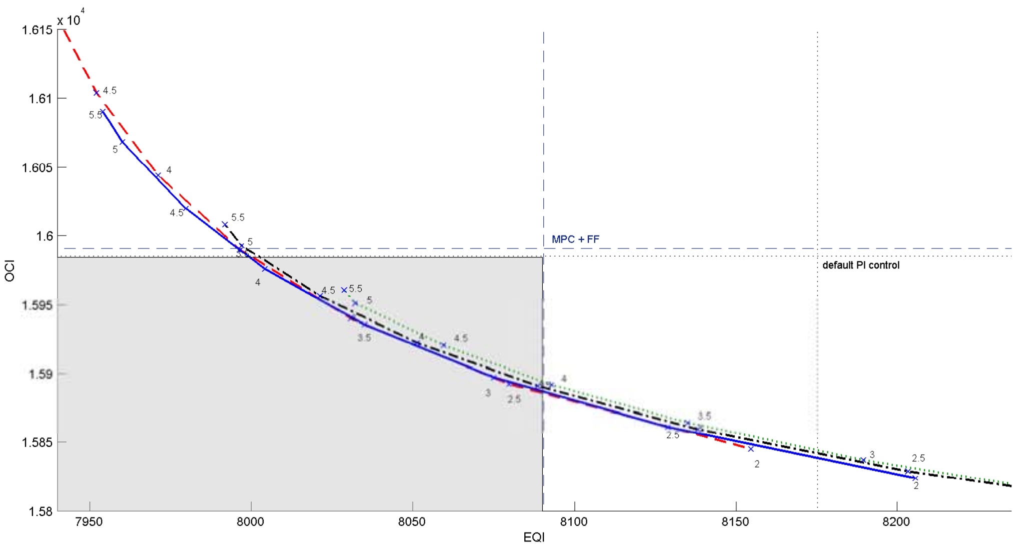


FIGURE 4.9: Rain influent: OCI and EQI trade-off with higher level FC for a range of $MaxOut$ values (points marked with crosses) and $MaxIn = 3$ (dashed line), 5 (solid line), 7 (dash-dotted line) and 9 (dotted line)

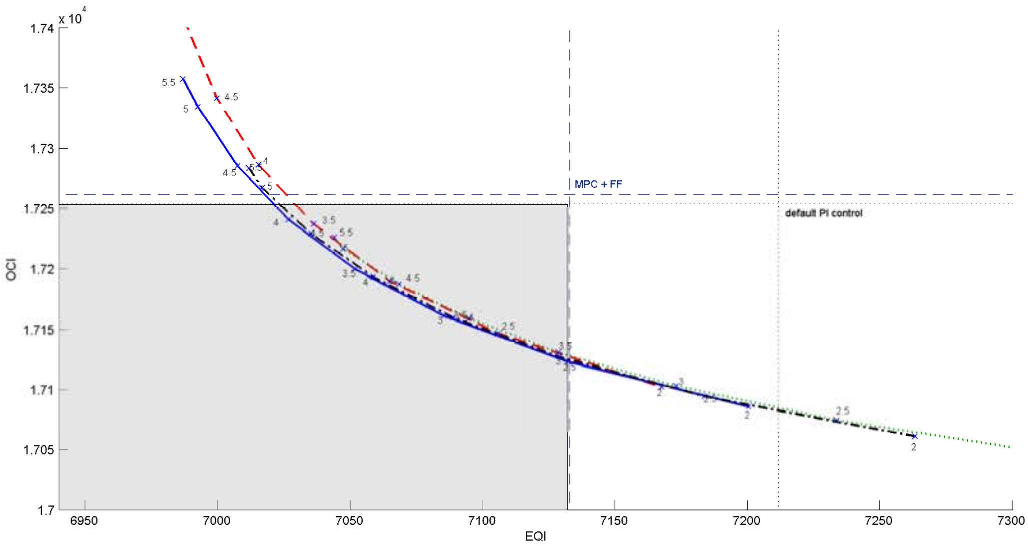


FIGURE 4.10: Storm influent: OCI and EQI trade-off with higher level FC for a range of $MaxOut$ values (points marked with crosses) and $MaxIn = 3$ (dashed line), 5 (solid line), 7 (dash-dotted line) and 9 (dotted line)

The areas of the tuning regions, which result in a simultaneous improvement of OCI and EQI in comparison with MPC+FF alone and with default PI controllers alone, are similar to the ones corresponding to the higher level with affine function.

Table 4.3 shows the $MaxIn$ and $MaxOut$ values for the extreme cases of lowest EQI without increasing OCI and lowest OCI without worsening EQI in comparison with MPC+FF alone and default PI controllers alone for the three influents.

	dry		rain		storm	
	lowest EQI	lowest OCI	lowest EQI	lowest OCI	lowest EQI	lowest OCI
$MaxIn$	5	9	5	3	5	5
$MaxOut$	4.78	2.76	4.1	2.41	4.14	2.5

TABLE 4.3: Higher level FC tuning: $MaxIn$ and $MaxOut$ values

4.1.3 Simulations results

Higher level MPC: In order to improve EQI, the values of S_{NH} and S_{NO} have to be reduced because they are the pollutants with largest influence on the effluent quality. Fig. 4.11 shows $S_{NH,5}$, S_{NO} in the fifth tank ($S_{NO,5}$) and $S_{O,5}$ for dry influent with the tuning parameters where the best EQI without increasing OCI is obtained. As it is shown in Fig. 4.11, by varying $S_{O,5}$ set-point with two level hierarchical control, $S_{NH,5}$

peaks and $S_{NO,5}$ are reduced. In the case of higher level MPC, when $S_{NH,5}$ is over the fixed set-point, $S_{O,5}$ reference of the lower level control is increased, which produces more oxidation of $S_{NH,5}$ and consequently softens its peaks, while $S_{NO,5}$ and the aeration costs grow. In opposition, when the $S_{NH,5}$ is under the fixed set-point, $S_{O,5}$ reference is decreased, $S_{NH,5}$ goes up and $S_{NO,5}$ and aeration costs go down. The final balance from day 7 to day 14 is a reduction of 1.8% of EQI in comparison with MPC+FF alone (see Table 4.4).

The same concentrations ($S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$) for rain and storm influents are shown in Fig. 4.12 and Fig. 4.13 respectively. Within 7 days of simulation (day 7 to 14), two days are shown coinciding with a rainfall (Fig. 4.12) and a storm (Fig. 4.13) events. As it is observed, during the rain and storm events, the differences of $S_{NH,5}$ peaks and $S_{NO,5}$ for higher level MPC and MPC+FF are lower compared with dry weather. This has a direct consequence on the EQI results shown in Table 4.4. As it can be seen, there is also an improvement by working with higher level MPC in comparison with MPC+FF alone, but with a lower percentage compared with dry weather. For the rain influent case, EQI is decreased by 0.4% and for the storm influent case, EQI is decreased by 0.5%.

In the opposite point of the trade-off representations (Fig. 4.2, 4.3, 4.4 (best OCI without worsening effluent quality), OCI results are compared for the different control structures with the three weather conditions. Fig. 4.14 shows K_La_5 for the higher level MPC. The aeration costs depend directly on the K_La_5 values. Fig. 4.14 shows that the values of K_La_5 with higher level MPC are lower most of the time than those obtained with MPC+FF alone, proving that costs can be reduced without increasing EQI with a better optimization of K_La_5. This reduction of K_La_5 results in a reduction of 0.8% of OCI (Table 4.4).

The K_La_5 evolution is also shown for rain and storm influents (Fig. 4.15 and 4.16 respectively), obtaining also an OCI reduction when working with the higher level MPC in comparison with MPC+FF alone. In this case, with less percentage in comparison with dry influent results (see Table 4.4): For rain influent, higher level MPC reduces OCI by 0.3%, and for storm influent the reduction is 0.4%. The optimization of the $S_{O,5}$ set-point value results in an AE reduction of 202.2 KWh/d, 96.42 KWh/d and 137.92 KWh/d for dry, rain and storm influents respectively, compared with default BSM1 control, which corresponds, in terms of percentage, to an AE reduction of 5.4%, 2.6% and 3.7% respectively.

Higher level affine function: With the tuning parameters where the best EQI without increasing OCI is obtained (see Table 4.2), comparing $S_{NH,5}$ peaks and $S_{NO,5}$ for higher level affine function and higher level MPC for the three influents (see Fig. 4.11, Fig. 4.12 and Fig. 4.13), a remarkable difference is not observed. However Table 4.4 show that affine function is able to reduce EQI in comparison with higher level MPC by 0.6% for dry influent, 0.7% for rain influent and 1% for storm influent. In comparison with MPC+FF alone the reduction is 2.4% for dry influent, 1.1% for rain influent and 1.5% for storm influent.

Applying the tuning parameters to obtain the best OCI without worsening effluent quality, K_La_5 is compared with the other control structures for the three weather conditions (see Fig. 4.14, Fig. 4.15 and Fig. 4.16), obtaining better K_La_5 optimization compared with MPC+FF alone and higher level MPC for the three influents, which result in an OCI reduction in comparison with higher level MPC of 0.3% for dry influent, 0.3% for rain influent and 0.4% for storm influent. In comparison with MPC+FF the reduction is 1.1% for dry influent, 0.6% for rain influent and 0.8% for storm influent (see Table 4.4).

This cost reduction is due primarily to an AE reduction of 259.45 KWh/d, 170.87 KWh/d and 209.85 KWh/d for dry, rain and storm influents respectively, compared with default BSM1 control, which corresponds, in terms of percentage, to an AE reduction of 7%, 4.7%, 5.6% respectively.

Higher level Fuzzy Controller: For the case of the best EQI obtained, Fig. 4.11, Fig. 4.12 and Fig. 4.13 show that $S_{NH,5}$ and $S_{NO,5}$ for the three influents are similar compared to higher level affine function. The EQI results are shown in Table 4.4 and they are very similar to the ones obtained with the higher level affine function.

Applying the tuning parameters for obtaining the lowest OCI, Fig. 4.14, Fig. 4.15 and Fig. 4.16 show K_La_5 for the three weather conditions. Looking at the OCI results in Table 4.4, there is no significant difference compared with higher level affine function, getting also the same percentages of improvement over MPC+FF alone and higher level MPC.

The reduction of AE is also similar to the results obtained using an affine function as higher level controller: 255.67 KWh/d, 199.99 KWh/d and 199.72 KWh/d for dry, rain and storm influents respectively, compared with default BSM1 control, which corresponds, in terms of percentage, to an AE reduction of 6.9%, 5.4%, 5.3% respectively. As a result, for the higher level control, with affine function and FC, the following improvements are obtained in comparison with higher level MPC: For dry influent, AE reduction of 57.25 KWh/d and 53.47 KWh/d respectively. For rain influent, 74.45 KWh/d and 103.57 KWh/d respectively. And for storm influent, 71.93 KWh/d and 61.8 KWh/d respectively.

The reason of the improvement of the results of EQI and OCI by using the higher level FC or the higher level affine function compared to the higher level MPC is that the higher level MPC tries to maintain the value of $S_{NH,5}$ at a fixed reference, but the error is too high. Specifically, the ISE is 36.21 to achieve the best EQI and the ISE is 22.69 to achieve the best OCI. Conversely, higher level affine function and higher level FC regulate $S_{O,5}$ set-point based on the biological process dynamics that take place in the reactors (2.1, 2.2, 2.3, 2.4, 2.5, 2.6). On the one hand improving the nitrification process (2.5) when $S_{NH,5}$ increases, and therefore reducing its peaks. On the other hand, reducing the $S_{O,5}$ set-point level when $S_{NH,5}$ decreases in order to reduce the S_{NO} generation (2.2) and the operational costs (2.13).

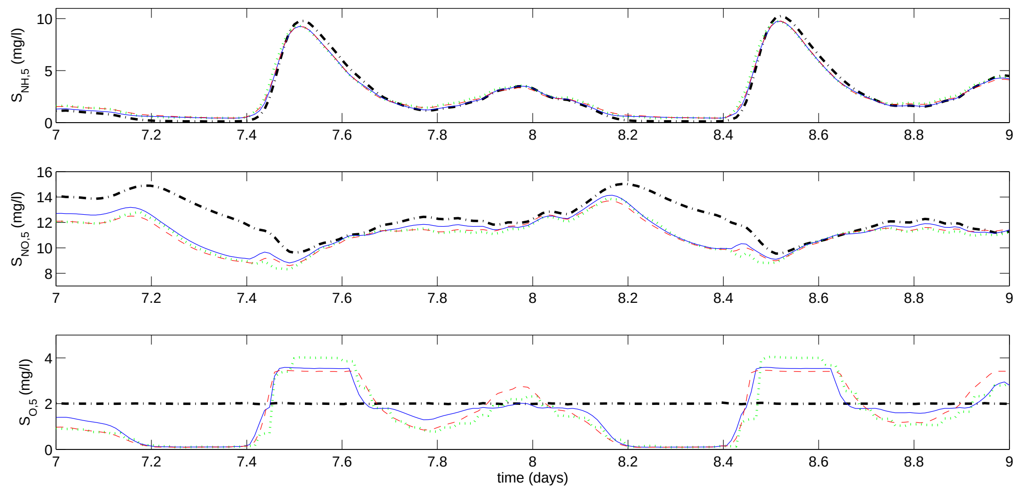


FIGURE 4.11: Dry influent: Comparison of $S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$. MPC+FF (dash-dotted line), higher level MPC (dotted line), higher level affine function (dashed line) and higher level FC (solid line)

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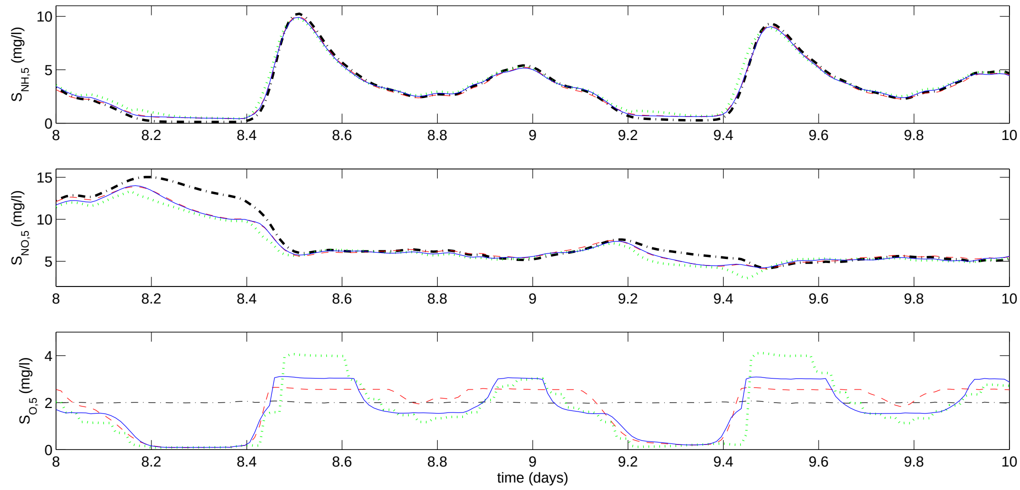

FIGURE 4.12: Rain influent: Comparison of $S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$. MPC+FF (dash-dotted line), higher level MPC (dotted line), higher level affine function (dashed line) and higher level FC (solid line)

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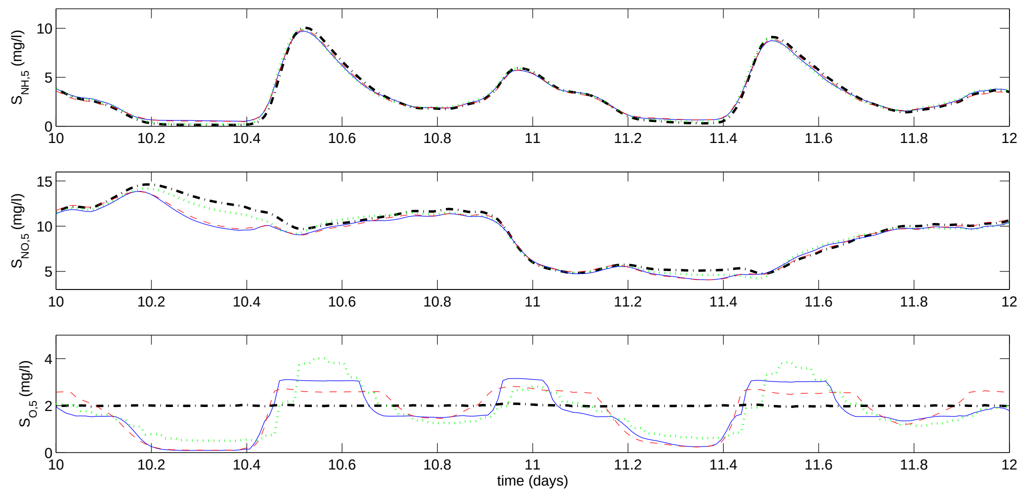

FIGURE 4.13: Storm influent: Comparison of $S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$. MPC+FF (dash-dotted line), higher level MPC (dotted line), higher level affine function (dashed line) and higher level FC (solid line)

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4.2 Application of variable dissolved oxygen in the three aerobic reactors

As it is shown in previous section, the results of OCI and EQI with higher level affine function and higher level FC were similar and better than those obtained with higher level MPC. Thus, the manipulation of the three aerobic reactors (see Fig. 4.17) has been

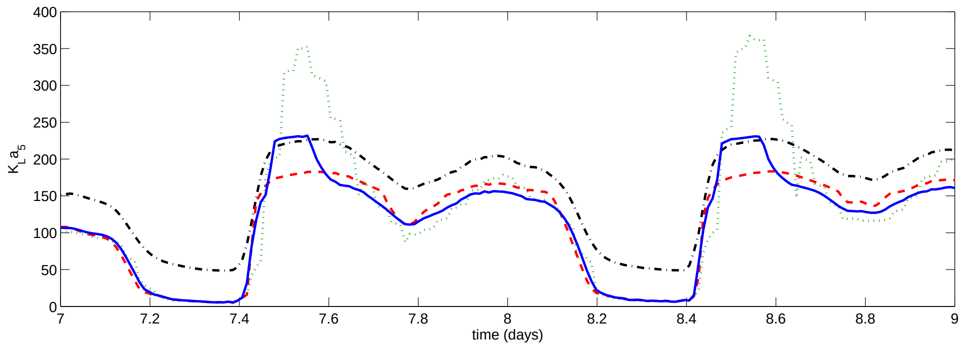

FIGURE 4.14: Dry influent: Comparison of K_La_5 in the fifth tank. MPC+FF (dash-dotted line), higher level MPC (dotted line), higher level affine function (dashed line) and higher level FC (solid line)

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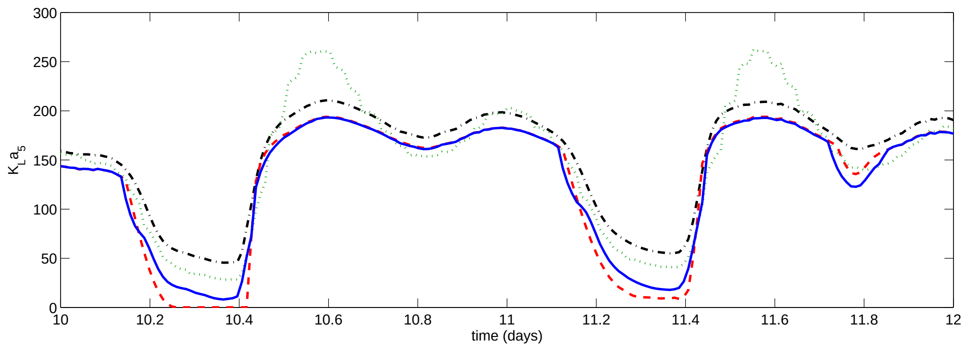

FIGURE 4.15: Rain influent: Comparison of K_La_5 in the fifth tank. MPC+FF (dash-dotted line), higher level MPC (dotted line), higher level affine function (dashed line) and higher level FC (solid line)

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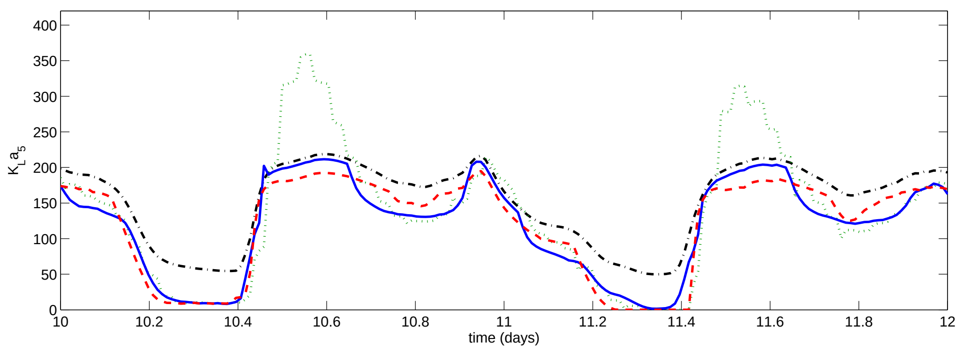

FIGURE 4.16: Storm influent: Comparison of K_La_5 in the fifth tank. MPC+FF (dash-dotted line), higher level MPC (dotted line), higher level affine function (dashed line) and higher level FC (solid line)

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Dry weather										
	MPC+FF	Higher level MPC			Higher level affine function			Higher level FC		
		lowest EQI	lowest OCI	%	lowest EQI	lowest OCI	%	lowest EQI	lowest OCI	%
EQI (kg pollutans/d)	6048.31	5936.16	6045.44	-1.8%	5900.98	6047.52	-2.4%	5900.73	6047.95	-2.4%
OCI	16382.97	16382.64	16248.79	-0.8%	16381.54	16196.68	-1.1%	16382.67	16197.86	-1.1%
Rain weather										
	MPC+FF	Higher level MPC			Higher level affine function			Higher level FC		
		lowest EQI	lowest OCI	%	lowest EQI	lowest OCI	%	lowest EQI	lowest OCI	%
EQI (kg pollutans/d)	8090.29	8056.07	8089.98	-0.4%	7994.58	8090.38	-1.1%	7998.78	8090.27	-1.1%
OCI	15990.85	15982.47	15939.32	-0.3%	15984.16	15887.47	-0.6%	15984.23	15884.21	-0.6%
Storm weather										
	MPC+FF	Higher level MPC			Higher level affine function			Higher level FC		
		lowest EQI	lowest OCI	%	lowest EQI	lowest OCI	%	lowest EQI	lowest OCI	%
EQI (kg pollutans/d)	7132.60	7094.90	7131.57	-0.5%	7019.08	7132.21	-1.5%	7020.83	7132.25	-1.5%
OCI	17261.39	17252.84	17186.58	-0.4%	17252.51	17126.55	-0.8%	17252.6	17123.01	-0.8%

Table 4.4: EQI and OCI results with MPC+FF, higher level MPC, higher level affine function and higher level FC for dry, rain and storm influents

tested with an affine function and a FC in the higher level of the hierarchical structure, but not with an MPC.

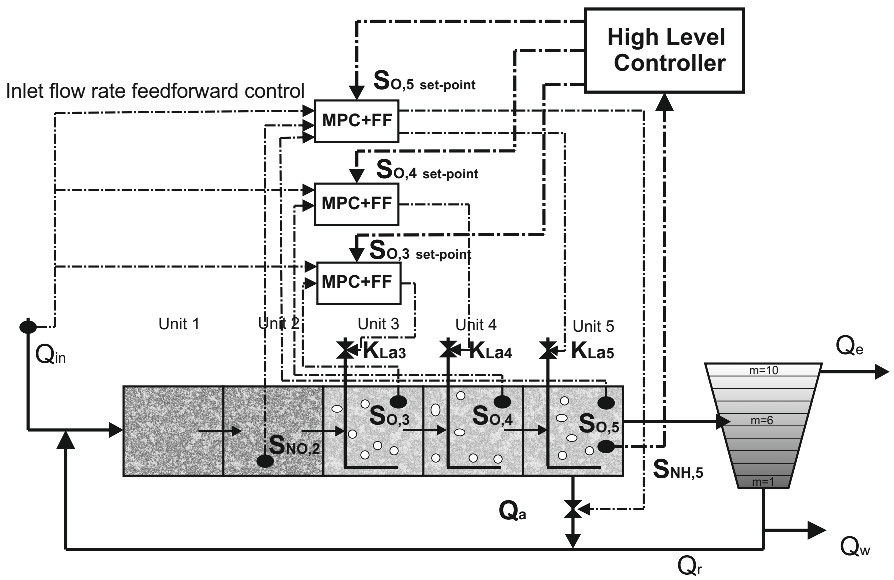


Figure 4.17: BSM1 with MPC+FF and Hierarchical control for the three aerobic reactors

4.2.1 Controllers tuning

Higher level affine function: The same affine function (4.1) is proposed to manipulate the three aerobic reactors. Thus, the $S_{O,5}$ set-point value is also applied to $S_{O,3}$ and $S_{O,4}$ set-points. Also a constraint for the maximum $S_{O,3}$, $S_{O,4}$ and $S_{O,5}$ values has been considered. The OCI and EQI trade-off representations of the higher level affine function are made based on k and S_O maximum values, which is the same for the three aerobic tanks. These trade-off analysis for the three weather conditions are shown in Fig.4.18, Fig.4.19 and Fig. 4.20. Each line corresponds to one of the S_O maximum values considered: 2, 3, 4, and 4.5. And each point of one line, marked with crosses, is obtained with a different value of k.

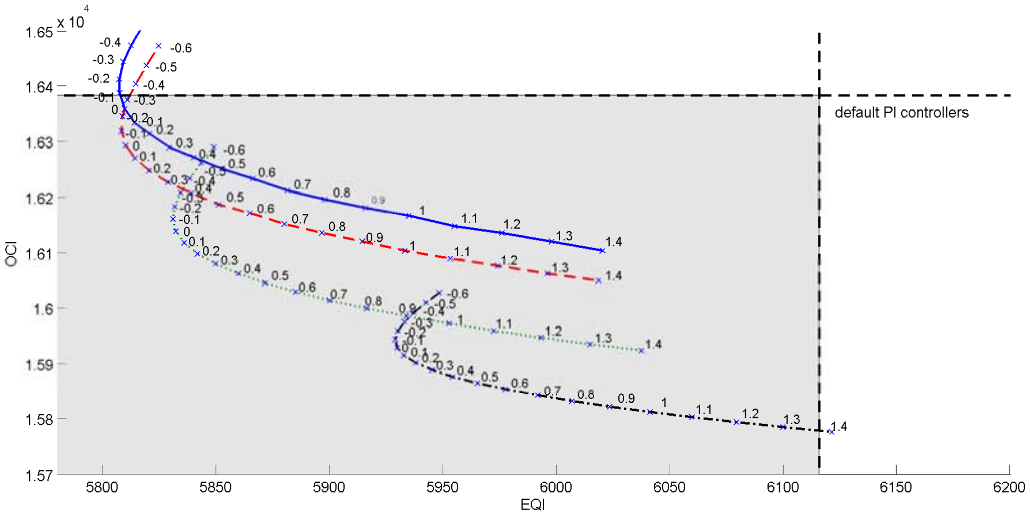


FIGURE 4.18: Dry weather: OCI and EQI trade-off representation with higher level affine function for a range of k values from -0.6 to 1.4 with increments of 0.1 (points marked with crosses) and S_O maximum = 4 (solid line), 3.5 (dashed line), 3 (dotted line), 2 (dash-dotted line)

A tuning area is obtained where OCI and EQI are reduced compared to the default PI controllers. S_O maximum and k values have been selected for the extreme cases of lowest EQI without increasing OCI and the lowest OCI without worsening EQI are achieved. Table 4.5 shows these tuning parameters selection for the three influents.

Higher level Fuzzy Controller: For the higher level FC, three triangular membership functions for input and for output are used (*low*, *medium* and *high*). The rules implemented are:

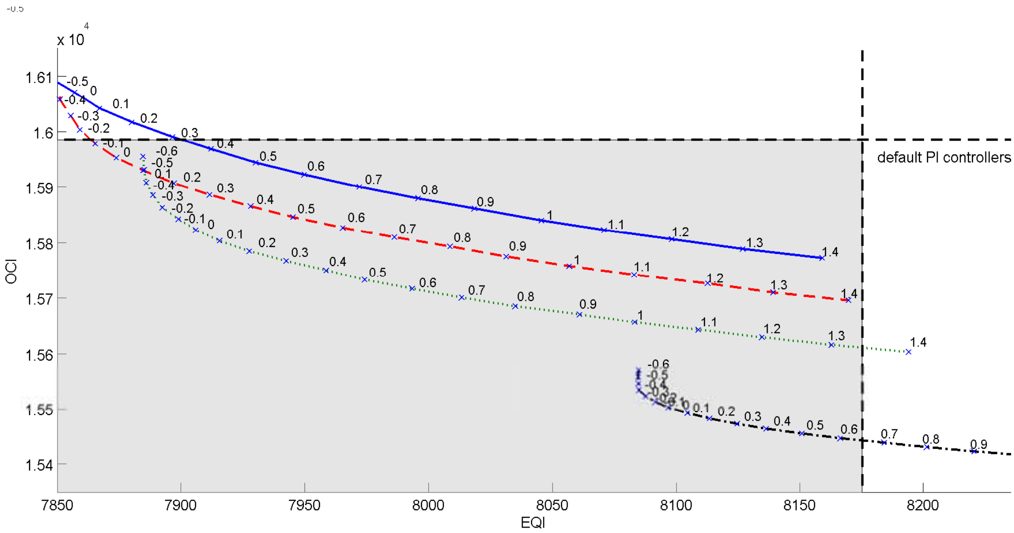


FIGURE 4.19: Rain weather: OCI and EQI trade-off representation with higher level affine function for a range of k values from -0.6 to 1.4 with increments of 0.1 (points marked with crosses) and S_O maximum = 4 (solid line), 3.5 (dashed line), 3 (dotted line), 2 (dash-dotted line)

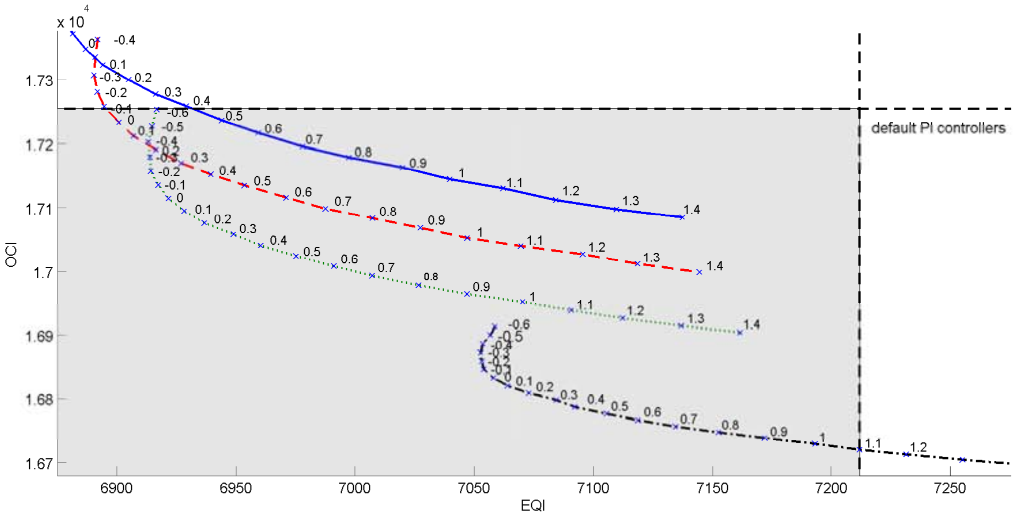


FIGURE 4.20: Storm weather: OCI and EQI trade-off representation with higher level affine function for a range of k values from -0.6 to 1.4 with increments of 0.1 (points marked with crosses) and S_O maximum = 4 (solid line), 3.5 (dashed line), 3 (dotted line), 2 (dash-dotted line)

if ($S_{NH,5}$ is *low*) **then** (S_O is *low*)

if ($S_{NH,5}$ is *medium*) **then** (S_O is *medium*)

if ($S_{NH,5}$ is *high*) **then** (S_O is *high*)

$MinIn$ and $MinOut$ are 0.1 and 0.8 respectively. $MaxIn$ and $MaxOut$ have been determined with OCI and EQI trade-off representations, for the three weather conditions,

	dry		rain		storm	
	lowest EQI	lowest OCI	lowest EQI	lowest OCI	lowest EQI	lowest OCI
k	-0.08	1.37	-0.1	0.62	-0.09	1.08
S_O maximum	4.5	2	3.5	2	3.5	2

TABLE 4.5: Higher level affine function tuning of the three aerobic tanks: k and S_O maximum values

shown in Fig. 4.21, Fig. 4.22 and Fig. 4.23. Each one of the lines corresponds to the results obtained with different $MaxIn$, i.e. 3, 5, 7, and each one of the points marked with crosses is the result of a different $MaxOut$. The results obtained with default PI controllers are also shown.

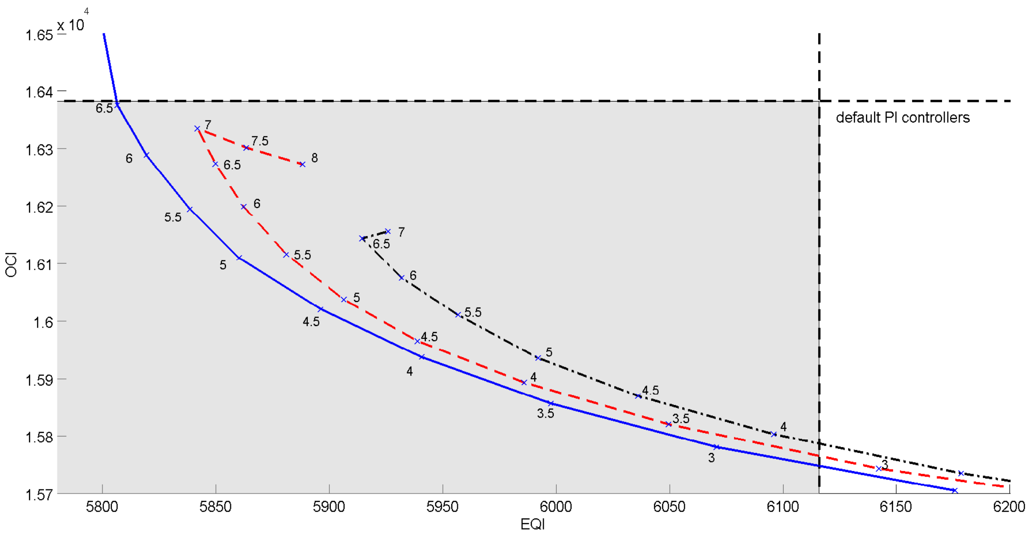


FIGURE 4.21: Dry weather: OCI and EQI trade-off with higher level FC for a range of $MaxOut$ from 2.5 to 8 with increments of 0.5 (points marked with crosses) and $MaxIn$ = 3 (solid line), 5 (dashed line), 7 (dash-dotted line)

In the same way as higher level affine function, for the three weather conditions, a tuning region is obtained where OCI and EQI are improved in comparison with default PI controllers. The $MaxIn$ and $MaxOut$ values of the extreme cases of lowest EQI without increasing OCI and lowest OCI without worsening EQI are shown in Table 4.6.

	dry		rain		storm	
	lowest EQI	lowest OCI	lowest EQI	lowest OCI	lowest EQI	lowest OCI
$MaxIn$	3	3	3	3	3	3
$MaxOut$	6.5	2.75	5.6	3.4	5.6	3.15

TABLE 4.6: Higher level FC tuning of the three aerobic tanks: $MaxIn$ and $MaxOut$ values

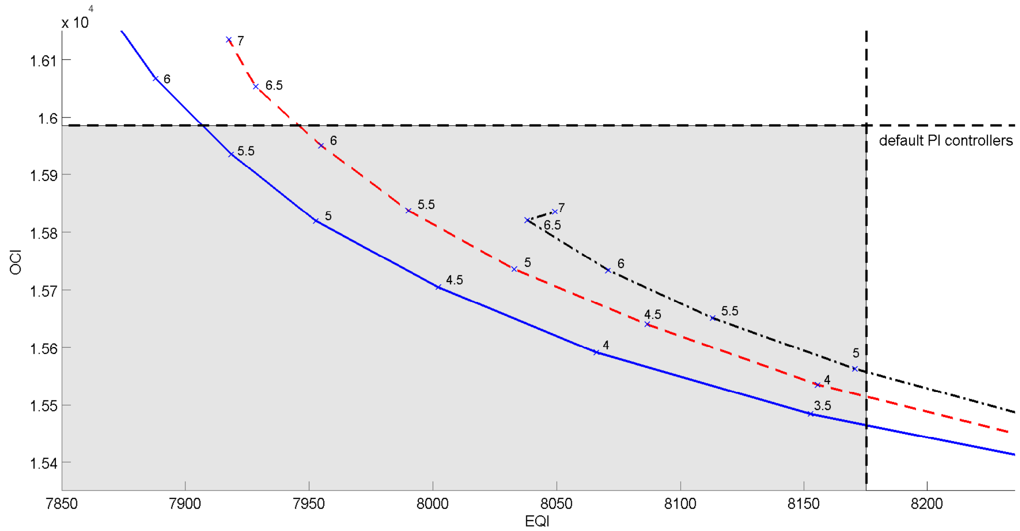


FIGURE 4.22: Rain weather: OCI and EQI trade-off with higher level FC for a range of $MaxOut$ from 2.5 to 7 with increments of 0.5 (points marked with crosses) and $MaxIn$ = 3 (solid line), 5 (dashed line), 7 (dash-dotted line)

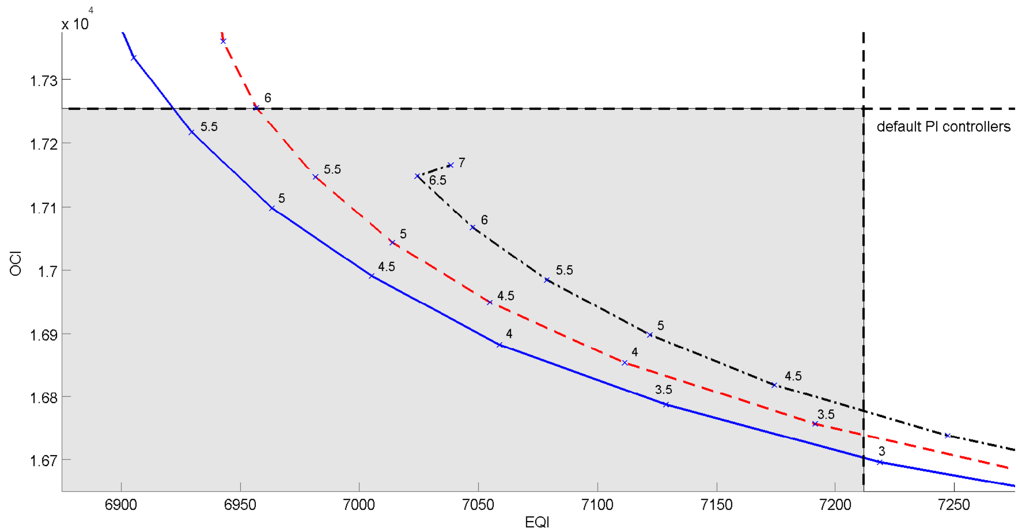


FIGURE 4.23: Storm weather: OCI and EQI trade-off with higher level FC for a range of $MaxOut$ from 2.5 to 7 with increments of 0.5 (points marked with crosses) and $MaxIn = 3$ (solid line), 5 (dashed line), 7 (dash-dotted line)

4.2.2 Simulations results

Table 4.7 presents the results of best EQI without increasing OCI and best OCI without worsening EQI of the hierarchical control for the three aerobic reactors in comparison with the default control strategy. The comparison is done with the two higher level alternatives (affine function and FC), using the three influent files (dry, rain and storm). As it is shown, a satisfactory reduction in OCI and EQI is achieved with the proposed hierarchical control. This reduction is higher in dry weather conditions, especially the EQI reduction. The results obtained with higher level affine function and higher level FC are similar, in the same way as the hierarchical control by manipulating only $S_{O,5}$, as shown in the previous section.

Dry weather							
	Default PI controllers	Hierarchical Control (three aerobic tanks) higher level affine function			Hierarchical Control (three aerobic tanks) higher level FC		
		lowest EQI	lowest OCI	% of reduction	lowest EQI	lowest OCI	% of reduction
EQI (kg pollutans/d)	6115.63	5807.77	6046.51	5%	5804.38	6037.07	5%
OCI	16381.93	16381.51	15779.58	3.7%	16377.51	15743.91	3.9%
Rain weather							
	Default PI controllers	Hierarchical Control (three aerobic tanks) higher level affine function			Hierarchical Control (three aerobic tanks) higher level FC		
		lowest EQI	lowest OCI	% of reduction	lowest EQI	lowest OCI	% of reduction
EQI (kg pollutans/d)	8174.98	7865.31	8172.01	3.8%	7910.26	8168.45	3.2%
OCI	15984.85	15977.56	15445.31	3.4%	15959.92	15466.01	3.2%
Storm weather							
	Default PI controllers	Hierarchical Control (three aerobic tanks) higher level affine function			Hierarchical Control (three aerobic tanks) higher level FC		
		lowest EQI	lowest OCI	% of reduction	lowest EQI	lowest OCI	% of reduction
EQI (kg pollutans/d)	7211.48	6895.74	7211.48	3.3%	6919.2	7200.51	3%
OCI	17253.75	17251.71	16721.06	3.1%	17254.25	16711.96	3.1%

TABLE 4.7: EQI and OCI results with default PI controllers and hierarchical control of the three aerobic tanks

In order to explain the EQI improvement, Fig. 4.24 shows the behaviour of S_O of the aerated tanks, $S_{NH,5}$ and $S_{NO,5}$ from day 7 to day 14. This is performed with the default control strategy and the proposed hierarchical control with the tuning parameters that give the lowest EQI for dry weahter. Due to the results obtained with higher level affine function and higher level FC are very similar, only the variables of one of the two controllers (specifically affine function) are shown. As it is shown, with hierarchical control, when S_{NH} increases more S_O is added for nitrification, reducing S_{NH} peaks (2.1 and 2.5). On the contrary, when S_{NH} decreases, less S_O is required, producing less S_{NO} in comparison with the default control strategy (2.2 and 2.5).

In order to clarify the reason of the cost reduction, Table 4.8 shows the average values of the parameters that compose the OCI equation. They are the values obtained for dry influent by using the default control strategy and by applying hierarchical control with higher level FC that is the alternative that achieves the lowest OCI. As it is seen, the cost reduction is the result of an AE reduction of 683.72 KWh/d. This fact is due to the reduction of S_O (and hence a reduction of K_La) of the aerated tanks when $S_{NH,5}$ is low. Although there is a PE increase of 53.43 kWh/d, the saving energy, considering both parameters, is 630.29 kWh/d.

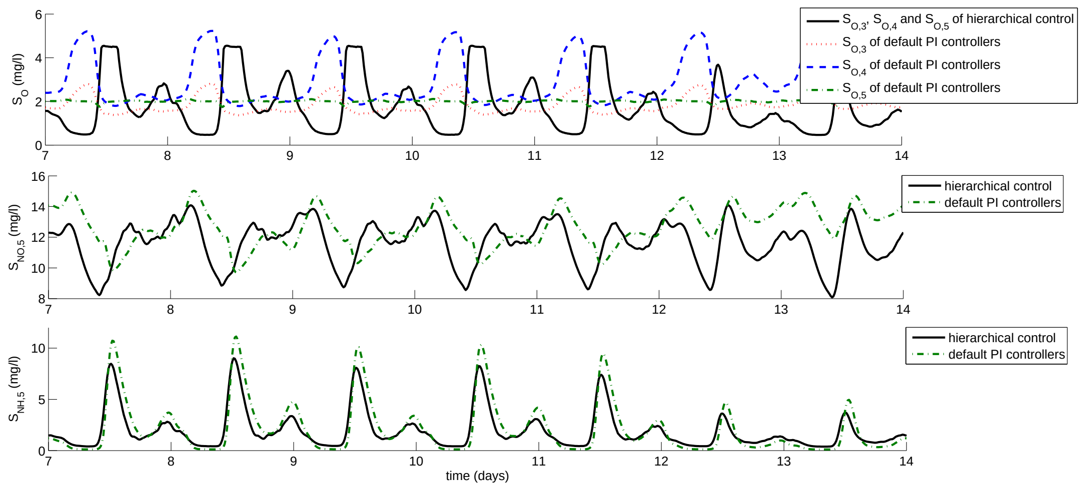


FIGURE 4.24: S_O in the aerated tanks, $S_{NO,5}$ and $S_{NH,5}$ evolution form day 7 to day 14 with the default PI controllers and with the proposed hiearchical control with higher level affine function for the case of lowest EQI

Average values of the OCI parameters	Default PI controllers	Hierarchical control	Reduction
AE (KWh/d)	3696.67	3012.95	683.72
PE (KWh/d)	241.72	295.15	-53.43
ME (KWh/d)	240	240	0
EC (Kg/d)	0	0	0
SP (Kg/d)	2440.71	2439.16	1.55

TABLE 4.8: Average values of the parameters that compose the OCI equation for PI controllers of the default control strategy and the proposed hierarchical control of the three aerobic tanks with higher level FC for the case of lowest OCI

4.3 Summary

In this chapter, the higher level control of the hierarchical structure has been applied using BSM1 as testing plant. This level regulates the S_O set-points of the aerated tanks based on $S_{NH,5}$.

First, for the selection of the higher level controller, three different alternatives were proposed manipulating only $S_{O,5}$ set-point: a MPC, an affine function and a FC. They were tested and compared in the three weather conditions: dry, rain and storm. As a result, EQI and OCI were reduced significantly. The results of OCI and EQI with higher level affine function and higher level FC were similar and better than those obtained with higher level MPC. This is due to the fact that the higher level MPC tries to keep the value of $S_{NH,5}$ at a reference level, but this is not possible. For that reason, the alternatives of affine function and FC for the higher level were tested with the idea of varying $S_{O,5}$ based on the $S_{NH,5}$ measured, taking into account the variables behavior in the biological processes, but without trying to keep $S_{NH,5}$ at a fixed reference. Thus, improving the nitrification process when $S_{NH,5}$ increases, to oxidize more S_{NH} and worsening the nitrification process when $S_{NH,5}$ decreases to generate less S_{NO} and to reduce costs. To ensure the right tuning of the controllers and therefore the correct relationship between the applied control and the results, a trade-off analysis between OCI and EQI has been performed by varying two tuning parameters for each controller.

Next, the higher level control has been extended, manipulating the three aerobic tanks. Simulation results show that manipulating the S_O set-points of the three aerobic tanks, an EQI reduction of 5% and an OCI reduction of 3.9% is achieved for dry weather compared to the default control strategy. For the rain and storm influent cases, also a satisfactory reduction of EQI and OCI is obtained, higher than 3%.

Part II

Effluent limits violations removal

Chapter 5

Control Strategies for denitrification and nitrification processes improvement

Some works of the literature put their focus on avoiding violations of the effluent limits by applying a direct control of the effluent variables, mainly $S_{NH,e}$ and $S_{N_{tot},e}$ (Corriou and Pons [9], Shen et al. [10, 11]). 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.

In this chapter, different control strategies are applied with the aim of avoiding $S_{N_{tot},e}$ or $S_{NH,e}$ violations using BSM1 as testing plant. These control strategies are implemented simultaneously with the hierarchical control structure explained in previous chapter, in order to achieve, at the same time, an EQI and OCI reduction. The tuning of both higher level controllers is modified based on the required objective.

The controllers applied for the proposed control strategies are divided into two alternatives: functions that relate the inputs and the manipulated variables, and FCs. Therefore, on one hand, an affine function is proposed to eliminate $S_{N_{tot},e}$ violations and a combination of a linear function with an exponential function to remove $S_{NH,e}$ violations. At the same time, the higher level affine function (4.1) is applied. On the other hand, two FCs are proposed to avoid $S_{N_{tot},e}$ and $S_{NH,e}$ violations. The higher level FC is also applied.

For the cases of a rain or storm event and for the simultaneous $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal, an extra control is added based on affine functions, for both alternatives.

5.1 Control for $S_{N_{tot,e}}$ violations removal

The variables with the highest influence in $S_{N_{tot,e}}$ are S_{NO} and S_{NH}. Further efforts to reduce more S_{NH} increasing nitrification results also in an increment of S_{NO} and consequently $S_{N_{tot,e}}$ is not decreased. According to the biological processes of ASM1, an increase of substrate produces a growth of $X_{B,H}$ 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 (2.13), 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 $q_{EC,1}$ according to $S_{NH,5}$ plus $S_{NO,5}$ (see Fig. 5.1). An affine function with a sliding window and a FC are proposed for this control strategy.

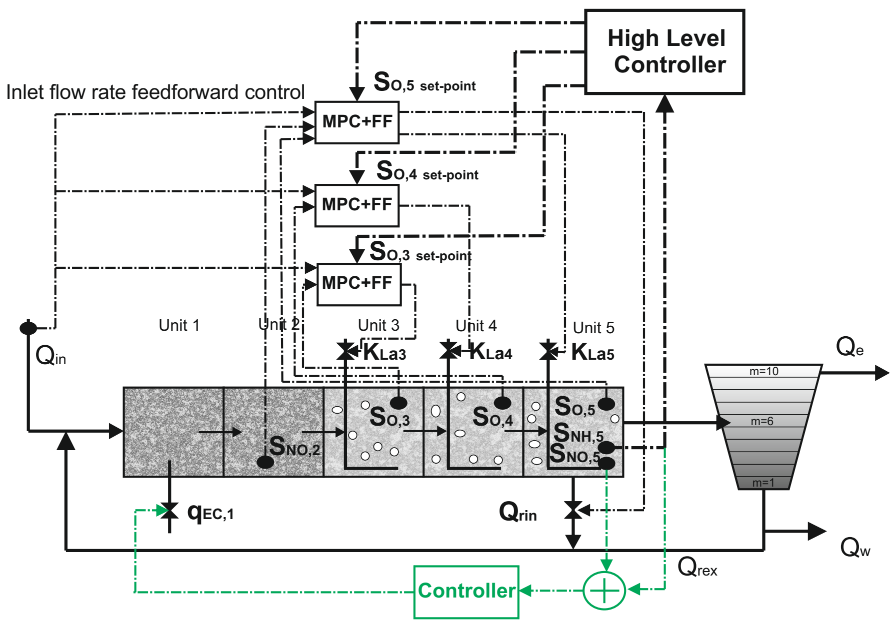


FIGURE 5.1: BSM1 with a control strategy for $S_{N_{tot,e}}$ violations removal

5.1.1 Controllers tuning

Functions: Here, the tunings of the both affine functions, for the higher level control and for the control for $S_{N_{tot,e}}$ violations removal, are described.

First, for the higher level affine function, a trade-off analysis is made considering the percentage of operating time that $S_{NH,e}$ and $S_{N_{tot,e}}$ is over the limits. The purpose of this trade-off analysis is, besides the $S_{N_{tot,e}}$ violations removal, not to increase OCI and to reduce EQI and the percentage of time of $S_{NH,e}$ violations in comparison with the default control strategy. This is done with hierarchical control strategy and without adding EC1 (see Fig. 5.2). Tuning parameters are chosen for the point where the percentage of operating time of $S_{NH,e}$ over the limits is the same as with default control strategy (17.26%). The tuning parameters of the higher level affine function are $k = 1.07$ and S_O maximum $= 3$, and the percentage of operating time of $S_{N_{tot,e}}$ violation with these parameters is 6.35%.

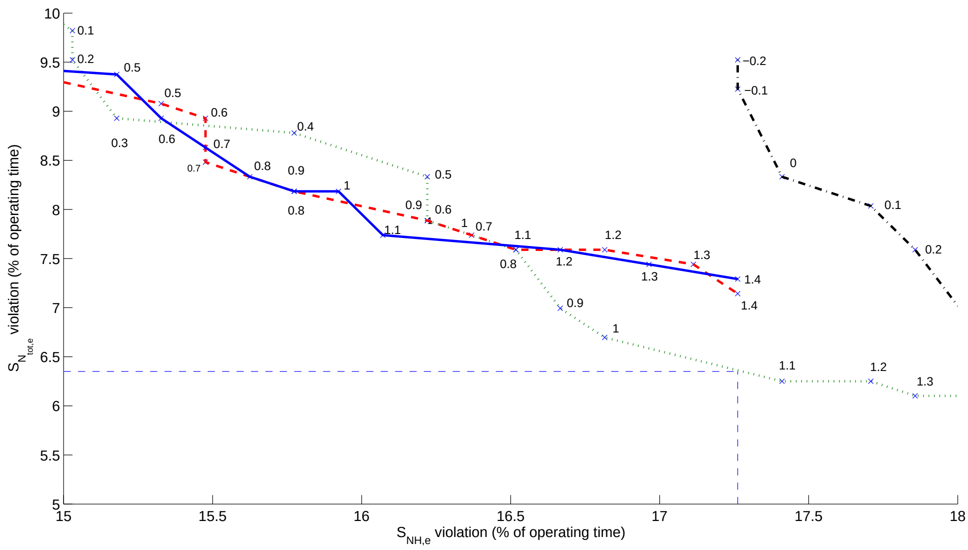


FIGURE 5.2: Trade-off representation of the percentage of the operating of $S_{NH,e}$ and $S_{N_{tot,e}}$ violations for a range of k values from -0.6 to 1.4 with increments of 0.1 (points marked with crosses) and $S_{O,5}$ maximum $= 4.5$ (solid line), 4 (dashed line), 3 (dotted line), 2.5 (dash-dotted line)

The OCI and EQI trade-off representation shown in Fig. 4.18, in the points of the tuning parameters mentioned, a difference in OCI of 2.5% is observed regarding the default control strategy, which may be used for the EC1 dosage.

Then, the following affine function is proposed for $q_{EC,1}$ manipulation with the objective of $S_{N_{tot,e}}$ violations removal:

$$q_{EC1} = ((S_{NH,5} + S_{NO,5}) - a) \cdot b \tag{5.1}$$

where a and b are used as tuning parameters, whose values are set depending on the maximum value of $S_{N_{tot,e}}$ given by a sliding window, which is shift at each sample time and presents only the values measured the day one week before. Specifically, following are shown the chosen equations for a and b values:

$$b = M_d \cdot 2 - 35.5 \tag{5.2}$$

$$a = 34.25 - M_d \tag{5.3}$$

where M_d is the maximum value of the day, one week before. This approach tries to dosage the minimum of $q_{EC,1}$ to remove $S_{N_{tot,e}}$ violations. The maximum $q_{EC,1}$ value was limited to $5m^3/d$.

Fuzzy Controllers: The tuning of the FCs is implemented with the objectives of removing $S_{N_{tot,e}}$ violations and, at the same time, reducing EQI, OCI and the percentage of time of $S_{NH,e}$ violations. First for the higher level FC and next for the FC that manipulates $q_{EC,1}$ for $S_{N_{tot,e}}$ violations removal.

For the tuning parameters selection of the higher level FC, a trade-off analysis of the percentage of time over the limits of $S_{NH,e}$ and $S_{N_{tot,e}}$ is made (see Fig. 5.3). For this analysis, the hierarchical control strategy is included but not the addition of EC1. The tuning parameters of the higher level FC are selected in the point whose percentage of operating time of $S_{NH,e}$ over the limits is the same as with the default control strategy (17.26%). These tuning parameters are $MaxIn = 3$ and $MaxOut = 4.1$, and the percentage of operating time of $S_{N_{tot,e}}$ violation with these parameters is 6.39%.

The OCI and EQI trade-off representation shown in Fig. 4.21, in the points of the tuning parameters mentioned, a difference in OCI of 2.6% is observed regarding the default control strategy, which may be used for the EC1 dosage.

With these parameters selected for the higher level, a FC is added to manipulate $q_{EC,1}$. For this controller, three triangular membership functions for input and for output are

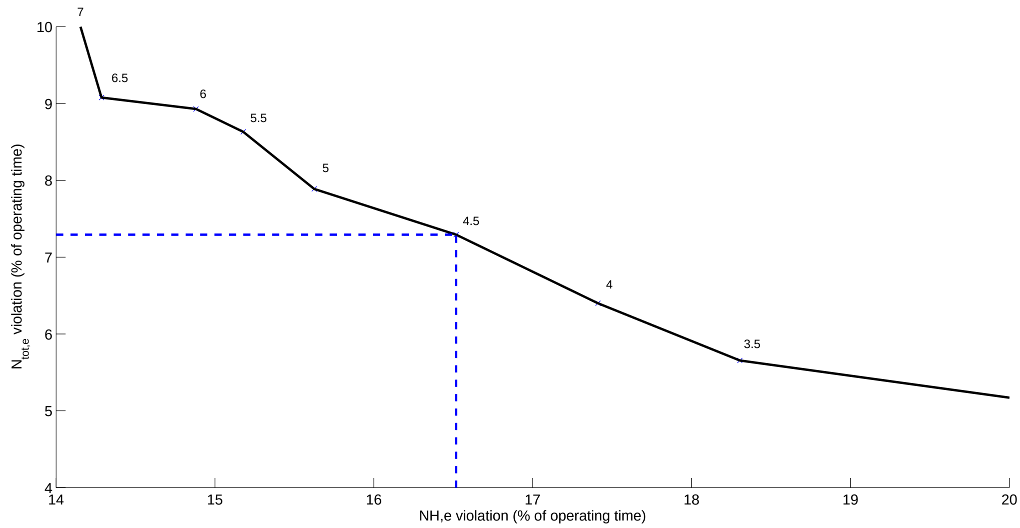


FIGURE 5.3: Higher level FC: trade-off of the time percentage of $S_{NH,e}$ and $S_{N_{tot,e}}$ violations for $MaxIn$ = 3 and a range of $MaxOut$ values from 3 to 7 with increments of 0.5 (points marked with crosses)

used (*low*, *medium* and *high*). The rules implemented are:

if ($S_{NH,5}$+$S_{NO,5}$ is *low*) **then** ($q_{EC,1}$ is *low*)

if ($S_{NH,5}$+$S_{NO,5}$ is *medium*) **then** ($q_{EC,1}$ is *medium*)

if ($S_{NH,5}$+$S_{NO,5}$ is *high*) **then** ($q_{EC,1}$ is *high*)

The range of membership functions values are: $MinIn$ = 10, $MaxIn$ = 17.5, $MinOut$ = -8, $MaxOut$ = 6.75.

5.1.2 Control for rain and storm influents

During a rain or storm event, Q_{in} increases and S_{NH} in the influent ($S_{NH,in}$) decreases. The Q_{in} increment has the effect of reducing the hydraulic retention time and the $S_{NH,in}$ reduction decreases the growth of $X_{B,A}$ and therefore the nitrification process (2.5) is worsened. Due to this reason, there is an increase of S_{NH} without incrementing the generation of S_{NO} (2.2 and 2.5). Therefore, the resulting $S_{N_{tot,e}}$ is lower than for dry weather. However, in the periods after the rain or storm events, the Q_{in} reduction has an immediate effect on the hydraulic retention time, but $X_{B,H}$ and $X_{B,A}$ need more time to recover their normal levels and it causes a small $S_{N_{tot,e}}$ increase. To compensate this,

$q_{EC,1}$ is added based on $S_{NH,5}$ plus $S_{NO,5}$ and on the average of $S_{NH,in}$ of the two days before ($S_{NH,inmean_2}$) with the following affine function:

$$q_{EC,1} = (S_{NH,5} + S_{NO,5}) \cdot 5 - S_{NH,inmean_2} \cdot 0.2857 - 75.7143 \tag{5.4}$$

where the constants values are found by three experimental cases.

5.2 Control for $S_{NH,e}$ violations removal

With the goal of removing $S_{NH,e}$ violations, Q_a is manipulated based on $S_{NH,5}$ and $S_{NH,in}$. Therefore the MPC of the lower level that controls $S_{O,5}$ and $S_{NO,2}$ by manipulating K_La_5 and Q_a is replaced by a MPC with one input ($S_{O,5}$) and one output (K_La_5) (see Fig. 5.4).

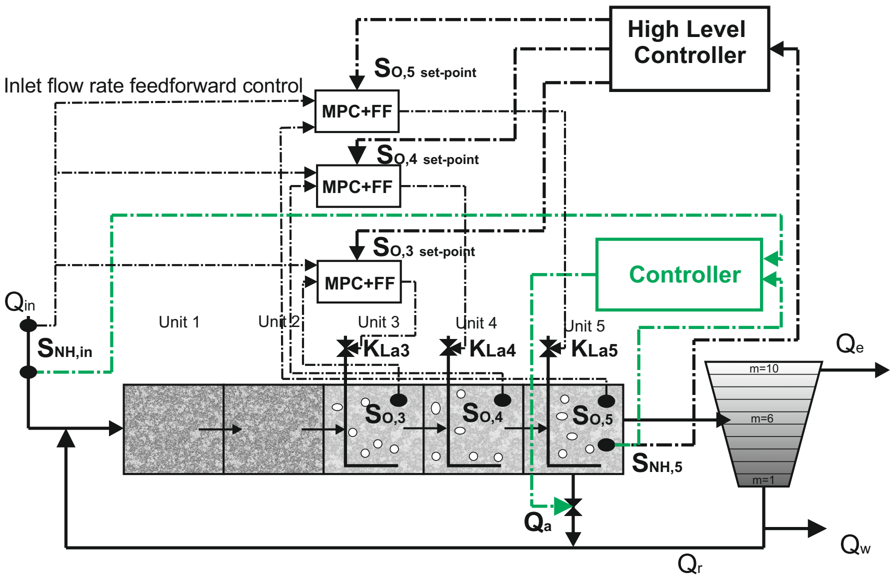


FIGURE 5.4: BSM1 with a control strategy for $S_{NH,e}$ violations removal

To facilitate the understanding of the proposed solution some considerations about the propagation of the peaks in the reactor are provided: 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_{in} 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 in the first reactor (2.7), when $S_{NH,in}$ 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.

Two controllers are proposed for this control strategy: first, a combination of a linear function and a exponential function, and next, a FC with two different tunings.

5.2.1 Controllers tuning

MPC+FF: As mentioned, to perform the control for removing violations of $S_{NH,e}$, the MIMO MPC+FF that controls $S_{O,5}$ and $S_{NO,2}$ by manipulating K_La_5 and Q_a, has been replaced by a SISO MPC+FF that controls $S_{O,5}$ by manipulating K_La_5, because Q_a is manipulated based on $S_{NH,5}$ and $S_{NH,in}$.

The model identification of the new MPC+FF was performed with the same methodology as with the previous controller, but with one input and one output. However, in this case it is a second order state-space model:

$$\begin{aligned}
A &= \begin{bmatrix} 0.8349 & 0.2746 \\ 0.2512 & 0.2894 \end{bmatrix} \\
B &= \begin{bmatrix} 0.008745 & -2.729 \cdot 10^{-5} \\ -0.02118 & 1.307 \cdot 10^{-5} \end{bmatrix} \\
C &= \begin{bmatrix} 1.512 & -0.3525 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned} \tag{5.5}$$

The selected values to tune the MPC are $m = 5$, $p = 20$, $\triangle t = 0.00025$ days (21.6 seconds), $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 0.01$ and overall estimator gain = 0.8.

Functions: Here, the tunings of the controllers based on functions are described. First, the tuning of the higher level affine function, and next, the combination of the linear function and the exponential function for $S_{NH,e}$ violations removal.

For the higher level affine function (4.1), any parameters value inside the tuning region given by the OCI and EQI trade-off representation (see Fig. 4.18) can be selected. In this case the chosen parameters are: $k = 0.1$ and S_O maximum $= 4.5$.

For the control of $S_{NH,e}$ violations removal, a combination of exponential function and linear function is proposed for this control strategy. When there are peaks of $S_{NH,in}$ or $S_{NH,5}$, the following exponential function is applied:

$$Q_a = \frac{c}{exp(S_{NH,5} \cdot d)} \tag{5.6}$$

Otherwise the following linear function is applied:

$$Q_a = \frac{S_{NH,in}}{S_{NH,5}} \cdot e \tag{5.7}$$

where c, d and e are used as tuning parameters.

A trade-off analysis of OCI and percentage of operating time of $S_{N_{tot,e}}$ violation is made by varying the tuning parameters c and e of the exponential and linear functions, reflecting only the results that avoid the $S_{NH,e}$ violations. It is obtained an area where OCI and the operating time of $S_{N_{tot,e}}$ violation are decreased compared to default PI controllers (see Fig. 5.5). The value of d is fixed at 6, and c and e values are chosen according with the Nash Solution (Aumann and Hart [33]): $c = 2.5 \cdot 10^{14}$ and $e = 7 \cdot 10^{-4}$.

Fuzzy Controllers: Following, the tuning parameters of the higher level FC and the FC for $S_{NH,e}$ violations removal are defined.

The $MaxIn$ and $MaxOut$ values of the higher level FC have been selected by a trade-off analysis of OCI and percentage of operating time of $S_{NH,e}$ violation (see Fig. 5.6), choosing the less percentage of $S_{NH,e}$ violation in order to facilitate its later total elimination, but considering the increased costs that will be generated by the new control strategy. In this case the chosen parameters are: $MaxIn = 3$ and $MaxOut = 5.5$.

In the case of the FC for the $S_{NH,e}$ violations removal, two tunings are determined, one when there are peaks of $S_{NH,in}$ or $S_{NH,5}$, and the other the rest of the time. For both cases three triangular membership functions for input and for output are used (*low*, *medium* and *high*). The rules implemented are:

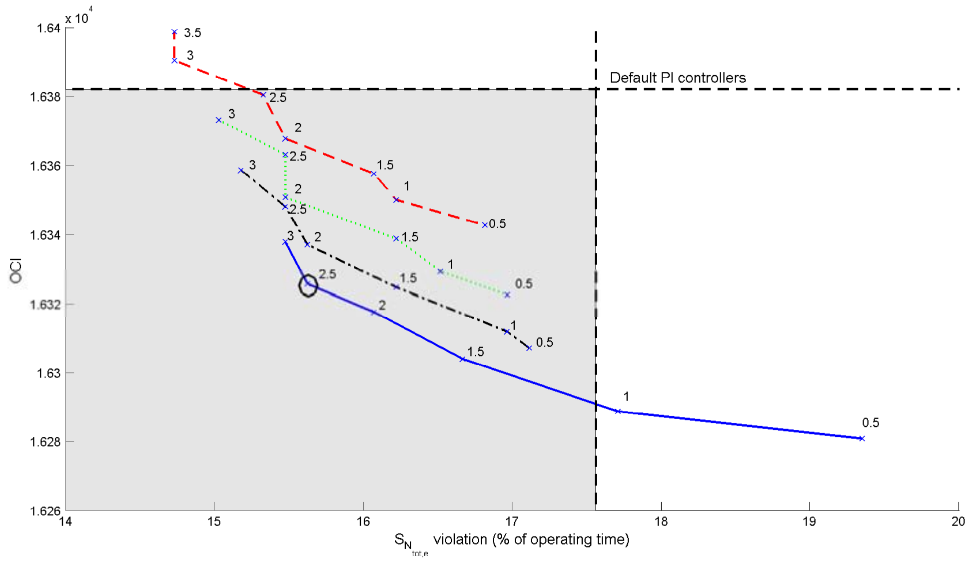


FIGURE 5.5: Trade-off representation of OCI and the percentage of operating time of $S_{N_{tot,e}}$ violations for a range of c values from 0.5 to 4 with increments of 0.5 (points marked with crosses) and e values = 7 (solid line), 6 (dash-dotted line), 5.5 (dotted line), 5 (dashed line)

if ($S_{NH,5}$ is *low*) **then** (Q_a is *high*)

if ($S_{NH,5}$ is *medium*) **then** (Q_a is *medium*)

if ($S_{NH,5}$ is *high*) **then** (Q_a is *low*)

When there are peaks of $S_{NH,in}$ or $S_{NH,5}$, the tuning parameters are set looking for a great variation in Q_a when $S_{NH,e}$ is increasing. Therefore, $MinIn$, $MaxIn$, $MinOut$ and $MaxOut$ are 3.5, 4.1, -2·10^4 and 14·10^4 respectively. For the rest of the time, $MinOut$ and $MaxOut$ are set by a trade-off analysis of OCI and percentage of operating time of $S_{N_{tot,e}}$ violation, reflecting only the results that avoid the $S_{NH,e}$ violations. An area is obtained where OCI and the operating time of $S_{N_{tot,e}}$ violation are decreased compared to default PI controllers (see Fig. 5.7). Each one of the lines corresponds to the results obtained with $MaxIn$ = 2, 2.2, 2.4 and 2.6 and each one of the points marked with crosses is the result of a different $MaxOut$ that varies from 90000 to 180000 with increments of 10000. The results obtained with default PI controllers alone are also shown. The parameters have been selected according to the Nash Solution ([33]): $MaxIn$ = 2.4 and $MaxOut$ = 100000.

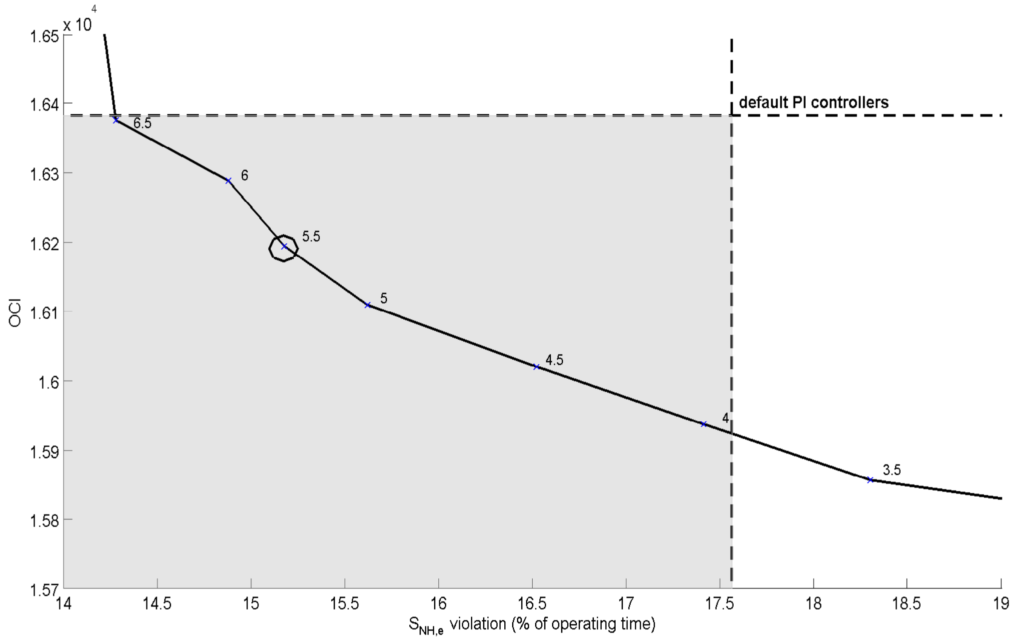


FIGURE 5.6: Trade-off representation of OCI and the percentage of operating time of $S_{NH,e}$ violations for $MaxIn = 3$ and a range of $MaxOut$ from 3 to 7 with increments of 0.5 (points marked with crosses).

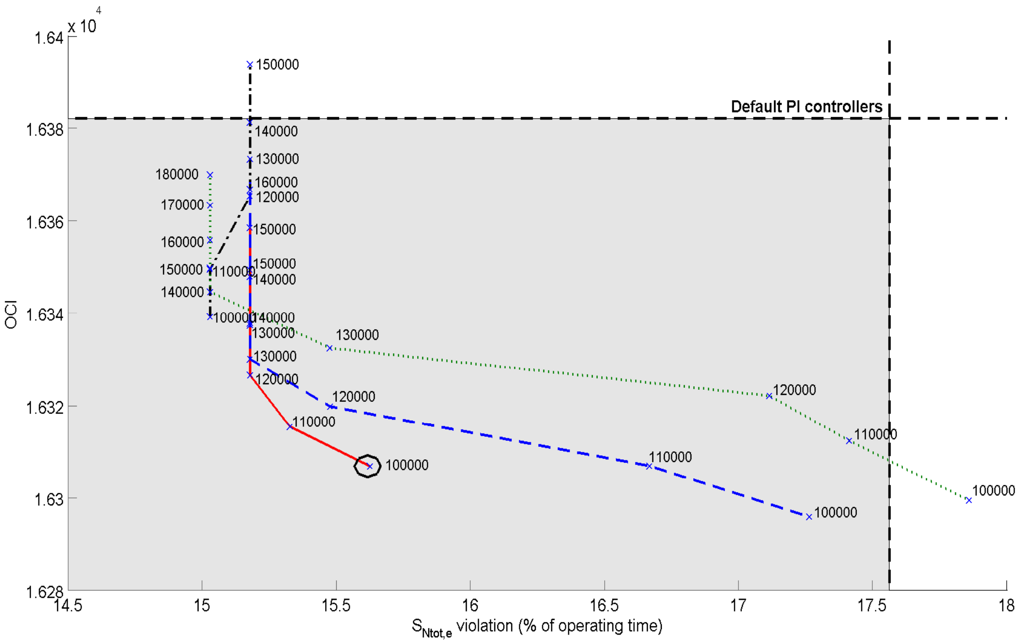


FIGURE 5.7: Trade-off representation of OCI and the percentage of operating time of $S_{N_{tot,e}}$ violations for a range of $MaxOut$ from 90000 to 180000 with increments of 10000 (points marked with crosses) and $MaxIn = 2$ (dotted line), 2.2 (dashed line), 2.4 (solid line), 2.6 (dash-dotted line)

5.2.2 Control for rain and storm influents

For rain and storm events the reduction of $S_{NH,e}$ using this control strategy is not enough to eliminate violations. This is due to that, during rain and storm periods, the $Q_{in} \cdot S_{NH,in}$ relationship is similar to that of dry weather, but Q_{in} increases and $S_{NH,in}$ decreases. This $S_{NH,in}$ reduction decreases the growth of $X_{B,A}$ and therefore the nitrification process (2.5) is worsened. For this reason, during a rain or storm event, when there is a peak of $S_{NH,in} \cdot Q_{in}$ and until $S_{NH,5}$ is decreased, a dosage of 5 m^3/d of q_{EC} in the fourth and fifth tanks ($q_{EC_{4-5}}$) is added, which is the maximum limit value. Normally, $q_{EC_{4-5}}$ is added to reduce S_{NO}, nevertheless in r_{NH} equation (2.1) it is observed that although the elimination of S_{NH} largely depends on nitrification (2.5), S_{NH} is also reduced with the growth of $X_{B,H}$ (2.3, 2.4).

The days after the rain and storm events present also problems with $S_{NH,e}$ limits violations due to the fact that the $X_{B,A}$ population decreases during those periods and does not recover its normal level until some days later. During those days $q_{EC_{4-5}}$ is added. As $X_{B,A}$ reduction is due to a $S_{NH,in}$ decrease, the addition of $q_{EC_{4-5}}$ is based on $S_{NH,inmean_2}$, using the following affine function:

$$q_{EC_{4-5}} = S_{NH,inmean_2} \cdot (-0.2667) + 7; \tag{5.8}$$

where the constants values are found by two experimental cases, which correspond to the extreme cases of highest and lowest dosage of $q_{EC_{4-5}}$ that is needed to eliminate violations of $S_{NH,e}$.

5.3 Simulation results

5.3.1 $S_{N_{tot,e}}$ violations removal

Fig. 5.8 correspond to the evolution of $q_{EC,1}$, $S_{N_{tot,e}}$ and $S_{NH,e}$ from day 7 to 14, with default PI controllers, applying control strategies for $S_{N_{tot,e}}$ violations removal with functions and applying control strategies for $S_{N_{tot,e}}$ violations removal with FCs. It is observed that, for both alternatives (functions and FCs), $S_{N_{tot,e}}$ violations are removed and the behavior of the variables are very similar. As it is shown, $q_{EC,1}$ dosage varies every day, while $S_{N_{tot,e}}$ peaks are very similar. It proves that the minimum necessary $q_{EC,1}$ is added, increasing the lowest possible costs. For this reason, and with the correct selection of the tuning parameters of the higher level explained in previous sections, the removal of $S_{N_{tot,e}}$ violations without increasing OCI, in comparison with default control strategy is possible. The choice of the right tuning parameters of the higher level affine function also makes possible to reduce the time of $S_{NH,e}$ violation.

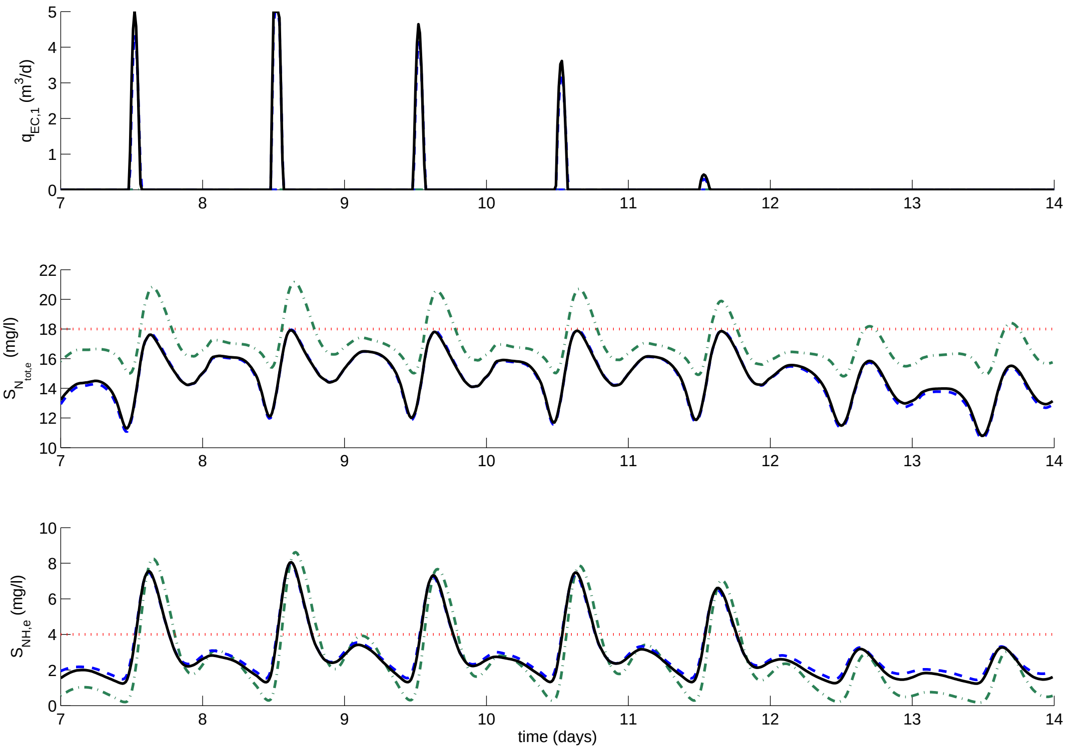


FIGURE 5.8: $q_{EC,1}$, $S_{NH,e}$ and $S_{N_{tot,e}}$ evolution form day 7 to day 14 with default PI controllers (dash-dotted line), applying control strategies for $S_{N_{tot,e}}$ violations removal with functions (dashed line) and applying control strategies for $S_{N_{tot,e}}$ violations removal with FCs (solid line)

Table 5.1 presents the results for EQI and OCI as well as the percentage of operating time out of the limits of $S_{N_{tot,e}}$ and $S_{NH,e}$ obtained with the control strategies for $S_{N_{tot,e}}$ violations removal and compared to the default control strategy of BSM1. It is shown that by adding $q_{EC,1}$ and applying a hierarchical control of S_O in the three aerated tanks, the violations of $S_{N_{tot,e}}$ can be avoided. Moreover, the results of EQI and OCI as well as the operating time percentage of $S_{NH,e}$ violations are also improved in comparison with the default PI controllers. This is achieved for the three influents provided by the BSM1 scenario.

Fig 5.9 and Fig. 5.10 show the time evolution of the most important variables for the cases of simulating with rain and storm influents. Due to the great similarity of the results between functions and FCs, only the simulated variables using functions are shown. During a rain or storm event, the nitrification process (2.5) is worsened as explained in Section 5.2.2. Due to this reason, there is an increase of S_{NH} without incrementing the generation of S_{NO} (2.2 and 2.5). Therefore, the resulting $S_{N_{tot,e}}$ is lower than for dry weather and less $q_{EC,1}$ is nedded for removing $S_{N_{tot,e}}$ violations. In the periods after the rain or storm events, $q_{EC,1}$ needs to be added until $X_{B,H}$ and $X_{B,A}$ recover their normal levels. Even so, this $q_{EC,1}$ addition is small, and OCI is reduced for the three influents with the proposed control strategy in comparison with the default control strategy. Nonetheless, it has to be said that that the reduction of costs would be greater if the savings costs obtained by avoiding effluent violations were considered.

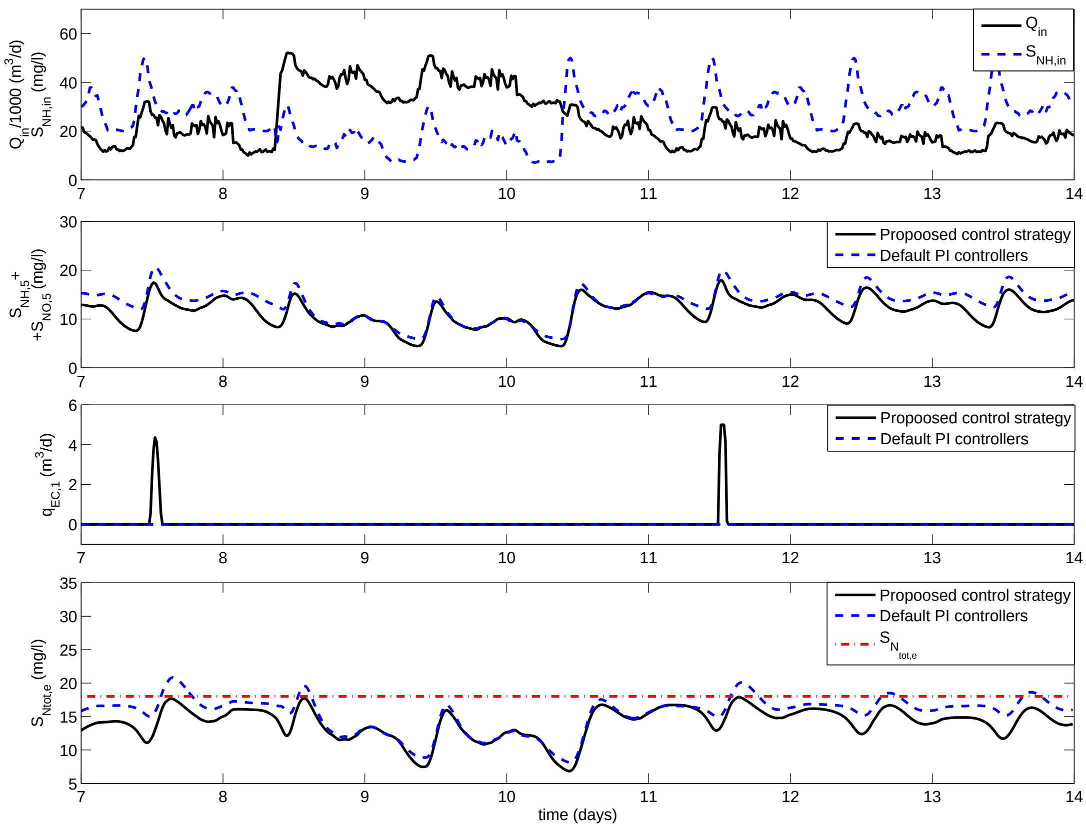


FIGURE 5.9: Rain influent: time evolution of the most important variables applying the proposed control strategy for $S_{N_{tot,e}}$ violations removal with functions and applying the default control strategy of BSM1.

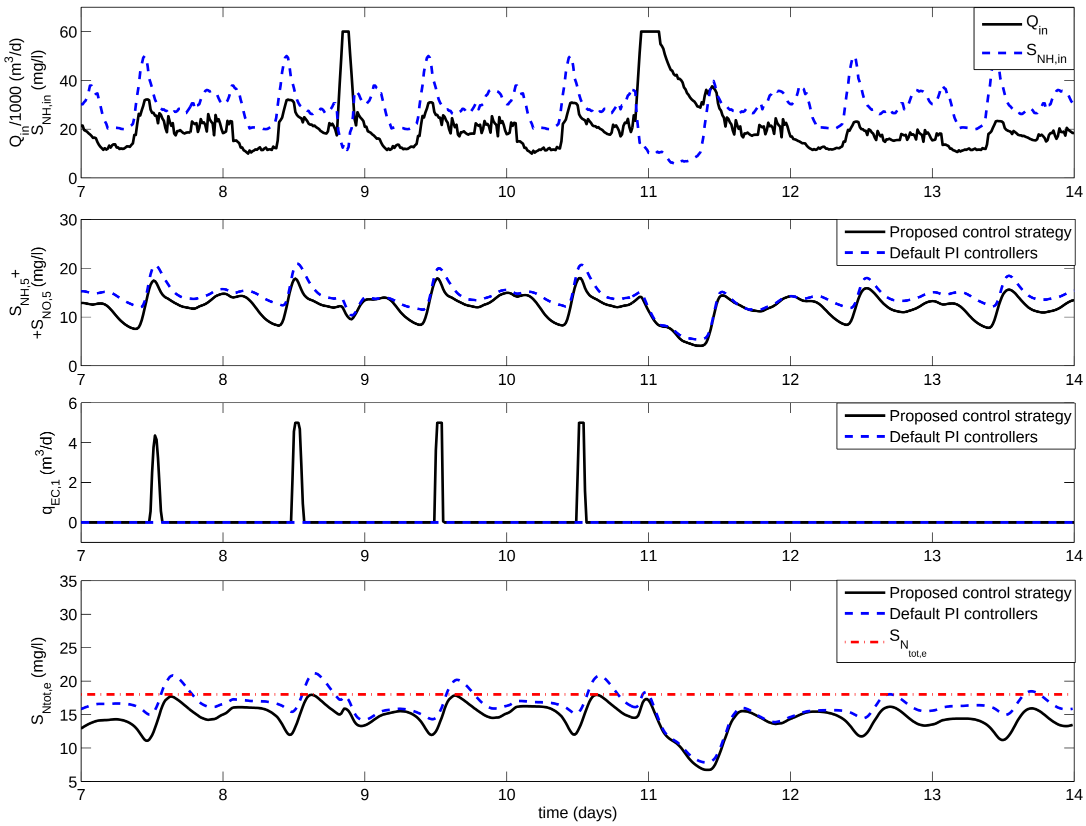


FIGURE 5.10: Storm influent: time evolution of the most important variables applying the proposed control strategy for $S_{N_{tot,e}}$ violations removal with functions and applying the default control strategy of BSM1.

5.3.2 $S_{NH,e}$ violations removal

Fig. 5.11 shows the evolutions of Q_a, $S_{N_{tot,e}}$ and $S_{NH,e}$ from day 7 to 14 with default PI controllers, applying control strategies for $S_{NH,e}$ violations removal with functions and applying control strategies for $S_{NH,e}$ violations removal with FCs. It can be observed that, with this control strategy, $S_{NH,e}$ peaks are reduced under the limits established. This fact is due to the increment of S_O by the hierarchical control (explained in the previous section) and mainly to the Q_a manipulation. As shown in Fig. 5.11, Q_a evolution by applying control strategies for $S_{N_{tot,e}}$ violations removal is very different from the one obtained with the default control strategy. When a $S_{NH,in}$ peak is detected, Q_a is increased to its maximum allowed value (92280 m^3/d) in order to dilute S_{NH}, and when this increase of S_{NH} arrives to the fifth tank, the exponential function rapidly reduces Q_a in order to decrease also the hydraulic retention time and so to improve the nitrification process. As a result, a large decrease of $S_{NH,e}$ peaks is achieved and limits

Dry influent					
	Default PI controllers	Control for $S_{N_{tot,e}}$ violations removal with functions	% of reduction	Control for $S_{N_{tot,e}}$ violations removal with FCs	% of reduction
EQI	6115.63	5910.83	3.3%	5862.03	4.1%
OCI	16381.93	16242.97	0.8%	16336.36	0.3%
$S_{N_{tot,e}}$ violations (% of operating time)	17.56	0	100%	0	100%
$S_{NH,e}$ violations (% of operating time)	17.26	16.81	2.6%	16.66	3.4%
Rain influent					
	Default PI controllers	Control for $S_{N_{tot,e}}$ violations removal with functions	% of reduction	Control for $S_{N_{tot,e}}$ violations removal with FCs	% of reduction
EQI	8174.98	8072.5	1.2%	8021.54	1.88%
OCI	15984.85	15780.83	1.3%	15770.78	1.34%
$S_{N_{tot,e}}$ violations (% of operating time)	10.86	0	100%	0	100%
$S_{NH,e}$ violations (% of operating time)	27.08	26.04	3.8%	25.3	6.57%
Storm influent					
	Default PI controllers	Control for $S_{N_{tot,e}}$ violations removal with functions	% of reduction	Control for $S_{N_{tot,e}}$ violations removal with FCs	% of reduction
EQI	7211.48	7022.25	2.6%	6979.22	3.22%
OCI	17253.75	17243.73	0.06%	17229.49	0.14%
$S_{N_{tot,e}}$ violations (% of operating time)	15.03	0	100%	0	100%
$S_{NH,e}$ violations (% of operating time)	26.79	25	6.6%	25	6.6%

Table 5.1: Results with default PI controllers and with control for $S_{N_{tot,e}}$ violations removal for dry, rain and storm influents

violations are avoided. The correct choice of the tuning parameters of the higher level controller results also in obtaining a decrease in OCI and time of $S_{N_{tot,e}}$ violation.

Table 5.2 shows the results of EQI, OCI and percentage of time over the limits of $S_{NH,e}$ and $S_{N_{tot,e}}$ for the three weather conditions. It can be seen that with the regulation of Q_a based on $S_{NH,5}$ and $S_{NH,in}$, and also with the hierarchical control of S_O in the three aerated tanks, it is possible to avoid $S_{NH,e}$ violations. In addition, an improvement of 5.8% or 4.26% of EQI and 0.4% or 0.45% of OCI in comparison with the default control strategy of BSM1 is achieved for dry influent.

For rain and storm events, the elimination of $S_{NH,e}$ violations is completely achieved with the proposed control strategy and, in addition, a reduction of EQI and the percentage of time of $S_{N_{tot,e}}$ violation is achieved. However, an increase of costs is required, due to the

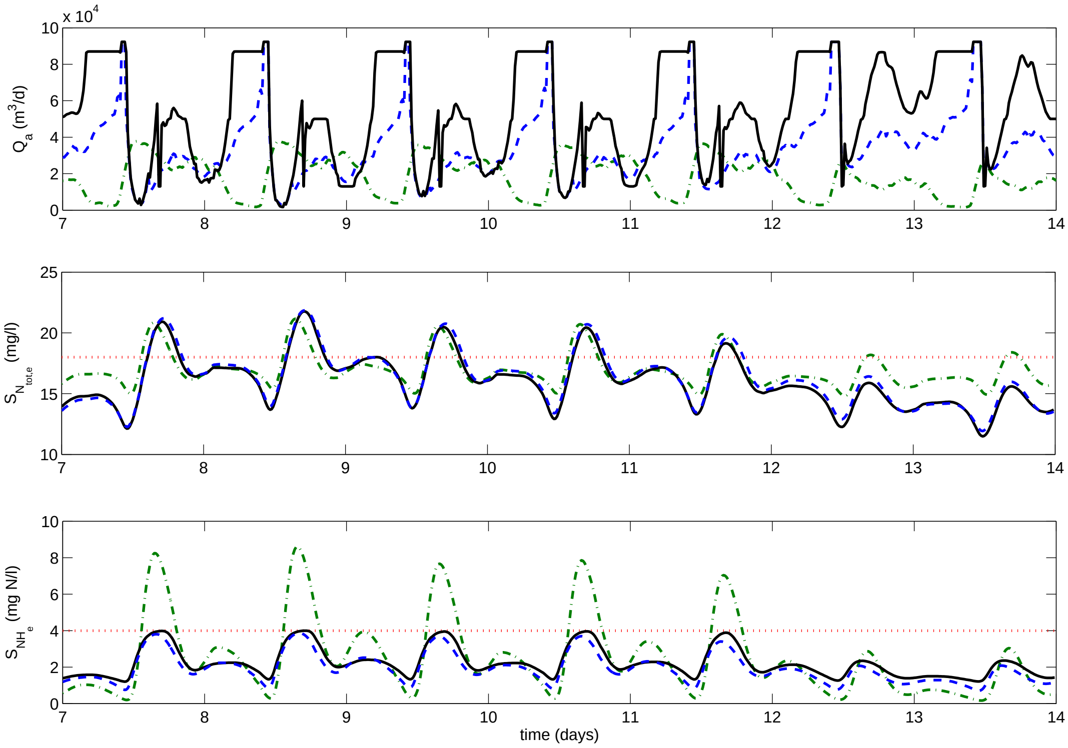


FIGURE 5.11: Q_a, $S_{NH,e}$ and $S_{N_{tot,e}}$ evolution form day 7 to day 14 with default PI controllers (dash-dotted line), applying control strategies for S_{NH_e} violations removal with functions (dashed line) and applying control strategies for S_{NH_e} violations removal with FCs (solid line)

fact that, during rain and storm periods, the nitrification process (2.5) is worsened as explained in Section 5.2.2. For this reason, extra addition of q_{EC} is needed when there is a rain or storm event, generating an increase of costs (see Fig. 5.12 and Fig. 5.13). It should be noted that costs saved due to avoid violations are not reflected in the OCI equation and therefore the cost comparison is not completely fair.

OCI and percentage of operating time of $S_{N_{tot,e}}$ violation are influenced by $q_{EC_{4-5}}$ value and therefore by the intensity and the duration of the rainfall. When there is rain or storm event, greater nitrification is performed by Q_a manipulation and therefore S_{NO} and also $S_{N_{tot,e}}$ increase. However, adding $q_{EC_{4-5}}$ also decreases the value of S_{NO} and thus $S_{N_{tot,e}}$. With storm influent, the percentage of the cost increase is lower than in the case of rain influent because less $q_{EC_{4-5}}$ is needed for the $S_{NH,e}$ removal. On the other hand, as in the case of rain influent the dosage of $q_{EC_{4-5}}$ is greater, there is a reduction in the percentage of operating time of $S_{N_{tot,e}}$ violation in comparison with the storm influent.

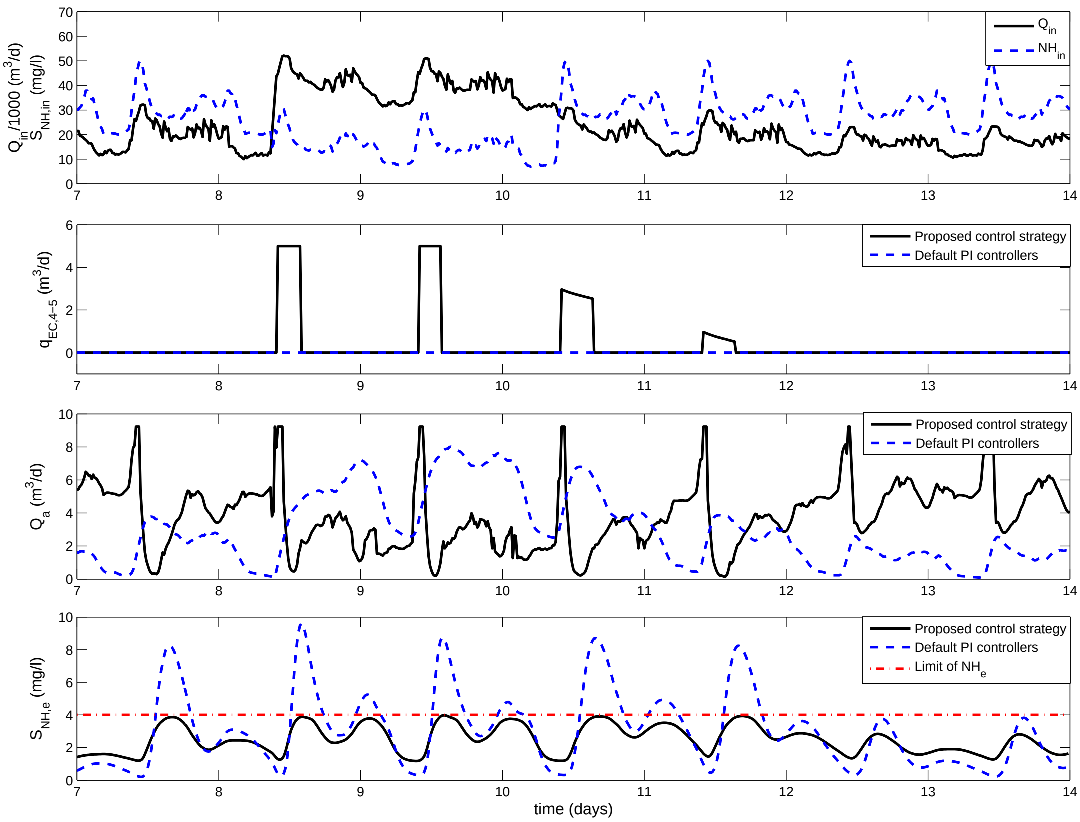


FIGURE 5.12: Rain influent: time evolution of the most important variables applying the proposed control strategy for $S_{NH,e}$ violations removal with functions and applying the default control strategy of BSM1.

5.3.3 $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal

Finally, both control strategies for $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal have been tested together. As $S_{NH,e}$ violations present more difficulties to be removed than the ones of $S_{N_{tot,e}}$, especially during rain and storm events, the tuning for the higher level determined to avoid $S_{NH,e}$ violations is also applied in this case.

Table 5.4 shows the results obtained by applying the control strategies to eliminate both $S_{N_{tot,e}}$ and S_{NH} violations for the three weather conditions. As it can be observed, the $S_{N_{tot,e}}$ and S_{NH} violations removal is possible for dry, rain and storm weather conditions. However, removing the two pollutants simultaneously gives rise to an increase of OCI. It is due to the fact that the reduction of S_{NH} peaks is based on an improvement in the nitrification process, what causes a great generation of S_{NO} (2.2 and 2.5) and also a

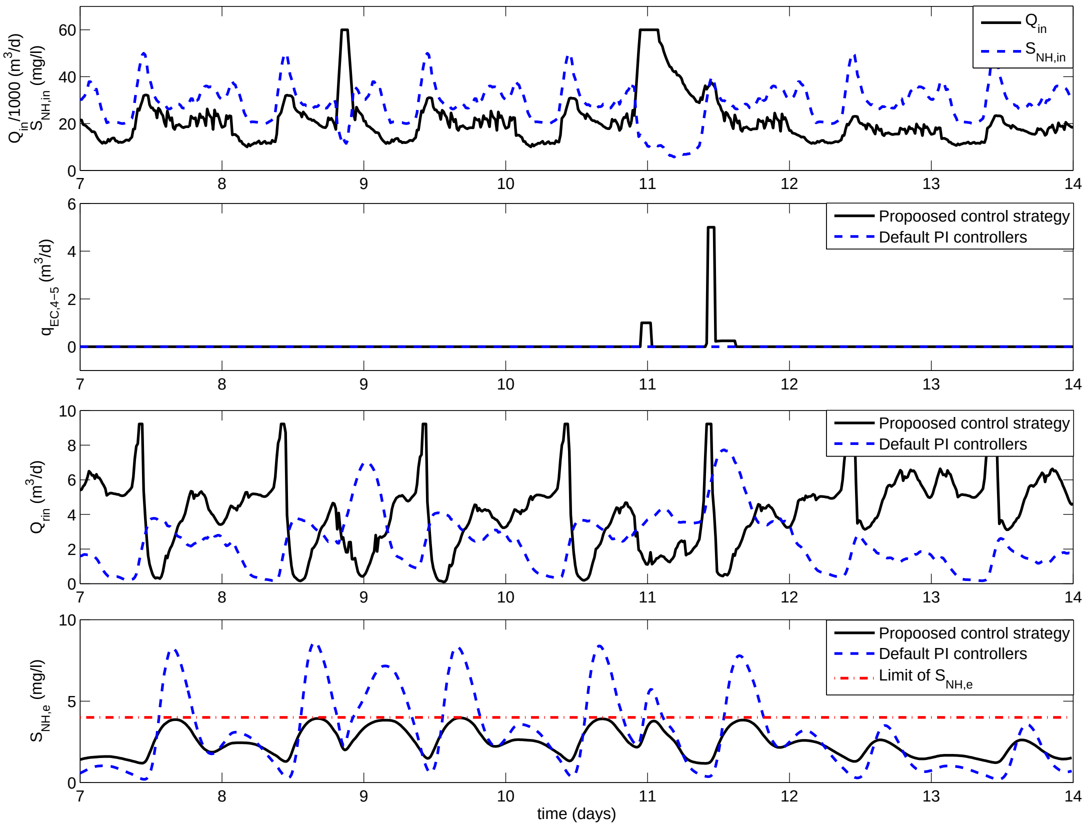


FIGURE 5.13: Storm influent: time evolution of the most important variables applying the proposed control strategy for $S_{NH,e}$ violations removal with functions and applying the default control strategy of BSM1.

$S_{N_{tot,e}}$ increase. To counteract it, the dosage of q_{EC} is increased, and q_{EC} in the second tank ($q_{EC,2}$) is also added, as shown in Fig. 5.14 in the case of applying functions, and in Fig. 5.15 for the application of FCs. Therefore, when a peak of $S_{NH,in} \cdot Q_{in}$, and there is not a rainfall or storm event, $q_{EC,1}$ is added at its maximum value ($5\text{m}^3/\text{d}$) and $q_{EC,2}$ is calculated with the affine function or the FC implemented for the control strategy for $S_{N_{tot,e}}$ violations removal. This q_{EC} increase results in the total elimination of $S_{N_{tot,e}}$ and $S_{NH,e}$ violations and an EQI reduction, but also in an OCI increase. However, as explained in the previous section, the OCI equation does not take into account the reduction of costs of avoiding violations and thus, the cost comparison is not completely fair. The OCI increase is higher using FCs because the addition of $q_{EC,2}$ is based on NH5 plus NO5. In the case of using functions, the addition of qEC2 is only based on the maximum value of the previous week. This alternative lets to add $q_{EC,2}$ in advance and therefore reduces their doses and consequently reduces costs. However, this option would not be entirely satisfactory in the case of having a more variable dry influent.

Dry influent					
	Default PI controllers	Control for $S_{NH,e}$ violations removal with functions	% of reduction	Control for $S_{NH,e}$ violations removal with FCs	% of reduction
EQI	6115.63	5760.95	5.8%	5854.06	4.26%
OCI	16381.93	16323.48	0.4%	16307.26	0.45%
$S_{N_{tot},e}$ violations (% of operating time)	17.56	15.62	11.04%	15.62	11.04%
$S_{NH,e}$ violations (% of operating time)	17.26	0	100%	0	100%
Rain influent					
	Default PI controllers	Control for $S_{NH,e}$ violations removal with functions	% of reduction	Control for $S_{NH,e}$ violations removal with FCs	% of reduction
EQI	8174.98	7814.98	4.4%	7829.12	4.23%
OCI	15984.85	17463.78	-9.2%	17675.26	-10.57%
$S_{N_{tot},e}$ violations (% of operating time)	10.86	13.84	-27.4%	8.93	17.77%
$S_{NH,e}$ violations (% of operating time)	27.08	0	100%	0	100%
Storm influent					
	Default PI controllers	Control for $S_{NH,e}$ violations removal with functions	% of reduction	Control for $S_{NH,e}$ violations removal with FCs	% of reduction
EQI	7211.48	6903.02	4.3%	6925.24	3.97%
OCI	17253.75	17582.3	-1.9%	17633.58	-2.2%
$S_{N_{tot},e}$ violations (% of operating time)	15.03	22.32	-48.5%	20.24	-34.66%
$S_{NH,e}$ violations (% of operating time)	26.79	0	100%	0	100%

TABLE 5.2: Results with default PI controllers and with control for $S_{NH,e}$ violations removal for dry, rain and storm influents

5.4 Summary

This chapter has been focused on the objective of effluent violations removal using BSM1 as testing plant. With this aim, two control loops are added to the hierarchical structure explained in previous chapters. These control loops consist in the manipulation of $q_{EC,1}$ based on $S_{NH,5}$ plus $S_{NO,5}$ and the manipulation of Q_a based on $S_{NH,5}$, $S_{NH,in}$ and Q_{in}. Functions and FCs are proposed for these control strategies basing their control on the biological processes.

The improvement of the denitrification process, by adding $q_{EC,1}$, achieves the complete elimination of $S_{N_{tot},e}$ violations. This control strategy has been tested with an affine function with a sliding window and with an FC. Both are implemented to dosage the minimum $q_{EC,1}$ necessary for this aim. The improvement of the nitrification process by

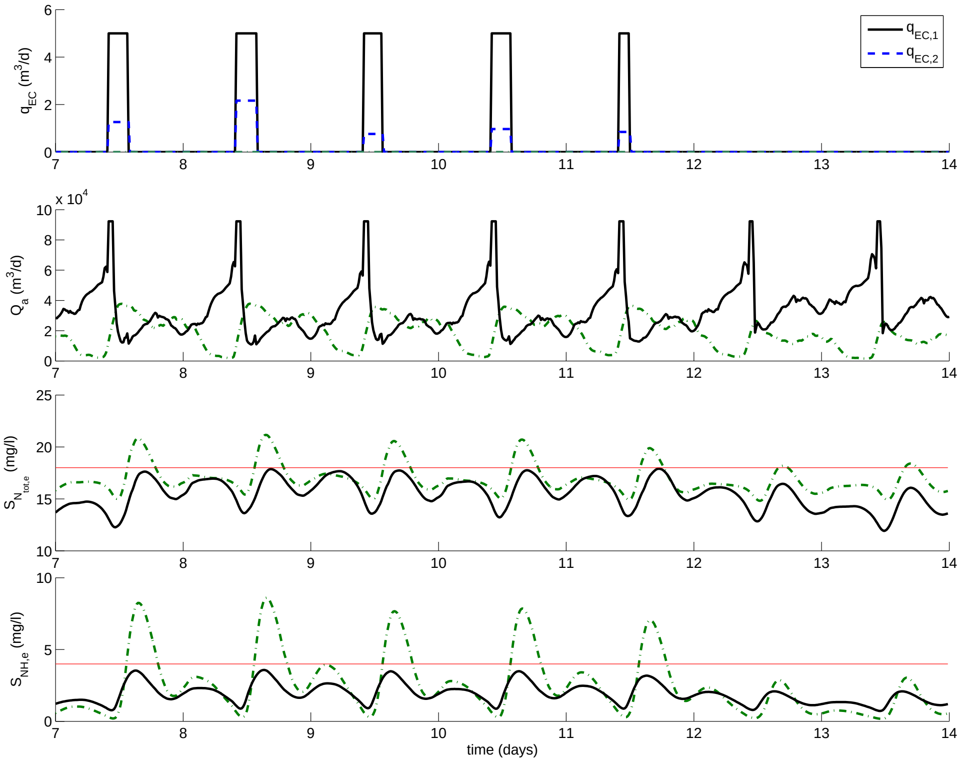


FIGURE 5.14: q_{EC}, Q_a, $S_{NH,e}$ and $S_{N_{tot,e}}$ evolution form day 7 to day 14 with default PI controllers (dash-dotted line) and with the control strategies for $S_{NH,e}$ and $S_{N_{tot,e}}$ violations removal using functions (solid line)

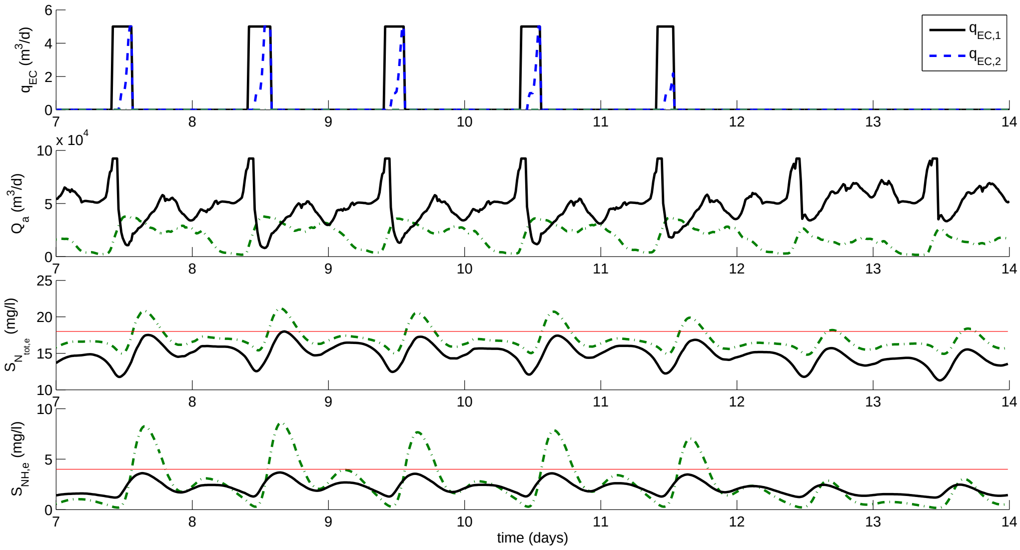


FIGURE 5.15: q_{EC}, Q_a, $S_{NH,e}$ and $S_{N_{tot,e}}$ evolution form day 7 to day 14 with default PI controllers (dash-dotted line) and with the control strategies for $S_{NH,e}$ and $S_{N_{tot,e}}$ violations removal using FCs (solid line)

manipulating Q_a makes possible the $S_{NH,e}$ violations removal. It has been tested first, with the combination of a linear function and an exponential function, and next, with an FC which uses different tuning parameters depending on if there are peaks of pollution

Dry influent					
	Default PI controllers	Control for $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal with functions	% of reduction reduction	Control for $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal with FCs	% of reduction reduction
EQI	6115.63	5624.41	8.03%	5598.4	8.46%
OCI	16381.93	17494.44	-6.8%	17747.85	-8.34%
$S_{N_{tot,e}}$ violations (% of operating time)	17.56	0	100%	0	100%
$S_{NH,e}$ violations (% of operating time)	17.26	0	100%	0	100%
Rain influent					
	Default PI controllers	Control for $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal with functions	% of reduction reduction	Control for $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal with FCs	% of reduction reduction
EQI	8174.98	7695.03	5.9%	7658.32	6.32%
OCI	15984.85	18524.71	-15.9%	18735.84	-17.21%
$S_{N_{tot,e}}$ violations (% of operating time)	10.86	0	100%	0	100%
$S_{NH,e}$ violations (% of operating time)	27.08	0	100%	0	100%
Storm influent					
	Default PI controllers	Control for $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal with functions	% of reduction reduction	Control for $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal with FCs	% of reduction reduction
EQI	7211.48	6685.15	7.3%	66615.09	7.75%
OCI	17253.75	19524.67	-13.2%	19672.72	-14.02%
$S_{N_{tot,e}}$ violations (% of operating time)	15.03	0	100%	0	100%
$S_{NH,e}$ violations (% of operating time)	26.79	0	100%	0	100%

TABLE 5.3: Results with default PI controllers and with control strategies for the simultaneous $S_{N_{tot,e}}$ and $S_{NH,e}$ violations removal with functions for dry, rain and storm influents.

in the tanks or not.

Simulation results show that $S_{N_{tot,e}}$ and $S_{NH,e}$ violations are removed for dry, rain and storm influents. In the cases of $S_{N_{tot,e}}$ violations removal for the three weather conditions and $S_{NH,e}$ violations removal for dry weather, a simultaneous reduction of EQI and OCI is achieved in comparison with the default control strategy. The $S_{NH,e}$ violations removal for rain and storm influents and the simultaneous elimination of $S_{N_{tot,e}}$ and $S_{NH,e}$ makes inevitable an increase of OCI. In any case, it has to be said that, with the removal of effluent violations, a reduction of costs is obtained for not paying fines, which is not considered in OCI.

Dry influent			
	Default PI controllers	Control for $S_{NH,e}$ and $S_{N_{tot},e}$ violations removal	% of reduction
EQI (kg pollutants/d)	6115.63	5624.41	8.03%
OCI	16381.93	17494.44	-6.8%
$S_{N_{tot},e}$ violations (% of operating time)	17.56	0	100%
$S_{NH,e}$ violations (% of operating time)	17.26	0	100%
Rain influent			
	Default PI controllers	Control for $S_{NH,e}$ and $S_{N_{tot},e}$ violations removal	% of reduction
EQI (kg pollutants/d)	8174.98	7695.03	5.9%
OCI	15984.85	18524.71	-15.9%
$S_{N_{tot},e}$ violations (% of operating time)	10.86	0	100%
$S_{NH,e}$ violations (% of operating time)	27.08	0	100%
Storm influent			
	Default PI controllers	Control for $S_{NH,e}$ and $S_{N_{tot},e}$ violations removal	% of reduction
EQI (kg pollutants/d)	7211.48	6685.15	7.3%
OCI	17253.75	19524.67	-13.2%
$S_{N_{tot},e}$ violations (% of operating time)	15.03	0	100%
$S_{NH,e}$ violations (% of operating time)	26.79	0	100%

Table 5.4: Results with default PI controllers and with control strategies for the simultaneous $S_{N_{tot},e}$ and $S_{NH,e}$ violations removal with functions for dry, rain and storm influents.

Chapter 6

Effluent predictions for violations risk detection

In the previous chapter, the elimination of $S_{N_{tot,e}}$ and $S_{NH,e}$ violations have been shown using BSM1 as working scenario. However, BSM2 provides a more elaborated and variable influent with an assessment of one year. Applying control strategies to avoid effluent violations, only when an increase of contaminants is already detected in the reactors, is not enough in BSM2. Due to this fact, an effluent prediction of the pollutants based on some variables in the influent is required. ANNs are implemented with this aim.

6.1 Implementation of Artificial Neural Networks

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 using FCs (explained in the next subsection) are applied to avoid them. When a risk of $S_{NH,e}$ violation is detected, Q_a is manipulated based on $S_{NH,5}$ to reduce $S_{NH,e}$ peak, instead of being manipulated to control $S_{NO,2}$, as it occurs the rest of the time. Regarding $S_{N_{tot,e}}$, when a risk of violation is detected, q_EC is manipulated based on this prediction, instead of being kept at a fixed value as usual.

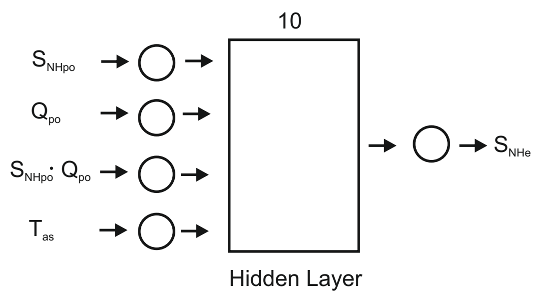
An accurate prediction of $S_{NH,e}$ and $S_{N_{tot,e}}$ is not possible due to the fact that ANNs use only influent variables as inputs, while the effluent concentrations also depend on other variables of the process. Those variables can not be taken into account because it is necessary to predict the risk of effluent violations with enough time in advance. Moreover, all data used to predict the risk has to be easily measurable. However, 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 (2.28 and 2.29). 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 (2.23; 2.24; and 2.25). $S_{NH,e}$ and $S_{N_{tot,e}}$ values are inversely proportional to the T_{as} values.

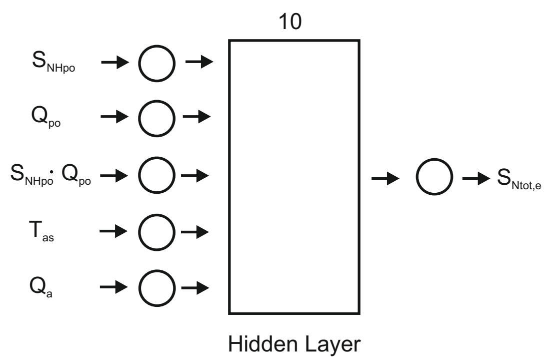
Finally, due to the mentioned reasons, the inputs for the ANNs are:

- 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 without the control strategies for avoiding $S_{N_{tot,e}}$ and $S_{NH,e}$ violations. 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.6.1.



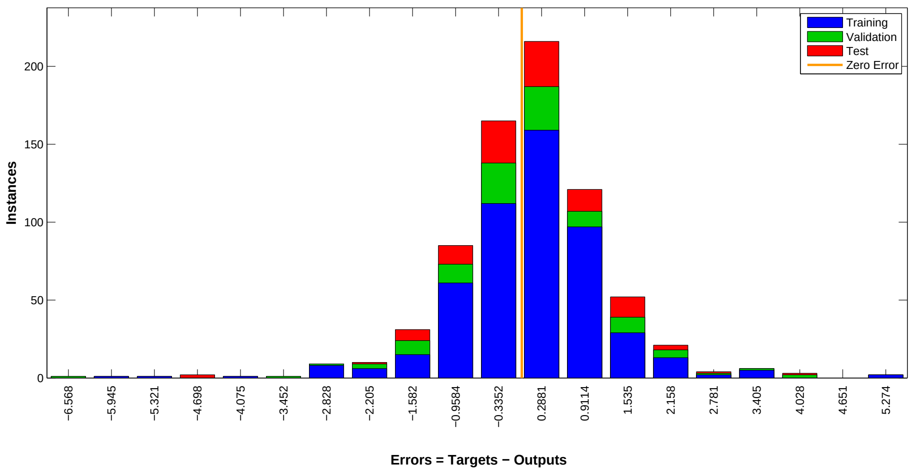
(a) ANN for $S_{NH,e}$ prediction



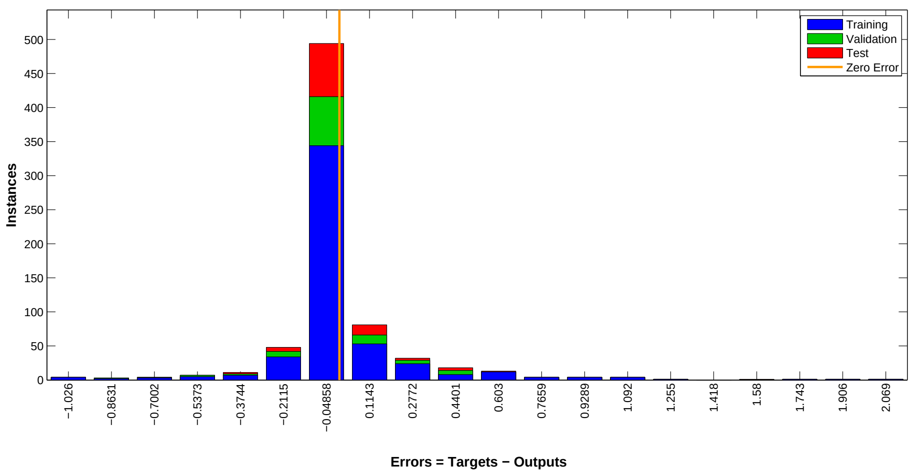
(b) ANN for $S_{N_{tot,e}}$ prediction

FIGURE 6.1: Structures of the proposed ANNs

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. 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 (6.2) 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.



(a) Error histogram of ANN for $S_{N_{tot,e}}$ prediction



(b) Error histogram of ANN for $S_{NH,e}$ prediction

FIGURE 6.2: ANN training error histograms.

As a result, figure 6.3 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.

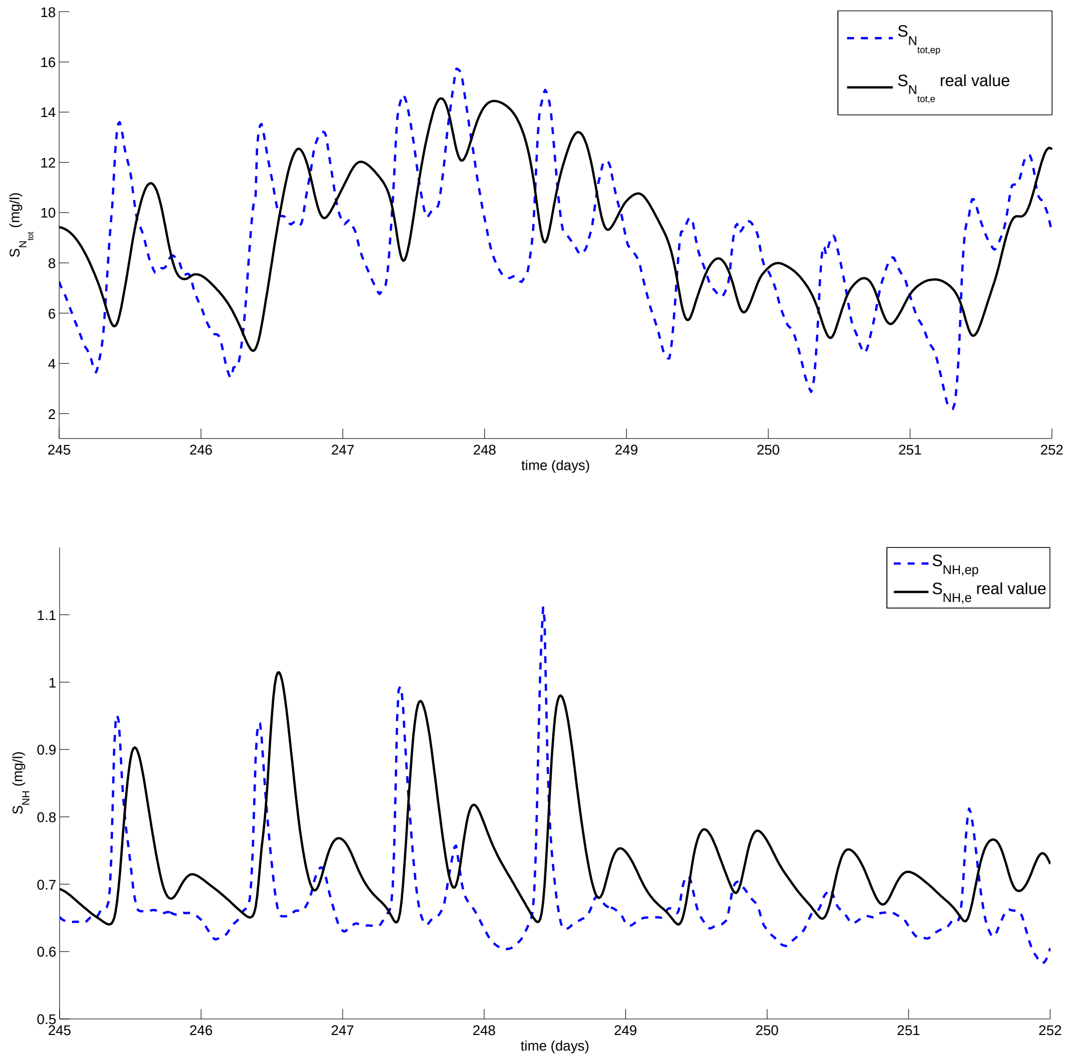


FIGURE 6.3: ANN Effluent prediction for $S_{NH,e}$ and $S_{N_{tot,e}}$

6.2 Simulation results

There are 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 violations.

The BSM2 is now simulated by applying the hierarchical control scheme explained in next chapter. 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. Figure 6.4 shows, 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, and only three risk situations are detected. It is in these cases when supplementary control actions will be needed.

In order to better show how the risk detection works, figures 6.5 and 6.6 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 of 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 6.6, 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 situation.

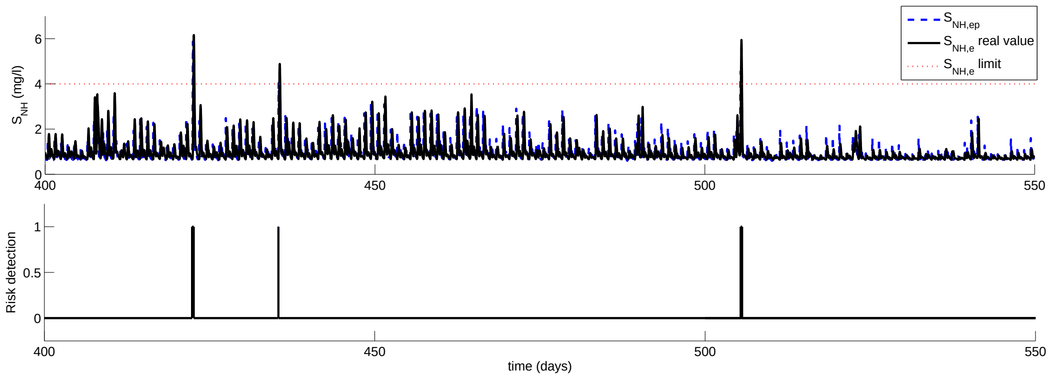


FIGURE 6.4: $S_{NH,e}$ limit violation risk detection. Long time window.

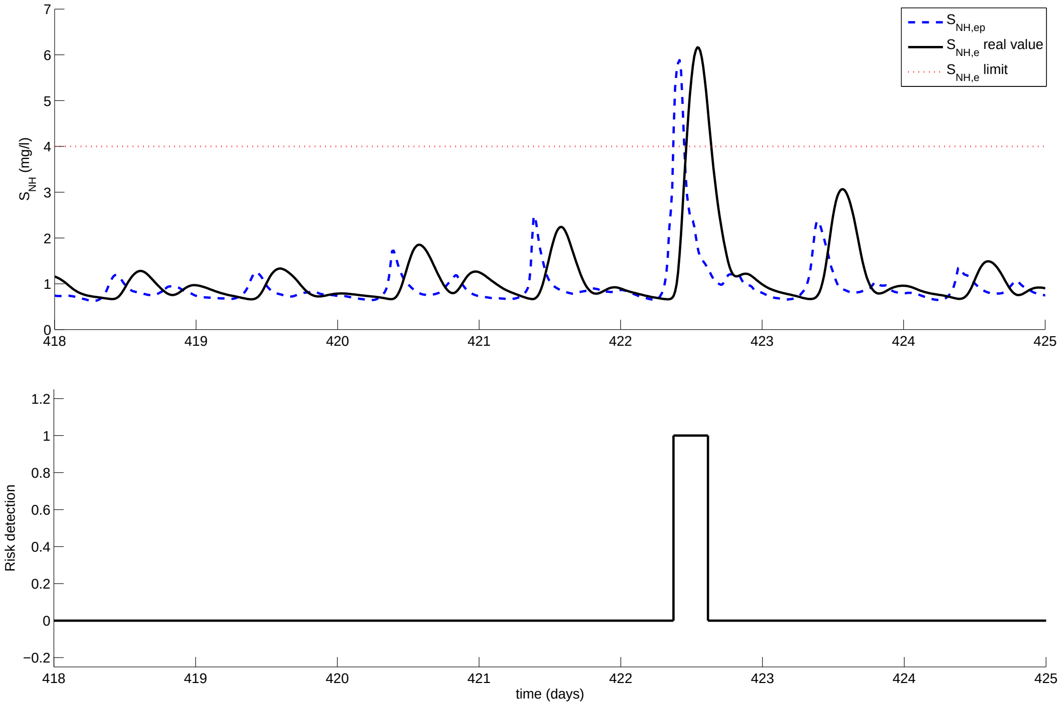


FIGURE 6.5: $S_{NH,e}$ limit violation risk detection

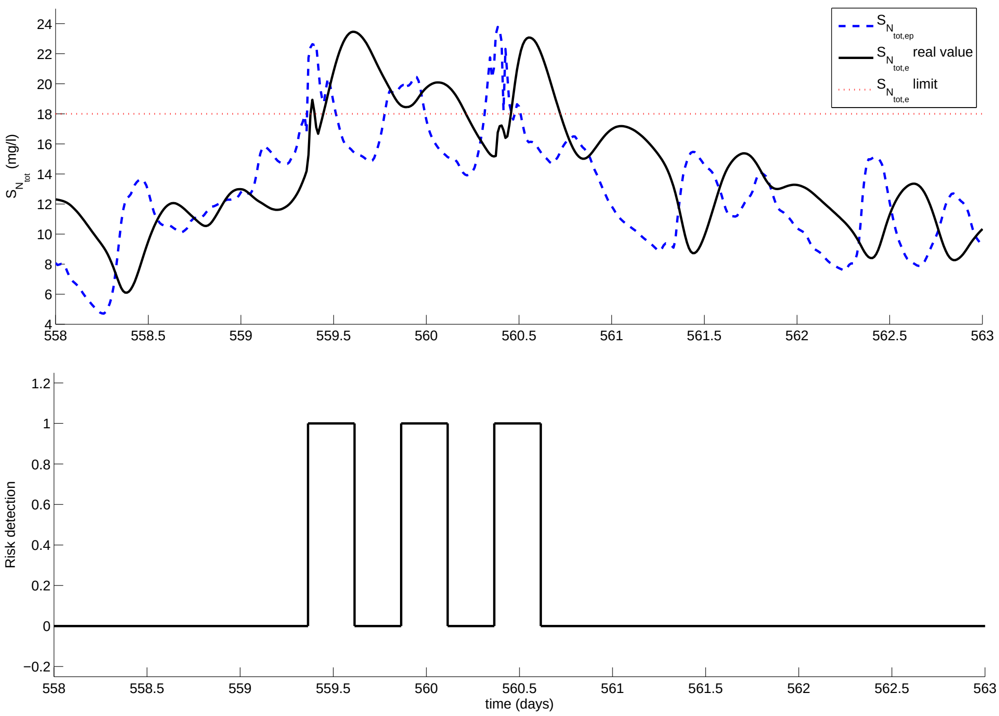


FIGURE 6.6: $S_{N_{tot,e}}$ limit violation risk detection

6.3 Summary

For the application of the control strategies for effluent violations removal in BSM2, effluent predictions are necessary in order to select the suitable control strategy to be applied. In this chapter, the implementation of the ANNs for these effluent predictions is described.

Specifically two ANNs have been applied, one for $S_{N_{tot,e}}$ prediction and the other for $S_{NH,e}$ prediction. For the case of $S_{N_{tot,e}}$ prediction, the input variables have been: Q_{po}, $S_{NH,po}$, $Q_{po} \cdot S_{NH,po}$ and T_{as}. And for $S_{NH,e}$ prediction: Q_{po}, $S_{NH,po}$, $Q_{po} \cdot S_{NH,po}$, T_{as} and Q_a.

Simulations show satisfactory predictions of $S_{N_{tot,e}}$ and $S_{NH,e}$, which are used for risk detection and thus for selecting the suitable control strategy. For $S_{NH,e}$ prediction, the threshold is established at 4 mg/l, the same as the limit value. For the case of $S_{N_{tot,e}}$ prediction, the threshold is reduced to 17 mg/l (1 mg/l less than the established limit) to ensure the avoidance of violation, but without reducing it too much for not increasing costs.

Chapter 7

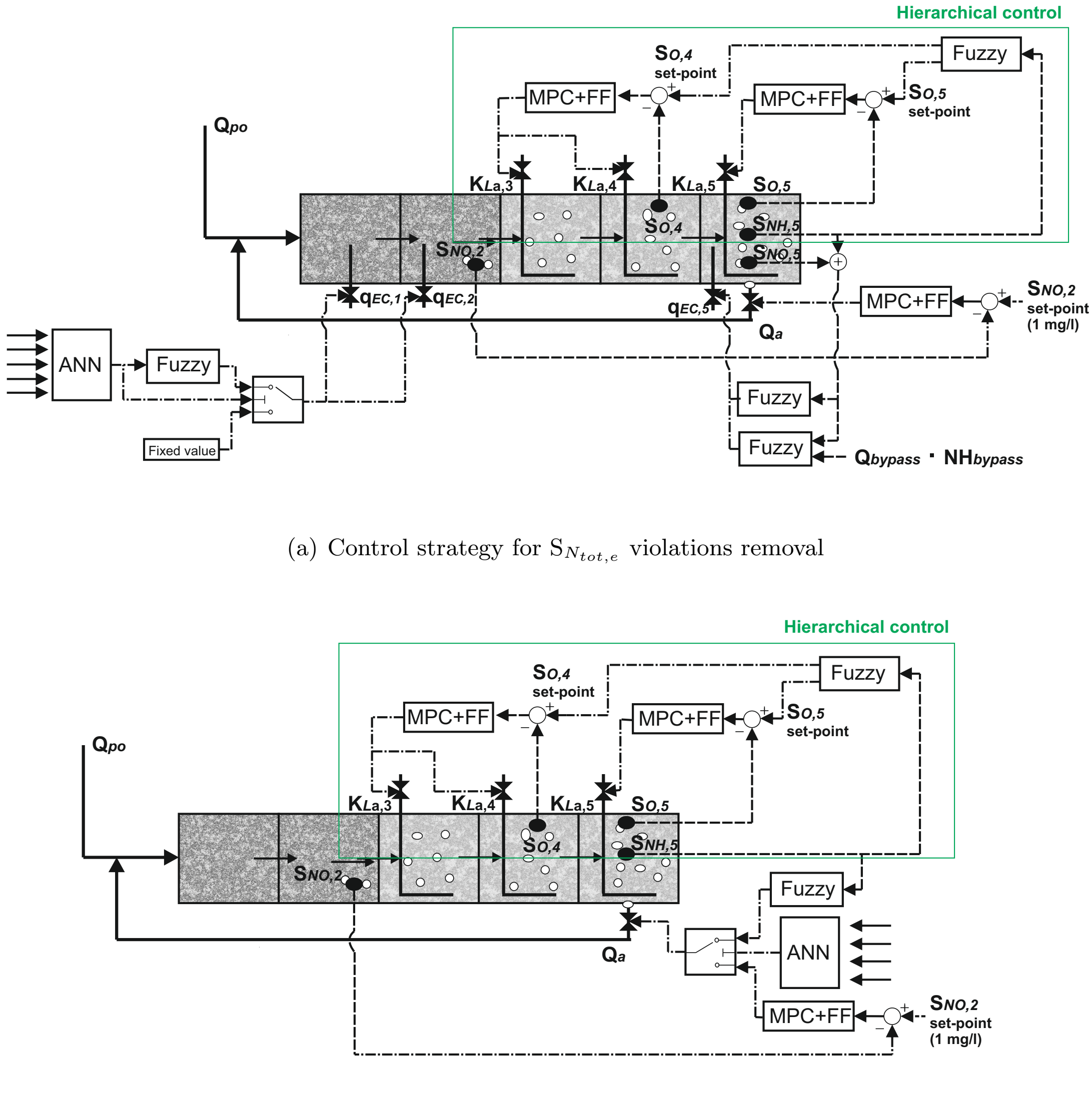
Intelligent decision control system

This chapter presents the control strategies applied in BSM2 for $S_{N_{tot,e}}$ or $S_{NH,e}$ violations removal. An intelligent control system selects the control strategies to be applied based on the effluent predictions explained in the previous chapter.

7.1 Control configurations for the proposed objectives

The simulations and evaluations of the control strategies presented in this chapter are carried out with BSM2. In the literature some works use BSM2 as testing plant. Some of them are focused on the implementation of control strategies in the biological treatment, as the present work. Specifically, they propose a multi-objective control strategy based on S_O control by manipulating K_La of the aerated tanks, S_{NH} hierarchical control by manipulating the S_O set-points, $S_{NO,2}$ control by manipulating Q_a or TSS control by manipulating Q_w ([34–37]).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 aim to avoid the limits violations of the effluent pollutants.

The control configurations proposed in this work are based on MPC+FF and FCs. MPC+FF are used in order to keep the $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ at the given set-point. FCs are applied, on one side, as higher level controller in a hierarchical structure to vary the S_O references to be tracked by the MPC controllers, and, on the other hand, to remove $S_{N_{tot,e}}$ and $S_{NH,e}$ violations by determining $q_{EC,1}$ and Q_a values. The application of FCs are based on the biological processes, but without the goal of keeping the controlled variable at a set-point. In this case, the control objectives are: the improvement of OCI and EQI, and the violations removal of $S_{N_{tot,e}}$ and $S_{NH,e}$. An intelligent control system selects the control strategies to be applied based on the effluent predictions explained the in previous chapter (see Fig. 7.1).



(a) Control strategy for $S_{N_{tot,e}}$ violations removal

(b) Control strategy for $S_{NH,e}$ violations removal

FIGURE 7.1: Proposed control strategies for $S_{N_{tot,e}}$ or $S_{NH,e}$ violations removal with a simultaneously EQI and OCI reduction

7.1.1 $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ tracking

Two MPC+FF controllers are proposed for the aerated zone, to control $S_{O,5}$ by manipulating K_La_5 and to control $S_{O,4}$ by manipulating K_La_3 and K_La_4 based on [1]. The aim of these MPC+FF controllers is to improve the set-points tracking regarding the PI controllers of defCL. Also, an MPC+FF is applied to control $S_{NO,2}$ at a reference value of 1mg/l by manipulating Q_a, based on the default strategy of BSM1. In the same way as in BSM1, in order to adjust the manipulated variables immediately to compensate the disturbances, Q_{po} has been selected for the feedforward action of the MPC+FF controllers.

In this work, unlike the defCL, $S_{O,4}$ and $S_{O,5}$ references are not maintained at a fixed value. Instead of this, a FC varies the set-point, adapting it based on the conditions of the nitrification process. Due to this reason, it should be noted the importance of the MPC+FF controllers performance to ensure that the $S_{O,4}$ and $S_{O,5}$ values are as close as possible to the set-point given by the FC.

The variables of the state-space model (2.40) for the three MPC+FF controllers are described following: $u_1(k)$ is K_La_4 and K_La_3, $u_2(k)$ is Q_{po} and $y_1(k)$ is $S_{O,4}$ in the MPC+FF for $S_{O,4}$ control; $u_1(k)$ is K_La_5, $u_2(k)$ is Q_{po} and $y_1(k)$ is $S_{O,5}$ in the MPC+FF for $S_{O,5}$ control; $u_1(k)$ is Q_a, $u_2(k)$ is Q_{po} and $y_1(k)$ is $S_{NO,2}$ in the MPC+FF for $S_{NO,2}$ control.

The identification of the linear predictive models of the MPC+FF controllers was performed using Matlab® System Identification toolbox. The data of the output variables ($S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$) are obtained by making changes to the input variables (K_La_3, K_La_4, K_La_5 and Q_a) with a maximum variation of 10% regarding its operating point, which is the value of K_La necessary to obtain 2 mg/l of $S_{O,4}$, 1 mg/l of $S_{O,5}$ and the value of Q_a necessary to obtain 1 mg/l of $S_{NO,2}$. Specifically, the working points are 120 day $^{-1}$, 60 day $^{-1}$ and 61944 m^3/day for K_La_3 / K_La_4, K_La_5 and Q_a respectively. PEM was selected to determine the model with the obtained data. Therefore the following second order state-space models are obtained:

- $S_{O,4}$ control

$$
\begin{aligned}
A &= \begin{bmatrix} 0.9768 & 0.1215 \\ 0.09664 & 0.2635 \end{bmatrix} \\
B &= \begin{bmatrix} 0.002984 & -3.673 \cdot 10^{-6} \\ -0.01796 & 8.318 \cdot 10^{-6} \end{bmatrix} \\
C &= \begin{bmatrix} 3.682 & -0.4793 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned}
\tag{7.1}
$$

- $S_{O,5}$ control

$$
\begin{aligned}
A &= \begin{bmatrix} 0.9794 & 0.1109 \\ 0.0976 & 0.3544 \end{bmatrix} \\
B &= \begin{bmatrix} 0.001836 & -1.259 \cdot 10^{-5} \\ -0.01153 & 7.04e-005 \end{bmatrix} \\
C &= \begin{bmatrix} 8.412 & -0.1429 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned}
\tag{7.2}
$$

- $S_{NO,2}$ control

$$
\begin{aligned}
A &= \begin{bmatrix} 0.8301 & 0.2828 \\ 0.0578 & 0.8674 \end{bmatrix} \\
B &= \begin{bmatrix} 3.264 \cdot 10^{-6} & -1.358 \cdot 10^{-5} \\ -1.767 \cdot 10^{-6} & -2.87 \cdot 10^{-6} \end{bmatrix} \\
C &= \begin{bmatrix} 5.035 & 0.2777 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned}
\tag{7.3}
$$

The selected values to tune the MPC+FF controllers are $m = 5$, $p = 20$, $\triangle t = 0.00025$ days (21.6 seconds), $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 1{\cdot}10^{-5}$ and overall estimator gain = 0.8 for $S_{O,4}$ control; $m = 5$, $p = 20$, $\triangle t = 0.00025$ days (21.6 seconds), $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 5{\cdot}10^{-4}$ and overall estimator gain = 0.8 for $S_{O,5}$ control; $m = 5$, $p = 50$, $\triangle t = 0.00025$ days (21.6 seconds), $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 1{\cdot}10^{-5}$ and overall estimator gain = 0.9 for $S_{NO,2}$ control.

7.1.2 Manipulation of S_O set-points, q_{EC} and Q_a

Five FCs have been implemented in the proposed control strategies with three objectives: to reduce EQI and OCI, to remove $S_{N_{tot,e}}$ violations and to eliminate $S_{NH,e}$ violations. They are based on the biological processes given by ASM1.

For the five FCs applied, Mamdani ([15]) is the method selected to defuzzify. The design of the FCs was based on the observation of the simulations results obtained by operating the plant with the default control of BSM2.

7.1.2.1 Fuzzy Controller for EQI and OCI reduction

A FC is applied as higher level controller to manipulate $S_{O,4}$ and $S_{O,5}$ set-points based on the $S_{NH,5}$ with the aim to reduce EQI and OCI. Specifically, it is based on the nitrification process, improving it or making it worse based on a trade-off between the values of S_{NH} and S_{NO}. The idea of this control is to improve the nitrification process by increasing $S_{O,4}$ and $S_{O,5}$ references (2.24) when there is an $S_{NH,5}$ increase caused by the influent, reducing thus $S_{NH,e}$ peaks. Conversely, to reduce the XB,H growth when the $S_{NH,5}$ level is low, in order to produce less S_{NO} (2.24) and (2.20) and at the same time to reduce operational costs (2.31).

For the higher level FC, three triangular membership functions for input and for output are used (*low*, *medium* and *high*). The implemented $if - then$ rules are:

if ($S_{NH,5}$ is *low*) **then** ($S_{O,4}$ set is *low*)
if ($S_{NH,5}$ is *medium*) **then** ($S_{O,4}$ is *medium*)
if ($S_{NH,5}$ is *high*) **then** ($S_{O,4}$ is *high*)

The range of the input values is from 0.2 to 4, and the range for the output values is from -0.75 to 4.5. $S_{O,5}$ set-point is equal to the half value of $S_{O,4}$.

7.1.2.2 Fuzzy Controllers for $S_{N_{tot,e}}$ violations removal

The idea of this control strategy is to add q_{EC} only when there is a risk of violation in order to reduce operational costs, unlike the default control strategy, which keeps $q_{EC,1}$

at 2 m^3/d continuously. Three FCs are proposed. One FC is used as predictive control, adding q_{EC} in the first and second reactors ($q_{EC,1-2}$) when a violation is predicted, based on $S_{N_{tot,ep}}$ value given by the ANN (explained above). This control strategy is necessary, because acting only when a high $S_{N_{tot}}$ value in the reactors is detected could not be enough if $S_{N_{tot}}$ is quite high. The second FC adds q_{EC} in the fifth tank ($q_{EC,5}$) based on $S_{NH,5}$ plus $S_{NO,5}$, which are the contaminants with more influence on $S_{N_{tot}}$. This control acts when, in spite of the predictive control, $S_{NH,5}$+$S_{NO,5}$ increases excessively. As the biological process is designed to treat a maximum flow rate of 60420 m^3/d, when the flow rate coming from the primary treatment surpasses this value, the excess is bypassed directly to the effluent without being treated. In state of bypass, the third fuzzy control manipulates $q_{EC,5}$ based on the bypass flow rate (Q_{bypass}) multiplied by S_{NH} in the bypass ($S_{NH,bypass}$), in order to compensate the increase of $S_{NH,e}$ due to the flow rate that cannot be treated.

The first FC, which is based on the $S_{N_{tot,ep}}$, has one input and one output, with three membership functions for each (*low*, *medium* and *high*). The implemented $if - then$ rules are:

if ($S_{N_{tot,ep}}$ is *low*) **then** ($q_{EC,1-2}$ is *low*)
if ($S_{N_{tot,ep}}$ is *medium*) **then** ($q_{EC,1-2}$ is *medium*)
if ($S_{N_{tot,ep}}$ is *high*) **then** ($q_{EC,1-2}$ is *high*)

If $q_{EC,1-2}$ value is less than the maximum value of q_{EC} set in each reactor (5 m^3/d), it is only added to the first reactor. If q_{EC} is greater than 5 m^3/d, $q_{EC,1}$ is equal to 5 m^3/d and $q_{EC,2}$ is equal to the value of $q_{EC,1-2}$ minus 5. The range of the input values of the fuzzifier is from 17 to 19.5, and the range for the output values is from 4 to 15. Therefore, $q_{EC,1-2}$ is added when $S_{N_{tot,ep}}$ is over 17 mg/l instead of 18 mg/l which is the limit value, thus a margin of error of 5.5% in the prediction is established.

Since a situation of risk is detected ($S_{N_{tot,ep}} > 17$ mg/l), the predict control is kept running until the three following conditions are met to ensure that the risk has disappeared: $S_{N_{tot,ep}}$ is lower than 16 mg/l, $S_{NH,5}$ plus $S_{NO,5}$ is lower than 13.5 mg/l and the controller has been operating 6 hours at least. The controller calculates a $q_{EC,1-2}$ value at each sample time, but the true value applied to the plant is the maximum of all the previous samples, in order to ensure that the effluent violation is avoided.

The second FC, which manipulates $q_{EC,5}$ based on $S_{NH,5}$+$S_{NO,5}$, has one input and one output, with three membership functions for each input and output (*low*, *medium* and *high*). The range of the input values is from 15.3 to 15.9, and the range of the output values is from -1 to 6. The implemented $if - then$ rules are:

if ($S_{NH,5}$+$S_{NO,5}$ is *low*) **then** ($q_{EC,5}$ is *low*)
if ($S_{NH,5}$+$S_{NO,5}$ is *medium*) **then** ($q_{EC,5}$ is *medium*)
if ($S_{NH,5}$+$S_{NO,5}$ is *high*) **then** ($q_{EC,5}$ is *high*)

The third FC, which manipulates $q_{EC,5}$ based on $S_{NH,5}$+$S_{NO,5}$ and $Q_{bypass} \cdot S_{NH,bypass}$, has two inputs and one output, with three membership functions for each input and output (*low*, *medium* and *high*). The range of the $S_{NH,5}$+$S_{NO,5}$ input values is from 12 to 12.5, the range of the $Q_{bypass} \cdot S_{NH,bypass}$ input values is from 0 to $1.4 \cdot 10^5$ and the range for the output values is from $-1 \cdot 10^4$ to $6 \cdot 10^5$. The implemented $if - then$ rules are:

if ($S_{NH,5}$+$S_{NO,5}$ is *low* and $Q_{bypass} \cdot S_{NH,bypass}$ is *low*) **then** ($q_{EC,5}$ is *low*)
if ($S_{NH,5}$+$S_{NO,5}$ is *medium* and $Q_{bypass} \cdot S_{NH,bypass}$ is *medium*) **then** ($q_{EC,5}$ is *medium*)
if ($S_{NH,5}$+$S_{NO,5}$ is *high* and $Q_{bypass} \cdot S_{NH,bypass}$ is *high*) **then** ($q_{EC,5}$ is *high*)

This controller works while there is bypass. As in the first FC, the $q_{EC,5}$ value applied to the plant by the second and third FCs is the maximum of all the previous calculated values during the situation of risk.

7.1.2.3 Fuzzy Controller for S_{NH_e} violations removal

A FC is proposed to eliminate $S_{NH,e}$ violations by manipulating Q_a based on $S_{NH,5}$. This control strategy is applied only when a $S_{NH,e}$ violation is predicted by the ANN, explained in the previous chapter. The rest of the time Q_a is manipulated to control $S_{NO,2}$.

When a risk of violation is detected ($S_{NH,ep} > 4$ mg/l), the proposed FC is applied, first to dilute $S_{NH,po}$ and subsequently to reduce the hydraulic retention time when the increase of S_{NH} reaches the reactors. Thus, according to the mass balance equation in the first reactor (2.28), when $S_{NH,po}$ increases, Q_a is incremented to reduce the rise of $S_{NH,1}$, 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. When, in spite of this control, $S_{NH,5}$ reaches the value of 3.5 mg/l, a complementary action is applied and the $S_{O,4}$ ans $S_{O,5}$ set-points are increased by multiplying its value by 1.5.

The FC has one input and one output, with three membership functions for each (*low*, *medium* and *high*). The implemented $if - then$ rules are:

if ($S_{NH,5}$ is *low*) **then** (Q_a is *high*)
if ($S_{NH,5}$ is *medium*) **then** (Q_a is *medium*)
if ($S_{NH,5}$ is *high*) **then** (Q_a is *low*)

The tuning parameters are set looking for a great variation in Q_a. Thus, the range of the input values is from 3 to 4.1, and the range for the output values is from $-3{\cdot}10^4$ to $2{\cdot}10^5$.

This control is interrupted when the risk of violation disappears ($S_{NH,ep} < 4$ mg/l and $S_{NH,5} < 3.5$ mg/l). When it happens, the MPC+FF controller needs time to recover a successfully $S_{NO,2}$ control. In order to avoid abrupt changes in the manipulated variable, variations of Q_a are limited during one day after of the control strategy application.

7.2 Simulation Results

In this section the control configurations proposed in the above section are tested and compared. Ideal sensors have been considered. The simulation protocol is established in [2]: First, a steady state simulation of 200 days, and next a dynamic simulations of 609 days. Nevertheless, only the data generated during the final 364 days of the dynamic simulation are used for plant performance evaluation.

In Table 7.1 the results obtained with the proposed control strategies are shown. The chosen indicators to show the results obtained are based on the proposed objectives: EQI to evaluate the quality of effluent, OCI to evaluate costs, and the percentages of time of $S_{NH,e}$ and $S_{N_{tot,e}}$ violations.

		EQI	OCI	$S_{N_{tot,e}}$ violation (% of time)	$S_{NH,e}$ violation (% of time)
[2]	defCL	5577.97	9447.24	1.18	0.41
[1]	CL1	5447	9348	N/A	0.29
	%	2.35	1.05	N/A	29.27
	CL2	5274	8052	N/A	0.23
	%	5.45	14.77	N/A	43.9
[37] (different simulation time)	S1	5249	7154	N/A	N/A
	%	5.9	24.27	N/A	N/A
	S2	5927	8773	N/A	N/A
	%	-62.6	7.14	N/A	N/A
	S3	5530	8072	N/A	N/A
	%	0.86	14.56	N/A	N/A
	S4	5593	7442	N/A	N/A
	%	0.27	21.22	N/A	N/A
[36] (different EQI equation)	A1	6239	13324	2.17	19.44
	%	-11.85	-41.04	-83.9	-4641.46
	A2	6172	13323	1.09	20.83
	%	-10.65	-41.02	7.63	-4980.49
	A3	5995	13580	1.35	5.4
	%	-7.48	-43.74	-14.4	-1217.07
Control strategy for $S_{N_{tot,e}}$ violations removal	$q_{EC,1}$=0	5318.95	6289.59	0.046	0.15
	%	4.64	33.42	96.1	63.41
	$q_{EC,1}$=0.5	5197.49	6873.65	0.037	0.14
	%	6.82	27.24	96.86	65.85
	$q_{EC,1}$=1	5069.51	7573.34	0.037	0.14
	%	9.11	19.83	96.86	65.85
	$q_{EC,1}$=2	4852.49	9196.59	0.028	0.13
	%	13	2.65	97.63	68.29
Control strategy for $S_{NH,e}$ violations removal	$q_{EC,1}$=0	5387.81	5942.77	2.39	0
	%	3.41	37.09	-102.54	100
	$q_{EC,1}$=0.5	5217.9	6680.66	1.027	0
	%	6.45	29.28	12.97	100
	$q_{EC,1}$=1	5112.01	7399.13	0.69	0
	%	8.17	21.68	41.52	100
	$q_{EC,1}$=2	4875.14	9066.01	0.25	0
	%	12.6	4.03	78.81	100

Table 7.1: Comparative results of control strategy for S_{NH_e} violations removal and control strategy for $S_{N_{tot,e}}$ violations removal

The results have been compared with the default control strategy provided in [2], and with the two control strategies presented in the finalization of the plant layout in [1]. In addition, the results of [37] and [36] are also shown for for illustrative purposes. However, it should be noted that the comparison in these cases is not completely fair. In the case of [36], the EQI equation includes the different oxidized nitrogen forms, what makes worse the EQI result, and the simulation in [37] is carried out using only 275 days of influent data, what results in lower EQI and OCI. On the other hand, the comparison with the referenced works [34, 35, 38] is not possible. The reason is that [34] and [35] use an earlier version of BSM2 (instead of the modified version in [1]), and [38] presents EQI and OCI graphs, but they do not provide numeric values.

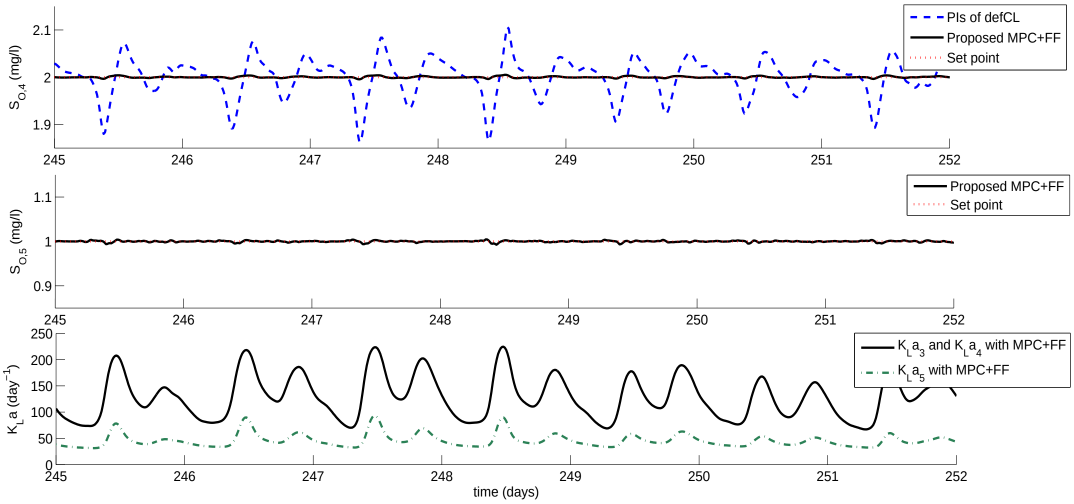
As shown in Table 7.1, the results of the proposed strategies are obtained for various fixed $q_{EC,1}$ values. Obviously, when the control strategy for $S_{N_{tot,e}}$ violations removal is applied, the $q_{EC,1}$ value is modified. Logically, as $q_{EC,1}$ is increased, EQI is reduced but OCI is increased. In comparison with defCL, [37] and [36], applying $q_{EC,1} = 0.5$, both OCI and EQI are reduced, while the percentage of time of $S_{N_{tot,e}}$ and $S_{NH,e}$ violations is lower and sometimes zero. EQI and OCI reduction is mainly achieved with the hierarchical control structure. Important aspects to be considered in this hierarchical control are: first to get a good tracking through the lower level MPC+FF controllers and, on the other hand, to give a suitable S_O set-points by the higher level FC.

Regarding the tracking of the lower level control, Fig. 7.2 shows one week evolution of $S_{O,4}$ control, where the improvement of MPC+FF controller compared to the PI controllers of defCL can be observed. Table 7.2 shows the numerical results of the performance of both controllers, including the percentage of improvement of MPC+FF for the $S_{O,4}$ control. The results of $S_{O,5}$ and $S_{NO,2}$ control obtained in this work are also shown. To the best knowledge of the authors, the performance results of the lower level control in other works of the literature based on BSM2 are not shown. Therefore they can not be compared.

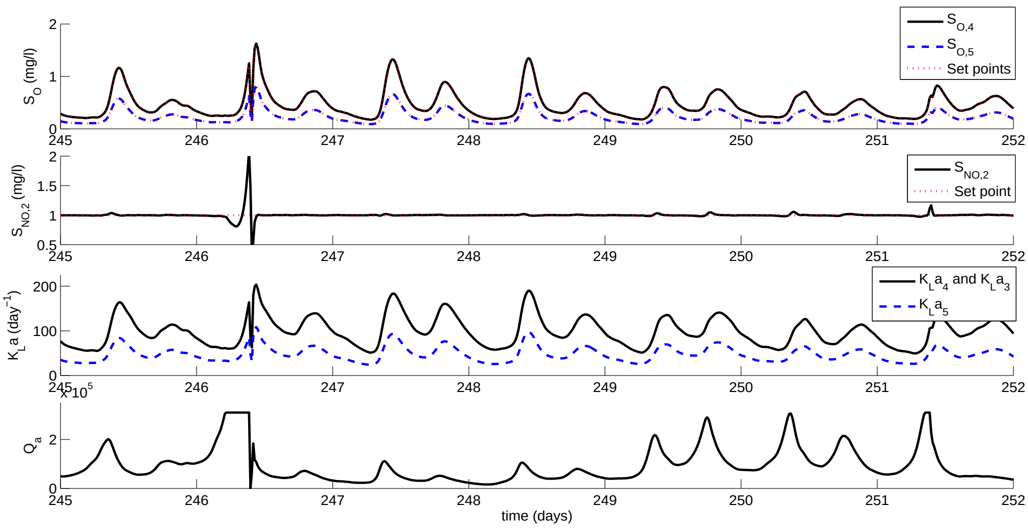
	Fixed S_O set-points and fixed Q_a				Hierarchical control and $S_{NO,2}$ control		
	$S_{O,4}$ control			$S_{O,5}$ control	$S_{O,4}$ control	$S_{O,5}$ control	$S_{NO,2}$ control
	PI of defCL	MPC+FF	%	MPC+FF	MPC+FF	MPC+FF	MPC+FF
IAE	9.079	0.33	96.36	0.44	0.44	0.37	3.91
ISE	0.4	0.0005	99.87	0.001	0.0049	0.0011	2.76

Table 7.2: Control performance results with fixed $S_{O,4}$ and $S_{O,5}$ set-points (2 mg/l and 1 mg/l respectively) and fixed Q_a (61944 m^3/d) and with $S_{NO,2}$ control at a set-point of 1 mg/l and varying $S_{O,4}$ and $S_{O,5}$ set-points with hierarchical control

One reason of the EQI and OCI reduction obtained with the proposed control strategies, in comparison with the referred works of Table 7.1, is the way how the controllers of the



(a) Control performance with fixed S_O set-points and fixed Q_a



(b) Control performance with $S_{NO,2}$ control and varying S_O set-points with hierarchical control

Figure 7.2: Simulation of the first evaluated week of the control performance of the MPC+FF controllers with fixed $S_{O,4}$ and $S_{O,5}$ set-points (2 mg/l and 1 mg/l respectively) and fixed Q_a (61944 m^3/d) (a); and with $S_{NO,2}$ control at a set-point of 1 mg/l and varying $S_{O,4}$ and $S_{O,5}$ set-points with hierarchical control (b)

higher level work. The referred papers try always to control S_{NH} at a fixed reference, but always with a very large error. This is not the case of the FC of the present work, which modifies the S_O set-points based on the biological processes, but without trying to maintain $S_{NH,5}$ at a fixed reference. It is also important to note that the referred works only vary the S_O set-point of one aerobic reactor, whereas in the present work $S_{O,4}$ and $S_{O,5}$ set-points are modified. Fig. 7.3 shows one week evolution of the most important variables when there are $S_{NH,5}$ peaks. It shows the comparison between hierarchical control and the control strategy with fixed S_O set-points. In the case of hierarchical control, when $S_{NH,5}$ increases, $S_{O,4}$ and $S_{O,5}$ set-points are also increased and $S_{NH,e}$ peaks are reduced, and when $S_{NH,5}$ decreases, $S_{O,4}$ and $S_{O,5}$ are also decremented generating less S_{NO} and reducing operational costs.

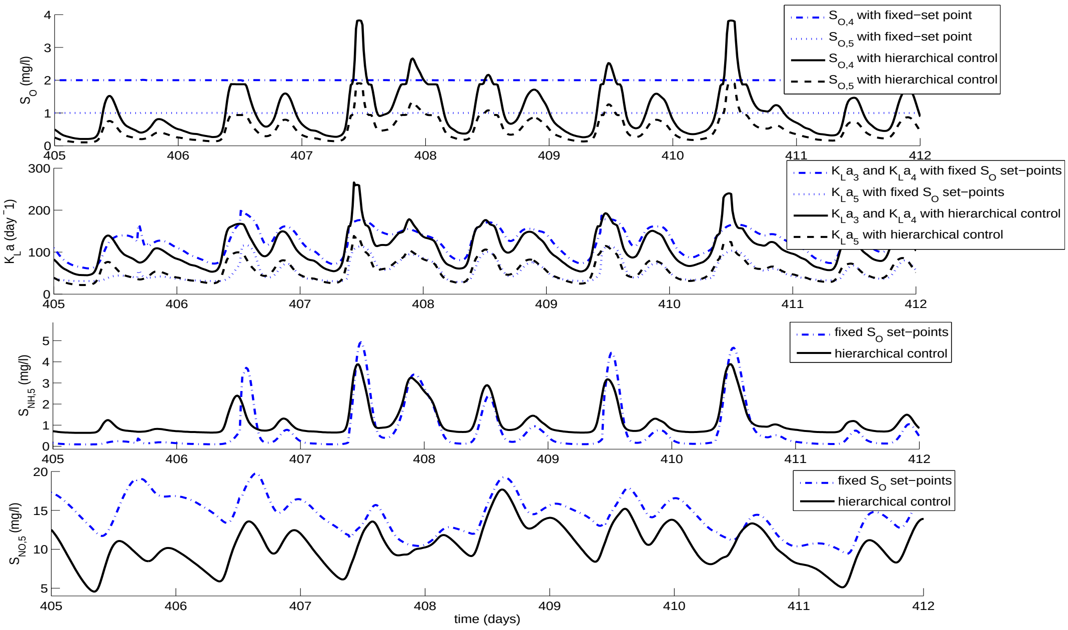


FIGURE 7.3: One week simulation comparison between control strategy with fixed S_O set-points and varying S_O set-points with hierarchical control

Regarding the effluent violations, Table 7.1 shows that all $S_{NH,e}$ violations are removed, while the vast majority of $S_{N_{tot,e}}$ violations are also eliminated. There are a few special cases where the $S_{N_{tot,e}}$ violation is not possible to be avoided. Specifically, it happens three times in the simulation year in the cases of $q_{EC,1}$ is equal to 0, 0.5 and 1; and one time in the simulation year in the case of $q_{EC,1}$ is equal to 2. These violations are due to an increased flow rate just when peaks of pollutants are in the last reactors, possibly due to a heavy rain. Furthermore, in two of these three times, the influent flow rate exceeds the capacity of the plant and is partially led directly to the effluent through the bypass, without being treated. Therefore, although the FC acts adding $q_{EC,5}$, there is not enough time in advance to avoid the violation. Fig. 7.5 and Fig. 7.4 show some cases where $S_{N_{tot,e}}$ and $S_{NH,e}$ violations are eliminated, unlike what happens with only hierarchical control. Fig. 7.5 (c) shows one case where $S_{N_{tot,e}}$ violation removal is not possible.

As explained in previous sections, the most important novelty of this work is the application of ANNs to predict the values of $S_{N_{tot,e}}$ and $S_{NH,e}$. As seen in Fig. 7.4 and Fig.

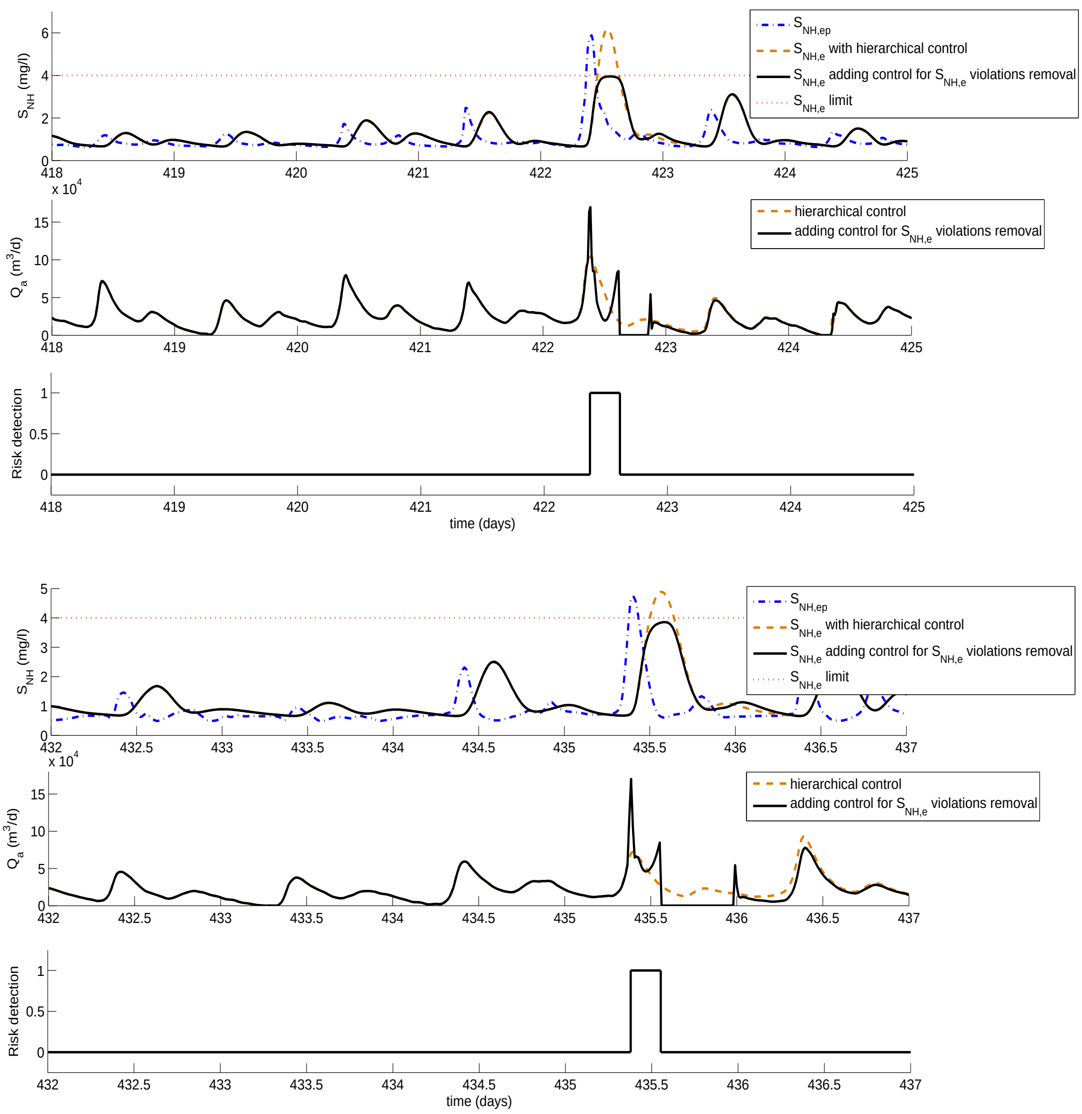


FIGURE 7.4: Simulation of two cases of the control strategy for $S_{NH,e}$ violations removal aplication and its comparison with hierarchical control alone

7.5, the prediction made by the ANNs allows to apply the appropriate control strategy enough in advance to prevent violations. In case that a violation of $S_{NH,e}$ is predicted, Q_a is increased by a FC to dilute S_{NH}, and when the increasing of S_{NH} reaches the fifth reactor, Q_a is decreased to reduce the hydraulic retention time and thus to improve the nitrification process. In the case that a violation of $S_{N_{tot,e}}$ is predicted, $q_{EC,1-2}$ is added according to the value calculated by a FC.

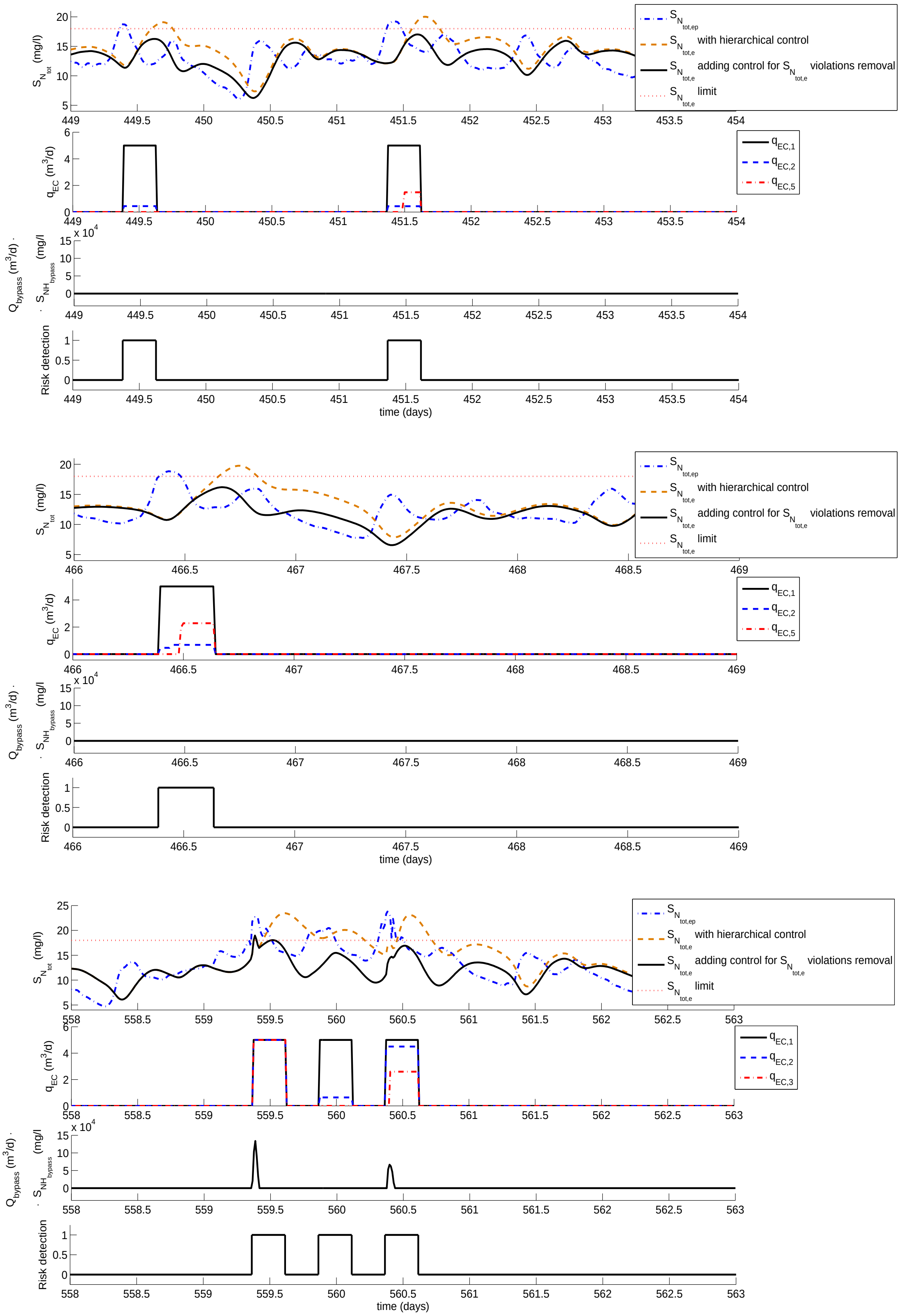


FIGURE 7.5: Simulation of some cases of the control strategy for $S_{N_{tot,e}}$ violations removal aplication and its comparison with hierarchical control alone

7.3 Summary

In this chapter, control strategies for effluent violations removal, similar to the ones applied in BSM1 in previous chapters, have been tested in BSM2. The main novelty is that, due to the variability of the influent, an intelligent control system selects the control strategies to be applied based on the effluent predictions.

For the lower level of the hierarchical structure, a satisfactory $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ control performance, by applying MPC+FF controllers, have been also achieved. Due to the similar results obtained with functions and FCs in BSM1, in this case only FCs have been proposed for the higher level and also to manipulate q_{EC} and Q_a when a risk of $S_{N_{tot,e}}$ or $S_{NH,e}$ violation is detected.

Simulation results have shown the complete elimination of $S_{NH,e}$ violations. Regarding $S_{N_{tot,e}}$ violations, they have been avoided except one time in a simulation year, in which a large increase of flow rate coincides with a peak of pollutants in the last reactor and with a situation of bypass. In addition, an EQI and OCI reduction has been achieved in comparison with defCL, CL1, CL2 and the referred articles. The percentage of reduction is compared to defCL, obtaining a maximum EQI reduction of 13% and a maximum OCI reduction of 37%.

Conclusions and future works

Conclusions

In this paper new control strategies have been applied in WWTPs, with the objectives of improving effluent quality, reducing operating costs (evaluated by EQI and OCI indices respectively) and avoiding to exceed the established limits of effluent pollutants concentrations.

The evaluation and comparison of different control strategies have been based on two benchmarks, developed by IWA: BSM1 and BSM2. First, BSM1 has been used as a testing plant because it requires a smaller simulation time and therefore different control strategies can be tested more quickly. Subsequently, the operation of these control strategies, adding some modifications, has been tested in BSM2. This is an updated version of BSM1, closer to a real plant, extending to one year of simulation, with a much more complex plant model, including also a pre-treatment process and a sludge treatment processes. In this case, a prediction of the effluent has been required for the election of the control strategy to be applied. In any case, control strategies have been applied in the zone of the activated sludge reactors.

The proposed control strategies have been based on MPC, FC, functions that relate the input with the manipulated variable and ANN. MPC controllers have been applied in order to improve the tracking. The control of the FCs and the functions was based on the biological processes that take place in the reactors. ANNs have been proposed in BSM2 to detect risks of violation by effluent predictions, in order to apply the appropriate control strategy. Both benchmarks and these control approaches have been explained in Chapter 2.

The thesis has been divided in two parts. In the first part, a hierarchical control has been applied in order to improve effluent quality and to reduce operational costs. In Chapter 4 the lower level has been implemented, where the MPC+FF controllers track the S_O in the aerated tanks and $S_{NO,2}$, improving the control performance with an ISE reduction of more than 90% compared to the default PI controllers. The control performance of the MPC+FF controllers has been also compared to the referenced papers, showing the improvement of the proposed method and thus the successful tracking. In Chapter 5, the higher level has been performed, which regulates the S_O set-points of the aerated tanks based on $S_{NH,5}$. First, for the selection of the higher level controller, three different alternatives were proposed manipulating only $S_{O,5}$ set-point: a MPC, an affine function and a FC. They were tested and compared in the three weather conditions: dry, rain and storm. As a result, EQI and OCI were reduced significantly. The results of OCI and EQI with higher level affine function and higher level FC were similar and better than those obtained with higher level MPC. This is due to the fact that the higher level MPC tries to keep the value of $S_{NH,5}$ at a reference level, but this is not possible. For that reason, the alternatives of affine function and FC for the higher level were tested with the idea of varying $S_{O,5}$ based on the $S_{NH,5}$ measured, taking into account the variables behavior in the biological processes, but without trying to keep $S_{NH,5}$ at a fixed reference. Thus, improving the nitrification process when $S_{NH,5}$ increases, to oxidize more S_{NH} and worsening the nitrification process when $S_{NH,5}$ decreases to generate less S_{NO} and to reduce costs. To ensure the right tuning of the controllers and therefore the correct relationship between the applied control and the results, a trade-off analysis between OCI and EQI has been performed by varying two tuning parameters for each controller. Next, the higher level control has been extended, manipulating the three aerobic tanks, achieving a greater reduction in EQI and OCI. Simulation results show that manipulating the S_O set-points of the three aerobic tanks, an EQI reduction of 5% and an OCI reduction of 3.9% is achieved for dry weather compared to the default control strategy. For the rain and storm influent cases, also a satisfactory reduction of EQI and OCI is obtained, higher than 3%.

In the second part of the thesis, control strategies have been added with the objective of effluent violations removal. In Chapter 5, BSM1 has been used as testing plant. Functions and FCs are proposed for these control strategies basing their control on the biological processes. The improvement of the denitrification process, by adding $q_{EC,1}$, achieves the complete elimination of $S_{N_{tot,e}}$ violations. This control strategy has been tested with an affine function with a sliding window and with an FC. Both are implemented to dosage the minimum $q_{EC,1}$ necessary for this aim. The improvement of the nitrification process by manipulating Q_a makes possible the $S_{NH,e}$ violations removal. It has been tested first, with the combination of a linear function and an exponential function, and next, with an FC which uses different tuning parameters depending on if there are peaks of pollution in the tanks or not. Simulation results show that $S_{N_{tot,e}}$ and $S_{NH,e}$ violations are removed for dry, rain and storm influents. In the cases of $S_{N_{tot,e}}$ violations removal for the three weather conditions and $S_{NH,e}$ violations removal for dry weather, a simultaneous reduction of EQI and OCI is achieved in comparison with the default control strategy. The $S_{NH,e}$ violations removal for rain and storm influents and the simultaneous elimination of $S_{N_{tot,e}}$ and $S_{NH,e}$ makes inevitable an increase of OCI. In any case, it has to be said that, with the removal of effluent violations, a reduction of costs is obtained for not paying fines, which is not considered in OCI.

In Chapter 6 and Chapter 7, BSM2 is used as working scenario. For the application of the control strategies for effluent violations removal in BSM2, effluent predictions are necessary in order to detect risks of violation and thus selecting the suitable control strategy to be applied. In Chapter 6, the implementation of the ANNs for these effluent predictions is described. Simulations have shown a satisfactory predictions of $S_{N_{tot,e}}$ and $S_{NH,e}$, which are used for detection of risk violations and thus for selecting the suitable control strategy.

In Chapter 7, the control strategies selected by an intelligent control system have been implemented. For the lower level of the hierarchical structure, a satisfactory $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ control performance, by applying MPC+FF controllers, have been also achieved. Due to the similar results obtained with functions and FCs in BSM1, in this case only FCs have been proposed for the higher level. Also, FCs are implemented to manipulate q_{EC} and Q_a when a risk of $S_{N_{tot,e}}$ or $S_{NH,e}$ violation is detected. The simulation results have been presented for different fixed values of $q_{EC,1}$. They have shown the complete elimination of $S_{NH,e}$ violations. Regarding $S_{N_{tot,e}}$ violations, they have been avoided except one time in a simulation year, in which a large increase of flow rate coincides with a peak of pollutants in the last reactor and with a situation of bypass. In addition, an EQI and OCI reduction has been achieved in comparison with defCL, CL1, CL2 and the referred articles. The percentage of reduction is compared to defCL, obtaining a maximum EQI reduction of 13% and a maximum OCI reduction of 37%.

Future works

This work has been focused on improving the biological treatment of wastewater, with BSM1 and BSM2 as working scenarios. Further interesting works in this area would be the simultaneous removal of $S_{N_{tot,e}}$ and $S_{NH,e}$ violations in BSM2 and the elimination of TSS violations by manipulating Q_r.

Moreover, as explained, BSM2 includes, in addition to the biological wastewater treatment, 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. These areas should be studied in order to achieve a possible improvement of the plant by applying control strategies.

Between these areas of a WWTP, anaerobic digestion must be highlighted in order to reduce costs through energy production. Anaerobic digestion is a process in which the material in the absence of oxygen, and by the action of a group of organic bacteria, decomposes into biogas, which contains a high percentage of methane, which is susceptible of energy use. Regarding the thickener and the dewatering, they can be studied in order to reduce TSS and to avoid violations in the effluent.

In addition, an update version of BSM2 takes also into account greenhouse gases, phosphorus, sulphur and micropollutants. Next to methane and carbon dioxide that are intrinsically part of the plant-wide benchmark simulation model, recent work has focused significantly on nitrogen oxides emissions. Phosphorus removal has been a focus of WWTP design and operation, but its inclusion in whole plant models is lagging behind that of Nitrogen removal. Efforts to control hydrogen sulfide emissions and induced corrosion in sewer systems will benefit from such Sulphur-focused modelling efforts. Finally, recent interest in micropollutants has led to a diversity of model developments. The diversity of micropollutants remains a challenge, but consensus can probably be found regarding models of the overall fate-determining mechanisms.

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Applying variable dissolved oxygen set point in a two level hierarchical control structure to a wastewater treatment process

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ABSTRACT

This paper presents a two-level hierarchical control structure for biological wastewater treatment plants, with the goal of improving effluent quality and reducing operational costs. The Benchmark Simulation Model No. 1 is used as working scenario. The hierarchical structure allows to adjust the dissolved oxygen in the fifth tank ($S_{O,5}$) according with the working conditions, instead of keeping it in a fixed value. Model Predictive Control (MPC) with inlet flow rate feedforward control (MPC + FF) is proposed for the lower level to control nitrate nitrogen concentration of the second tank and $S_{O,5}$. MPC, Affine Function and fuzzy controller are tested for the higher level to adjust the $S_{O,5}$ set point of the lower level based on the ammonium and ammonia nitrogen concentration in the fifth tank. Modifying the tuning parameters of the higher level, a tuning region is determined, in which the effluent quality and operational costs are simultaneously improved.

1. Introduction

Biological wastewater treatment plants (WWTPs) are complex, nonlinear systems with very different time constants. The intricate behaviour of the micro-organisms and the large disturbances in concentrations and flow rates of the influent makes the control of the WWTP a complex task. In addition, there are effluent requirements defined by the European Union (European Directive 91/271 Urban wastewater) with economic penalties. The purpose of this work is to operate WWTPs with the aim of improving the effluent quality and reduce operational costs.

Many control strategies have been proposed in the literature but their evaluation and comparison, either practical or based on simulation is difficult. This is due to the variability of the influent, the complexity of the biological and biochemical phenomena, the large range of time constants (varying from a few minutes to several days), and the lack of standard evaluation criteria (among other things, due to region specific effluent requirements and cost levels). In order to face this complexity, the evaluation and comparison of the different strategies can be based on the Benchmark Simulation Model No. 1 (BSM1), developed by the International Association on Water Pollution Research and Control [1–3]. This benchmark includes a plant layout, influent loads, test procedures and evaluation criteria.

Advanced control research for theoretical progress and practical implementation is today very necessary to reduce operational costs, to improve quality, to optimize the use of energy resources and to reduce environmental contamination [4]. Authors in [5] show that with a highly loaded plant and with stringent effluent fines imposed by legislation, more advanced control algorithms are advantageous. For the challenging task of controlling WWTPs, model predictive control (MPC) has demonstrated to be effective: Holenda et al. [6] tried an indirect control, with the dissolved oxygen concentration in the fifth tank ($S_{O,5}$) as controlled variable; Shen et al. [5] tested a direct control, with the quality indices as controlled variables, with feedforward control of the influent flow rate (Q_0) to reject disturbances; Shen et al. [7] applied also quality indices as controlled variables with feedforward control of the influent ammonium and ammonia nitrogen concentration ($S_{NH,in}$) and Q_0, and in addition experimented with hard constraints in the manipulated variables and soft constraints in the controlled variables; Cristea et al. [8] employed a multivariable control strategy with two controlled variables, $S_{O,5}$ and nitrite and nitrate nitrogen concentration of the second tank ($S_{NO,2}$), with feedforward control of nitrite and nitrate nitrogen (S_{NO}) and dissolved oxygen (S_O) concentrations in the inlet flow of the first anoxic reactor, improving the performance of $S_{NO,2}$ control, but not of $S_{O,5}$ control in comparison with default PI controllers. PI and PID controllers have attracted the research interest for process control looking for good robustness/performance trade-off [9]. However WWTPs

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exhibit highly complex dynamics that need for more advanced alternatives.

Other works have experimented in the S_{NH} in the fifth tank ($S_{NH,5}$) control by manipulating $S_{O,5}$ set point. Vrecko et al. [10] tested with PI controllers, Stare et al. [11] and Ostace et al. [12] experimented with PI controllers and a MPC, and Ostace et al. [13] used MPC for both lower and higher level controls. These references worked with a variation of BSM1.

This paper proposes first an MPC with Q_0 feedforward compensation (MPC + FF) to control $S_{NO,2}$ and $S_{O,5}$ by manipulating the oxygen transfer coefficient (K_La) in the fifht tank (K_La_5) and the internal recirculation flow rate (Q_a), based upon the work [8]. However, in the present work, a different feedforward control is proposed and an improvement of $S_{O,5}$ and $S_{NO,2}$ performance control is achieved.

Next, a two-level hierarchical control strategy is investigated, in which the lower level is MPC + FF, and the higher level modifies $S_{O,5}$ set point of the lower level according with the working conditions of the plant. This paper is mainly focused in the higher level control. For the $S_{NH,5}$ control, Vrecko et al. [10], Stare et al. [11], Ostace et al. [12], and Ostace et al. [13] used MPC and PI controllers but with a modified BSM1: Vrecko et al. [10] and Stare et al. [11] with four aerobic tanks and one anoxic tank, and Ostace et al. [12], and Ostace et al. [13] with a variation of the activated sludge model of the reactors. These referenced works try to maintain the level of $S_{NH,5}$ at a fixed reference by manipulating the $S_{O,5}$ set point of the lower level. In the proposed paper, three alternatives for the higher level controller are proposed and compared: an MPC, a fuzzy controller and a simple Affine Function. For the MPC, a set point of $S_{NH,5}$ is applied and, in the cases of the Affine Function and the fuzzy controller, $S_{NH,5}$ is not forced to follow a set point reference. Different improving options of OCI and EQI are shown by making a trade-off analysis for the three controllers of the higher level based on the tuning parameters. The extreme cases have been analyzed: the best EQI without worsening OCI and the best OCI without worsening EQI.

2. Working scenario: BSM1

This section provides a description of the working scenario provided by the BSM1 as well as the cost/performance evaluation criteria and indexes.

2.1. Models

The processes in the WWTPs are simulated by two internationally accepted models. The Activated Sludge Model No. 1 (ASM1) [14] for biological processes in the reactors and the double-exponential settling velocity model [15] for the vertical transfers between layers in the settler. The two models include thirteen state variables. Eight different biological processes are considered in the ASM1 and none in the settler.

2.2. Plant layout

The schematic representation of the WWTPs is presented in Fig. 1. The plant consists in five biological reactor tanks connected in series, followed by a secondary settler. The first two tanks have a volume of 1000 m^3 each and are anoxic and perfectly mixed. The other three tanks have a volume of 1333 m^3 each and are aerated. The settler has a total volume of 6000 m^3 and is modeled in ten layers, being the 6th layer, counting from bottom to top, the feed layer. Two recycle flows complete the system, the first from the last tank and the second from the underflow of the settler.

The plant is designed for an average influent dry-weather flow rate of 18.446 m^3/d and an average biodegradable chemical oxygen demand (COD) in the influent of 300 g/m^3. Its hydraulic retention time, based on average dry weather flow rate and total tank and settler volume (12,000 m^3), is 14.4 h. The wastage flow rate (Q_w) equals 385 m^3/d, which corresponds to a biomass sludge age of about 9 days, based on the total amount of biomass present in the system.

Table 1
Effluent quality limits.

Variable	Value
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}

The nitrogen removal is achieved using a denitrification step performed in the anoxic tanks and a nitrification step carried out in the aerated tanks. The internal recycle is used to supply the denitrification step with S_{NO}.

2.3. Influent loads

Three influent disturbances, representative of different weather conditions, have been defined in BSM1 [16,17]: dry weather, rain weather (a combination of dry weather and a long rain period) and storm weather (a combination of dry weather with two storm events). Each scenario contains 14 days of influent data with sampling intervals of 15 min.

The applied control strategies have been evaluated for the three weather conditions.

2.4. Evaluation criteria

A simulation/experiment protocol is established to assure that results and performance data are collected under the same conditions and can be compared. First, a 150 days period of stabilization in a closed-loop using constant influent data with no noise on the measurements has to be completed to drive the system to a steady-state, next running a dynamic simulation by using the dry weather file (14 days) and finally testing the desired influent data (dry, rain or storm).

The effluent concentrations of total Nitrogen (N_{tot}), Total Chemical Oxygen Demand (COD_t), S_{NH}, Total Suspended Solids (TSS) and Biological Oxygen Demand (BOD_5) over the three evaluation periods (dry, rain and storm weather: 7 days for each) should obey the limits given in Table 1.

N_{tot} is calculated as the sum of S_{NO} and S_{NKj}, where S_{NKj} is the Kjeldahl Nitrogen concentration which is the sum of organic nitrogen and S_{NH}.

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. It is assessed by ISE (Integral of the Squared Error) criterion.

$$ISE = \int_{t=7\,days}^{t=14\,days} e_i^2 \cdot dt \tag{1}$$

where e_i is the error in each sample between the set point and the measured value.

The second level provides measures for the effect of the control strategy on plant performance. It includes the Effluent Quality Index and the Operational Cost Index explained below.

2.4.1. Effluent quality index

An Effluent Quality Index (EQI) is defined to evaluate the quality of the effluent. It is related with the fines to be paid due to the discharge of pollution. EQI is averaged over a 7 days observation

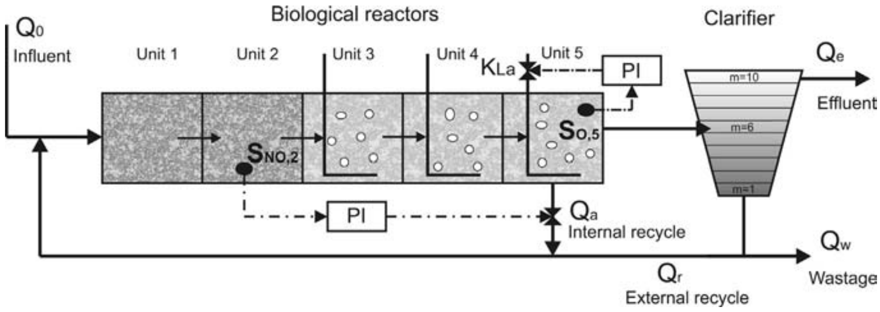

Fig. 1. Benchmark Simulation Model 1.

Table 2
B_i values.

Factor	B_{TSS}	B_{COD}	B_{NKj}	B_{NO}	B_{BOD_5}
Value (g pollution unit g^{-1})	2	1	30	10	2

period and it is calculated weighting the different compounds of the effluent loads.

$$\mathrm{EQI} = \frac{1}{1000 \cdot T} \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} (B_{\mathrm{TSS}} \cdot \mathrm{TSS}(t) + B_{\mathrm{COD}} \cdot \mathrm{COD}(t) + B_{\mathrm{NKj}} \cdot S_{\mathrm{NKj}}(t) + B_{\mathrm{NO}} \cdot S_{\mathrm{NO}}(t) + B_{\mathrm{BOD}_5} \cdot \mathrm{BOD}_5(t)) \cdot Q(t) \cdot dt \quad (2)$$

where B_i are weighting factors (Table 2) and T is the total time.

2.4.2. Overall cost index

The overall cost index (OCI) is defined as:

$$\mathrm{OCI} = \mathrm{AE} + \mathrm{PE} + 5 \cdot \mathrm{SP} + 3 \cdot \mathrm{EC} + \mathrm{ME} \quad (3)$$

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 and ME is the mixing energy.

The aeration energy AE is calculated according to the following relation:

$$\mathrm{AE} = \frac{8}{T \cdot 1.8 \cdot 1000} \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} \sum_{i=1}^{5} V_i \cdot K_L a_i(t) \cdot dt \quad (4)$$

The pumping energy PE is calculated as:

$$\mathrm{PE} = \frac{1}{T} \int_{7\,\mathrm{days}}^{14\,\mathrm{days}} (0.004 \cdot Q_0(t) + 0.008 \cdot Q_a(t) + 0.05 \cdot Q_w(t)) \cdot dt \quad (5)$$

The sludge production to be disposed SP is calculated from the total solid flow from wastage and the solids accumulated in the system over the period of time considered:

$$\mathrm{SP} = \frac{1}{T} \cdot (\mathrm{TSS}_a(14\,\mathrm{days}) - \mathrm{TSS}_a(7\,\mathrm{days}) + \mathrm{TSS}_s(14\,\mathrm{days}) - \mathrm{TSS}_s(7\,\mathrm{days}) + \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} \mathrm{TSS}_w \cdot Q_w \cdot dt) \quad (6)$$

where TSS_a is the amount of solids in the reactors, TSS_s is the amount of solids in the settler and TSS_w is the amount of solids in the wastage.

EC refers to the carbon that could be added to improve denitrification:

$$\mathrm{EC} = \frac{\mathrm{COD_{EC}}}{T \cdot 1000} \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} \left(\sum_{i=1}^{i=n} q_{\mathrm{EC},i} \right) \cdot dt \quad (7)$$

where $q_{EC,i}$ is the flow rate of external carbon added to compartment i, $\mathrm{COD_{EC}}$ = 400 gCOD m^{-3} is the concentration of readily biodegradable substrate in the external carbon source.

The mixing energy ME is a function of the compartment volume and is the energy employed to mix the anoxic tanks to avoid settling:

$$\mathrm{ME} = \frac{24}{T} \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} \sum_{i=1}^{5} \left[0.005 \cdot V_i \;\; \text{if} \;\; K_L a_i(t) < 20 d^{-1} \;\; \text{otherwise} \;\; 0 \right] \cdot dt \quad (8)$$

where V is the volume of the tank.

3. Control strategies

The original BSM1 definition includes the so called default control strategy that is commonly used as a reference [1–3]. This strategy uses two PI control loops as shown in Fig. 1. The first one involves the control of $S_{O,5}$ by manipulating K_La_5. The set point for $S_{O,5}$ is 2 mg/l. The second control loop has to maintain $S_{NO,2}$ at a set point of 1 mg/l by manipulation of Q_a.

In this work, a two levels hierarchical control structure is proposed. In the lower level an MPC + FF configuration is applied to track the $S_{NO,2}$ set point of 1 mg/l by manipulating Q_a and to track the $S_{O,5}$ set point given by the higher level by manipulating K_La_5. This MPC + FF solution is applied instead of the PI controllers of the BSM1 default control strategy with the aim of improving the tracking of the $S_{O,5}$ and $S_{NO,2}$ set points (see Fig. 2). The higher level manipulates $S_{O,5}$ set point of the lower level based on $S_{NH,5}$, instead of keeping it at a fixed value of 2 mg/l (see Fig. 3). Three controllers are proposed for this higher level: MPC, Affine Function and fuzzy control. The importance of the control performance of MPC + FF for $S_{O,5}$ set point tracking should be noticed, to ensure that the value of $S_{O,5}$ is the closest possible to the set point calculated by the higher level controller.

3.1. MPC + FF configuration

The two PI controllers of the default BSM1 control strategy are replaced by an MPC with two inputs ($S_{O,5}$ and $S_{NO,2}$) and two outputs (K_La_5 and Q_a), in order to improve the tracking of $S_{O,5}$ and $S_{NO,2}$ set points, whose results are evaluated by the ISE criterion.

The basis of MPC is the use of an optimization algorithm to solve the control problem and the use of a model of the plant to make predictions of the output variables [18]. At each control interval, $\triangle t$, for a prediction horizon, p, and a control horizon, m, ($m < p$), the MPC algorithm computes the sequences of control moves over the horizon m:

$$\triangle u(k), \triangle u(k+1), \ldots, \triangle u(k+m-1) \quad (9)$$

This sequence of control moves is based on predictions of the process variables over a future horizon p:

$$\hat{y}(k+1|k), \hat{y}(k+2|k), \ldots, \hat{y}(k+p|k) \quad (10)$$

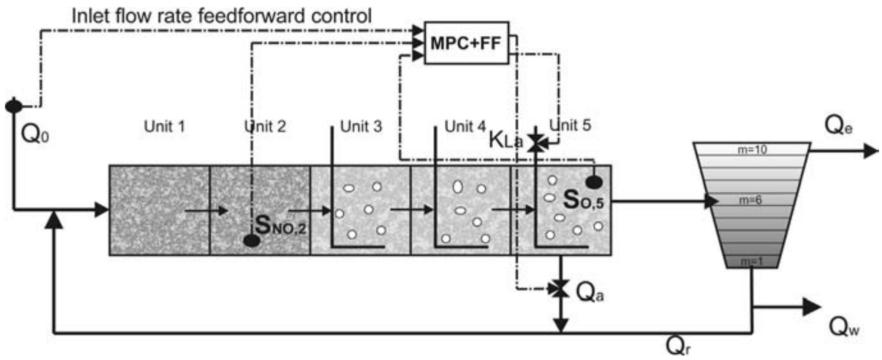

Fig. 2. BSM1 with MPC + FF instead of default PI controllers.

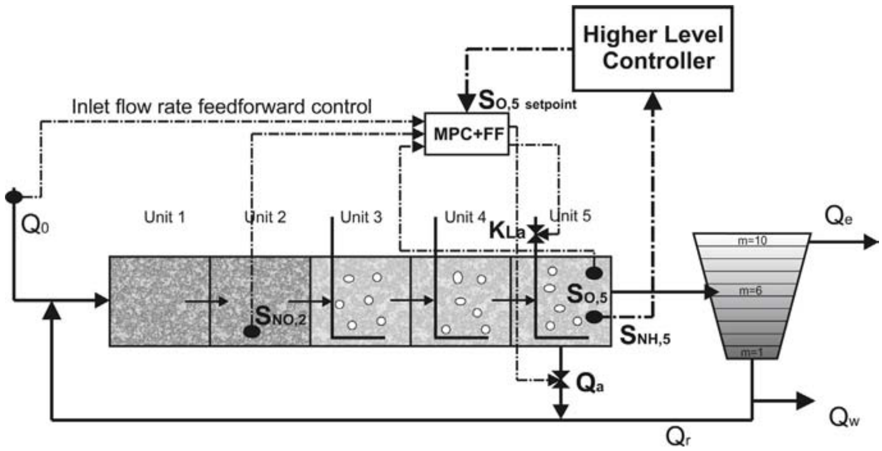

Fig. 3. BSM1 with MPC + FF and hierarchical control.

and is selected in such a way that minimizes a quadratic objective of the form:

$$J = \sum_{l=1}^{p} ||\Gamma_y[y(k+l|k) - r(k+l)]||^2 + \sum_{l=1}^{m} ||\Gamma_{\triangle u}[\triangle u(k+l-1)]||^2 \quad (11)$$

where the output prediction $y(k+l|k)$ means a predicted controlled output for the future sampling instant $k+1$, performed at the current instant k, and Γ_y and $\Gamma_{\triangle u}$ are the output weight and input rate weight respectively, that penalize the residual between the future reference and the output variable prediction, and the control moves.

Due to the presence of strong disturbances on WWTPs, MPC has difficulties in keeping the controlled variables at their reference level. To compensate the disturbances, a feedforward control action is added, as in [5,7,8,19] (see Fig. 2). MPC provides feedforward compensation for the measured disturbances as they occur to minimize their impact on the output. The combination of feedforward plus feedback control can significantly improve the performance over simple feedback control whenever there is a major disturbance that can be measured before it affects the process output. The idea of the feedforward control is to act on the process when the disturbances appear and before they cause deterioration in the effluent quality. Different variables have been considered for the feedforward action in the referred works, but in our case Q_0 has been selected for its better results. Any change in Q_0 affects directly the flow rates of all the tanks, modifying their hydraulic retention time. Therefore, it is necessary to adjust the manipulated variables immediately to compensate the Q_0 disturbances. The MPC algorithm requires a state-space linear model to foresee how the plant outputs, $y(k)$, react to the possible variations of the control variables, $u(k)$, and to compute at each $\triangle t$ the control moves. WWTPs are complex nonlinear systems. Nevertheless, previous works [6–8,19] among others, show that the operation can be carried out in the vicinity of a working point by assuming the following linear state-space model:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned} \quad (12)$$

where $x(k)$ is the state vector, and A, B, C and D are the state-space matrices. In concrete terms, $u_1(k)$ is Q_a, $u_2(k)$ is K_La_5, $u_3(k)$ is Q_0 and $y_1(k)$ is $S_{NO,2}$ and $y_2(k)$ is $S_{O,5}$.

The tuning parameters are: $\triangle t$, m, p, $\Gamma_{\triangle u}$, Γ_y and the overall estimator gain.

- $\triangle t$ has a significant effect on the effectiveness of the controller. High $\triangle t$ can give less controller performance, mainly when there are important input disturbances, and low $\triangle t$ can produce changes too quickly in the actuators and also high energy consumption.
- Lower $\Gamma_{\triangle u}$ or higher Γ_y give better performance of the controlled variable that could otherwise produce strong oscillations in the actuators that must be avoided.
- m and p should be adjusted depending of system control in each case. However values that are too high can increase the computational time in excess, and on the other hand, values that are too small may result in oscillatory responses or may not work at all.
- At each $\triangle t$ the controller compares the real value of the outputs with the expected values. The difference can be due to noise, to measurements errors and to unmeasured disturbances. With the overall estimator gain parameter it is determined the percentage of this difference that is attributed to unmeasured disturbances

and the calculation matrix is consequently adjusted. Higher overall estimator gains improve the results, but too high values can make the controller unfeasible.

3.2. Two level hierarchical control configuration

In this section a two-level hierarchical control scheme is proposed. The lower level controller is responsible of the $S_{O,5}$ and $S_{NO,2}$ tracking by manipulating K_La_5 and Q_a. The higher level controller has to manipulate $S_{O,5}$ set point of the lower level controller according with $S_{NH,5}$ (see Fig. 3). The biological treatment of S_{NH} and S_{NO} is the result of various processes given by the Activated Sludge Model No 1 (ASM1) [1,2,14], which describes the biological phenomena that take place in the biological reactors:

$$r_{NH} = -0.08\rho_1 - 0.08\rho_2 - \left(0.08 + \frac{1}{0.24}\right)\rho_3 + \rho_6 \tag{13}$$

$$r_{NO} = -0.1722\rho_2 + 4.1667\rho_3 \tag{14}$$

$$\rho_1 = 4\left(\frac{S_S}{10+S_S}\right)\left(\frac{S_O}{0.2+S_O}\right)X_{B,H} \tag{15}$$

$$\rho_2 = 4\left(\frac{S_S}{10+S_S}\right)\left(\frac{0.2}{0.2+S_O}\right)\left(\frac{S_{NO}}{0.5+S_{NO}}\right)0.8\cdot X_{B,H} \tag{16}$$

$$\rho_3 = 0.5\left(\frac{S_{NH}}{1+S_{NH}}\right)\left(\frac{S_O}{0.4+S_O}\right)X_{B,A} \tag{17}$$

$$\rho_6 = 0.05\cdot S_{ND}\cdot X_{B,H} \tag{18}$$

where r_{NH} is the reaction rate of S_{NH}, r_{NO} is the reaction rate of S_{NO}, S_S is the readily biodegradable substrate, S_{ND} the soluble biodegradable organic nitrogen, $X_{B,H}$ the active heterotrophic biomass and $X_{B,A}$ the active autotrophic biomass. The biological parameters values used in the BSM1 correspond approximately to a temperature of 15°C.

When S_{NH} increases, more S_O is needed for nitrification (13, 17). On the contrary, when S_{NH} decreases, less S_O is required, producing less S_{NO} (14, 17).

Other works have experimented in the $S_{NH,5}$ control by manipulating $S_{O,5}$ set point [10,11]. Nevertheless, these investigations use default PI controllers at the lower level. Vrecko et al. [10] tested a higher level PI controller, and Stare et al. [11] experienced with PI and MPC controllers as higher level (working with a variation of BSM1, with one anoxic tank and four aerobic tanks). The proposed configuration of this paper uses the MPC + FF as lower level control explained before (Section 3.1). Three alternatives are tested for the higher level: MPC, Affine Function and fuzzy control. For each of these alternatives a range of tuning parameters are proposed.

3.2.1. Higher level MPC

First, a MPC is proposed for the higher level control, with the aim of keeping $S_{NH,5}$ at a fixed set point by manipulating $S_{O,5}$.

As it has been done with lower level MPC (Section 3.1), a linear model (12) of the plant is needed to compute predictions of the output variables of the MPC. In this case, the plant model has one input and one output. Concretely, $u(t)$ is the set point value of $S_{O,5}$ and $y(t)$ is $S_{NH,5}$.

3.2.2. Higher level Affine Function

The nitrification process is performed by the autotrophic bacteria whose growth is obtained by ρ_3 (17). As it can be observed, higher S_{NH} and S_O produce a greater S_{NH} removal. However, increasing the S_O value also increases S_{NO} and operational costs, as it can be observed in Eqs. (14) and (3). For this reason it is important to increase S_O when S_{NH} increases to reduce S_{NH} peaks, and decrease S_O when S_{NH} decreases, producing less S_{NO} and reducing costs.

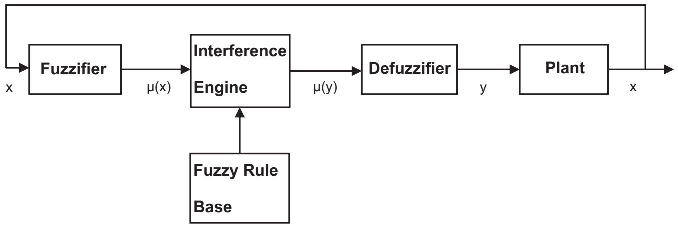

Fig. 4. Architecture of a fuzzy controller.

Due to these reasons, an Affine Function has been tested as higher level controller. The difference between this controller and the MPC is that the Affine Function regulates $S_{O,5}$ set point based on $S_{NH,5}$, to obtain the $S_{O,5}$ value, but without having the aim of keeping $S_{NH,5}$ at a reference level. Thus the following Affine Function is proposed:

$$S_{O,5}\ \text{set point}(t) = S_{NH,5}(t) - k \tag{19}$$

where k is a constant. $S_{O,5}$ value obtained is directly proportional to $S_{NH,5}$, subtracting the k value. Also, a constraint of a maximum value of $S_{O,5}$ has been added to improve the EQI and OCI trade-off. Values of k and $S_{O,5}$ maximum are considered tuning parameters and they are analyzed in Section 4.2.2 with OCI and EQI trade-off representations.

3.2.3. Higher level fuzzy controller

A higher level fuzzy controller is also implemented, with the same idea of the higher level Affine Function. Thus, the higher level fuzzy controller modifies $S_{O,5}$ based on $S_{NH,5}$, but does not try to keep $S_{NH,5}$ at a given set point. The $S_{O,5}$ set point value is increased when $S_{NH,5}$ increases to enhance the nitrification process and to reduce $S_{NH,5}$ peaks. Conversely, the $S_{O,5}$ set point is decreased when $S_{NH,5}$ is low to reduce S_{NO} and operating costs. However, the methodology to obtain the $S_{O,5}$ set point is modified, using fuzzy logic in this case.

Fuzzy logic can be described as an interpretative system in which objects or elements are related with borders not clearly defined, granting them a relative membership degree and not strict, as it is customary in traditional logic.

The typical architecture of a fuzzy controller, shown in Fig. 4, consists of: a fuzzifier, a fuzzy rule base, an inference engine and a defuzzifier [20].

The fuzzy control can be defined as a control based on human expertise, determined by words instead of numbers and sentences instead of equations. However, process variables are measured in numbers instead of words. For this reason, the fuzzifier adapts the input variables into suitable linguistic values by membership functions. There are different forms of membership functions, e.g. triangular, trapezoidal or Gaussian, and are chosen according to the user's experience.

The fuzzy rule base is a set of if-then rules that store the empirical knowledge of the experts about the operation of the process. A series of relationships that interpret common sense are defined and can generate a desired action that is applied to the plant. First the fuzzy logic computes the grade of membership of each condition of a rule, and then aggregates the partial results of each condition using fuzzy set operator.

The inference engine combines the results of the different rules to determine the actions to be carried out, and the defuzzifier converts the control actions of the inference engine into numerical variables of control that are applied to the plant. There are two different methods to operate these modules: Mamdani [21] and Sugeno [22]. Mamdani system aggregates the area determined by each rule and the output is determined by the center of gravity of that area. In a Sugeno system, the condition of a rule determines the weight of the output of the rule that is a linear combination of the inputs.

The implementation of the proposed fuzzy controller was based on the observation of the simulations results obtained by operating the plant with the default control of BSM1.

The input of the fuzzy controller is $S_{NH,5}$. Three triangular membership functions are applied to the input to fuzzyfy. The following fuzzy sets have been used: *low*, *medium* and *high*. The range of the input values is defined as follows: The minimum value of the input (*minin*) and the maximum value of the input (*maxin*).

The output is the $S_{O,5}$ set point of the lower level control. Also three triangular membership functions have been applied to the output with the same fuzzy sets: *low*, *medium* and *high*. The range of the output values is defined as follows: The minimum value of the output (*minout*) and the maximum value of the output (*maxout*). The values of *maxin* and *maxout* are considered tuning parameters and are analyzed in Section 4.2.3.

The if-then fuzzy rules that relate the input and output are:

if ($S_{NH,5}$ is *low*) **then** ($S_{O,5}$ is *low*)
if ($S_{NH,5}$ is *medium*) **then** ($S_{O,5}$ is *medium*)
if ($S_{NH,5}$ is *high*) **then** ($S_{O,5}$ is *high*)

The Mamdani method has been chosen to defuzzify the results of the above if-then fuzzy rules and thereby obtain a single value of the $S_{O,5}$ set point based on the value of $S_{NH,5}$.

4. Simulation results

In this section the control configurations proposed in the above section are tested and compared. Ideal sensors have been considered for the simulations.

4.1. MPC + FF configuration

$S_{O,5}$ and $S_{NO,2}$ values to get the linear model (12) have been obtained by varying K_La_5 around ±10% of 131.6514 day^{-1} and Q_a around ±10% of 16,486 m^3/day and applying a step change of +50% to Q_0.

By using Matlab System Identification Toolbox with prediction error method [23], the following third order state-space model (12) is obtained:

$$A = \begin{bmatrix} 0.8748 & 0.04463 & 0.1314 \\ 0.04091 & 0.7331 & 0.1796 \\ 0.2617 & -0.1318 & 0.3007 \end{bmatrix}$$
$$B = \begin{bmatrix} 7.641 \cdot 10^{-6} & 0.004551 & -2.749 \cdot 10^{-5} \\ -2.631 \cdot 10^{-5} & 0.006562 & -4.551 \cdot 10^{-6} \\ -9.63 \cdot 10^{-6} & -0.02161 & 2.447 \cdot 10^{-5} \end{bmatrix} \tag{20}$$
$$C = \begin{bmatrix} 0.8812 & -0.5948 & 0.02114 \\ 1.187 & 0.9893 & -0.3754 \end{bmatrix}$$
$$D = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

The selected values to tune the MPC are $m = 20$ and $p = 5$. It should be noted that these values are not critical and they can slightly be changed with similar results. $\triangle t$ is 0.00025 days (21.6 s). The following weights have been used for $S_{O,5}$ control: $\Gamma_y = 1$, $\Gamma_{\triangle u} = 0.01$, and for $S_{NO,2}$ control: $\Gamma_y = 1$, $\Gamma_{\triangle u} = 0.0001$. The selected overall estimator gain value is 0.8.

Fig. 5 shows $S_{O,5}$ and $S_{NO,2}$ for the dry weather case compared with the default PI control. Table 3 shows that MPC + FF reduces ISE of $S_{NO,2}$ control more than 99% and ISE of $S_{O,5}$ control more than 97% in comparison with the default PI controllers. This control performance improvement results in a 1.1% of EQI reduction, keeping a similar OCI (increase of 0.0063%).

Table 3
ISE, EQI and OCI results using default PI controllers and MPC + FF for dry, rain and storm influents.

	PI	MPC + FF	%
Dry weather			
ISE ($S_{NO,2}$ control)	0.47	0.0013	−99.7
ISE ($S_{O,5}$ control)	0.022	0.00067	−96.9
EQI (kg pollutants/d)	6115.63	6048.25	−1.1
OCI	16,381.93	16,382.97	+0.0063
Rain weather			
ISE ($S_{NO,2}$ control)	0.69	0.0028	−99.6
ISE ($S_{O,5}$ control)	0.016	0.0013	−92.02
EQI (kg pollutants/d)	8174.98	8090.29	−1.03
OCI	15,984.85	15,990.85	+0.037
Storm weather			
ISE ($S_{NO,2}$ control)	0.69	0.0032	−99.5
ISE ($S_{O,5}$ control)	0.020	0.0018	−90.8
EQI (kg pollutants/d)	7211.48	7132.60	−1.09
OCI	17,253.75	17,261.39	+0.044

This comparison is also done for the rain (see Fig. 6 and Table 3) and storm influents (see Fig. 7 and Table 3), obtaining similar percentages of improvement: ISE 99.6% (rain) and 99.5% (storm) for $S_{NO,2}$ control and 92.02% (rain) and 90.8% (storm) for $S_{O,5}$ control, and reducing EQI with MPC + FF 1.03% for rain and 1.09% for storm. OCI is similar, increasing a 0.037% for rain and 0.044% for storm; nevertheless this difference is not significant.

For a more comprehensive comparison, the results of the referenced papers which provide indicators of the control performance have been added and compared with the proposed MPC + FF for dry influent in Table 4. To ensure a fair comparison, it is done with the referenced papers, which control $S_{O,5}$ at the set point of 2 mg/l and/or $S_{NO,2}$ at the set point of 1 mg/l and use the original version of BSM1. To allow the comparison with the greatest possible number of papers, two control performance criteria have been added to the usual ISE: integral of the absolute error (IAE) and average of the absolute error (mean(|e|)).

$$\mathrm{IAE} = \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} |e_i| \cdot dt \tag{21}$$

$$\mathrm{mean}(|e|) = \frac{1}{T\_s}\sum_{i=1}^{i=T\_s} |e_i| \tag{22}$$

where T_s is the total number of samples.

The improvement of $S_{NO,2}$ and $S_{O,5}$ tracking as a result of applying MPC + FF compared to the rest of the referenced papers is shown. The importance of the satisfactory $S_{O,5}$ tracking achieved is remarkable, especially for the implementation of the hierarchical control structure, to ensure that the value of $S_{O,5}$ is as close as possible to the set point provided by the higher level.

4.2. Two level hierarchical control configuration

For the hierarchical control structure, OCI and EQI trade-off representations have been implemented for the three proposed controllers and for the three weather conditions. OCI and EQI results are obtained assessing the extreme points where the best EQI without increasing OCI and the best OCI without increasing EQI are achieved compared to MPC + FF alone.

4.2.1. Higher level MPC

In order to identify the linear model, $S_{NH,5}$ has been determined by varying $S_{O,5}$ set point around 2 mg/l, with maximum values of ±10%.

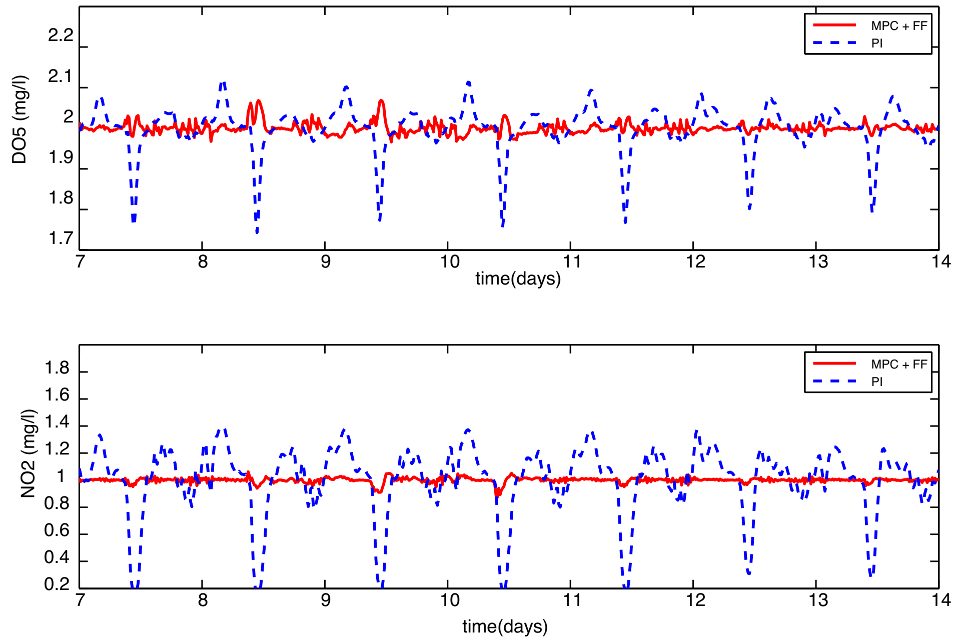

Fig. 5. Dry influent: performance control of $S_{O,5}$ and $S_{NO,2}$ with default PI controllers and with MPC + FF.

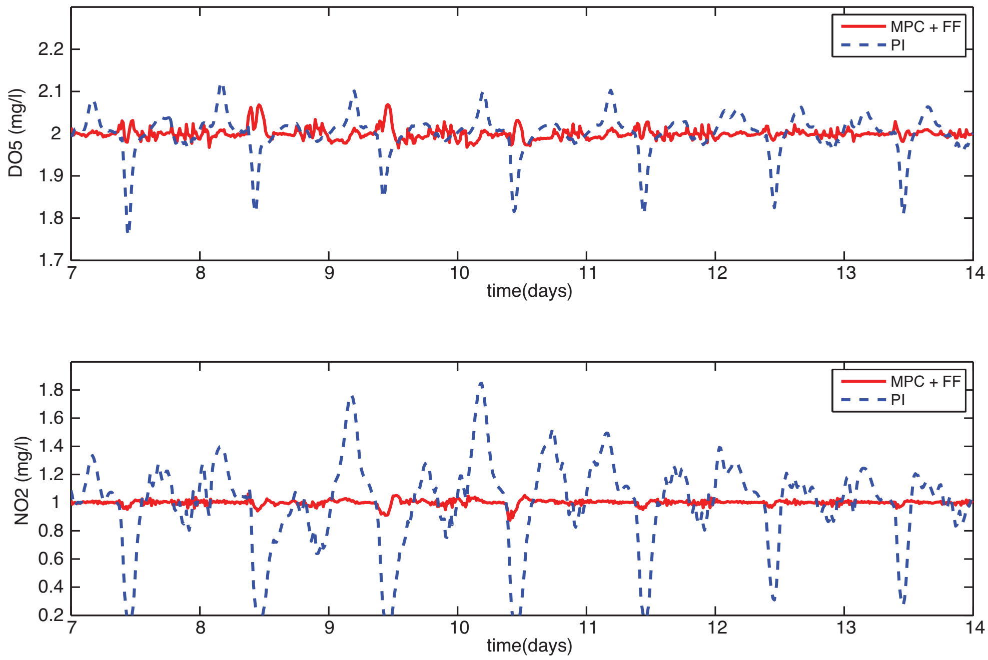

Fig. 6. Rain influent: performance control of $S_{O,5}$ and $S_{NO,2}$ with default PI controllers and with MPC + FF.

Table 4
Comparison of the performance of $S_{O,5}$ and $S_{NO,2}$ control between MPC + FF and the referenced works.

	$S_{O,5}$ control			$S_{NO,2}$ control			$S_{O,5}$ and $S_{NO,2}$ control
	ISE	IAE	mean(|e|)	ISE	IAE	mean(|e|)	mean(|e|)
Proposed MPC + FF	0.00067	0.047	0.0068	0.0013	0.067	0.0096	0.0082
[24]	–	–	–	–	–	–	0.024
[25]	–	–	0.9	–	–	–	–
[6]	0.0026	0.0892	–	–	–	–	–
[26]	0.0012	0.0792	–	–	–	–	–
[27]	0.00092	0.049	–	0.408	1.21	–	–

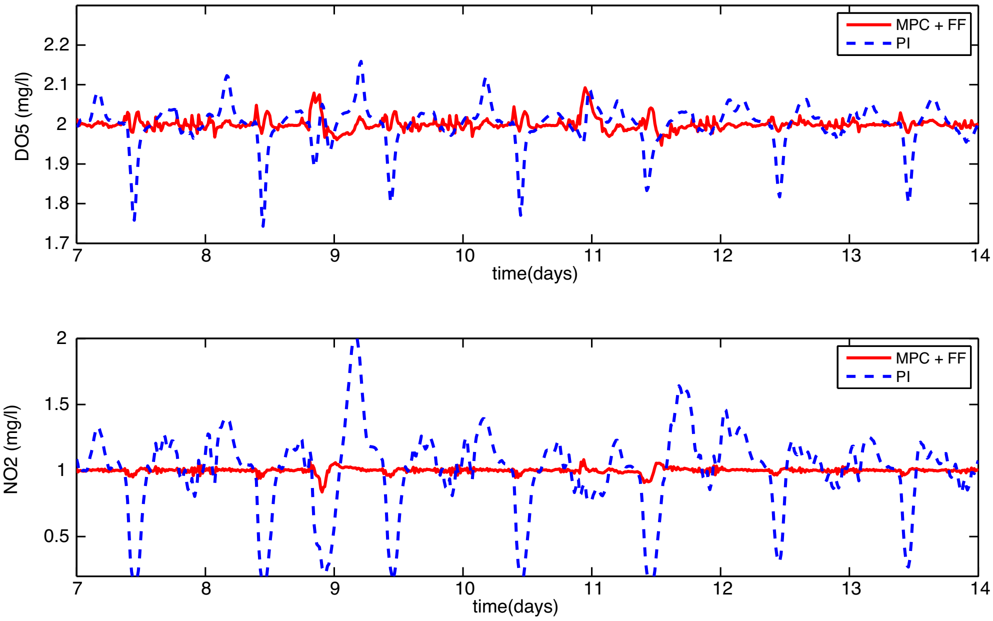

Fig. 7. Storm influent: performance control of $S_{O,5}$ and $S_{NO,2}$ with default PI controllers and with MPC + FF.

By using a prediction error method, a second order state-space model (12) is obtained, as:

$$A = \begin{bmatrix} 0.2531 & 0.3691 \\ 0.2781 & -0.2695 \end{bmatrix} \quad B = \begin{bmatrix} -0.4507 \\ -0.1712 \end{bmatrix} \quad (23)$$
$$C = \begin{bmatrix} 0.08655 & -0.01681 \end{bmatrix} \quad D = \begin{bmatrix} 0 \end{bmatrix}$$

The following tuning parameters have been selected: $\triangle t = 0.035$ days (50.4 min), $m = 2$, $p = 10$. To determine $\Gamma_{\triangle u}$ and $S_{NH,5}$ set point values, a trade-off representation for OCI and EQI is provided and showed in Fig. 8. Every line corresponds to the results obtained for different $\Gamma_{\triangle u}$ (0.1, 0.05, 0.01 and 0.001), and the points marked with crosses are the results for a range of $S_{NH,5}$ set point values, from 0.5 to 6.5 with increments of 0.25.

The results with MPC + FF alone and with default PI controllers alone are also represented. Fig. 8 shows an area in which results obtained with higher level MPC controller improve simultaneously OCI and EQI in comparison with MPC + FF and with default PI controllers alone. This is the proposed tuning region.

The OCI and EQI trade-off representation has also been done for rain and storm influents (Figs. 9 and 10 respectively), obtaining also the corresponding tuning regions. However, they are smaller than the one obtained for the dry influent.

Taking into account the OCI and EQI trade-off representations for dry, rain and storm influents (Figs. 8–10 respectively), $\Gamma_{\triangle u}$ and $S_{NH,5}$ set points have been selected for the cases of lowest EQI without increasing OCI and the lowest OCI without worsening EQI for every influent in comparison with MPC + FF alone (Table 5).

In order to improve EQI, S_{NH} and S_{NO} concentrations have to be reduced because they are the pollutants with largest influence in the effluent quality. Fig. 17 shows $S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$ for dry influent with the tuning parameters where the best EQI without increasing OCI is obtained. As it is shown in Fig. 17, by varying $S_{O,5}$ set point with two level hierarchical control, $S_{NH,5}$ peaks and $S_{NO,5}$ are reduced. In the case of higher level MPC, when $S_{NH,5}$ is over the fixed set point, $S_{O,5}$ reference of the lower level control is increased, which produces more oxidation of $S_{NH,5}$ and consequently softens its peaks, while $S_{NO,5}$ and the aeration costs grow. In opposition, when the $S_{NH,5}$ is under the fixed set point, $S_{O,5}$ reference is decreased, $S_{NH,5}$ goes up and $S_{NO,5}$ and aeration costs go down. The final balance from day 7 to day 14 is a reduction of 1.8% of EQI in comparison with MPC + FF alone (see Table 8).

The same concentrations ($S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$) for rain and storm influents are shown in Figs. 18 and 19 respectively. Within 7 days of simulation (day 7–14), two days are shown coinciding with a rainfall (Fig. 18) and a storm (Fig. 19) events. As it is observed, during the rain and storm events, the differences of $S_{NH,5}$ peaks and $S_{NO,5}$ for higher level MPC and MPC + FF are lower compared with dry weather. This has a direct consequence on the EQI results shown in Table 8. As it can be seen, there is also an improvement by working with higher level MPC in comparison with MPC + FF alone, but with a lower percentage compared with dry weather. For the rain influent case, EQI is decreased by 0.4% and for the storm influent case, working with higher level MPC, EQI is decreased by 0.5%.

In the opposite point of the trade-off representations (Figs. 8, 11 and 14) (best OCI without worsening effluent quality), OCI results are compared for the different control structures. Fig. 20 shows K_La_5 for the higher level MPC. The aeration costs depend directly on the K_La_5 values. Fig. 20 shows that the values of K_La_5 with higher level MPC are lower most of the time than those obtained with MPC + FF alone, proving that costs can be reduced without increasing EQI with a better optimization of K_La_5. This reduction of K_La_5 results in a reduction of 0.8% of OCI (Table 8).

The K_La_5 evolution is also shown for rain and storm influents (Figs. 21 and 22 respectively), obtaining also an OCI reduction when working with the higher level MPC in comparison with MPC + FF alone. In this case, with less percentage in comparison with dry influent results (see Table 8): For rain influent, higher level MPC reduces OCI by 0.3%, and for storm influent the reduction is 0.4%. The optimization of the $S_{O,5}$ set point value results in an AE reduction of 202.2, 96.42 and 137.92 $KWh\,d^{-1}$ for dry, rain and storm influents respectively, compared with default BSM1 control, which corresponds, in terms of percentage, to an AE reduction of 5.4, 2.6 and 3.7% respectively.

4.2.2. Higher level Affine Function

For the Affine Function, k values and maximum values of $S_{O,5}$ have been selected with the OCI and EQI trade-off representation showed in Fig. 11. In this case, each line corresponds to the results obtained with different $S_{O,5}$ maximum values (2.5-k; 3-k; 3.5-k;

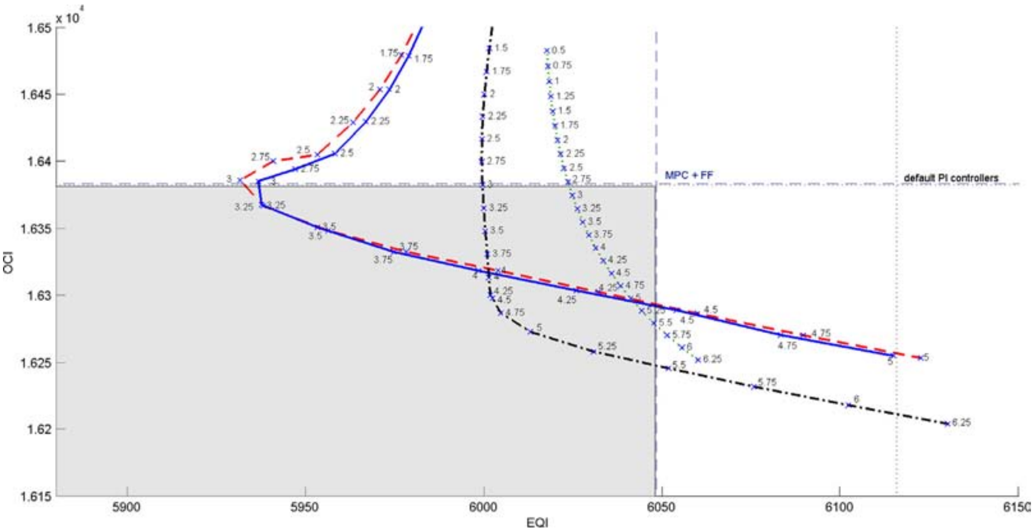

Fig. 8. Dry influent: OCI and EQI trade-off with higher level MPC for a range of $S_{NH,5}$ values (points marked with crosses) and $\Gamma_{\Delta u}$ = 0.001 (dashed line), 0.01 (solid line), 0.05 (dash-doted line) and 0.1 (doted line).

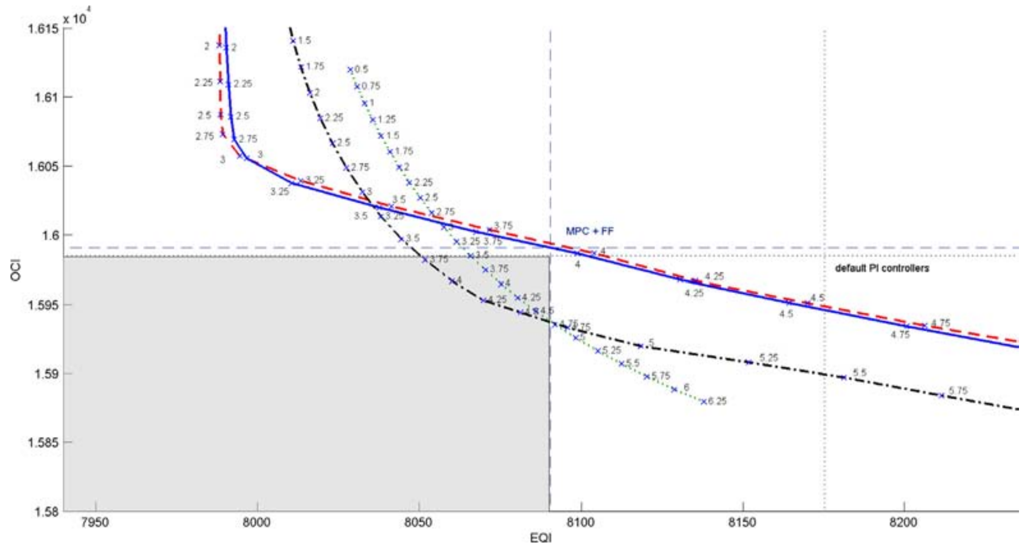

Fig. 9. Rain influent: OCI and EQI trade-off with higher level MPC for a range of $S_{NH,5}$ values (points marked with crosses) and $\Gamma_{\Delta u}$ = 0.001 (dashed line), 0.01 (solid line), 0.05 (dash-doted line) and 0.1 (doted line).

Table 5
Higher level MPC tuning: $\Gamma_{\Delta u}$ and $S_{NH,5}$ set point.

	Dry		Rain		Storm	
	Lowest EQI	Lowest OCI	Lowest EQI	Lowest OCI	Lowest EQI	Lowest OCI
$\Gamma_{\Delta u}$	0.001	0.05	0.05	0.05	0.05	0.05
$S_{NH,5}$ set point	3.1	5.4	3.75	4.6	3.7	5

4-*k* and 4.5-*k*), while each one of the points marked with crosses are the results obtained for different values of *k* (from 0.3 to 1.6 with increments of 0.1). In the same way, the results obtained with MPC + FF alone and with PI default controllers alone are also shown.

The same range of *k* and $S_{O,5}$ maximum values have been tested for rain and storms influents, obtaining also the trade-off representations (Figs. 12 and 13 respectively).

The areas of the tuning regions, which result in a simultaneous improvement of OCI and EQI in comparison with MPC + FF alone and with default PI controllers alone, are larger than those obtained with higher level MPC.

Taking into account the trade-off representations (see Figs. 11–13), Table 6 shows $S_{O,5}$ maximum and *k* values for the extreme cases of lowest EQI without increasing OCI and the lowest OCI without worsening EQI in comparison with MPC + FF alone and default PI controllers alone.

With the tuning parameters where the best EQI without increasing OCI are obtained, comparing $S_{NH,5}$ peaks and $S_{NO,5}$ for higher level Affine Function and higher level MPC for the three influents (see Figs. 17–19), a remarkable difference is not observed. However Table 8 show that Affine Function is able to reduce EQI in comparison with higher level MPC by 0.6% for dry influent, 0.7% for rain influent and 1% for storm influent. In comparison with MPC + FF

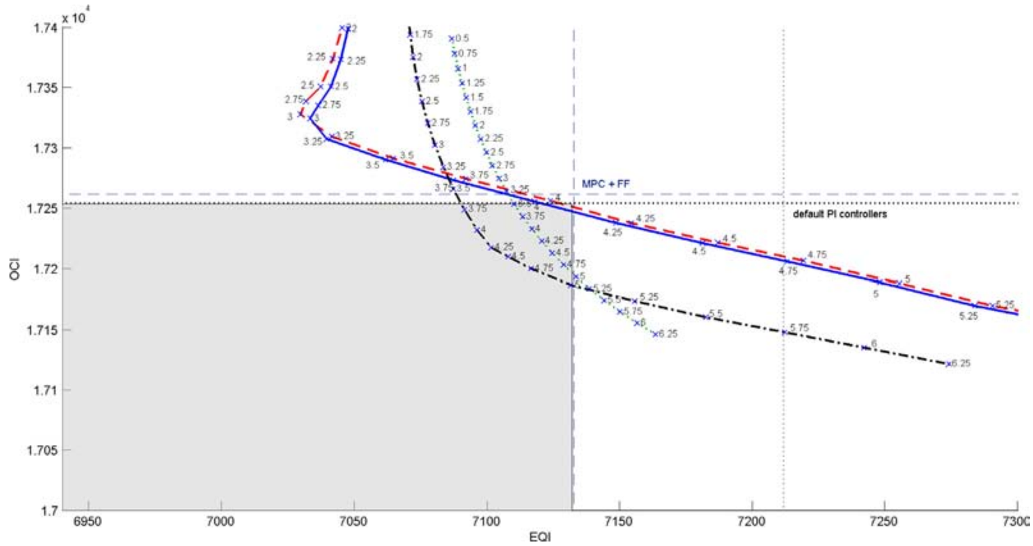

Fig. 10. Storm influent: OCI and EQI trade-off with higher level MPC for a range of $S_{NH,5}$ values (points marked with crosses) and $\Gamma_{\triangle u}$ = 0.001 (dashed line), 0.01 (solid line), 0.05 (dash-doted line) and 0.1 (doted line).

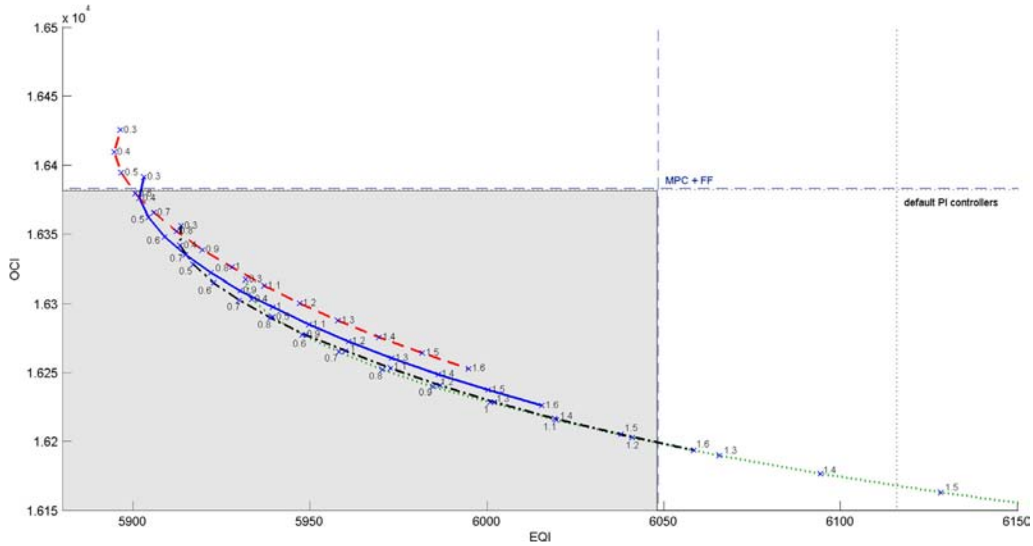

Fig. 11. Dry influent: OCI and EQI trade-off with higher level Affine Function for a range of *k* values (points marked with crosses) and $S_{O,5}$ maximum = 4 (dashed line), 3.5 (solid line), 3 (dash-doted line), 2.5 (doted line).

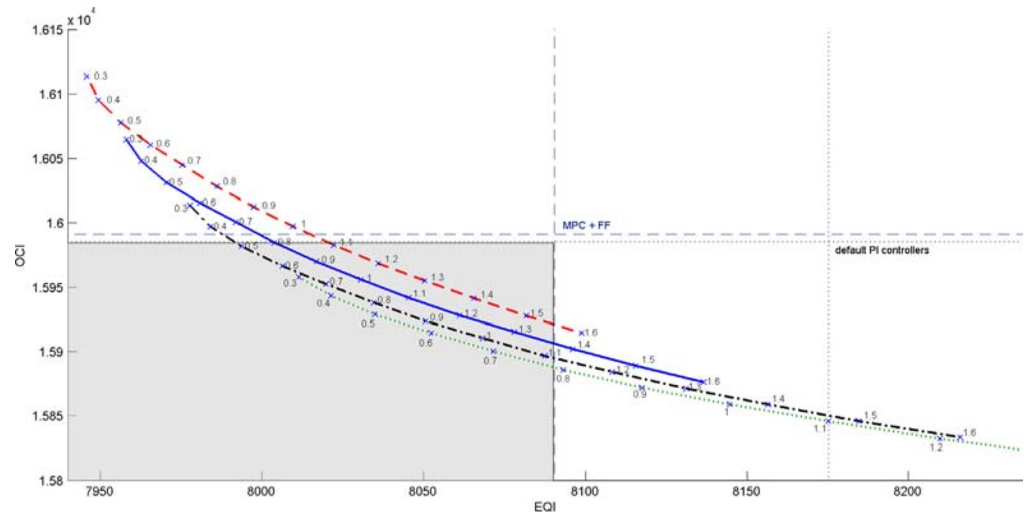

Fig. 12. Rain influent: OCI and EQI trade-off with higher level Affine Function for a range of *k* values (points marked with crosses) and $S_{O,5}$ maximum = 4 (dashed line), 3.5 (solid line), 3 (dash-doted line), 2.5 (doted line).

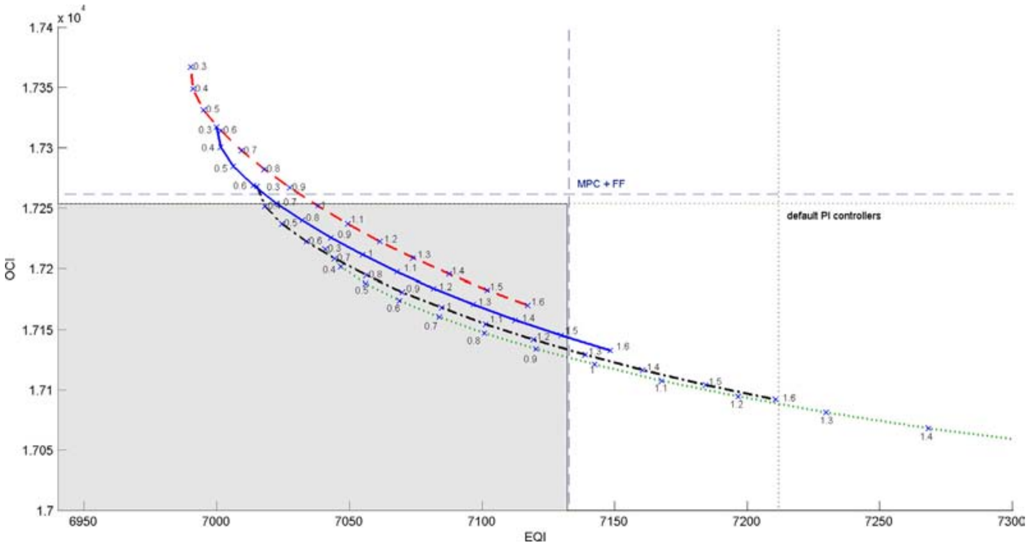

Fig. 13. Storm influent: OCI and EQI trade-off with higher level Affine Function for a range of *k* values (points marked with crosses) and $S_{O,5}$ maximum = 4 (dashed line), 3.5 (solid line), 3 (dash-doted line), 2.5 (doted line).

Table 6
Higher level Affine Function tuning: *k* and $S_{O,5}$ maximum values.

	Dry		Rain		Storm	
	Lowest EQI	Lowest OCI	Lowest EQI	Lowest OCI	Lowest EQI	Lowest OCI
k	0.59	1.23	0.48	0.79	0.39	0.96
$S_{O,5}$ maximum	3.41	1.27	2.52	1.71	2.61	1.54

alone the reduction is 2.4% for dry influent, 1.1% for rain influent and 1.5% for storm influent.

Applying the tuning parameters to obtain the best OCI without worsening effluent quality, K_La_5 is compared with the other control structures (see Figs. 20–22), obtaining better K_La_5 optimization compared with MPC + FF alone and higher level MPC for the three influents, that result in an OCI reduction in comparison with higher level MPC by 0.3% for dry influent, 0.3% for rain influent and 0.4% for storm influent. In comparison with MPC + FF the reduction is 1.1% for dry influent, 0.6% for rain influent and 0.8% for storm influent (see Table 8).

This cost reduction is due primarily to an AE reduction of 259.45, 170.87 and 209.85 KWh d^{-1} for dry, rain and storm influents respectively, compared with default BSM1 control, which corresponds, in terms of percentage, to an AE reduction of 7, 4.7 and 5.6% respectively.

4.2.3. Higher level fuzzy controller

Values of *minin* and *minout* are both fixed to 0.1. Several OCI and EQI results have been obtained for different values of *maxin* (3, 4, 5 and 7) and *maxout* (2, 2.5, 3, 3.5, 4, 4.5, 5 and 5.5). With these results, trade-off representations of EQI and OCI for the three

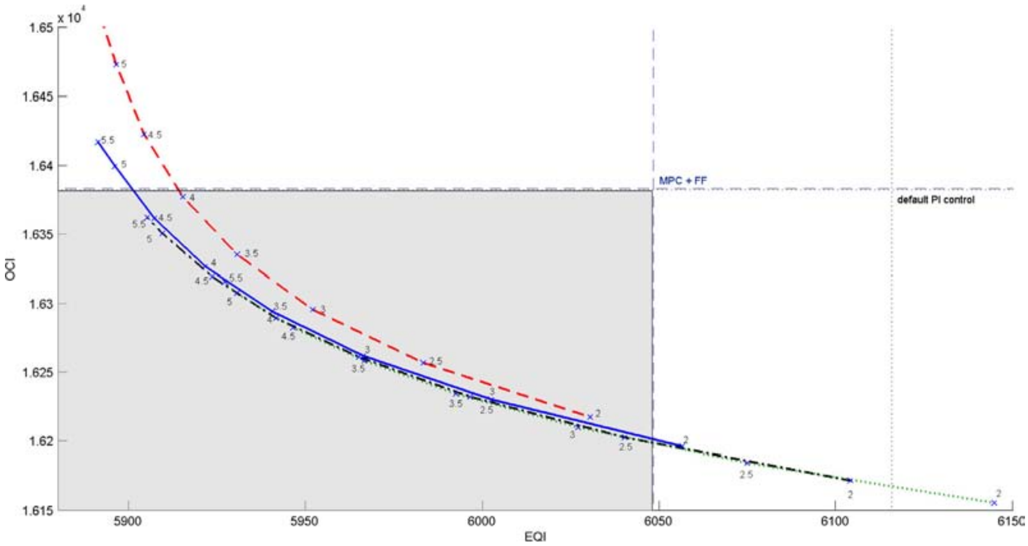

Fig. 14. Dry influent: OCI and EQI trade-off with higher level fuzzy controller for a range of maxout values (points marked with crosses) and maxin = 3 (dashed line), 5 (solid line), 7 (dash-doted line) and 9 (doted line).

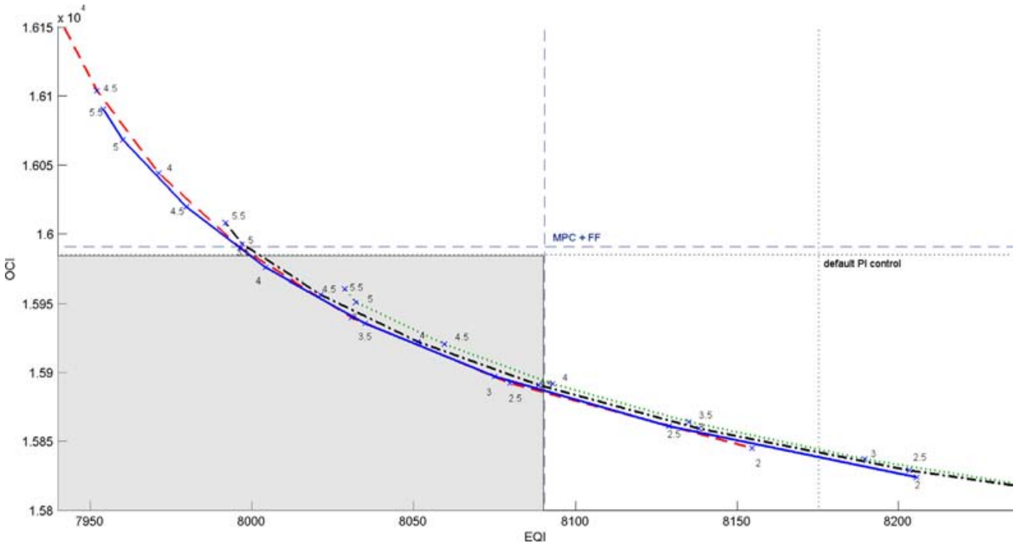

Fig. 15. Rain influent: OCI and EQI trade-off with higher level fuzzy controller for a range of maxout values (points marked with crosses) and maxin = 3 (dashed line), 5 (solid line), 7 (dash-doted line) and 9 (doted line).

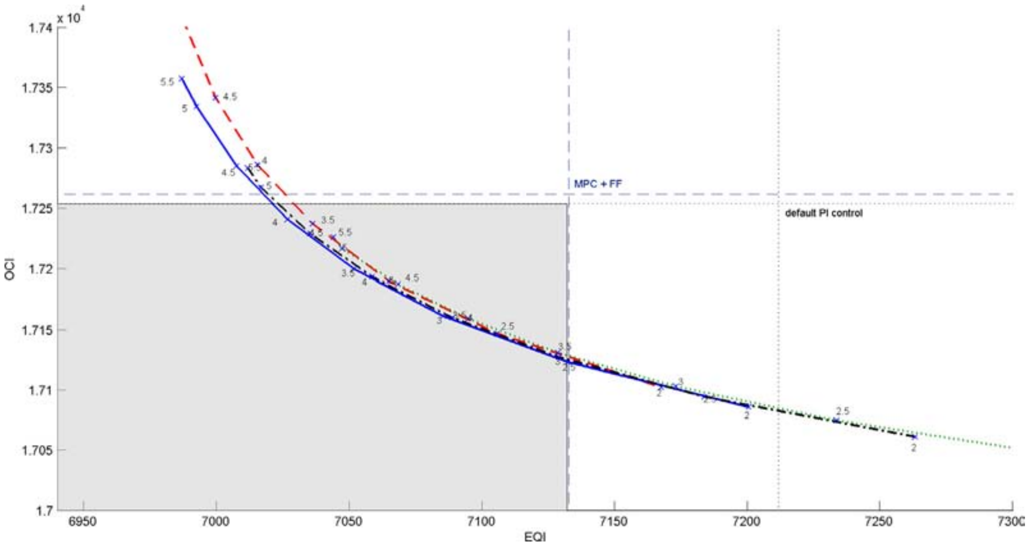

Fig. 16. Storm influent: OCI and EQI trade-off with higher level fuzzy controller for a range of maxout values (points marked with crosses) and maxin = 3 (dashed line), 5 (solid line), 7 (dash-doted line) and 9 (doted line).

influents (dry, rain and storm) are made (Figs. 14–16), obtaining a tuning area where both OCI and EQI are improved in comparison with MPC + FF alone and with the default PI controllers.

The areas of the tuning regions, which result in a simultaneous improvement of OCI and EQI in comparison with MPC + FF alone and with default PI controllers alone, are similar to the ones corresponding to the higher level with Affine Function.

Table 7 shows the maxin and maxout values for the extreme cases of lowest EQI without increasing OCI and lowest OCI without worsening EQI in comparison with MPC + FF alone and default PI controllers alone for the three influents.

For the case of best EQI obtained, Figs. 17–19 show that $S_{NH,5}$ and $S_{NO,5}$ for the three influents are similar compared to higher level Affine Function. The EQI results are shown in Table 8 and they are very similar to the ones obtained with the higher level Affine Function.

Applying the tuning parameters for obtaining the lowest OCI, Figs. 20–22 show K_La_5 for the three weather conditions. Looking at the OCI results in Table 8, there is no significant difference compared with higher level Affine Function, getting also the same percentages of improvement over MPC + FF alone and higher level MPC.

Table 7
Higher level fuzzy controller tuning: maxin and maxout values.

	Dry		Rain		Storm	
	Lowest EQI	Lowest OCI	Lowest EQI	Lowest OCI	Lowest EQI	Lowest OCI
Maxin	5	9	5	3	5	5
Maxout	4.78	2.76	4.1	2.41	4.14	2.5

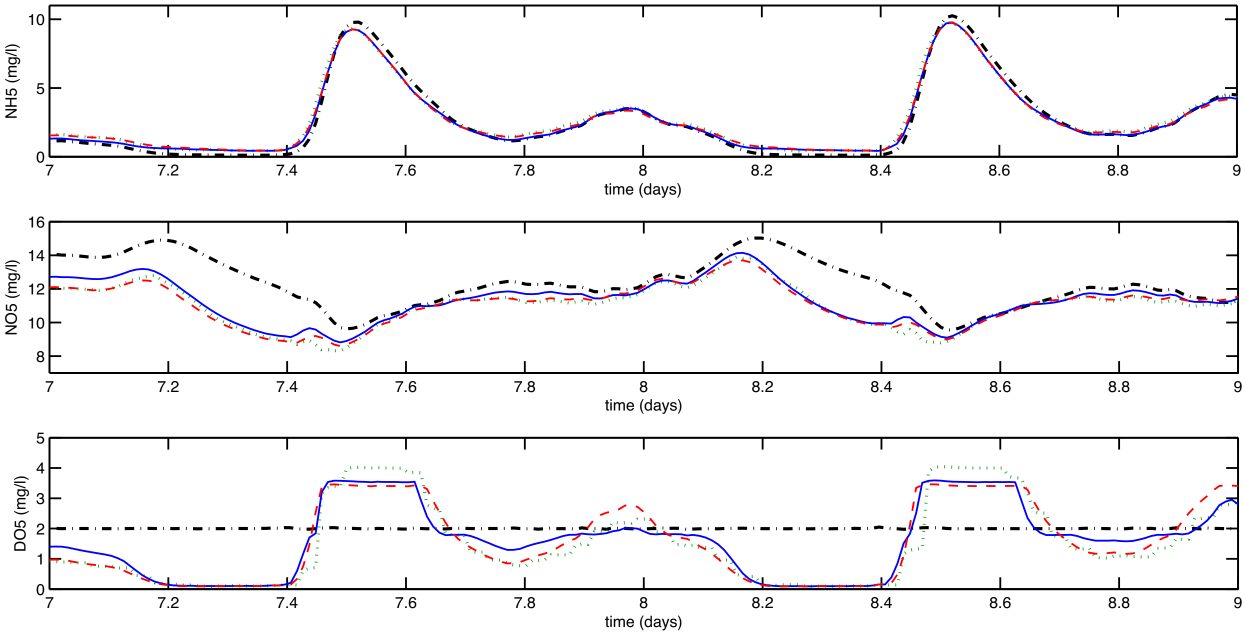

Fig. 17. Dry influent: comparison of $S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$. MPC + FF (dash-dotted line), higher level MPC (dotted line), higher level Affine Function (dashed line) and higher level fuzzy controller (solid line).

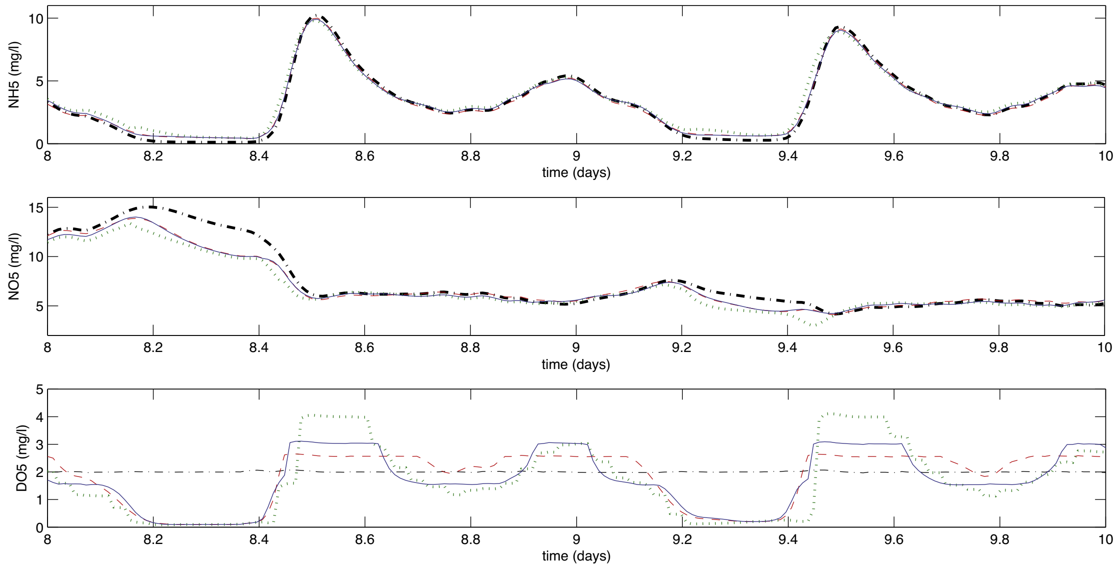

Fig. 18. Rain influent: comparison of $S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$. MPC + FF (dash-dotted line), higher level MPC (dotted line), higher level Affine Function (dashed line) and higher level fuzzy controller (solid line).

Table 8
EQI and OCI results with MPC + FF, higher level MPC, higher level Affine Function and higher level fuzzy controller for dry, rain and storm influents.

	MPC + FF	Higher level MPC			Higher level Affine Function			Higher level Fuzzy controller		
		Lowest EQI	Lowest OCI	%	Lowest EQI	Lowest OCI	%	Lowest EQI	Lowest OCI	%
Dry weather										
EQI (kg pollutans/d)	6048.31	5936.16	6045.44	−1.8%	5900.98	6047.52	−2.4%	5900.73	6047.95	−2.4%
OCI	16,382.97	16,382.64	16,248.79	−0.8%	16,381.54	16,196.68	−1.1%	16,382.67	16,197.86	−1.1%
Rain weather										
EQI (kg pollutans/d)	8090.29	8056.07	8089.98	−0.4%	7994.58	8090.38	−1.1%	7998.78	8090.27	−1.1%
OCI	15,990.85	15,982.47	15,939.32	−0.3%	15,984.16	15,887.47	−0.6%	15,984.23	15,884.21	−0.6%
Storm weather										
EQI (kg pollutans/d)	7132.60	7094.90	7131.57	−0.5%	7019.08	7132.21	−1.5%	7020.83	7132.25	−1.5%
OCI	17,261.39	17,252.84	17,186.58	−0.4%	17,252.51	17,126.55	−0.8%	17,252.6	17,123.01	−0.8%

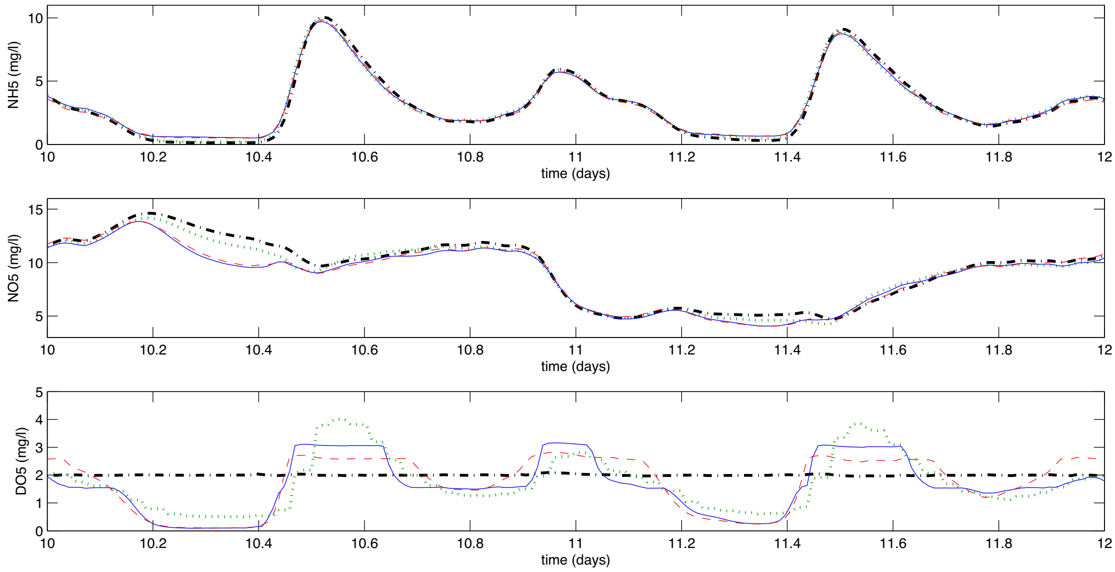

Fig. 19. Storm influent: comparison of $S_{NH,5}$, $S_{NO,5}$ and $S_{O,5}$. MPC + FF (dash-dotted line), higher level MPC (dotted line), higher level Affine Function (dashed line) and higher level fuzzy controller (solid line).

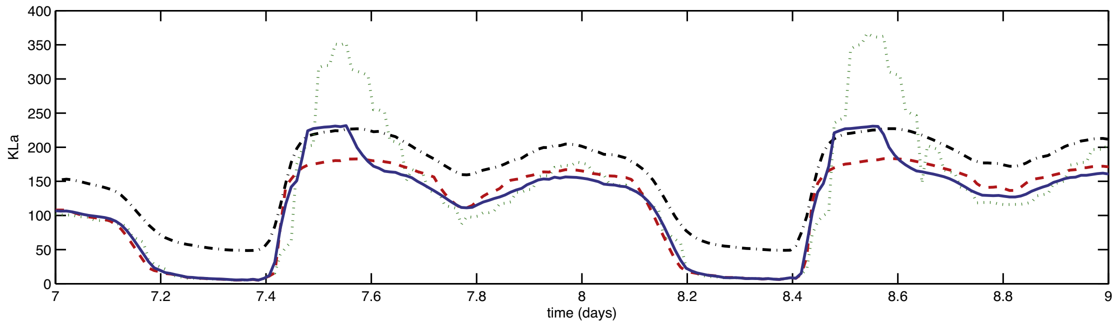

Fig. 20. Dry influent: comparison of K_La_5 in the fifth tank. MPC + FF (dash-dotted line), higher level MPC (dotted line), higher level Affine Function (dashed line) and higher level fuzzy controller (solid line).

The reduction of AE is also similar than using an Affine Function as higher level controller: 255.67, 199.99 and 199.72 KWh d^{-1} for dry, rain and storm influents respectively, compared with default BSM1 control, which corresponds, in terms of percentage, to an AE reduction of 6.9, 5.4 and 5.3% respectively. As a result, for the higher level control, with Affine Function and fuzzy controller, the following improvements are obtained with respect to MPC: For dry influent, AE reduction of 57.25 and 53.47 KWh d^{-1} respectively. For rain influent, 74.45 and 103.57 KWh d^{-1} respectively. And for storm influent, 71.93 and 61.8 KWh d^{-1} respectively.

The reason of the improvement of the results of effluent quality and operational costs by using the higher level fuzzy controller or the higher level Affine Function compared to the higher level MPC is that the higher level MPC tries to maintain the value of $S_{NH,5}$ at a fixed reference, but the error is too high. Specifically, the ISE is 36.21 to achieve the best EQI and the ISE is 22.69 to achieve the best OCI. Conversely, higher level Affine Function and higher level fuzzy controller regulate $S_{O,5}$ set point based on the biological process dynamics that take place in the reactors (13, 14, 15, 16, 17, 18). On the one hand improving the nitrification process (17) when

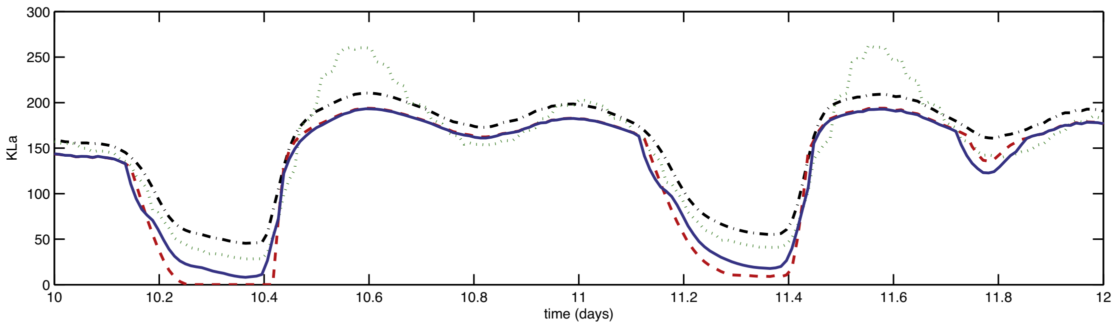

Fig. 21. Rain influent: comparison of K_La_5 in the fifth tank. MPC + FF (dash-dotted line), higher level MPC (dotted line), higher level Affine Function (dashed line) and higher level fuzzy controller (solid line).

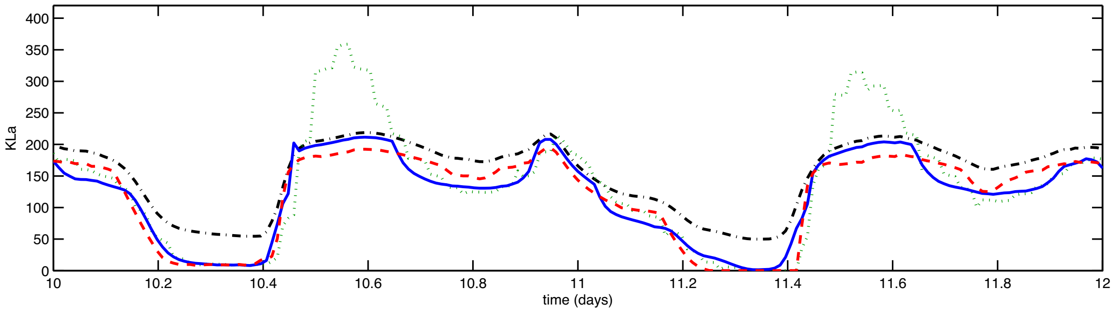

Fig. 22. Storm influent: comparison of K_La_5 in the fifth tank. MPC + FF (dash-dotted line), higher level MPC (dotted line), higher level Affine Function (dashed line) and higher level fuzzy controller (solid line).

$S_{NH,5}$ increases, and therefore reducing its peaks. On the other hand, reducing the $S_{O,5}$ set point level when $S_{NH,5}$ decreases in order to reduce the S_{NO} generation (14) and the operational costs (3).

5. Conclusion

In this paper different control techniques for the BSM1 with the aim of reducing EQI and OCI are evaluated and compared.

First, MPC + FF was proposed to control $S_{NO,2}$ and $S_{O,5}$ by manipulating Q_a and K_La_5. The performance control of $S_{NO,2}$ and $S_{O,5}$ was improved by more than 90 % for the three weather conditions in comparison with default PI controllers. This performance enhancement resulted in a slight improvement in EQI with similar OCI. The control performance of MPC + FF has been also compared to the referenced papers, showing the improvement of the proposed method and thus the successful $S_{O,5}$ and $S_{NO,2}$ tracking.

Next, a two level hierarchical control strategy was proposed, where the lower level controls $S_{NO,2}$ and $S_{O,5}$ by manipulating Q_a and K_La_5 respectively, and the higher level controller regulates the $S_{O,5}$ set point of the lower level controller according to the $S_{NH,5}$. For the lower level, MPC + FF was used. For the higher level, three different controllers were proposed: a MPC, an Affine Function and a fuzzy controller. They were tested and compared in the three weather conditions: dry, rain and storm. As a result, EQI and OCI were reduce significatively with respect to MPC + FF alone. These improvements have been greater in dry weather conditions.

The results of OCI and EQI with higher level Affine Function and higher level fuzzy controller were similar and better than those obtained with higher level MPC. This is due to the fact that the higher level MPC tries to keep the value of $S_{NH,5}$ at a reference level, but this is not possible. For that reason, the alternatives of Affine Function and fuzzy Controller for the higher level were tested with the idea of varying $S_{O,5}$ based on the $S_{NH,5}$ measured, but without trying to keep it at a fixed reference. To ensure the right tuning of the controllers and therefore the correct relationship between the applied control and the results, a trade-off analysis between OCI and EQI has been performed by varying two tuning parameters for each controller. Thus, it can be concluded that, the performance provided by fuzzy controller and Affine Function in the higher level of the hierarchical control structure has been proven to be better than that offered by the MPC.

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Fuzzy Control and Model Predictive Control Configurations for Effluent Violations Removal in Wastewater Treatment Plants

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ABSTRACT: In this paper the following new control objectives for biological wastewater treatment plants (WWTPs) have been established: to eliminate violations of total nitrogen in the effluent ($N_{tot,e}$) or ammonium and ammonia nitrogen concentration (NH) in the effluent (NH_e) and at the same time handle the customary requirements of improving effluent quality and reducing operational costs. The Benchmark Simulation Model No. 1 (BSM1) is used for evaluation, and the control is based on Model Predicitive Control (MPC) and fuzzy logic. To improve effluent quality and to reduce operational costs, a hierarchical control structure is implemented to regulate the dissolved oxygen (DO) on the three aerated tanks. The high level of this hierarchical structure is developed with a fuzzy controller that adapts the DO set points of the low level based on the NH concentration in the fifth tank (NH5). The low level is composed of three MPC controllers with feedforward control (MPC + FF). For avoiding violations of $N_{tot,e}$, a second fuzzy controller is used to manipulate the external carbon flow rate in the first tank (q_{EC1}) based on nitrate nitrogen in the fifth tank (NO5) plus NH5. For avoiding violations of NH_e, a third fuzzy controller is applied to manipulate the internal recirculation flow rate (Q_{rin}) based on NH5 and NH in the influent. Simulation results show the benefit of the proposed approach.

■ INTRODUCTION

Biological wastewater treatment plants (WWTPs) are considered complex nonlinear systems, and their control is very challenging, due to the complexity of the biological and biochemical processes that take place in the plant and the strong fluctuations of the influent flow rate. In addition, there are effluent requirements defined by the European Union (European Directive 91/271 Urban wastewater) with economic penalties.

In the literature there are several papers working on modeling of WWTPs.[1−4] In this work the evaluation and comparison of the different control strategies is based on Benchmark Simulation Model No. 1 (BSM1), developed by the International Association on Water Pollution Research and Control.[5−7] This benchmark defines a plant layout, influent loads, test procedures and evaluation criteria. It provides also a default control strategy that includes two Proportional-Integrative (PI) control loops: control of the dissolved oxygen concentration (DO) in the fifth tank (DO5) at a set point value of 2 g/m^3 by manipulating the oxygen transfer coefficient (K_La) in the fifth tank (K_La5), and control of the nitrate nitrogen concentration (NO) in the second anoxic reactor (NO2) at a set point value of 1 g/m^3 by manipulating the internal recycle flow rate (Q_{rin}). A complete review of results for PI control can be found in ref 8.

Many works can be found in the literature that propose different methods for controlling WWTPs. Some of them apply a direct control on the effluent variables, mainly ammonium and ammonia nitrogen (NH) and total nitrogen (N_{tot})[9−11]. The difficulty in this method is that the fixed values for the effluent variables are constraints and not set points to be tracked. Other studies deal with the basic control strategy (DO of the aerated tanks and NO of the last anoxic tank), but testing with different controllers such Model Predictive Controller (MPC) and fuzzy controller.[12−14] These methods provide an acceptable balance between quality and costs. Finally, other investigations propose a hierarchical control that regulates the DO set points, depending on some states of the plant, usually NH and NO concentration values in any tank or in the influent[15−20] or DO in other tanks[21].

The control objectives of previous works are usually based on achieving an improvement in the effluent quality and/or cost indices. However, it is of significant importance to avoid violations of pollution in the effluent, regarding the quality of the water from a legal point of view, and certainly in terms of cost, as these violations involve fines to be paid.

This work proposes a control strategy with the goal of eliminating violations of the effluent pollutants, while achieving an improvement of effluent quality and a reduction of operational costs compared to the default control of BSM1. The proposed approach is implemented by making use of fuzzy and MPC controllers. First, a hierarchical control structure is implemented. The low level is composed by three MPCs with feedforward compensation (MPC + FF) of the influent flow rate (Q_{in}), to control NO2, DO in the third tank (DO3), DO in the fourth tank (DO4), and DO5. The high level is built with a fuzzy controller that adjusts the DO set points according to NH in the fifth tank (NH5). A trade-off analysis is made, which determines a tuning region that simultaneously improves the results of effluent quality and operational cost compared to the default control of BSM1. Next, two fuzzy controllers are added in order to eliminate effluent violations. NH in the effluent (NH_e) and N_{tot} in the effluent ($N_{tot,e}$) are the pollutants that present more difficulties for being kept under the established limits. For reducing peaks of $N_{tot,e}$, external carbon flow rate in the first tank (q_{EC1}) is manipulated based on NO in the fifth tank (NO5)

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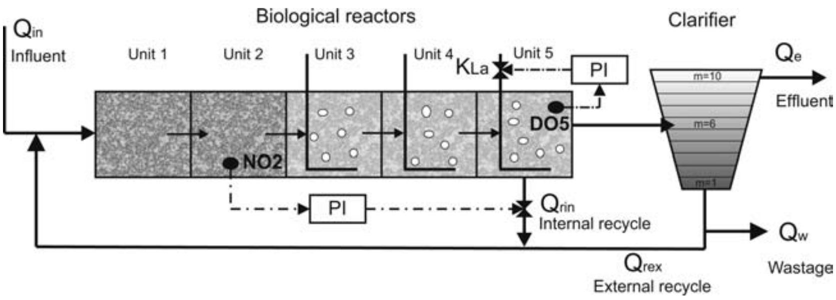

Figure 1. Benchmark Simulation Model No. 1.

plus NH5. For reducing peaks of NH_e, Q_{rin} is manipulated based on NH5, and the control of NO2 is removed.

Other works in the literature have presented proposals for avoiding effluent violations[9−11], with the quality indices as controlled variables. However, ref 9 does not provide costs results, and refs 10 and 11 present a cost increase. The novelty of this work is to simultaneously deal with the elimination of effluent violations, and the improvement of effluent quality and operational costs. Another meaningful novelty of this work is the regulation of Q_{rin} based in NH5 and NH in the influent (NH_{in}) in order to eliminate $N_{tot,e}$.

■ THE TESTING PLANT: BSM1

To make the evaluation and comparison of the different control strategies possible, BSM1[5−7] defines a plant layout, the influents loads of the plant, the procedures for carrying out the tests, and the criteria for evaluating the results. The more relevant aspects are described next:

Figure 1 shows the schematic representation of the wastewater treatment plant. It consists of five biological reactor tanks connected in series, followed by a secondary settler. The first two tanks have a volume of 1000 m^3 each and are anoxic and perfectly mixed. The other three tanks have a volume of 1333 m^3 each and are aerated. The settler has a total volume of 6000 m^3 and is modeled in ten layers, and the sixth layer from the bottom is the feed layer. Two recycle flows complete the system: the first from the last tank and the second from the underflow of the settler. The plant is designed for an average influent dry-weather flow rate of 18446 m^3/d and an average biodegradable chemical oxygen demand (COD) in the influent of 300 g/m^3. Its hydraulic retention time is 14.4 h, based on the average dry weather flow rate and the total tank and settler volume (12000 m^3). The default wastage flow rate (Q_w) is fixed to 385 m^3/d, which determines a biomass sludge age of about 9 days, based on the total amount of biomass present in the system. The nitrogen removal is achieved using a denitrification step performed in the anoxic tanks and a nitrification step carried out in the aerated tanks. The internal recycle is used to supply the denitrification step with NO.

The biological phenomena of the reactors are simulated by the Activated Sludge Model No. 1 (ASM1)[22] that considers eight different biological processes. The vertical transfers between layers in the settler are simulated by the double-exponential settling velocity model.[23] No biological reaction is considered in the settler. The two models are internationally accepted and include 13 state variables.

Despite the fact that BSM1 defines three different influent data, this paper only works with dry weather, that is the most common scenario, which contains 14 days of influent data with sampling intervals of 15 min.

A simulation protocol is established to ensure that results are obtained under the same conditions and can be compared. First, a 150 days period of stabilization has to be completed in a closed-loop using constant influent data to drive the system to a steady-state. Once the steady state is achieved, a simulation with dry weather is run and finally the desired influent data (dry, rain or storm) is tested. Only the results of the last 7 days are considered.

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 properly applied. It is assessed by the Integral of the Squared Error (ISE) criterion. The second level provides measures for the effect of the control strategy on plant performance. It includes the Effluent Quality Index (EQI) and Overall Cost Index (OCI).

The evaluation must include the percentage of time that the effluent limits are not met. The effluent concentrations of N_{tot}, Total Chemical Oxygen Demand (COD_t), NH, Total Suspended Solids (TSS) and Biochemical Oxygen Demand during 5 days (BOD_5) should obey the limits given in Table 1.

Table 1. Effluent Quality Limits

variable	value
N_{tot}	<18 g N·m^{-3}
COD_t	<100 g COD·m^{-3}
NH	<4 g N·m^{-3}
TSS	<30 g SS·m^{-3}
BOD_5	<10 g BOD·m^{-3}

N_{tot} is calculated as the sum of NO and Kjeldahl nitrogen (NKj), with this being the sum of organic nitrogen and NH.

Effluent Quality Index. EQI is defined to evaluate the quality of the effluent. It is related to the fines to be paid due to the discharge of pollution. EQI is averaged over a 7 days observation period, and it is calculated by weighting the different compounds of the effluent loads.

$$EQI = \frac{1}{1000T}\int_{t=7days}^{t=14days} (B_{TSS}\cdot TSS(t) + B_{COD}\cdot COD(t) + B_{NKj}\cdot NK_j(t) + B_{NO}\cdot NO(t) + B_{BOD_5}\cdot BOD_5(t))\cdot Q(t)\cdot dt \quad (1)$$

where B_i are weighting factors (Table 2) and T is the total time.

Overall Cost Index. OCI is defined as

$$OCI = AE + PE + 5\cdot SP + 3\cdot EC + ME \quad (2)$$

where AE is the aeration energy, PE is the pumping energy, SP is the sludge production to be disposed, EC is the external carbon source, and ME is the mixing energy.

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Table 2. B_i Values

factor	B_{TSS}	B_{COD}	B_{NKj}	B_{NO}	B_{BOD5}
Value (g pollution unit g^{-1})	2	1	30	10	2

AE is calculated according to the following relation:

$$AE = \frac{S_o^{sat}}{T \cdot 1.8 \cdot 1000} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} V_i \cdot K_L a_i(t) \cdot dt \tag{3}$$

where V_i is the volume of the tank i.

PE is calculated as

$$PE = \frac{1}{T} \int_{7days}^{14days} (0.004 \cdot Q_{in}(t) + 0.008 \cdot Q_{rin}(t) + 0.05 \cdot Q_w(t)) \cdot dt \tag{4}$$

SP is calculated from the TSS in the flow wastage (TSS_w) and the solids accumulated in the system:

$$SP = \frac{1}{T} \cdot (TSS_a(14days) - TSS_a(7days) + TSS_s(14days) - TSS_s(7days) + \int_{t=7days}^{t=14days} TSS_w \cdot Q_w \cdot dt) \tag{5}$$

where TSS_a is the amount of solids in the reactors and TSS_s is the amount of solids in the settler.

EC refers to the carbon that could be added to improve denitrification.

$$EC = \frac{COD_{EC}}{T \cdot 1000} \int_{t=7days}^{t=14days} (\sum_{i=1}^{i=n} q_{EC,i}) \cdot dt \tag{6}$$

where $q_{EC,i}$ is the flow rate of external carbon added to compartment i and COD_{EC} = 400 g COD·m^{-3} is the concentration of readily biodegradable substrate in the external carbon source.

ME is the energy employed to mix the anoxic tanks to avoid settling, and it is a function of the compartment volume:

$$ME = \frac{24}{T} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} [0.005 \cdot V_i \text{ if } K_L a_i(t) < 20 d^{-1} \text{ otherwise } 0] \cdot dt \tag{7}$$

■ CONTROL CONFIGURATION FOR THE PROPOSED OBJECTIVES

The original BSM1 definition includes the so-called default control strategy that is commonly used as a reference.[5−7] This strategy uses two PI control loops as shown in Figure 1. The first one involves the control of DO5 by manipulating K_La5. The set point for DO5 is 2 mg/L. The second control loop has to maintain NO2 at a set point of 1 mg/L by manipulating Q_{rin}.

The control techniques used in this work are based on MPC and fuzzy control. MPC controllers have been used in order to keep the NO2 and DO of the three aerobic reactors at the given set point. Fuzzy control has been applied, on one side, as high level controller in a hierarchical structure to vary the DO references tracked by the MPC controllers, and, on the other hand, to remove effluent violations by determining q_{EC1} and Q_{rin} values. The applied fuzzy controllers manipulate variables based on *if*−*then* rules, but without the goal of keeping the controlled variable at a set point given. In this case, the control objectives are the improvement of OCI and EQI, and the violations removal of $N_{tot,e}$ and NH_e.

Control Approaches. *Model Predictive Control.* The basis of MPC is the use of an optimization algorithm to solve the control problem and the use of a model of the plant to make predictions of the output variables.[24] At each control interval, Δt, for a prediction horizon, p, and a control horizon, m, ($m < p$), the MPC algorithm computes the sequences of control moves over the horizon m:

$$\Delta u(k), \Delta u(k+1), ..., \Delta u(k+m-1) \tag{8}$$

makes predictions of the outputs variables over a future horizon p (see Figure 2):

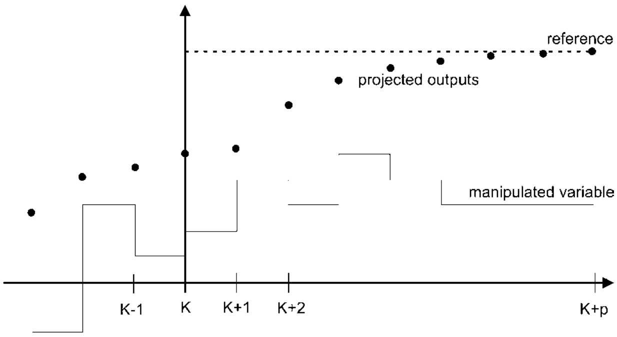

Figure 2. Model Predictive Control performance.

$$\hat{y}(k+1|k), \hat{y}(k+2|k), ..., \hat{y}(k+p|k) \tag{9}$$

and selects the sequence of control moves that minimizes a quadratic objective of the form

$$J = \sum_{l=1}^{p} \left\| \Gamma_y [y(k+l|k) - r(k+l)] \right\|^2 + \sum_{l=1}^{m} \left\| \Gamma_{\Delta u} [\Delta u(k+l-1)] \right\|^2 \tag{10}$$

where the output prediction $y(k + l|k)$ means a predicted controlled output for the future sampling instant $k + 1$, performed at the current instant k, and Γ_y and $\Gamma_{\Delta u}$ are the output weight and input rate weight, respectively, which penalize the residual between the future reference and the output variable prediction, and the control moves.

The MPC algorithm requires a state-space linear model to foresee how the plant outputs, $y(k)$, and reacts to the possible variations of the control variables, $u(k)$, and to compute the control moves at each Δt. WWTPs are nonlinear systems, but their operation can be approximated in the vicinity of a working point by a discrete-time state-space model as

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k) + Du(k) \tag{11}$$

where $x(k)$ is the state vector, and A, B, C and D are the state-space matrices.

Fuzzy Control. Fuzzy logic is described as an interpretative system in which objects or elements are related with borders not clearly defined, granting them a relative membership degree and not strict, as is customary in traditional logic. The typical architecture of a fuzzy controller, shown in Figure 3, consists of a fuzzifier, a fuzzy rule base, an inference engine, and a defuzzifier[25,26].

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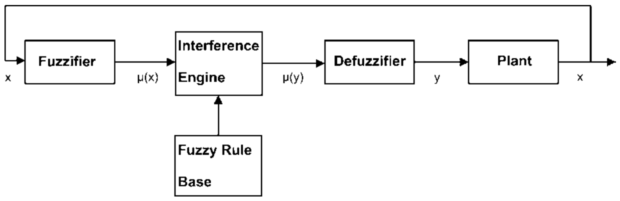

Figure 3. Architecture of a fuzzy controller.

Fuzzy control is defined as a control based on human expertise, determined by words instead of numbers and sentences instead of equations.[25,26] In fact, this does not mean at all that a knowledge of the process dynamics is not needed. Good knowledge of the dynamic behavior of the controlled plant is to be available to the designer. However, process variables are measured in numbers instead of words. For this reason, the fuzzifier adapts the input variables into suitable linguistic values by membership functions. There are different forms of membership functions, e.g. triangular, trapezoidal or Gaussian, and they are chosen according to the user's experience. Range of membership functions values are also set: minimum value of the input variable (*MinIn*), maximum value of the input variable (*MaxIn*), minimum value of the output variable (*MinOut*), maximum value of the output variable (*MaxOut*). The fuzzy rule base is a set of *if-then* rules that store the empirical knowledge of the experts about the operation of the process. A series of relationships that interprets common sense are also defined and can generate a desired action that is applied to the plant. First the fuzzy logic computes the grade of membership of each condition of a rule, and then it aggregates the partial results of each condition using a fuzzy set operator. The inference engine combines the results of the different rules to determine the actions to be carried out, and the defuzzifier converts the control actions of the inference engine into numerical variables, determining the final control action that is applied to the plant. There are two different methods to operate these modules: Mamdani[27] and Sugeno[28]. The Mamdani system aggregates the area determined by each rule, and the output is determined by the center of gravity of that area. In a Sugeno system the results of the *if-then* rules are already numbers determined by numerical functions of the input variables, and therefore, no deffuzifier is necessary. The output is determined weighting the results given by each rule with the values given by the *if* conditions.

For example, Figure 4 shows three triangular membership functions (*mf*1, *mf*2 and *mf*3) with *MinIn* = 0 and *MaxIn* = 5. Thus, an input of 1.5 can be transformed into fuzzy expressions as 0.25 of *mf*1 and simultaneously 0.5 of *mf*2. Figure 5 shows the three membership functions (*mf*4, *mf*5, *mf*6) of the Mamdani defuzzifier with *MinOut* = 0 and *MaxOut* = 5. The *if-then* rules implemented are as follows:

if (*Input* is *mf*1) **then** (*Output* is *mf*4)
if (*Input* is *mf*2) **then** (*Output* is *mf*5)
if (*Input* is *mf*3) **then** (*Output* is *mf*6)

The output is the result of the aggregation of two rules, one that gives 0.25 of *mf*4 and another that gives 0.5 of *mf*5.

EQI and OCI Improvement. To improve EQI and OCI, a hierarchical control is implemented (Figure 6). For the low level control, the two PI controllers of the default BSM1 control strategy are replaced by a MPC + FF configuration with DO5 and NO2 as controlled variables and K_La5 and Q_{rin} as manipulated variables. Two MPC + FF controllers are also added for controlling DO3 and DO4 by manipulating K_La in the third tank (K_La3) and in the fourth tank (K_La4), respectively. A fuzzy controller is proposed for the high level to regulate the DO set points of the low level based on NH5.

Low Level Control. MPC controllers are applied on the low level for the set points tracking of NO2 and DO of the three aerated tanks. Due to the presence of strong disturbances in WWTPs, MPC has difficulties in keeping the controlled variables at their reference level. To compensate the disturbances, a feedforward control is added, as in refs 9−12 and 20. MPC provides options for the feedforward compensation of the measured disturbances, in the same way as for the reference signals. Different variables have been considered for the feedforward action in those works, but in our case Q_{in} has been selected for its better results.

The variables of the state-space model (eq 11) for the three MPC controllers are described as follows: $u_1(k)$ is Q_{rin}, $u_2(k)$ is K_La5, $u_3(k)$ is Q_{in}, $y_1(k)$ is NO2, and $y_2(k)$ is DO5 in the controller of DO5 and NO2; $u_1(k)$ is K_La4, $u_2(k)$ is Q_{in}, and $y_1(k)$ is DO4 in the controller of DO4; and $u_1(k)$ is K_La3, $u_2(k)$ is Q_{in}, and $y_1(k)$ is DO3 in the controller of DO3.

The tuning parameters are Δt, m, p, $\Gamma_{\Delta u}$, Γ_y, and the overall estimator gain.

- Δt has a significant effect on the effectiveness of the controller. High Δt can give less controller performance,

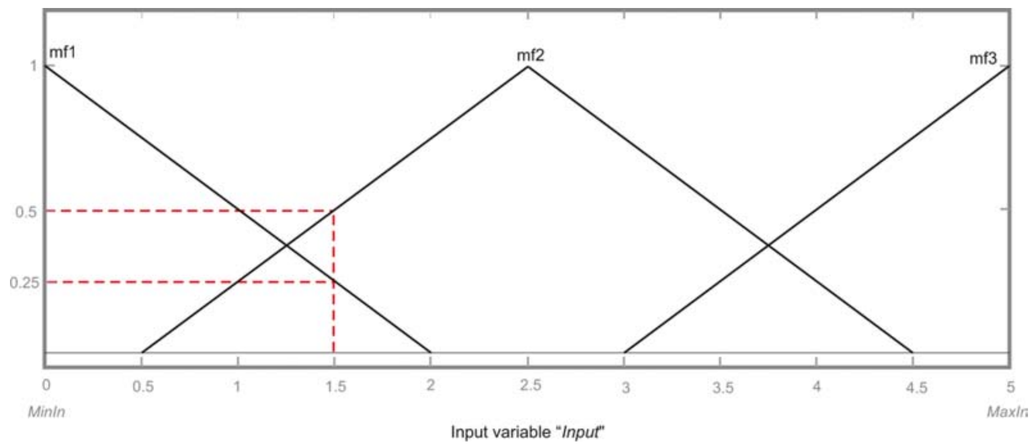

Figure 4. Example of membership functions of fuzzifier.

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Ind. Eng. Chem. Res. 2015, 54, 2763−2775

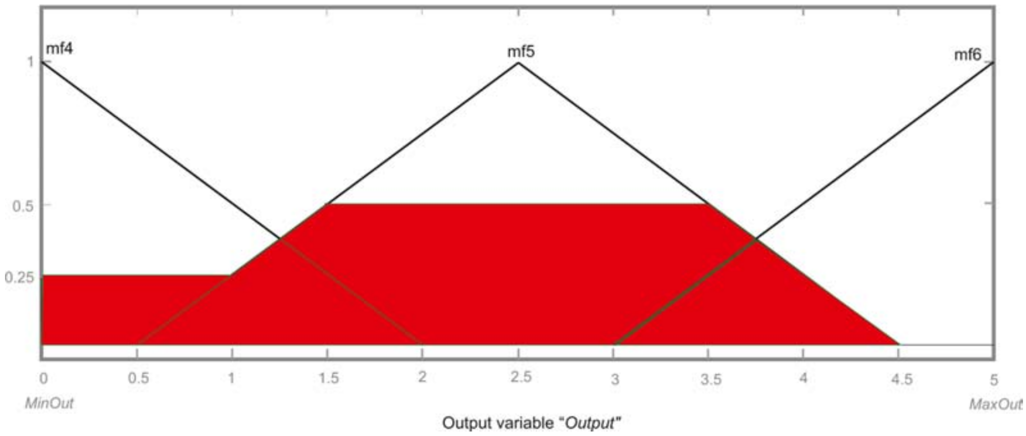

Figure 5. Example of membership functions of defuzzifier.

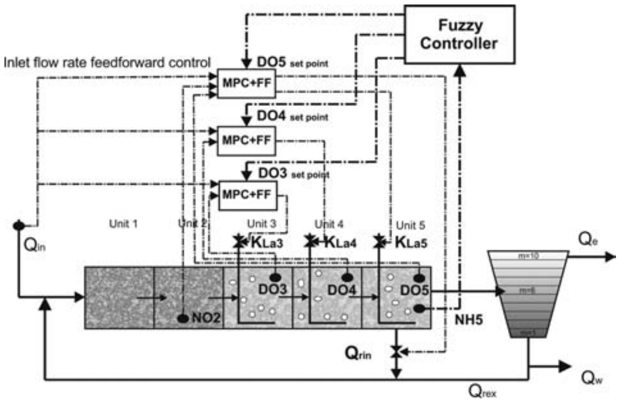

Figure 6. BSM1 with two-level hierarchical control for EQI and OCI improvement.

mainly when there are important input disturbances, and low Δt can produce changes too quickly in the actuators and also high energy consumption. Therefore, the chosen Δt has been the lowest one that allows achieving a successful tracking of the controlled variables, without abrupt changes in the actuators and without a significant aeration cost increase.

- Lower $\Gamma_{\Delta u}$ or higher Γ_y gives better performance of the controlled variable; otherwise, they could produce strong oscillations in the actuators that must be avoided.
- m and p should be adjusted in each case depending on the control system. However, values that are too high can increase the computational time in excess, and on the other hand, values that are too small may result in oscillatory responses or may not work at all.
- At each Δt the controller compares the measured values of the outputs with the expected values. The difference can be due to noise, to measurements errors, and to unmeasured disturbances. With the overall estimator gain parameter the percentage of this difference that is attributed to unmeasured disturbances is determined, and the calculation matrix is consequently adjusted. Higher overall estimator gains improve the results, but too high values can make the controller unfeasible.

High Level Control. The controller proposed for the high level is a fuzzy controller, that varies DO3, DO4 and DO5 set points based on NH5.

The values of NH and NO depend largely on their reaction rate, which is the result of several processes given by ASM1, which describes the biological phenomena that take place in the reactors. When NH increases, more DO is needed for nitrification. On the contrary, when NH decreases, less DO is required, producing less NO. NH5 is not forced to keep a fixed value since it has been observed that it is not possible by manipulating the DO set point due to the large disturbance[15−18,20].

Effluent Violations Removal. Two fuzzy controllers are applied for avoiding $N_{tot,e}$ or NH_e violations. These control strategies are implemented simultaneously with the hierarchical control structure, in order to achieve a reduction of EQI and OCI at the same time.

$N_{tot,e}$ Violation Removal. The variables with the highest influence in N_{tot} are NO and NH. Further efforts to reduce more NH increasing nitrification, result also in an increment of NO, and consequently $N_{tot,e}$ is not decreased. According to the biological processes of ASM1, an increase of substrate produces a growth of $X_{B,H}$ and therefore the denitrification process and the consequent reduction of NO are improved. Therefore, $N_{tot,e}$ is reduced with the dosage of EC in the first tank (EC1). However, dosing EC1 results in an increase of operational costs (eq 2), so it is important to dose EC1 only when a violation of $N_{tot,e}$ could take place. Consequently, the control strategy is based on the manipulation of q_{EC1} according to NH5 plus NO5. A fuzzy controller is proposed to regulate q_{EC1} as can be seen in Figure 7. The maximum q_{EC1} value was limited to $5m^3/d$. For this control objective, the tuning parameters of the high level fuzzy controller of the hierarchical structure are chosen with the aim to reduce as much as possible the percentage of time of NH_e violations and not to exceed the OCI value of the default PI controller when EC1 is added. A trade-off analysis is made for this tuning parameters selection.

NH_e Violations Removal. With the goal of removing NH_e violations, Q_{rin} is manipulated based on NH5 and NH_{in}. Therefore, the MPC of the low level that controls DO5 and NO2 by manipulating K_{La5} and Q_{rin} is replaced by a MPC with one input (DO5) and one output (K_{La5}) (see Figure 8).

To facilitate the understanding of the proposed solution some considerations about the propagation of the peaks in the reactor are provided: When a peak of pollution enters in the reactors, it is propagated through them with a delay determined by the retention time. So any change in the influent flow rate or in the Q_{rin} directly affects the propagation of the peaks of

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Ind. Eng. Chem. Res. 2015, 54, 2763−2775

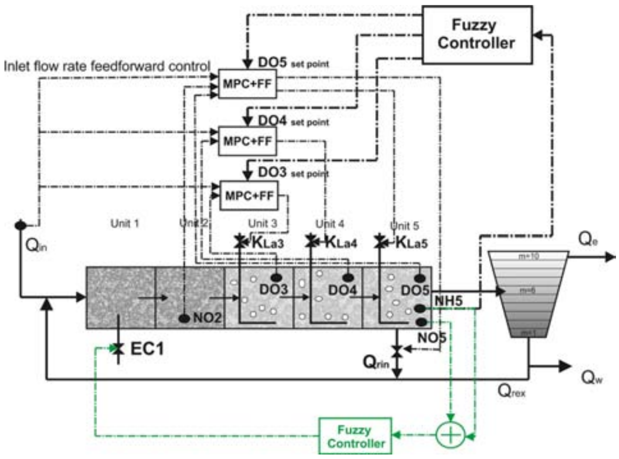

Figure 7. BSM1 with a control strategy for $N_{tot,e}$ removal.

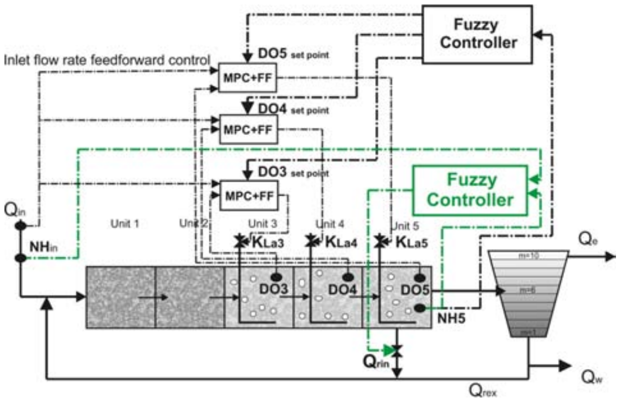

Figure 8. BSM1 with a control strategy for NH removal.

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 in the first reactor (eq 12), when NH_{in} increases, Q_{rin} is incremented to reduce the rise of NH in the first tank (NH1), and when the increase of NH arrives to the fifth tank, and Q_{rin} is reduced to increase the retention time and so to improve the de-nitrification process.

$$\frac{dNH1}{dt} = \frac{1}{V1}(Q_{rin}\cdot NH_{rin} + Q_{rex}\cdot NH_{rex} + Q_{in}\cdot NH_{in} + r_{NH1}\cdot V1 - Q1\cdot NH1) \quad (12)$$

$$Q1 = Q_{rin} + Q_{rex} + Q_{in}$$

where NH_{rin} is NH in the internal recirculation, NH_{rex} is NH in the external recirculation, r_{NH1} is r_{NH} in the first tank, and Q1 is the flow rate in the first tank.

A fuzzy controller is proposed for this control strategy. And the tuning parameters are different when there are peaks of NH_{in} or NH5 and the rest of the time. They are determined by a trade-off analysis of OCI and the percentage of operating time of $N_{tot,e}$ violation, reflecting only the results that avoid the NH_e violations.

■ SIMULATION RESULTS

In this section the control configurations proposed in the above section are tested and compared. Ideal sensors have been considered for the simulations. For the three fuzzy controllers applied, Mamdani[27] is the method selected to defuzzify. The design of the fuzzy controllers was based on the observation of the simulations results obtained by operating the plant with the default control of BSM1. MPC and fuzzy controllers are implemented using Matlab for the simulation and online control. Specifically, MPC controllers have been designed with a MPC tool, the identification of its prediction model with a System Identification Tool, and the fuzzy controllers with an FIS editor. To solve the quadratic objective of MPC in eq 10, the Quadratic Dynamic Matrix Control solver[29] with hard linear constraints in the inputs provided by Matlab MPC Tool has been used.

EQI and OCI Improvement. Here, the implementation of the hierarchical control with MPC + FF in the low level and the fuzzy controller in the high level stated in the previous sections is described.

The identification of the linear predictive models of the MPC controllers was performed using Matlab System Identification Tool. The data of the output variables (DO3, DO4, DO5 and NO2) are obtained by making changes to the input variables (K_La3, K_La4, K_La5 and Q_{rin}) with a maximum variation of 10% regarding its operating point, which is the value of K_La necessary to obtain 2 mg/L of DO and the value of Q_{rin} necessary to obtain 1 mg/L of NO2. Specifically, the working point is 264.09 day $^{-1}$, 209.23 day $^{-1}$, 131.65 day $^{-1}$ and 16486 m^3/day for K_La3, K_La4, K_La5 and Q_{rin} respectively. Different sources were tested to modify the input variables as random, sinusoidal or step, and finally the best fit was obtained with random source. These input variations are performed every 2.4 h, sufficient time to ensure the effect of these variations on the output signals. Furthermore, for the feedforward compensation, a step to Q_{in} of +10% is added over 18446 m^3/day, which is the average value during the stabilization period. Two methods were tested for determining the model with the obtained data, prediction error method (PEM)[30] and subspace state spacesystem identification (N4SID)[31]. Finally PEM were selected because it fits better with the real response of the plant. The order of the models was chosen from a trade-off between the best fit and the lowest order. Therefore, the following third order state-space models are obtained:

DO5 and NO2 control

$$A = \begin{bmatrix} 0.8748 & 0.04463 & 0.1314 \\ 0.04091 & 0.7331 & 0.1796 \\ 0.2617 & -0.1318 & 0.3007 \end{bmatrix}$$

$$B = \begin{bmatrix} 7.641 \times 10^{-6} & 0.004551 & -2.749 \times 10^{-5} \\ -2.631 \times 10^{-5} & 0.006562 & -4.551 \times 10^{-6} \\ -9.63 \times 10^{-6} & -0.02161 & 2.447 \times 10^{-5} \end{bmatrix}$$

$$C = \begin{bmatrix} 0.8812 & -0.5948 & 0.02114 \\ 1.187 & 0.9893 & -0.3754 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (13)$$

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Ind. Eng. Chem. Res. 2015, 54, 2763−2775

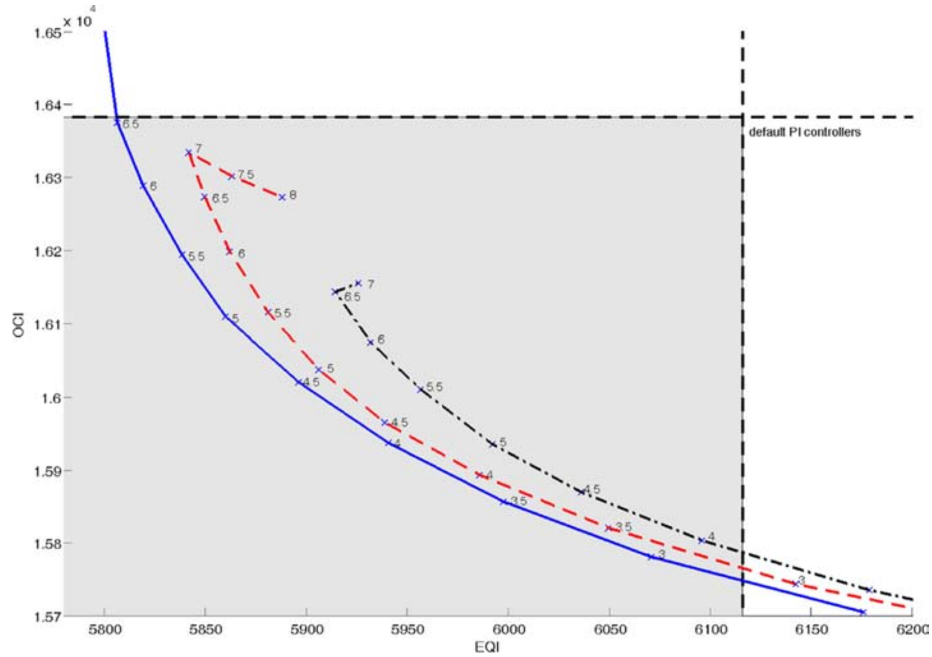

Figure 9. OCI and EQI trade-off with higher level fuzzy controller for a range of *MaxOut* from 2.5 to 8 with increments of 0.5 (points marked with crosses) and *MaxIn* = 3 (solid line), 5 (dashed line), and 7 (dash-dotted line).

DO3 control

$$A = \begin{bmatrix} 0.7859 & 0.4576 & -0.131 \\ 0.3334 & 0.2599 & 0.2718 \\ -0.003132 & 0.03235 & -1.003 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.009308 & -2.285 \times 10^{-5} \\ -0.01546 & 3.503 \times 10^{-6} \\ 0.003654 & -1.987 \times 10^{-5} \end{bmatrix}$$

$$C = [0.6376 \quad -0.4621 \quad 0.03698]$$

$$D = [0 \quad 0] \tag{14}$$

DO4 control

$$A = \begin{bmatrix} 0.8201 & 0.371 & -0.1016 \\ 0.3054 & 0.307 & 0.2544 \\ -0.003381 & 0.03144 & -0.9993 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.007712 & -4.65 \times 10^{-5} \\ -0.0148 & 8.164 \times 10^{-6} \\ 0.004523 & -2.526 \times 10^{-5} \end{bmatrix}$$

$$C = [0.947 \quad -0.496 \quad 0.02472]$$

$$D = [0 \quad 0] \tag{15}$$

The selected values to tune the MPC are $m = 5$, $p = 20$, $\Delta t = 0.00025$ days (21.6 s), $\Gamma_y = 1$ and $\Gamma_{\Delta u} = 0.01$ for DO3, DO4 and DO5 control and $\Gamma_y = 1$ and $\Gamma_{\Delta u} = 0.0001$ for NO2 control and overall estimator gain = 0.8. It should be noted that the values of m and p are not critical and they can be slightly changed with similar results.

Data acquisition for the model identification is based on simulations, as this work is a first step to be subsequently tested in a pilot plant and finally in a real plant. In order to predict the possible application in a real plant, the data acquisition for the identification is performed while the plant is kept at a certain desired operating point, whose values are considered suitable for the biological wastewater treatment of this plant, as the same way of K_La3 and K_La4. Therefore, what the identification needs is only the possibility of adding some incremental changes to those operating conditions. As mentioned before, the inputs used for identification purposes represent a maximum variation of 10%. Therefore, they will not disturb the actual plant operation. The generated outputs will reflect the effect of such input variables manipulation. Data for identification have been generated simulating 1 week. However, in the case of the real plant, the identification could be carried out in different periods and not necessarily in consecutive days. Plants operator knowledge can in addition be used to know the more appropriate days to perform the experiment.

For the high level fuzzy controller, three triangular membership functions for input and for output are used (low, medium and high). The rules implemented are as follows:

if (NH5 is *low*) **then** (DO is *low*)
if (NH5 is *medium*) **then** (DO is *medium*)
if (NH5 is *high*) **then** (DO is *high*)

MinIn and *MinOut* are 0.1 and 0.8, respectively. *MaxIn* and *MaxOut* have been determined with OCI and EQI trade-off

Table 3. EQI and OCI Results with Default PI Controllers and the Proposed Hierarchical Control

		Hierarchical Control		
	default PI controllers	lowest EQI	lowest OCI	% of improvement
EQI (kg pollutants/d)	6115.63	5804.38	6037.07	−5%
OCI	16381.93	16377.51	15743.27	−3.9%

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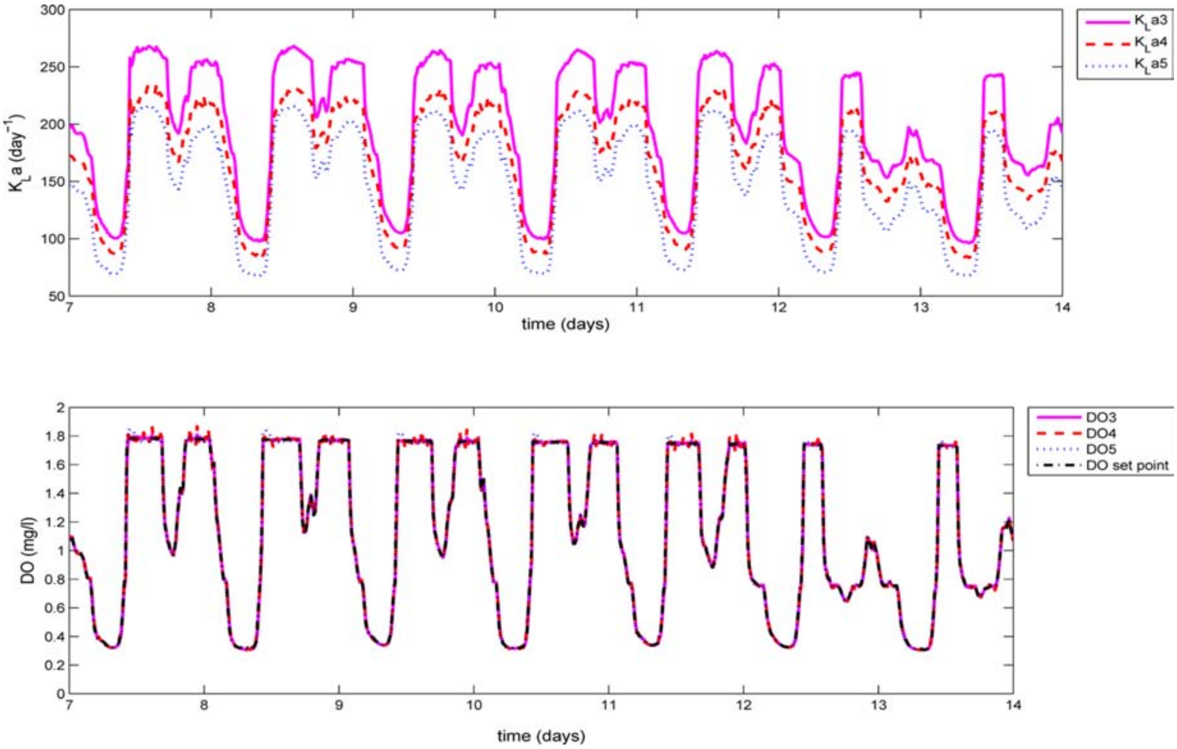

Figure 10. K_La and DO evolution of the three aerated tanks from day 7 to day 14 with hierarchical control structure.

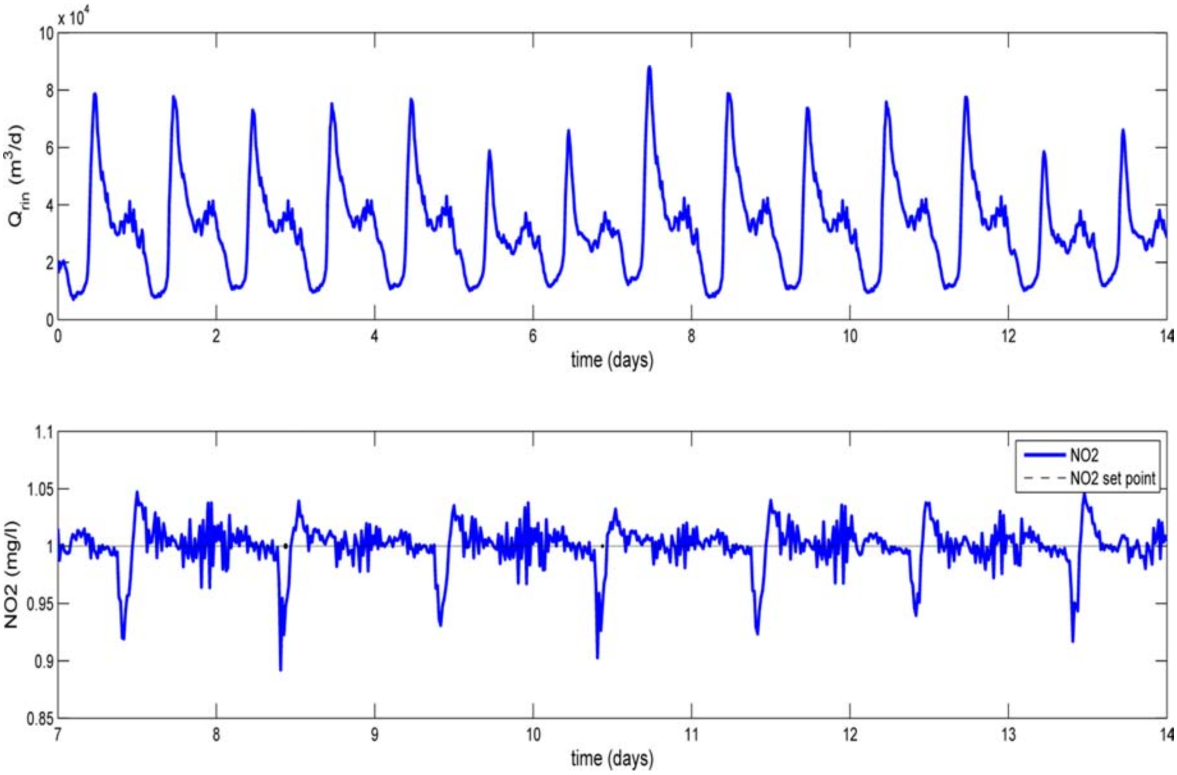

Figure 11. Q_{rin} and NO2 evolution from day 7 to day 14 with hierarchical control structure.

representations shown in Figure 9. Each one of the lines corresponds to the results obtained with different *MaxIn*, i.e. 3, 5, 7, and each one of the points marked with crosses is the result of a different *MaxOut* that varies from 2.5 to 8 with increments of 0.5. The results obtained with default PI controllers are also shown.

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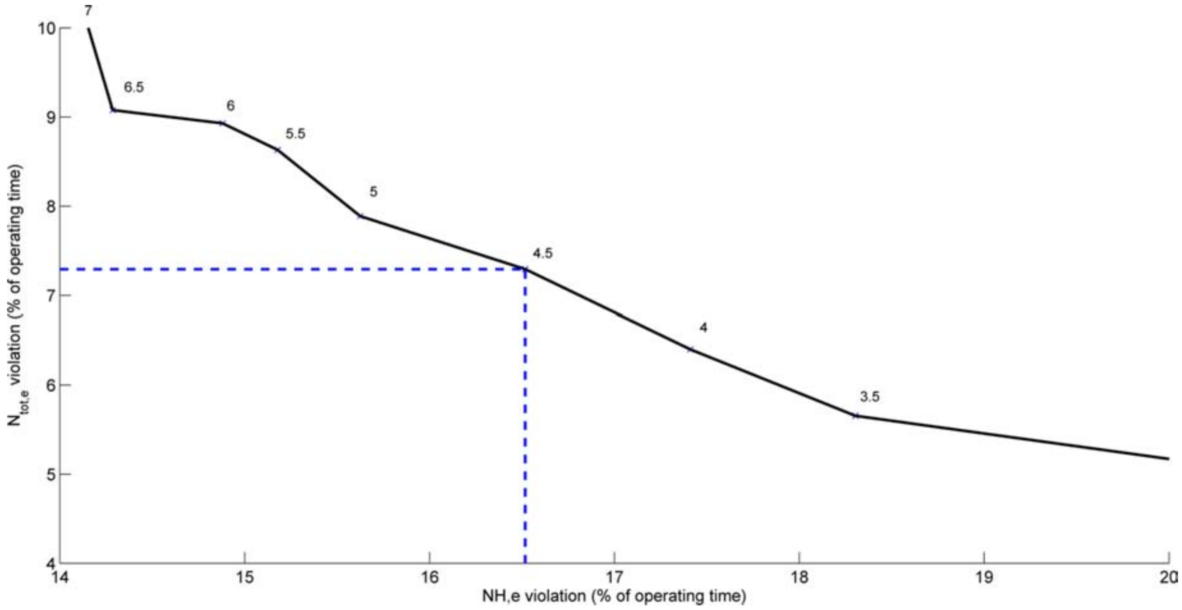

Figure 12. High level fuzzy controller: trade-off of the time percentage of NH_e and $N_{tot,e}$ violations for *MaxIn* = 3 and a range of *MaxOut* values from 3 to 7 with increments of 0.5 (points marked with crosses).

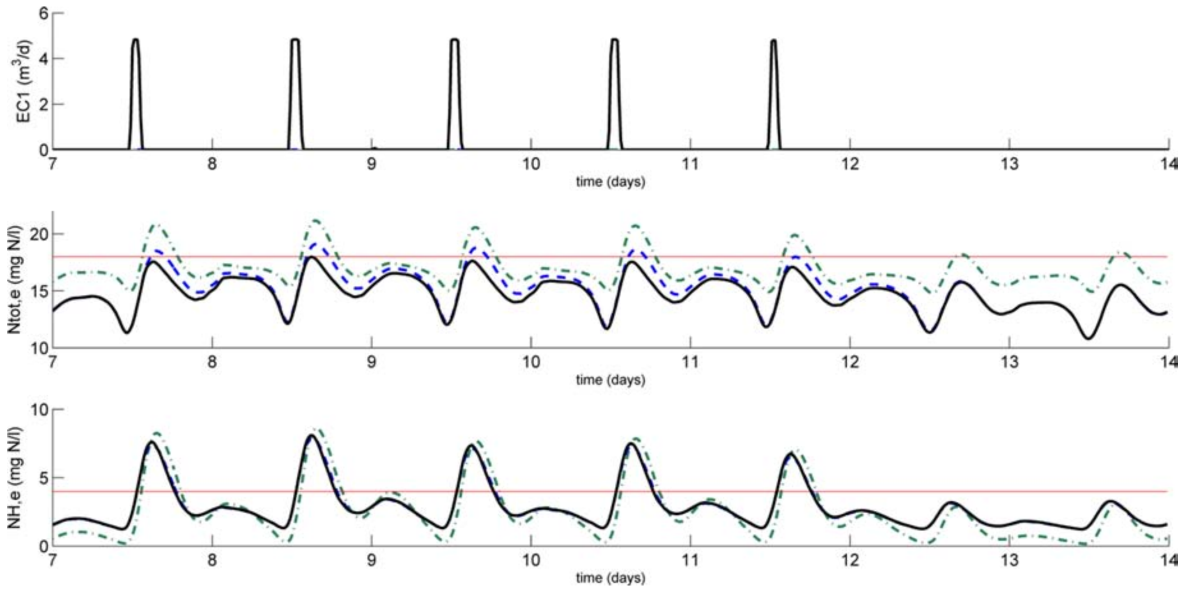

Figure 13. q_{EC1}, NH_e and $N_{tot,e}$ evolution from day 7 to day 14 with default PI controllers (dash-dotted line), with hierarchical control without adding EC1 (dashed line) and with hierarchical control adding EC1 (solid line).

The *MaxIn* and *MaxOut* values of the extreme cases of lowest EQI without increasing OCI and lowest OCI without worsening EQI in comparison with default PI controllers are *MaxIn* = 3 and *MaxOut* = 6.5 for the best EQI and *MaxIn* = 3 and *MaxOut* = 2.75 for the best OCI. Table 3 presents the results of best EQI without increasing OCI and best OCI without worsening EQI of high level fuzzy controller in comparison with default control strategy. The improvement of EQI is 5% and the reduction of OCI is 3.9%. Figures 10 and 11 show the evolution of the control and manipulated variables from day 7 to 14.

$N_{tot,e}$ Violations Removal. The objectives of this control strategy besides $N_{tot,e}$ violations removal are to improve EQI, not to increase OCI and to reduce the percentage of time of NH_e violations in comparison with the default control strategy. For this purpose, a trade-off analysis of the percentage of time over the limits of NH_e and $N_{tot,e}$ is made (see Figure 12). For this analysis, the hierarchical control strategy is included but not the addition of EC1. The tuning parameters of the high level fuzzy controller are selected at the point whose percentage of operating time of NH_e over the limits is the same as with the default control strategy (17.26%). These tuning parameters are *MaxIn* = 3 and *MaxOut* = 4.1, and the percentage of operating time of the $N_{tot,e}$ violation with these parameters is 6.39%.

In the OCI and EQI trade-off representation shown in Figure 9, in the points of the tuning parameters mentioned, a difference in OCI of 2.6% is observed regarding the default control strategy,

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Ind. Eng. Chem. Res. 2015, 54, 2763−2775

which may be used for the EC1 dosage. The dashed line in Figure 13 shows the evolution of $N_{tot,e}$ from day 7 to 14 with the parameters selected for high level fuzzy controller and without adding EC1. The constant line is the $N_{tot,e}$ limit.

With these parameters selected for the high level, a fuzzy controller is added to manipulate q_{EC1}. For this controller, three triangular membership functions for input and for output are used (low, medium and high). The rules implemented are as follows:

if (NH5+NO5 is *low*) **then** (q_{EC1} is *low*)
if (NH5+NO5 is *medium*) **then** (q_{EC1} is *medium*)
if (NH5+NO5 is *high*) **then** (q_{EC1} is *high*)

The ranges of membership functions values are *MinIn* = 10, *MaxIn* = 17.5, *MinOut* = −8, *MaxOut* = 6.75. The solid lines of Figure 13 correspond to the evolution of q_{EC1}, $N_{tot,e}$ and NH_e from day 7 to 14. It is observed that $N_{tot,e}$ violations are removed.

Table 4 presents the results of EQI, OCI and the percentage of operating time out of the limits of NH and $N_{tot,e}$ obtained with hierarchical control adding EC1 and compared with the default control strategy of BSM1. It is shown that by adding EC1 and a hierarchical control of DO in the three aerated tanks, the violations of $N_{tot,e}$ can be avoided, also improving the results of EQI and OCI and the percentage of operating time of NH_e violations with respect to default PI controllers.

Table 4. Results with Default PI Controllers and with Control for $N_{tot,e}$ Violations Removal

	default PI controllers	control for $N_{tot,e}$ violations removal	% of improvement
EQI (kg pollutants/d)	6115.63	5862.03	−4.1%
OCI	16381.93	16336.36	−0.3%
$N_{tot,e}$ violations (% of operating time)	17.56	0	−100%
NH_e violations (% of operating time)	17.26	16.66	−3.4%

NH_e Violations Removal.

As mentioned in the previous section, to perform the control for removing violations of NH_e, the MIMO MPC + FF, that controls DO5 and NO2 by manipulating K_La5 and $Q_{a,in}$, has been replaced by a SISO MPC + FF that controls DO5 by manipulating K_La5, because $Q_{a,in}$ is manipulated based on NH5 and NH_{in}.

The model identification of the new MPC + FF was performed with the same methodology as with the previous controller, but with one input and one output. However, in this case it is a second order state-space model:

$$A = \begin{bmatrix} 0.8349 & 0.2746 \\ 0.2512 & 0.2894 \end{bmatrix}$$
$$B = \begin{bmatrix} 0.008745 & -2.729 \times 10^{-5} \\ -0.02118 & 1.307 \times 10^{-5} \end{bmatrix}$$
$$C = \begin{bmatrix} 1.512 & -0.3525 \end{bmatrix}$$
$$D = \begin{bmatrix} 0 & 0 \end{bmatrix} \tag{16}$$

The *MaxIn* and *MaxOut* values of the high level fuzzy controller have been selected by a trade-off analysis of OCI and percentage of operating time of NH_e violation (see Figure 14), choosing the less percentage of NH_e violation in order to facilitate its later total elimination, but considering the increased costs that will be generated by the new control strategy. In this case the chosen parameters are *MaxIn* = 3 and *MaxOut* = 5.5. In the case of the fuzzy controller for the NH_e violations removal, two tunings are determined, one when there are peaks of NH_{in} or NH5, and the other the rest of the time. For both cases three triangular membership functions for input and for output are used (low, medium and high). The rules implemented are as follows:

if (NH5 is *low*) **then** ($Q_{a,in}$ is *high*)
if (NH5 is *medium*) **then** ($Q_{a,in}$ is *medium*)
if (NH5 is *high*) **then** ($Q_{a,in}$ is *low*)

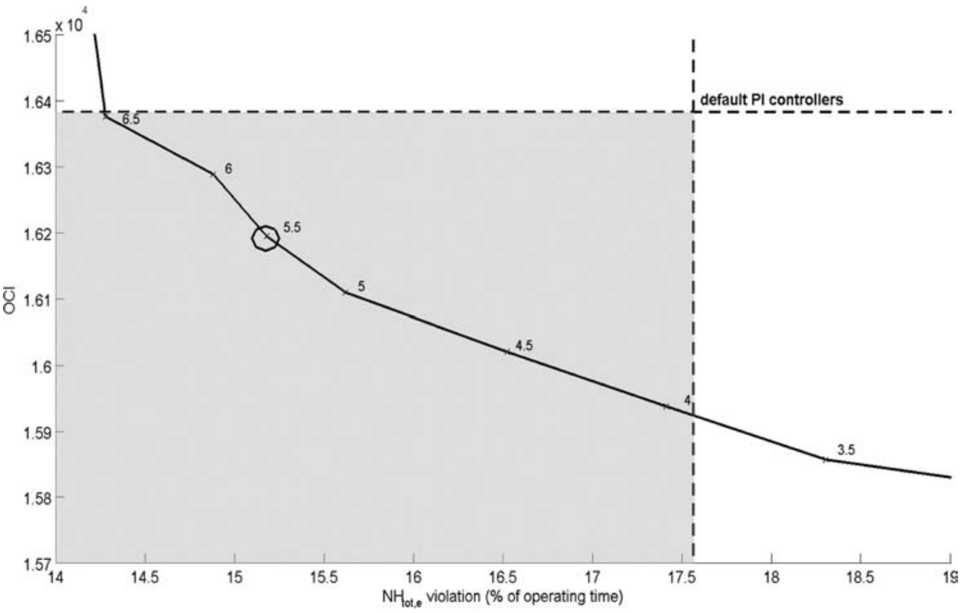

Figure 14. Trade-off representation of OCI and the percentage of operating time of NH_e violations for *MaxIn* = 3 and a range of *MaxOut* from 3 to 7 with increments of 0.5 (points marked with crosses).

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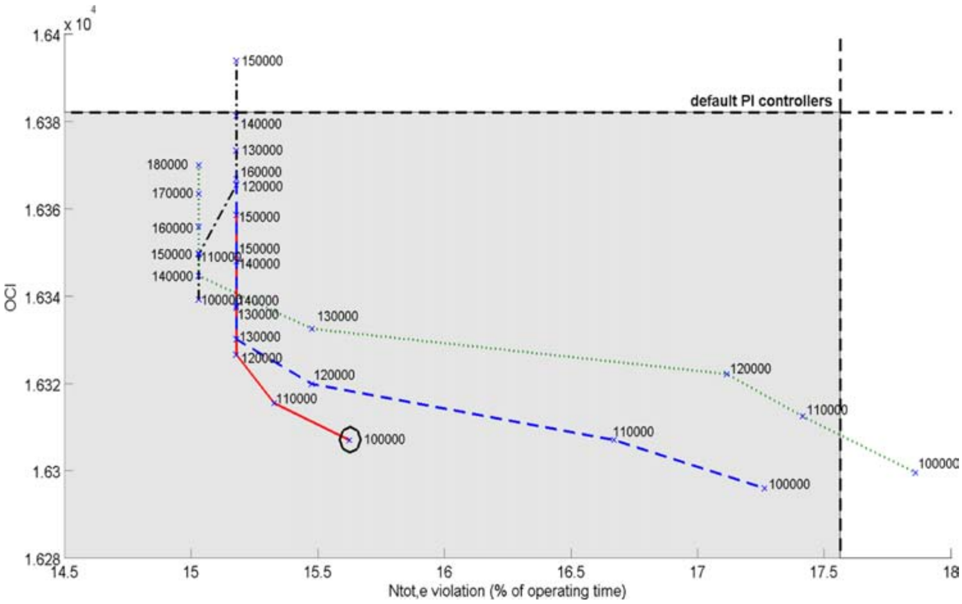

Figure 15. Trade-off representation of OCI and the percentage of operating time of $N_{tot,e}$ violations for a range of *MaxOut* from 90000 to 180000 with increments of 10000 (points marked with crosses) and *MaxIn* = 2 (dotted line), 2.2 (dashed line), 2.4 (solid line), 2.6 (dash-dotted line).

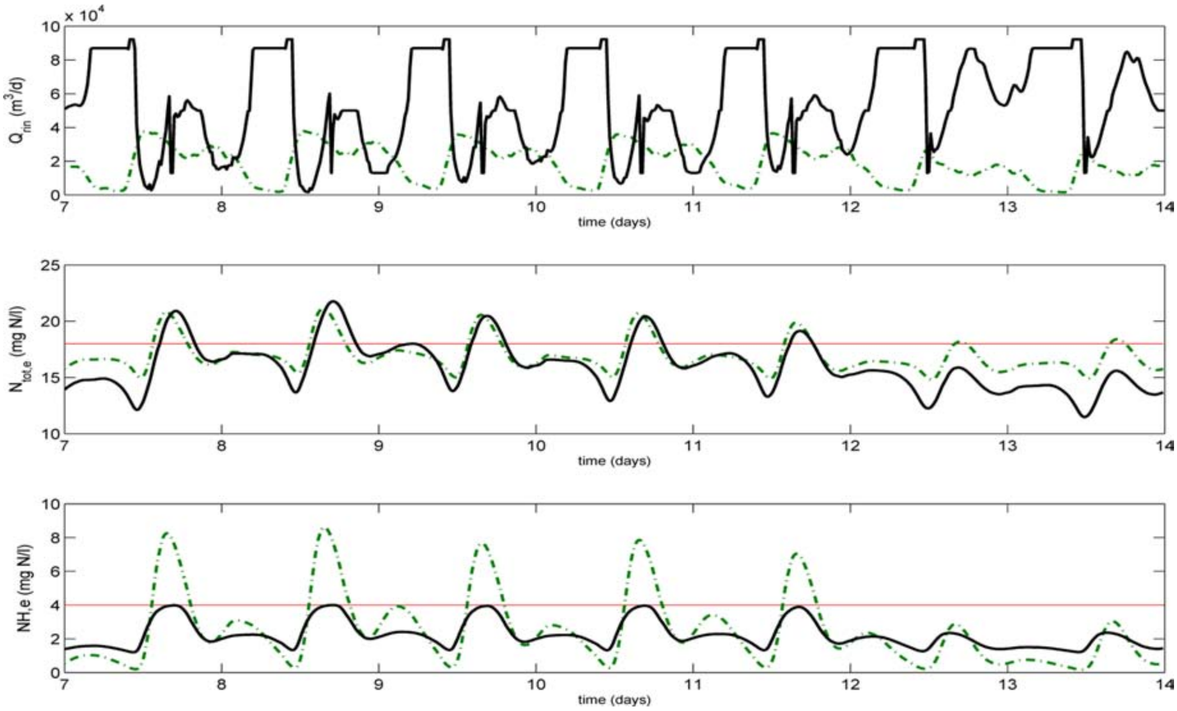

Figure 16. Q_{rin}, NH_e and $N_{tot,e}$ evolution from day 7 to day 14 with default PI controllers (dash-dotted line) and with the control for NH_e violations removal (solid line).

When there are peaks of NH_{in} or NH5, the tuning parameters are set looking for a great variation in Q_{rin} when NH_e is increasing. Therefore, *MinIn*, *MaxIn*, *MinOut* and *MaxOut* are 3.5, 4.1, -2×10^4, and 14×10^4, respectively. For the rest of the time, *MinOut* and *MaxOut* are set by a trade-off analysis of OCI and percentage of operating time of $N_{tot,e}$ violation, reflecting only the results that avoid the NH_e violations. An area is obtained where OCI and the operating time of the $N_{tot,e}$ violation are decreased compared to default PI controllers (see Figure 15). Each one of the lines corresponds to the results obtained with *MaxIn* = 2, 2.2, 2.4, and 2.6, and each one of the points marked with crosses is the result of a different *MaxOut* that varies from 90000 to 180000 with increments of 10000. The results obtained with default PI controllers alone are also shown. The parameters have been selected according to the Nash Solution[32]: *MaxIn* = 2.4 and *MaxOut* = 100000.

Q_{rin}, $N_{tot,e}$ and NH_e evolutions from day 7 to 14 are shown in Figure 16. The results with default PI controllers are also shown.

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Table 5. Results with Default PI Controllers and with Control for NH_e Violations Removal

	default PI controllers	control for NH_e violations removal	% of improvement
EQI (kg pollutants/d)	6115.63	5854.06	−4.26%
OCI	16381.93	16307.26	−0.45%
$N_{tot,e}$ violations (% of operating time)	17.56	15.62	−11.04%
NH_e violations (% of operating time)	17.26	0	−100%

It can be observed that, with this control strategy, NH_e peaks are reduced under the limits established.

Table 5 shows the results of EQI, OCI and percentage of time over the limits of NH_e and $N_{tot,e}$. It can be seen that it is possible to avoid NH_e violations with the regulation of Q_{rin} based on NH5 and NH_{in} applying a fuzzy controller with two different alternative settings of the tuning parameters and also with the hierarchical control of DO in the three aerated tanks. In addition, a reduction of 4.26% of EQI and 0.45% of OCI, with respect to the default control strategy of BSM1, is achieved.

CONCLUSION

In this paper, different control configurations based on MPC and fuzzy logic have been used in WWTPs to eliminate $N_{tot,e}$ violations or NH_e violations and at the same time improve the results of OCI and EQI in comparison with the default control strategy of BSM1.

The elimination of $N_{tot,e}$ violations is achieved by manipulating q_{EC1} based on NO5 plus NH5. The removal of NH_e violations is carried out by manipulating Q_{rin} based on NH5 and NH_{in}, which uses different tuning parameters depending on if there are peaks of pollution in the tanks or not.

In both cases, a two-level hierarchical control structure is simultaneously implemented to perform an EQI and OCI improvement. The low level of this structure is composed by three MPC + FF that manipulate K_La3, K_La4, K_La5 and Q_{rin} to control DO3, DO4, DO5 and NO2 in the first case and KLa3, KLa4 and KLa5 to control DO3, DO4 and DO5 in the second case. For the high level, a fuzzy controller is implemented to manipulate DO set points of the low level according to NH5.

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Notes

The authors declare no competing financial interest.

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Removing violations of the effluent pollution in a wastewater treatment process

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HIGHLIGHTS

- Performance improvement of wastewater treatment plants applying control strategies.
- Effluent quality improvement and costs reduction with a hierarchical control.
- Effluent violations removal for dry, rain and storm weather conditions.
- Simultaneously removal of total nitrogen and ammonia violations.

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ABSTRACT

This paper presents different control strategies for biological wastewater treatment plants, with the goal of avoiding violations of effluent pollution limits while, at the same time, improving effluent quality and decreasing operational costs. The control strategies are based on Model Predictive Control (MPC) and functions that relate the input and manipulated variables. The Benchmark Simulation Model No.1 (BSM1) is used for evaluation. A hierarchical structure regulates the dissolved oxygen (DO) of the three aerated tanks based on the ammonium and ammonia nitrogen concentration (NH) in the fifth tank (NH5). An MPC with feedforward compensation is proposed for the lower level and an affine function is selected for the higher level. A tuning region is determined modifying the tuning parameters of the higher level, in which the effluent quality and operational costs are simultaneously improved in comparison with the default control strategy of BSM1. To eliminate violations of total nitrogen in the effluent ($N_{tot,e}$), an affine function, implemented with a sliding window, adds external carbon flow rate in the first tank based on nitrate nitrogen in the fifth tank (NO5) plus NH5. To avoid violations of NH in the effluent (NH_e), a combination of a linear function and an exponential function that manipulates the internal recirculation flow rate based on NH5 and NH in the influent is proposed. As a result, $N_{tot,e}$ violations and NH_e violations are avoided for dry, rain and storm weather conditions. In addition, an improvement of effluent quality and a reduction of operational costs are achieved at the same time, except in the cases of rain and storm weathers for NH_e violations removal, in which the costs increase.

1. Introduction

The control of biological wastewater treatment plants (WWTPs) is not an easy task due to the complexity of the biological and biochemical processes that take place inside them, the diversity of time constants involved, the large disturbances in concentration and flow rate of the influent and the legal requirements for the effluent (see for instance the European Directive 91/271 "Urban wastewater" established by European Union).

In this work the evaluation and comparison of the different control strategies is based on Benchmark Simulation Model No.1 (BSM1), developed by the International Association on Water Pollution Research and Control [1–3]. This benchmark includes a plant layout, influent loads, test procedures and evaluation criteria.

The BSM1 provides a default control strategy that includes two Proportional-Integral (PI) control loops: control of the dissolved oxygen concentration (DO) in the fifth tank (DO5) at a set point value of 2 g/m^3 by manipulating the oxygen transfer coefficient (K_La) in the fifth tank (K_La5), and control of the nitrate nitrogen concentration (NO) in the second anoxic reactor (NO2) at a set point value of

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1 g/m^3 by manipulating the internal recycle flow rate (Q_{rin}). A complete review of results for PI control can be found in [4].

There are previous works that propose different methods for controlling WWTPs. Some of them apply a direct control of the effluent variables, mainly ammonium and ammonia nitrogen (NH) and total nitrogen (N_{tot}) [5–7]. The difficulty in this method is that the fixed values for the effluent variables are constraints and not set points. Other studies deal with the basic control strategy (DO of the aerated tanks and NO of the last anoxic tank), but testing with different controllers such as Model Predictive Controller (MPC) and fuzzy controller [8–11]. These methods provide an acceptable balance between quality and costs. Finally other investigations propose a hierarchical control that regulates the DO set points, depending on some states of the plant, usually NH and NO values in any tank or in the influent [12–17] or DO in other tanks [18].

Unlike the referred articles, the present work deals with the avoidance of N_{tot} in the effluent ($N_{tot,e}$) and NH in the effluent (NH_e) violations for dry, rain and storm weather conditions, taking also into account the effluent quality and operational costs. The proposed control strategies are based on improving the nitrification process by oxidizing the aerated tanks [19] and by manipulating Q_{rin} [20], and on improving the denitrification process by adding external carbon flow rate (q_{EC}) [21]. Other important innovation is the introduction of a sliding window to dosage the minimum q_{EC1} necessary for the $N_{tot,e}$ violations removal in order to minimize operational costs.

First, a hierarchical control structure is implemented to improve simultaneously OCI and EQI. The lower level is composed by three MPC with feedforward compensation of the influent flow rate (MPC + FF) [22], to control NO2, DO in the third tank (DO3), DO in the fourth tank (DO4) and DO5. The higher level adjusts the DO set points according with NH in the fifth tank (NH5), and an affine function is proposed for this level. A trade-off analysis is made, which determines a tuning region that improves simultaneously the results of effluent quality and operational cost in comparison with default control strategy of BSM1. Next, two controls are added in order to eliminate effluent violations. NH_e and $N_{tot,e}$ are the pollutants that present more difficulties for being kept under the established limits. For reducing peaks of $N_{tot,e}$, q_{EC} in the first tank (q_{EC1}) is added based on NO in the fifth tank (NO5) plus NH5. An affine function is proposed for this control, with a sliding window for its implementation. And for reducing peaks of NH_e, Q_{rin} is manipulated based on NH5, and the control of NO2 is removed. A combination of linear function and exponential function is proposed for this control.

2. Working scenario: BSM1

This section provides a description of the working scenario provided by the BSM1. This is a simulation environment defining a plant layout, a simulation model, influent loads, test procedures and evaluation criteria.

2.1. Plant layout

The schematic representation of the WWTP is presented in Fig. 1. The plant consists in five biological reactor tanks connected in series, followed by a secondary settler. The first two tanks have a volume of 1000 m^3 each and are anoxic and perfectly mixed. The rest three tanks have a volume of 1333 m^3 each and are aerated. The settler has a total volume of 6000 m^3 and is modeled in ten layers, being the 6th layer, counting from bottom to top, the feed layer. Two recycle flows, the first from the last tank and the second from the underflow of the settler, complete the system. The plant is designed for an average influent dry-weather flow rate of 18,446 m^3/d and an average biodegradable chemical oxygen demand (COD) in the influent of 300 g/m^3. Its hydraulic retention time, based on the average dry weather flow rate and the total tank and settler volume (12,000 m^3), is 14.4 h. The default wastage flow rate (Q_w) is fixed to 385 m^3/d that determines, based on the total amount of biomass present in the system, a biomass sludge age of about 9 days. The nitrogen removal is achieved using a denitrification step performed in the anoxic tanks and a nitrification step carried out in the aerated tanks. The internal recycle is used to supply the denitrification step with NO.

2.2. Models

The biological phenomena of the reactors are simulated by the Activated Sludge Model Nº 1 (ASM1) [23] that considers eight different biological processes. The vertical transfers between layers in the settler are simulated by the double-exponential settling velocity model [24]. None biological reaction is considered in the settler. The two models are internationally accepted and include thirteen state variables. The proposed control strategies in this work are based on the conversion rates of NH (r_{NH}) and NO (r_{NO}). They are shown following:

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

$$r_{NO} = -0.1722\rho_2 + 4.1667\rho_3 \quad (2)$$

where $\rho_1, \rho_2, \rho_3, \rho_6$ 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:

$$\rho_1 = 4\left(\frac{S}{10+S}\right)\left(\frac{DO}{0.2+DO}\right)X_{B,H} \quad (3)$$

$$\rho_2 = 4\left(\frac{S}{10+S}\right)\left(\frac{0.2}{0.2+DO}\right)\left(\frac{NO}{0.5+NO}\right)0.8 \cdot X_{B,H} \quad (4)$$

$$\rho_3 = 0.5\left(\frac{NH}{1+NH}\right)\left(\frac{DO}{0.4+DO}\right)X_{B,A} \quad (5)$$

$$\rho_6 = 0.05 \cdot ND \cdot X_{B,H} \quad (6)$$

where S is the readily biodegradable substrate, ND the soluble biodegradable organic nitrogen, $X_{B,H}$ the active heterotrophic biomass and $X_{B,A}$ the active autotrophic biomass. The biological parameter values used in the BSM1 correspond approximately to a temperature of 15 ºC.

2.3. Influent loads

BSM1 defines three different influent data [25,26]: dry weather, rain weather and storm weather. Each scenario contains 14 days of influent data with sampling intervals of 15 mins.

2.4. Test procedures

A simulation protocol is established to assure that results are got under the same conditions and can be compared. So first a 150 days period of stabilization in closed-loop using constant influent data has to be completed to drive the system to a steady-state, next a simulation with dry weather is run and finally the desired influent data (dry, rain or storm) is tested. Only the results of the last seven days are considered.

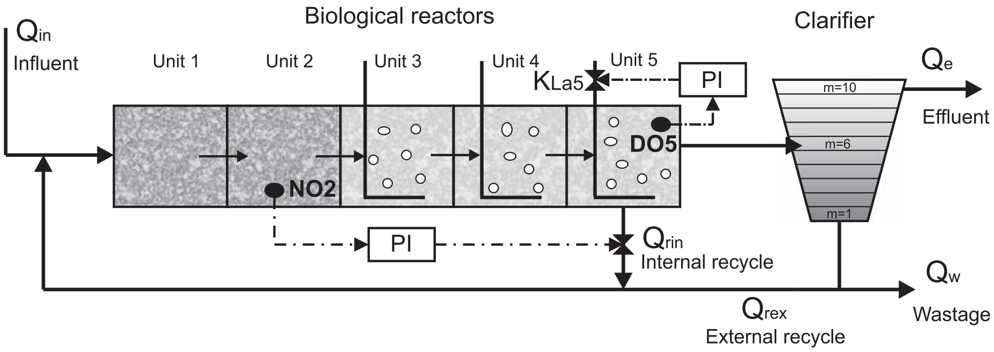

Fig. 1. Benchmark Simulation Model 1.

2.5. Evaluation criteria

In order to compare the different control strategies, different criteria are defined.

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. It is assessed by Integral of the Squared Error (ISE) criterion. The second level provides measures for the effect of the control strategy on plant performance. It includes Effluent Quality Index (EQI) and Overall Cost Index (OCI).

The evaluation must include the percentage of time that the effluent limits are not met and the number of violations. This last term is defined as the number of crossings of the limit, from below to above the limit.

2.5.1. Effluent limits

The effluent concentrations of N_{tot}, Total COD (COD_t), NH, Total Suspended Solids (TSS) and Biological Oxygen Demand (BOD_5) should obey the limits given in Table 1.

N_{tot} is calculated as the sum of NO and Kjeldahl nitrogen (NKj), being this the sum of organic nitrogen and NH.

2.5.2. Effluent Quality Index

EQI is defined to evaluate the quality of the effluent. It is related with the fines to be paid due to the discharge of pollution. EQI is averaged over a 7 days observation period and it is calculated weighting the different compounds of the effluent loads.

$$EQI = \frac{1}{1000 \cdot T} \int_{t=7days}^{t=14days} (B_{\mathrm{TSS}} \cdot \mathrm{TSS}(t) + B_{\mathrm{COD}} \cdot \mathrm{COD}(t) + B_{NKj} \cdot NK_j(t) + B_{\mathrm{NO}} \cdot \mathrm{NO}(t) + B_{\mathrm{BOD_5}} \cdot \mathrm{BOD_5}(t)) \cdot Q(t) \cdot dt \quad (7)$$

where B_i are weighting factors (Table 2) and T is the total time.

2.5.3. Overall Cost Index

OCI is defined as:

$$\mathrm{OCI} = \mathrm{AE} + \mathrm{PE} + 5 \cdot \mathrm{SP} + 3 \cdot \mathrm{EC} + \mathrm{ME} \quad (8)$$

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 and ME is the mixing energy.

Table 1
Effluent quality limits.

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

Table 2
B_i values.

Factor	B_{TSS}	B_{COD}	B_{NKj}	B_{NO}	B_{BOD_5}
Value(g pollution unit g^{-1})	2	1	30	10	2

AE is calculated according to the following relation:

$$\mathrm{AE} = \frac{S_o^{sat}}{T \cdot 1.8 \cdot 1000} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} \mathrm{V}_i \cdot K_L a_i(t) \cdot dt \quad (9)$$

where V_i is the volume of the tank i.

PE is calculated as:

$$\mathrm{PE} = \frac{1}{T} \int_{7days}^{14days} (0.004 \cdot Q_{in}(t) + 0.008 \cdot Q_{rin}(t) + 0.05 \cdot Q_w(t)) \cdot dt \quad (10)$$

SP is calculated from the TSS in the flow wastage (TSS_w) and the solids accumulated in the system:

$$\mathrm{SP} = \frac{1}{T} \cdot (\mathrm{TSS}_a(14days) - \mathrm{TSS}_a(7days) + \mathrm{TSS}_s(14days) - \mathrm{TSS}_s(7days) + \int_{t=7days}^{t=14days} TSS_w \cdot Q_w \cdot dt) \quad (11)$$

where TSS_a is the amount of solids in the reactors and TSS_s is the amount of solids in the settler.

EC refers to the carbon that could be added to improve denitrification.

$$\mathrm{EC} = \frac{\mathrm{COD_{EC}}}{T \cdot 1000} \int_{t=7days}^{t=14days} \left(\sum_{i=1}^{i=n} q_{\mathrm{EC},i} \right) \cdot dt \quad (12)$$

where $q_{EC,i}$ is q_{EC} added to compartment i, COD_{EC} = 400 gCOD m^{-3} is the concentration of readily biodegradable substrate in the external carbon source.

ME is the energy employed to mix the anoxic tanks to avoid settling and it is a function of the compartment volume:

$$\mathrm{ME} = \frac{24}{T} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} \left[0.005 \cdot V_i \; if \; K_L a_i(t) < 20d^{-1} \; otherwise \; 0 \right] \cdot dt \quad (13)$$

3. Control objectives

With the aim to simultaneously improve EQI and OCI, first a hierarchical control structure is presented. For the lower level, the PI controllers of the default control strategy are replaced by MPC + FF to control the DO of the three aerated tanks and the

NO2. The higher level adjusts the DO set points of the lower level according with NH5. An affine function is proposed for the higher level. The objective of the hierarchical structure is to increase DO in the aerated tanks when NH5 is high, in order to facilitate the nitrification process increasing NH removal and therefore improving the effluent quality, and to reduce DO when NH5 is low, with the purpose of reducing operational costs and NO production.

With the goal of avoiding $N_{tot,e}$ violations, an affine function that manipulates q_{EC1} based on NO5 plus NH5 is added. In order to avoid the limit violations of NH_e, a controller that regulates Q_{rin} based on NH5 and NH_{in} is proposed, and NO2 control is eliminated. For this control, a combination of an affine function and a exponential function is used. These control strategies for removing violations of the effluent pollution are implemented keeping the hierarchical control structure, because the goal includes also the reduction of EQI and OCI.

3.1. EQI and OCI improvement

In the proposed hierarchical control structure, the lower level is the responsible for controlling DO3, DO4, DO5 and NO2, and the higher level adjusts the DO set points of the three aerobic tanks according with NH5 (see Fig. 2).

For the lower level control, the two PI controllers of the default BSM1 control strategy are replaced by a MPC + FF configuration with DO5 and NO2 as controlled variables and K_La5 and Q_{rin} as manipulated variables. Two MPC + FF controllers are also added for controlling DO3 and DO4 by manipulating K_La in the third tank (K_La3) and in the fourth tank (K_La4) respectively. An affine function is a satisfactory alternative for manipulating the DO set points, as it is shown in [16], and it is proposed for the higher level. OCI and EQI trade-off representations have been implemented for the tuning of the affine function, assessing the extreme points where the best EQI without increasing OCI and the best OCI without increasing EQI are achieved compared to default PI controllers.

Other works have experimented in the hierarchical control of DO based on NH5, but with other controllers: Vrecko et al. [12] with PIs in both levels and Stare et al. [27] with PI in the lower level and PI and MPC in the higher level.

3.1.1. Lower level control

The basis of MPC is the use of an optimization algorithm to solve the control problem and the use of a model of the plant to make predictions of the output variables [28]. At each control interval, $\triangle t$, for a prediction horizon, p, and a control horizon, m, ($m < p$), the MPC algorithm computes the sequences of control moves over the horizon m:

$$\triangle u(k), \triangle u(k+1), \ldots, \triangle u(k+m-1) \tag{14}$$

makes predictions of the outputs variables over a future horizon p (see Fig. 3):

$$\hat{y}(k+1|k), \hat{y}(k+2|k), \ldots, \hat{y}(k+p|k) \tag{15}$$

and selects the sequence of control moves that minimizes a quadratic objective of the form:

$$J = \sum_{l=1}^{p} ||\Gamma_y[y(k+l|k) - r(k+l)]||^2 + \sum_{l=1}^{m} ||\Gamma_{\triangle u}[\triangle u(k+l-1)]||^2 \tag{16}$$

where the output prediction $y(k+l|k)$ means a predicted controlled output for the future sampling instant $k+1$, performed at the current instant k, and Γ_y and $\Gamma_{\triangle u}$ are the output weight and input rate weight respectively, which penalize the residual between the future reference and the output variable prediction, and the control moves. Due to the presence of strong disturbances in WWTPs, MPC has difficulties in keeping the controlled variables at their reference level. MPC provides options for the feedforward compensation of the measured disturbances, in the same way as for the reference signals. To compensate the disturbances, a feedforward control is added, as in [5,6,8,7,15]. Different variables have been considered for the feedforward action in those works, but in our case the influent flow rate has been selected for its better results.

The MPC algorithm requires a state-space linear model to foresee how the plant outputs, $y(k)$, reacts to the possible variations of the control variables, $u(k)$, and to compute at each $\triangle t$ the control moves. WWTPs are nonlinear systems, but their operation can be approximated in the vicinity of a working point by a continuous-time state-space model as:

$$x(k+1) = Ax(k) + Bu(k)$$

$$y(k) = Cx(k) + Du(k) \tag{17}$$

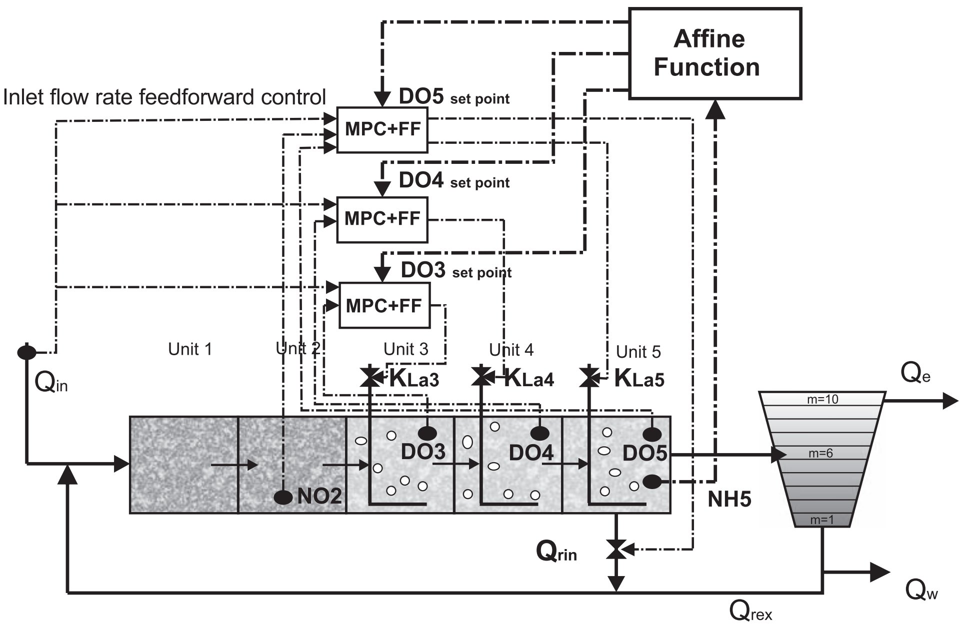

Fig. 2. BSM1 with two-level hierarchical control for EQI and OCI improvement.

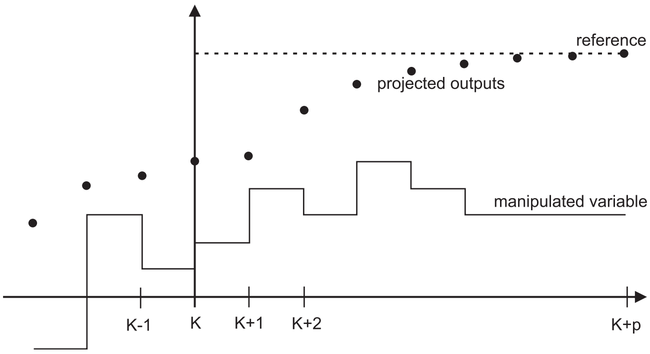

Fig. 3. Model Predictive Control performance.

where $x(k)$ is the state vector, and A, B, C and D are the state-space matrices. In concrete terms, the inputs $u(k)$ are Q_{rin}, K_La5 and Q_{in} in the first controller, K_La4, and Q_{in} in the second controller and K_La3 and Q_{in} in the third controller, and the outputs y(k) are NO2 and DO5 in the first controller, DO4 in the second controller and DO3 in the third controller.

The tuning parameters are: $\triangle t, m, p, \Gamma_{\triangle u}, \Gamma_y$ and the overall estimator gain.

- $\triangle t$ has a significant effect on the effectiveness of the controller. High $\triangle t$ can give less controller performance, mainly when there are important input disturbances, and low $\triangle t$ can produce too rapid changes in the actuators and high energy consumption.
- Lower $\Gamma_{\triangle u}$ or higher Γ_y give better performance of the controlled variable, otherwise they could produce strong oscillations in the actuators that must be avoided.
- m and p should be adjusted in each case depending on the control system. However too high values can increase the computational time too much, and on the other hand, too small values may results in oscillatory responses or may not work at all.
- At each $\triangle t$ the controller compares the measured values of the outputs with the expected values. The difference can be due to noise, to measurements errors and to unmeasured disturbances. With the overall estimator gain parameter it is determined the percentage of this difference that is attributed to unmeasured disturbances and the calculation matrix is consequently adjusted. Higher overall estimator gains improve the results, but too high values can make the controller unfeasible.

3.1.2. Higher level control

Due to the large disturbances, it is not possible to maintain NH5 at a fixed reference value by manipulating DO set points of the lower level controllers. For this reason, the controller proposed for the higher level is a simple affine function, that varies DO3, DO4 and DO5 set points based on NH5, but without keeping NH5 at a reference level. The following affine function is proposed:

$$DO_{setpoint}(t) = \mathrm{NH5}(t) - k \tag{18}$$

where k is a constant that is used as a tuning parameter. Also a constraint for the maximum DO3, DO4 and DO5 values has been considered. The values of k and DO3, DO4 and DO5 maximum values are determined by an OCI and EQI trade-off analysis.

3.2. $N_{tot,e}$ violations removal

NH and NO are the pollutants present in N_{tot} that contribute with more weight. For this reason, in order to eliminate violations of $N_{tot,e}$, q_{EC1} is added based on NO5 plus NH5 (see Fig. 4). The following affine function is proposed for this control:

$$q_{EC1} = ((\mathrm{NH5} + \mathrm{NO5}) - a) \cdot b \tag{19}$$

where a and b are used as tuning parameters whose values are set depending on the maximum value of $N_{tot,e}$ given by a sliding window, which is shift at each sample time and presents only the values measured the day one week before. Specifically, following are shown the chosen equations for a and b values:

$$b = M_d \cdot 2 - 35.5 \tag{20}$$

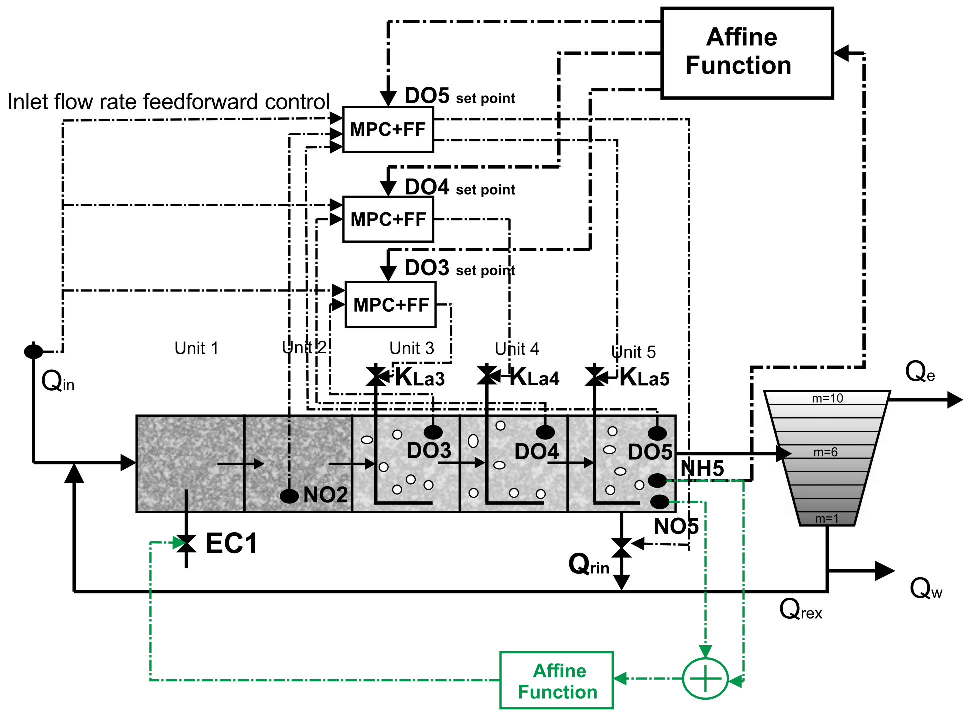

Fig. 4. BSM1 with a control strategy for $N_{tot,e}$ removal.

$$a = 34.25 - M_d \tag{21}$$

where M_d is the maximum value of the day, one week before. This approach tries to dosage the minimum of q_{EC1} to remove $N_{tot,e}$ violations. The maximum q_{EC1} value was limited to 5 m^3/d.

3.3. NH_e violations removal

With the goal of removing NH_e violations, Q_{rin} is manipulated based on NH5 and NH_{in}. Therefore, the MPC of the lower level that controls DO5 and NO2 by manipulating K_La5 and Q_{rin} is replaced by a MPC with one input (DO5) and one output (K_La5) (see Fig. 5).

To facilitate the understanding of the proposed solution some considerations about the propagation of the peaks in the reactor are provided: When a peak of pollution enters into the reactors, it is propagated through them with a delay determined by the retention time. So any change in the influent flow rate or in the Q_{rin} affects directly 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.

The NH5 controller is designed to act in two different ways, depending on NH peaks. When the peaks are present in the influent, it is convenient to increase Q_{rin} for diluting them, and when the peaks are already in the aerated tanks, it is convenient to reduce Q_{rin} for increasing the retention time.

A combination of exponential function and linear function is proposed for this control strategy. When there are peaks of NH_{in} or NH5, the following exponential function is applied:

$$Q_{rin} = \frac{c}{exp(\mathrm{NH5} \cdot d)} \tag{22}$$

Otherwise the following linear function is applied:

$$Q_{rin} = \frac{\mathrm{NH}_{in}}{\mathrm{NH5}} \cdot e \tag{23}$$

where c, d and e are used as tuning parameters, whose values are determined by a trade-off analysis of OCI and percentage of operating time of $N_{tot,e}$ violation, reflecting only the results that avoid NH_e violations.

4. Simulation results

In this section the control configurations proposed in the above section are tested and compared. Ideal sensors have been considered for the simulations. The proposed control strategies are evaluated for the three influents provided by BSM1 (dry, rain and storm).

4.1. EQI and OCI improvement

Here, it is described the implementation of the hierarchical control with a MPC + FF in the lower level and an affine function in the higher level stated in Sections 3.1.1 and 3.1.2.

DO3, DO4, DO5 and NO2 values to get the linear models of the MPC + FF controllers have been obtained by varying K_La3, K_La4 and K_La5 in a range of ±10% around 264.09 day^{-1}, 209.23 day^{-1} and 131.65 day^{-1} respectively and Q_{rin} in a range of ±10% around 16,486 m^3/d and applying a step of +50% to Q_{in} (measured variable for the feedforward compensation).

By using Matlab System Identification Toolbox with prediction error method [29], the following third order state-space models (24)–(26) are obtained:

- DO5 and NO2 control

$$\begin{aligned}
A &= \begin{bmatrix} 0.8748 & 0.04463 & 0.1314 \\ 0.04091 & 0.7331 & 0.1796 \\ 0.2617 & -0.1318 & 0.3007 \end{bmatrix} \\
B &= \begin{bmatrix} 7.641 \cdot 10^{-6} & 0.004551 & -2.749 \cdot 10^{-5} \\ -2.631 \cdot 10^{-5} & 0.006562 & -4.551 \cdot 10^{-6} \\ -9.63 \cdot 10^{-6} & -0.02161 & 2.447 \cdot 10^{-5} \end{bmatrix} \\
C &= \begin{bmatrix} 0.8812 & -0.5948 & 0.02114 \\ 1.187 & 0.9893 & -0.3754 \end{bmatrix} \\
D &= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}
\end{aligned} \tag{24}$$

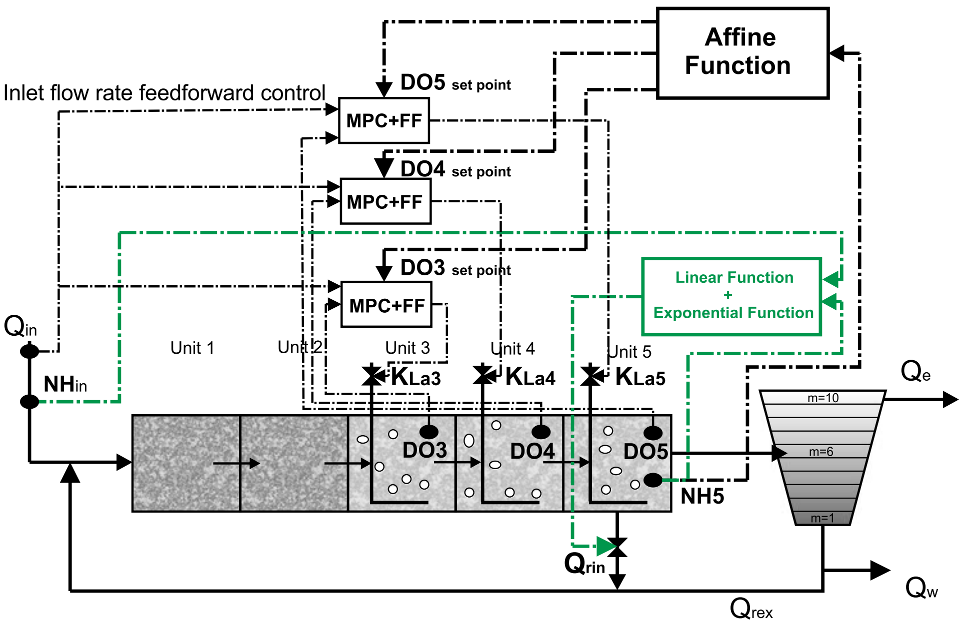

Fig. 5. BSM1 with a control strategy for NH_e removal.

- DO3 control

$$A = \begin{bmatrix} 0.7859 & 0.4576 & -0.131 \\ 0.3334 & 0.2599 & 0.2718 \\ -0.003132 & 0.03235 & -1.003 \end{bmatrix}$$
$$B = \begin{bmatrix} 0.009308 & -2.285 \cdot 10^{-5} \\ -0.01546 & 3.503 \cdot 10^{-6} \\ 0.003654 & -1.987 \cdot 10^{-5} \end{bmatrix} \tag{25}$$
$$C = [0.6376 \quad -0.4621 \quad 0.03698]$$
$$D = [0 \quad 0]$$

- DO4 control

$$A = \begin{bmatrix} 0.8201 & 0.371 & -0.1016 \\ 0.3054 & 0.307 & 0.2544 \\ -0.003381 & 0.03144 & -0.9993 \end{bmatrix}$$
$$B = \begin{bmatrix} 0.007712 & -4.65 \cdot 10^{-5} \\ -0.0148 & 8.164 \cdot 10^{-6} \\ 0.004523 & -2.526 \cdot 10^{-5} \end{bmatrix} \tag{26}$$
$$C = [0.947 \quad -0.496 \quad 0.02472]$$
$$D = [0 \quad 0]$$

The selected values to tune the MPC are $m = 5$, $p = 20$, $\triangle t = 0.00025$ days (21.6 s), $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 0.01$ for DO3, DO4 and DO5 control and $\Gamma_y = 1$ and $\Gamma_{\triangle u} = 0.0001$ for NO2 control and overall estimator gain = 0.8. It should be noted that the values of m and p are not critical and they can slightly be changed with similar results.

The OCI and EQI trade-off representations of the higher level affine function (18) are made based on k and DO maximum values. Results are shown in Fig. 6. Each line corresponds to one of the DO maximum values considered: 2, 3, 4, and 4.5. And each point of one line, marked with crosses, is obtained with a different value of k that varies from −0.6 to 1.4 with increments of 0.1. The results obtained with default PI controllers are also shown.

DO maximum and k values have been selected for the extreme cases of lowest EQI without increasing OCI and the lowest OCI without worsening EQI in comparison with the default PI controllers alone. For the best EQI, $k = -0.08$ and DO maximum = 4.5 mg/l, and for the best OCI, $k = 1.37$ and DO maximum = 2 mg/l.

Table 3 presents the results of best EQI without increasing OCI and best OCI without worsening EQI of hierarchical control in comparison with the default control strategy. The improvement of EQI is 5% and the reduction of costs is 3.7%.

In order to explain the EQI improvement, Fig. 7 shows the behaviour of DO of the aerated tanks, NH5 and NO5 from day 7 to day 14. This is performed with the default control strategy and the proposed hierarchical control with the tuning parameters that give the lowest EQI. As it is shown, with hierarchical control, when NH increases more DO is added for nitrification, reducing NH peaks (1 and 5). On the contrary, when NH decreases, less DO is required, producing less NO in comparison with the default control strategy (2 and 5).

In order to clarify the reason of the cost reduction, Table 4 shows the average values of the parameters that compose the OCI equation for the case of lowest OCI. As it is seen, the cost reduction is the result of an AE reduction of 651.75 KWh/d. This fact is due to the reduction of DO (and hence a reduction of K_La) of the aerated tanks when NH5 is low. Although there is a PE increase of 56.62 kWh/d, the saving energy, considering both parameters, is 595.13 kWh/d.

4.2. $N_{tot,e}$ violations removal

The control strategy to remove $N_{tot,e}$ violations also takes into account not to worsen the percentage of NH_e above the limits, not to increase operational costs and to improve EQI in comparison with the default control strategy of BSM1. To get this, a trade-off analysis is made considering the percentage of operating time that NH_e and $N_{tot,e}$ is over the limits. This is done with hierarchical control strategy and without adding q_{EC1} (see Fig. 8). Tuning parameters are chosen for the point where the percentage of operating time of NH_e over the limits is the same as with the default control strategy (17.26%). The tuning parameters of the higher level affine function are $k = 1.07$ and DO maximum = 3, and the percentage of operating time of $N_{tot,e}$ violation with these parameters is 6.35%.

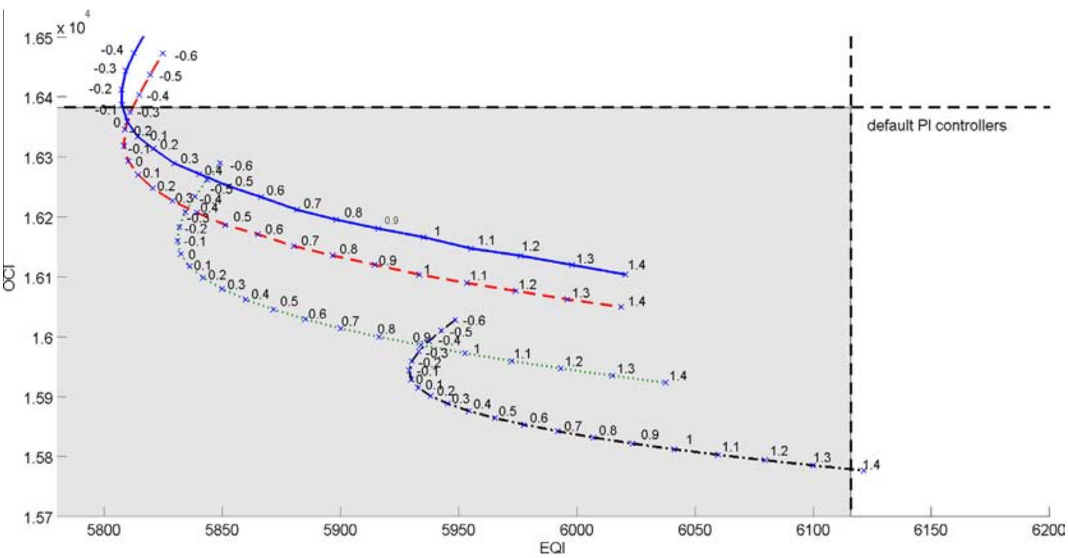

Fig. 6. OCI and EQI trade-off representation with higher level affine function for a range of k values from −0.6 to 1.4 with increments of 0.1 (points marked with crosses) and DO maximum = 4.5 (solid line), 4 (dashed line), 3 (doted line), 2 (dash-doted line).

Table 3
EQI and OCI results with default PI controllers and hierarchical control.

	Default PI controllers	Hierarchical control Lowest EQI	Lowest OCI	% of improvement
EQI (kg pollutans/d)	6115.63	5807.77	6046.51	−5%
OCI	16381.93	16381.51	15779.58	−3.7%

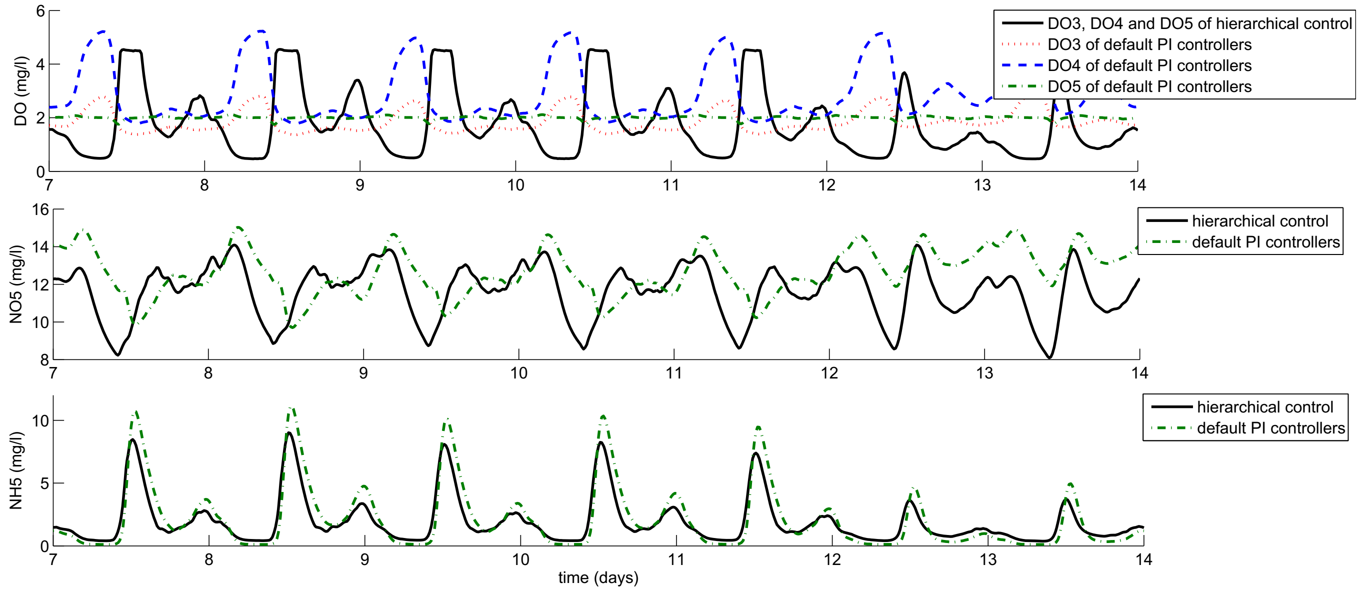

Fig. 7. DO in the aerated tanks, NO5 and NH5 evolution form day 7 to day 14 with the default PI controllers and with the proposed hierarchical control for the case of lowest EQI.

Table 4
Average values of the parameters that compose the OCI equation for PI controllers of the default control strategy and the proposed hierarchical control for the case of lowest OCI.

Average values of the OCI parameters	Default PI controllers	Hierarchical control	Reduction
AE (KWh/d)	3696.67	3044.92	651.75
PE (KWh/d)	241.72	298.34	−56.62
ME (KWh/d)	240	240	0
EC (Kg/d)	0	0	0
SP (Kg/d)	2440.71	2439.26	1.75

The OCI and EQI trade-off representation shown in Fig. 6, in the points of the tuning parameters mentioned, a difference in OCI of 2.5% is observed regarding the default control strategy, which may be used for the q_{EC1} dosage. Dashed line in Fig. 9 shows the evolution of $N_{tot,e}$ from day 7 to 14 with the parameters selected for higher level affine function and without adding q_{EC1}. The constant line is the $N_{tot,e}$ limit.

With these parameters selected for the higher level, the affine function (19) is added to manipulate q_{EC1}. The solid lines of Fig. 9 correspond to the evolution of q_{EC1}, $N_{tot,e}$ and NH_e from day 7 to

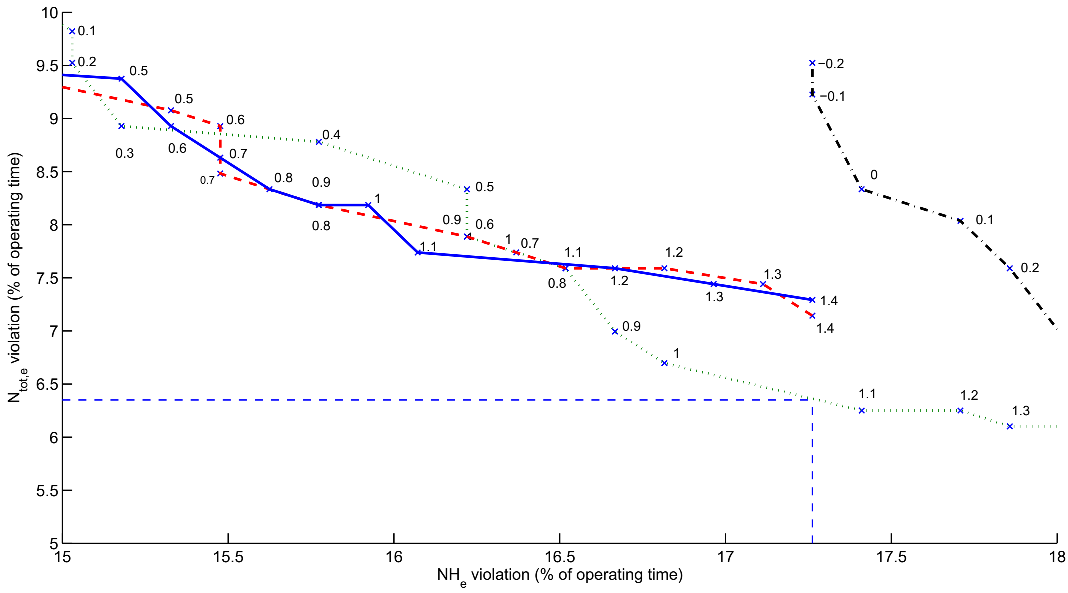

Fig. 8. Trade-off representation of the percentage of the operating of NH_e and $N_{tot,e}$ violations for a range of *k* values from −0.6 to 1.4 with increments of 0.1 (points marked with crosses) and DO maximum = 4.5 (solid line), 4 (dashed line), 3 (doted line), 2.5 (dash-doted line).

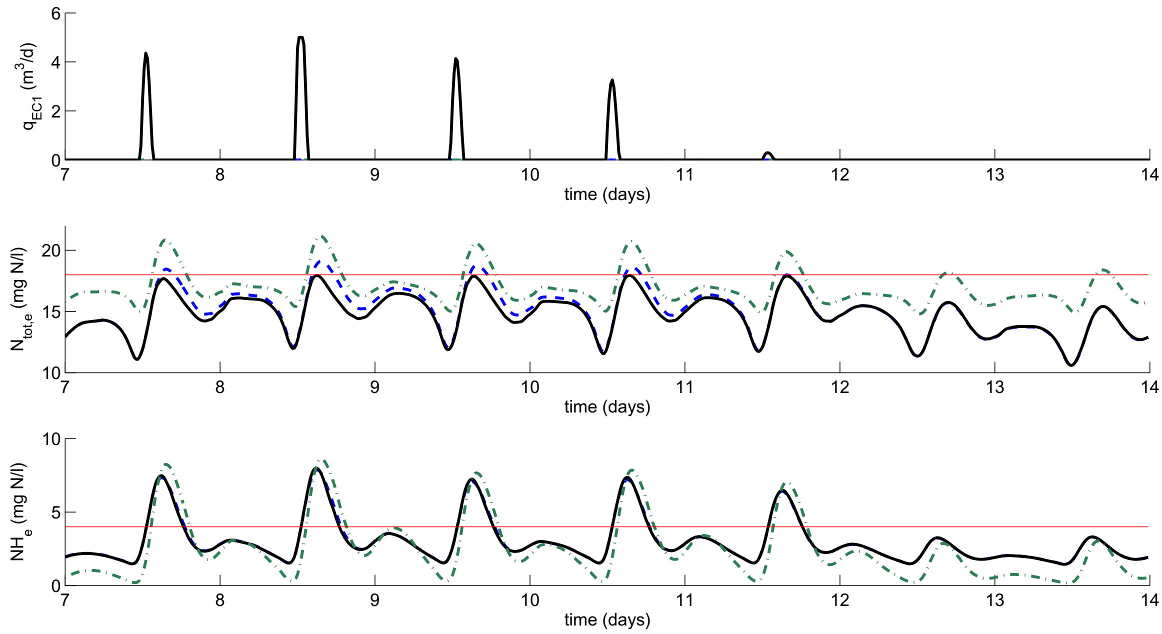

Fig. 9. q_{EC1}, NH_e and $N_{tot,e}$ evolution form day 7 to day 14 with default PI controllers (dash-doted line), with hierarchical control without adding q_{EC1} (dashed line) and with hierarchical control adding q_{EC1} (solid line).

Table 5
Results with default PI controllers and with control for $N_{tot,e}$ violations removal for dry, rain and storm influents.

	Default PI controllers	Control for $N_{tot,e}$ violations removal	% of reduction
Dry influent			
EQI (kg pollutants/d)	6115.63	5910.83	3.3
OCI	16381.93	16242.97	0.8
$N_{tot,e}$ violations (% of operating time)	17.56	0	100
NH_e violations (% of operating time)	17.26	16.81	2.6
Rain influent			
EQI (kg pollutants/d)	8174.98	8072.5	1.2
OCI	15984.85	15780.83	1.3
$N_{tot,e}$ violations (% of operating time)	10.86	0	100
NH_e violations (% of operating time)	27.08	26.04	3.8
Storm influent			
EQI (kg pollutants/d)	7211.48	7022.25	2.6
OCI	17253.75	17243.73	0.06
$N_{tot,e}$ violations (% of operating time)	15.03	0	100
NH_e violations (% of operating time)	26.79	25	6.6

14. It is observed that $N_{tot,e}$ violations are removed. As it is shown, q_{EC1} dosage varies every day, while $N_{tot,e}$ peaks are very similar. It proves that the minimum necessary q_{EC1} is added. It is due to the fact that the affine function for $N_{tot,e}$ violations removal is based on the M_d given by the sliding window. For this reason and with the correct selection of the tuning parameters of the higher level affine function by the trade-off analysis shown in Fig. 6, the removal of $N_{tot,e}$ violations without increasing OCI is possible. The choice of the right tuning parameters of the higher level affine function also makes possible to reduce the time of NH_e violation.

Table 5 presents the results for EQI and OCI as well as the percentage of operating time out of the limits of $N_{tot,e}$ and NH_e obtained with the hierarchical control adding q_{EC1} and compared to the default control strategy of BSM1. It is shown that by adding q_{EC1} and applying a hierarchical control of DO in the three aerated tanks, the violations of $N_{tot,e}$ can be avoided. Moreover, the results of EQI and OCI as well as the operating time percentage of NH_e violations are also improved in comparison with the default PI controllers. This is achieved for the three influents provided by the BSM1 scenario. During a rain or storm event, Q_{in} increases and NH_{in} decreases. The Q_{in} increment has the effect of reducing the hydraulic retention time and the NH_{in} reduction decreases the growth of $X_{B,A}$ and therefore the nitrification process (5) is worsened. Due to this reason, there is an increase of NH without incrementing the generation of NO (2 and 5). Therefore, the resulting $N_{tot,e}$ is lower than for dry weather. In the periods after the rain or storm events, the Q_{in} reduction has an immediate effect on the hydraulic retention time, but $X_{B,H}$ and $X_{B,A}$ need more time to recover their normal levels and it causes a small $N_{tot,e}$ increase. To compensate this, q_{EC1} is incremented. Even so, OCI is reduced for the three influents with the proposed control strategy. Nonetheless, it has to be said that the reduction of costs would be greater if the savings obtained by avoiding effluent violations were considered.

4.3. NH_e violations removal

For the higher level affine function (18), any parameters value inside the tuning region given by the OCI and EQI trade-off

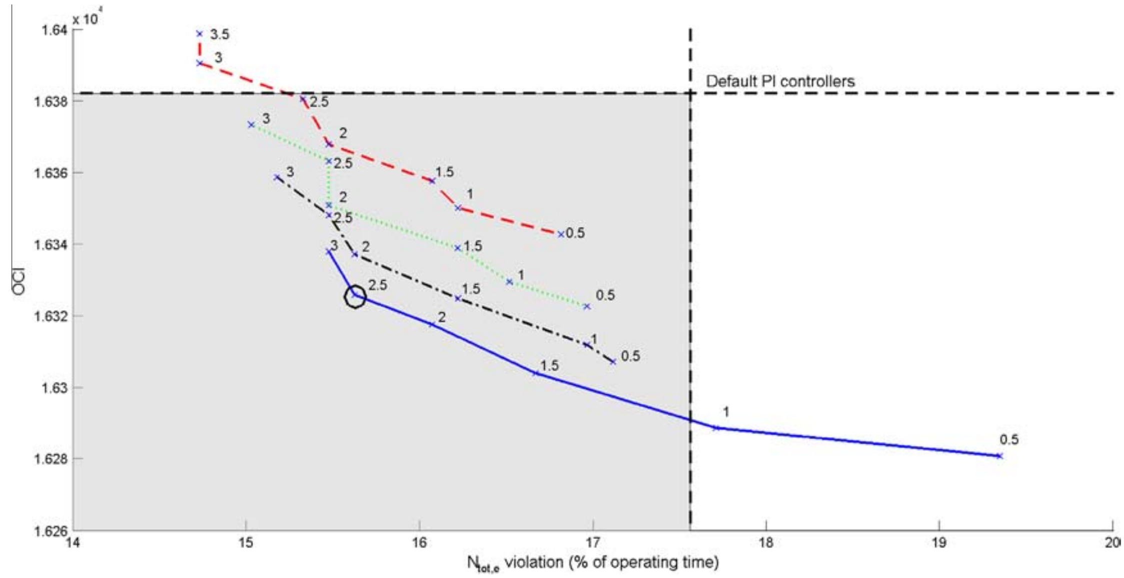

Fig. 10. Trade-off representation of OCI and the percentage of operating time of $N_{tot,e}$ violations for a range of c values from 0.5 to 4 with increments of 0.5 (points marked with crosses) and e values = 7 (solid line), 6 (dash-doted line), 5.5 (doted line), 5 (dashed line).

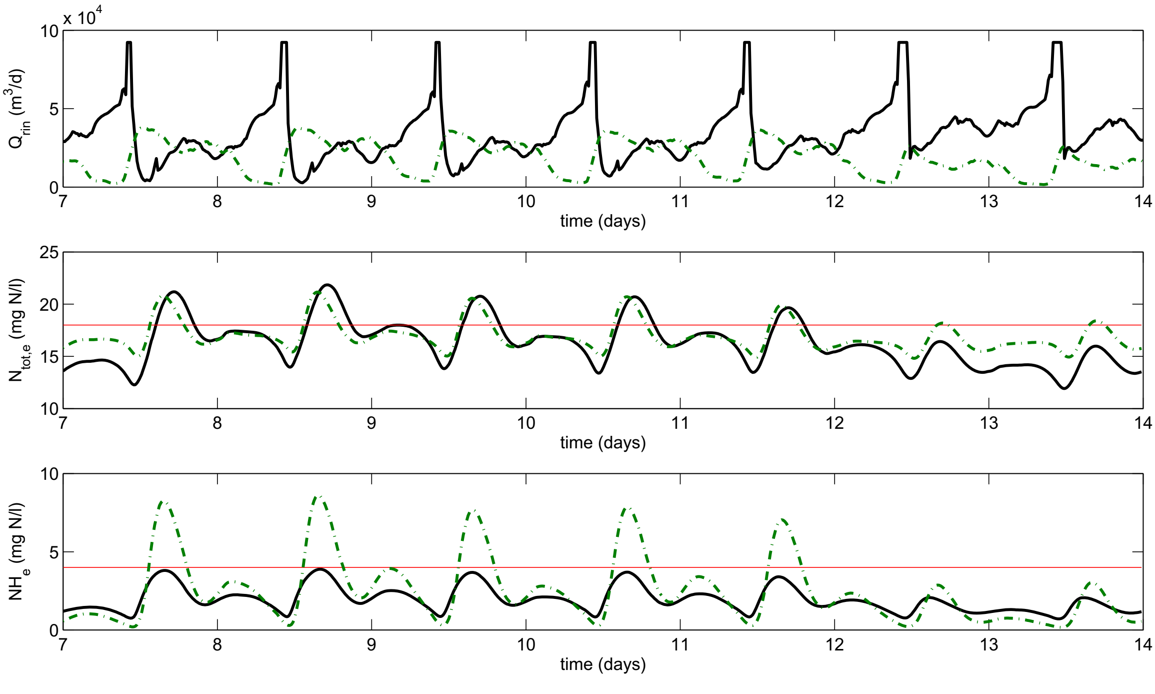

Fig. 11. Q_{rin}, NH_e and $N_{tot,e}$ evolution form day 7 to day 14 with default PI controllers (dash-doted line) and with the control for NH_e violations removal (solid line).

representation (see Fig. 6) can be selected. In this case the chosen parameters are: $k = 0.1$ and DO maximum = 4.5.

For the control of NH_e violations removal, when there are peaks of NH_{in} or NH5, the exponential function (22) is applied. The rest of the time the linear function (23) is used. A trade-off analysis of OCI and percentage of operating time of $N_{tot,e}$ violation is made by varying the tuning parameters c and e of the Exponential and Linear Functions, reflecting only the results that avoid the NH_e violations. It is obtained an area where OCI and the operating time of $N_{tot,e}$ violation are decreased compared to default PI controllers (see Fig. 10). The value of d is fixed at 6, and c and e values are chosen according with the Nash Solution [30]: $c = 2.5 \cdot 10^{14}$ and $e = 7 \cdot 10^{-4}$.

Q_{rin}, $N_{tot,e}$ and NH_e evolutions from day 7 to 14 are shown in Fig. 11. The results with default PI controllers are also shown. It can be observed that, with this control strategy, NH_e peaks are reduced under the limits established. This fact is due to the increment of DO by the hierarchical control (explained in the previous section) and mainly to the Q_{rin} manipulation. As shown in Fig. 11, Q_{rin} evolution is very different from the one obtained with the default control strategy. When a NH_{in} peak is detected, Q_{rin} is increased to its maximum allowed value (92,280 m^3/d) in order to dilute NH, and when this increase of NH arrives to the fifth tank, the exponential function rapidly reduces Q_{rin} in order to decrease also the hydraulic retention time and so to improve the nitrification process. As a result, a large decrease of NH_e peaks is achieved

Table 6
Results with default PI controllers and with control for NH_e violations removal for dry, rain and storm influents.

	Default PI controllers	Control for NH_e violations removal	% of reduction
Dry influent			
EQI (kg pollutants/d)	6115.63	5760.95	5.8
OCI	16381.93	16323.48	0.4
$N_{tot,e}$ violations (% of operating time)	17.56	15.62	11.04
NH_e violations (% of operating time)	17.26	0	100
Rain influent			
EQI (kg pollutants/d)	8174.98	7814.98	4.4
OCI	15984.85	17463.78	−9.2
$N_{tot,e}$ violations (% of operating time)	10.86	13.84	−27.4
NH_e violations (% of operating time)	27.08	0	100
Storm influent			
EQI (kg pollutants/d)	7211.48	6903.02	4.3
OCI	17253.75	17582.3	−1.9
$N_{tot,e}$ violations (% of operating time)	15.03	22.32	−48.5
NH_e violations (% of operating time)	26.79	0	100

Table 7
Results with default PI controllers and with control strategies for $N_{tot,e}$ and NH_e violations removal for dry, rain and storm influents.

	Default PI controllers	Control for NH_e violations removal	% of reduction
Dry influent			
EQI (kg pollutants/d)	6115.63	5624.41	8.03
OCI	16381.93	17494.44	−6.8
$N_{tot,e}$ violations (% of operating time)	17.56	0	100
NH_e violations (% of operating time)	17.26	0	100
Rain influent			
EQI (kg pollutants/d)	8174.98	7695.03	5.9
OCI	15984.85	18524.71	−15.9
$N_{tot,e}$ violations (% of operating time)	10.86	0	100
NH_e violations (% of operating time)	27.08	0	100
Storm influent			
EQI (kg pollutants/d)	7211.48	6685.15	7.3
OCI	17253.75	19524.67	−13.2
$N_{tot,e}$ violations (% of operating time)	15.03	0	100
NH_e violations (% of operating time)	26.79	0	100

and limits violations are avoided. The correct choice of the tuning parameters of the higher level affine function results also in obtaining a decrease in OCI and time of $N_{tot,e}$ violation.

Table 6 shows the results of EQI, OCI and percentage of time over the limits of NH_e and $N_{tot,e}$ for the three weather conditions. It can be seen that with the regulation of Q_{rin} based on NH5 and NH_{in} applying alternatively an exponential function and a linear function, and also with the hierarchical control of DO in the three aerated tanks, it is possible to avoid NH_e violations. In addition, an improvement of 5.5% of EQI and 0.6% of OCI in comparison with the default control strategy of BSM1 is achieved for dry influent. However, for rain and storm events an increase of costs is required. This is due to the fact that, during rain and storm periods, the nitrification process (5) is worsened as explained in the previous section. For this reason, extra addition of q_{EC} is needed when there is a rain or storm event, generating an increase of costs. Normally, q_{EC} is added to reduce NO. Nevertheless, in r_{NH} Eq. (1) it is observed that although the elimination of NH largely depends on nitrification (5), NH is also reduced with the growth of $X_{B,H}$ (3 and 4). Thus adding q_{EC}, besides applying the exponential function, NH_e violation removal is achieved for rain and storm scenarios. It should be noted that costs saved due to avoid violations are not reflected in the OCI equation and therefore the cost comparison is not completely fair.

4.4. $N_{tot,e}$ and NH_e violations removal

Finally, both control strategies for $N_{tot,e}$ and NH_e violations removal have been tested together. As NH_e violations present more difficulties to be removed than the ones of $N_{tot,e}$, especially during rain and storm events, the tuning for the higher level affine function determined to avoid NH_e violations, explained in Section 4.3, is also applied in this case. Table 7 shows the results obtained by applying the control strategies to eliminate both $N_{tot,e}$ and NH_e violations for the three weather conditions. As it can be observed, the $N_{tot,e}$ and NH_e violations removal is possible for dry, rain and storm weather conditions. However, removing the two pollutants simultaneously gives rise to an increase of OCI. It is due to the fact that the reduction of NH peaks by the exponential function is based on an improvement in the nitrification process, what causes a great generation of NO (2 and 5) and also a $N_{tot,e}$ increase. To counteract it, the dosage of q_{EC} is increased, and q_{EC} in the second tank ($q_{EC,2}$) is also added, as shown in Fig. 12. This q_{EC} increase results in the total elimination of $N_{tot,e}$ and NH_e violations and an EQI reduction, but also in an OCI increase. However, as explained in the previous section, the OCI equation does not take into account the reduction of costs of avoiding violations and thus, the cost comparison is not completely fair.

5. Conclusion

In this work different control strategies based on MPC + FF and affine, linear and exponential functions have been tested in a biological wastewater treatment process with the aim of avoiding effluent violations and decreasing EQI and OCI.

The correct variation of the DO set points of the aerated tanks given by the higher level affine function tuned by a trade-off

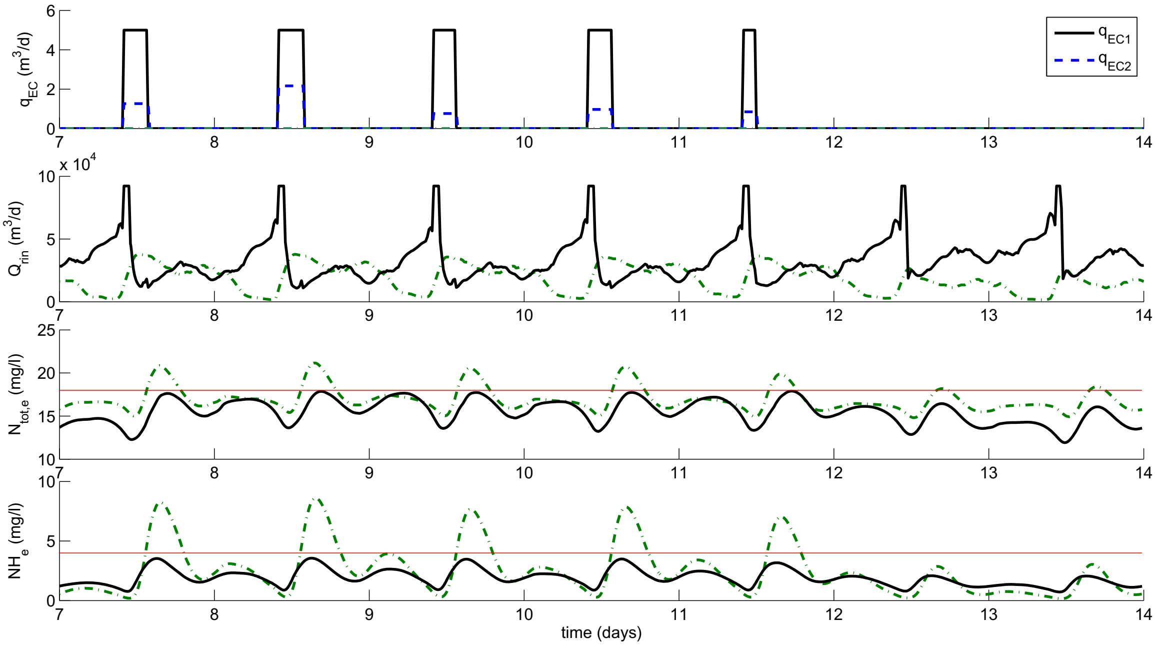

Fig. 12. q_{EC}, Q_{rin}, NH_e and $N_{tot,e}$ evolution form day 7 to day 14 with default PI controllers (dash-doted line) and with the control strategies for NH_e and $N_{tot,e}$ violations removal (solid line).

analysis and the tracking of the DO set points by MPC + FF controllers result in a satisfactory EQI and OCI reduction in comparison with the default control strategy. The improvement of the denitrification process, by adding q_{EC1}, achieves the complete elimination of $N_{tot,e}$ violations. The implemented affine function with a sliding window allows to dosage the minimum q_{EC1} necessary for this aim. Finally, the improvement of the nitrification process by manipulating Q_{rin} with the combination of a linear function and an exponential function makes possible the NH_e violations removal.

Simulation results show that $N_{tot,e}$ and NH_e violations are removal for dry, rain and storm influents. In the cases of $N_{tot,e}$ violations removal for the three weather conditions and NH_e violations removal for dry weather, a simultaneous reduction of EQI and OCI is achieved in comparison with the default control strategy. The NH_e violations removal for rain and storm influents and the simultaneous elimination of $N_{tot,e}$ and NH_e makes inevitable an increase of OCI. In any case, it has to be said that, with the removal of effluent violations, a reduction of costs is obtained for not paying fines, which is not considered in OCI.

Acknowledgment

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Intelligent decision control system for effluent violations removal in wastewater treatment plants

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Abstract

This paper presents the application of control strategies for wastewater treatment plants with the goal of effluent limits violations removal as well as achieving a simultaneous improvement of effluent quality and reduction of operational costs. The evaluation is carried out with the Benchmark Simulation Model No. 2. The automatic selection of the suitable control strategy is based on effluent predictions by Artificial Neural Networks to detect risk of violations. Fuzzy Controllers are implemented to improve the denitrification or nitrification process based on the proposed objectives. Model Predictive Control is applied for the improvement of dissolved oxygen tracking.

Keywords: Wastewater Treatment Process, BSM2 Benchmark, Model Predictive Control, Fuzzy Control, Artificial Neural Networks, effluent predictions

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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 (among others, the European Directive 91/271 Urban wastewater established by the European Union). In addition,

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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 Alex et al. (2008). This benchmark was extended in a new version, Benchmark Simulation Model No.2 (BSM2), in (Jeppsson et al. (2007)) which was updated in Nopens et al. (2010). 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 (Vilanova & Visioli (2012)). 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 ($S_{N_{tot}}$) (Corriou & Pons (2004); Shen et al. (2008, 2009)). 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 with the 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 ($S_{NO,2}$)) (Cristea et al. (2008); Holenda et al. (2008); Belchior et al. (2011)), or propose hierarchical control structures that regulate the S_O set-points according with some states of the plant, usually S_{NH} and S_{NO} values in any tank or in the influent (Vrecko et al. (2006); Stare et al. (2007); Ostace et al. (2010, 2011); Vilanova et al. (2011); Santín et al. (2014)) or S_O in other tanks (Ekman et al. (2006)).

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, as the present work. 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 manipulating the wastage flow rate (Q_w) (Flores-Alsina et al. (2010); Benedetti et al. (2009); Flores-Alsina et al. (2011); Kim & Yoo (2014)).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 aim to avoid the limits violations of the effluent pollutants. It 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 avoid S_{NH} in the effluent ($S_{NH,e}$) or $S_{N_{tot}}$ in the effluent ($S_{N_{tot,e}}$) limits violations and, at the same time, to improve effluent quality and to reduce operational costs. The paper uses BSM2 as working scenario and some of the control strategies are based on Santín et al. (2015b).In addition, it introduces a novelty method to deal with the effluent violations. On one hand, the situations of risk of effluent violations are predicted by forecasting the future output concentrations of pollutants based on the input variables. On the other hand, specific control strategies are applied in those situations. The proposed advanced control techniques are based on Model Predictive Control (MPC), Fuzzy Controller (FC) and Artificial Neural Networks (ANN). The MPC controllers aim to track the references of S_O in the fourth tank ($S_{O,4}$) and in the fifth tank ($S_{O,5}$) and $S_{NO,2}$. Three FCs are used based on the biological processes. The first one manipulates the S_O references of the MPC controllers based on S_{NH} in the fifth tank ($S_{NH,5}$), to improve effluent quality and to reduce operational costs. The second one manipulates the external carbon flow rate (q_{EC}) to eliminate $S_{N_{tot,e}}$ violations. Finally, the third one manipulates Q_a to eliminate violations of $S_{NH,e}$. The proposed control strategies to avoid violations of $S_{NH,e}$ and $S_{N_{tot,e}}$ are applied only when a risk of violation is predicted. To detect them, ANNs are applied to predict the $S_{NH,e}$ and $S_{N_{tot,e}}$ concentrations by evaluating the influent at each sample time.

The paper is organized as follows: In the following section the BSM2 working scenario is presented. Next, the applied control approaches are described. Then, the proposed control strategies and the tuning of the controllers are explained. After, results in terms of effluent quality, costs and percentage of time of effluent violations are shown and compared to the default control strategy of BSM2 and with the literature. Finally, the most important conclusions are drawn.

2. Benchmark Simulation Model No. 2

The simulation and evaluation of the proposed control strategy is carried out with BSM2 (Jeppsson et al. (2007)) which was updated by Nopens et al. (2010).

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.

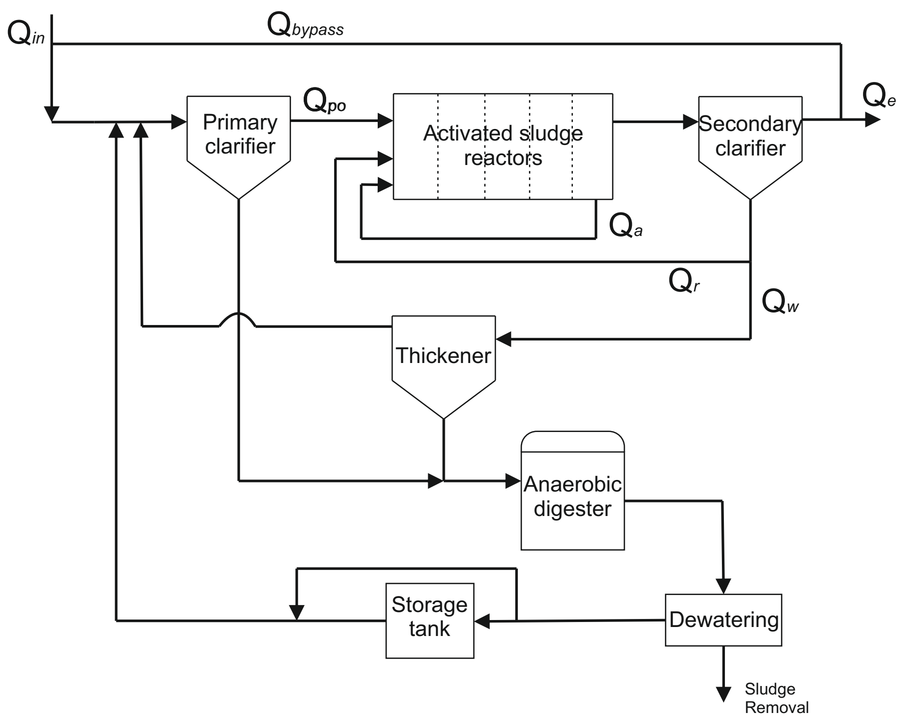


Figure 1: BSM2 plant with notation used for flow rates

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) Henze et al. (1987) 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:

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

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

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

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

The general equations for mass balancing are as follows:

- For reactor 1:

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

  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:

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

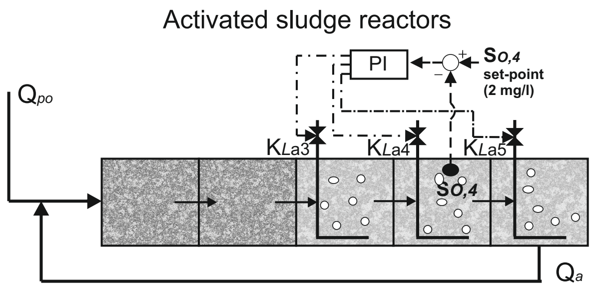
  where k is the number of reactor and Q_k is equal to Q_{k-1}

2.2. Default control strategies

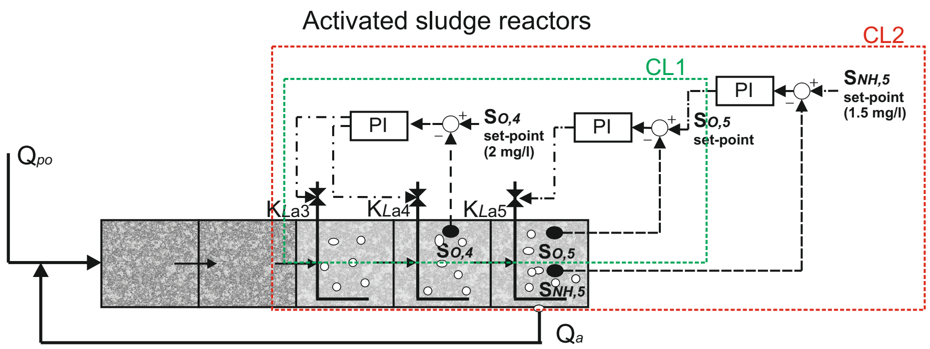
The original BSM2 definition (Jeppsson et al. (2007)) proposes a PI control strategy (defCL). The closed-loop control configuration consists of a PI (Vilanova & Visioli (2012)) that controls the $S_{O,4}$ at a set-point of 2 mg/l by manipulating K_La in the third tank (K_La_3), K_La in the fourth tank (K_La_4) and K_La in the fifth tank (K_La_5) with K_La_5 set to the half value of K_La_3 and K_La_4. q_{EC} in the first reactor ($q_{EC,1}$) is added at a constant flow rate of 2 m^3/d. Two different Q_w values are imposed dependent on time of the year: from 0 to 180 days and from 364 to 454 days Q_w is set to 300 m^3/d; and for the remaining time periods Q_w is set to 450 m^3/d.

The finalisation of BSM2 plant layout is reported by Nopens et al. (2010), in which two new control strategies are proposed. The first control strategy (CL1) is based on modifying the defCL, controlling the $S_{O,4}$ set-point at 2 mg/l, by manipulating K_La_3 and K_La_4, and adding another loop to control $S_{O,5}$ by manipulating K_La_5. PI controllers are applied for both control loops. The second control strategy (CL2) adds a hierarchical control to CL1. Therefore, a PI controller is applied to control $S_{NH,5}$ at a set-point of 1.5 mg/l by manipulating $S_{O,5}$ set-point. In the case of CL2, $q_{EC,1}$ is added at a constant value of 1 m^3/d.

Fig. 2 shows the three explained control strategies.



(a) defCL control strategy



(b) CL1 and CL2 control strategies

Figure 2: Default control strategies of BSM2

2.3. 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. It is assessed by Integral of the Squared Error (ISE) and Integral of the Absolute Error (IAE) criteria.

$$ISE = \int_{t=245days}^{t=609days} e_i^2 \cdot dt \qquad (12)$$

$$IAE = \int_{t=7days}^{t=14days} |e_i| \cdot dt \qquad (13)$$

where e_i is the error in each sample between the set-point and the measured value.

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

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

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.

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

$$+B_{NO} \cdot S_{NO}(t) + B_{BOD_5} \cdot BOD_5(t)) \cdot Q(t) \cdot dt \tag{14}$$

where B_i are weighting factors (Table 2) and T is the total time.

Factor	B_{TSS}	B_{COD}	B_{NKj}	B_{NO}	B_{BOD_5}
Value(g pollution unit g^{-1})	2	1	30	10	2

Table 2: B_i values

OCI is defined to evaluate the operational cost as:

$$OCI = AE + PE + 3 \cdot SP + 3 \cdot EC + ME - 6 \cdot MET_{prod} + HE_{net} \tag{15}$$

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.

AE is calculated according to the following relation:

$$AE = \frac{8}{T \cdot 1.8 \cdot 1000} \int_{t=245days}^{t=609days} \sum_{i=1}^{5} V_i \cdot K_L a_i(t) \cdot dt \tag{16}$$

where $K_L a_i$ is $K_L a$ in tank i.

The pumping energy PE is calculated as:

$$PE = \frac{1}{T} \int_{245days}^{609days} (0.004 \cdot Q_0(t) + 0.008 \cdot Q_a(t) + 0.06 \cdot Q_w(t)) + 0.06 \cdot Q_{to}(t)) + 0.004 \cdot Q_{du}(t)) \cdot dt \tag{17}$$

where Q_{to} is the overflow rate from the thickener and Q_{du} is the underflow rate.

SP is calculated from the total solid flow from wastage and the solids accumulated in the system over the period of time considered:

$$SP = \frac{1}{T} \cdot (TSS_a(609days) - TSS_a(245days) + TSS_s(609days) - TSS_s(245days) +$$

$$+0.75 \cdot \int_{t=245days}^{t=609days} TSS_w \cdot Q_w \cdot dt) \tag{18}$$

where TSS_a is the amount of solids in the reactors, TSS_s is the amount of solids in the settler and TSS_w is the amount of solids in the wastage.

EC refers to the carbon that could be added to improve denitrification:

$$EC = \frac{COD_{EC}}{T \cdot 1000} \int_{t=245days}^{t=609days} \left(\sum_{i=1}^{i=n} q_{EC,i} \right) \cdot dt \qquad (19)$$

where $q_{EC,i}$ is q_{EC} added to compartment i, COD_{EC} = 400 $gCOD.m^{-3}$ is the concentration of readily biodegradable substrate in the external carbon source.

ME is a function of the compartment volume and is the energy employed to mix the anoxic tanks to avoid settling (KWh/d):

$$ME = \frac{24}{T} \int_{t=245days}^{t=609days} \sum_{i=1}^{5} \left[0.005 \cdot V_i \; if \; K_L a_i(t) < 20 d^{-1} \; otherwise \; 0 \right] \cdot dt \qquad (20)$$

3. Control approaches

3.1. Model Predictive Control

The main characteristics of MPC are the use of an algorithm to find the optimal solution and the use of a model of the plant to forecast the future values of the outputs variables (Maciejowski (2002)). At each control interval, $\triangle t$, for a prediction horizon, p, and a control horizon, m, ($m < p$), the MPC algorithm computes the sequences of of future control moves ($\triangle \mathbf{u}$) over the horizon m:

$$\triangle \mathbf{u}(k), \triangle \mathbf{u}(k+1), ..., \triangle \mathbf{u}(k+m-1) \qquad (21)$$

makes predictions of the outputs variables ($\hat{\mathbf{y}}$) over a future horizon p (see Fig. 3):

$$\hat{\mathbf{y}}(k+1|k), \hat{\mathbf{y}}(k+2|k), ..., \hat{\mathbf{y}}(k+p|k) \qquad (22)$$

and selects the sequence of $\triangle \mathbf{u}$ that minimizes a quadratic objective of the form:

$$J = \sum_{l=1}^{p} ||\Gamma_{\mathbf{y}} [\mathbf{y}(k+l|k) - \mathbf{r}(k+l)]||^2 + \sum_{l=1}^{m} ||\Gamma_{\triangle \mathbf{u}} [\triangle \mathbf{u}(k+l-1)]||^2 \qquad (23)$$

where the output prediction $\hat{\mathbf{y}}(k+l|k)$ means a predicted controlled output for the future sampling instant $k+1$, performed at the current instant k, and $\Gamma_{\mathbf{y}}$ and

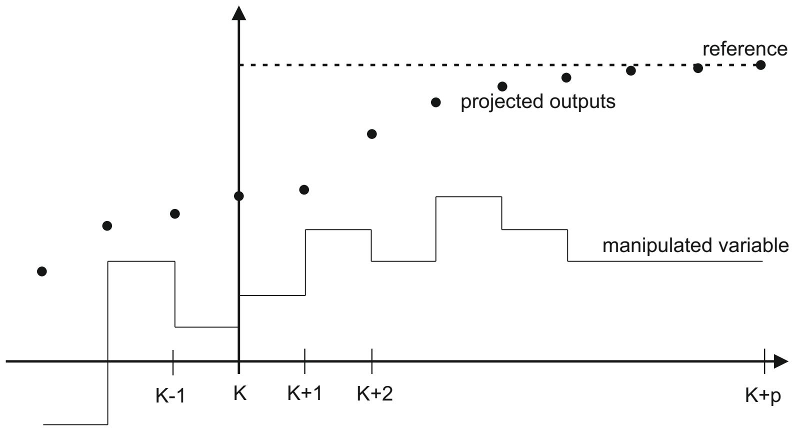


Figure 3: Model Predictive Control performance

$\Gamma_{\triangle\mathbf{u}}$ are the output weight and input rate weight respectively, which penalize the residual between the future reference and the output variable prediction, and the control moves.

WWTPs are nonlinear systems, but their operation can be approximated in the vicinity of a working point by a discrete-time state-space model as:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k)$$

$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) + \mathbf{D}\mathbf{u}(k) \tag{24}$$

where $\mathbf{x}(k)$ is the state vector, and **A**, **B**, **C** and **D** are the state-space matrices.

Due to the presence of strong disturbances on WWTPs, MPC has difficulties in keeping the controlled variables at their reference level. To compensate the disturbances, a feedforward control action is added (MPC+FF), as in Corriou & Pons (2004), Shen et al. (2008), Shen et al. (2009) and Cristea et al. (2008). MPC provides feedforward compensation for the measured disturbances as they occur to minimize their impact on the output. The combination of feedforward plus feedback control can significantly improve the performance over simple feedback control whenever there is a major disturbance that can be measured before it affects the process output. The idea of the feedforward control is to act on the process when the disturbances appear and before they cause deterioration in the effluent quality.

3.2. *Artificial Neural Network*

ANNs are inspired by the structure and function of nervous systems, where the neuron is the fundamental element (Yegnanarayana (2009)). 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 (Wang & Adeli (2015); Przystalka & Moczulski (2015)). 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 4 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 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.

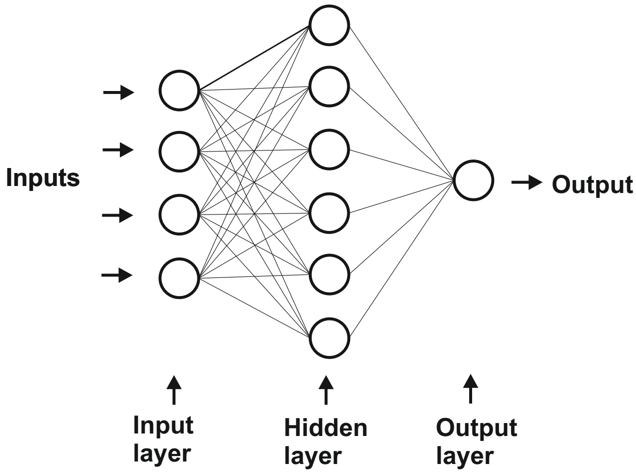


Figure 4: Structure of Artificial Neural Network layers

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 (Karunanithi et al. (1994)).

3.3. Fuzzy control

The fuzzy control is based on the practical knowledge acquired with the operation of the systems. This knowledge is determined by words and expressions and not, as in traditional logic, by numbers and equations. In fact this does not mean at all that knowledge of the process dynamics is not needed. Good knowledge of the dynamic behavior of the controlled plant is to be available to the designer. The architecture of a FC shown in Fig. 5 consists of: a fuzzifier, a fuzzy rule base, an inference engine and a defuzzifier (Bai et al. (2006); Chen & Pham (2000)).

The typical architecture of a FC, shown in Fig. 5, consists of: a fuzzifier, a fuzzy rule base, an inference engine and a defuzzifier (Bai et al. (2006); Chen & Pham (2000)).

As the variables are measured in numbers, a fuzzifier is used to convert the inputs into suitable linguistic values, granting them a relative membership degree and not strict. Conversely, a defuzzifier is used to transform de outputs from linguistic values into measured variables. The configuration of a fuzzifier and a

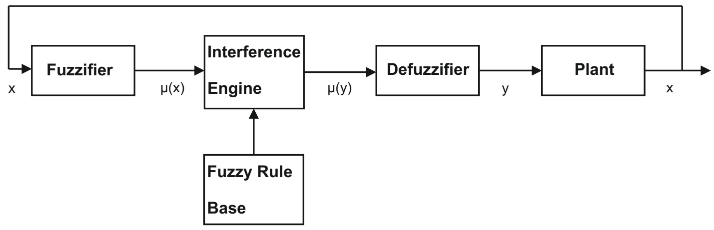


Figure 5: Architecture of a FC

defuzzifier implies the selection of the type of membership function: triangular, trapezoidal or Gaussian, the number of membership functions and the definition of the range of input and output values. The fuzzy rule base is a set of *if-then* rules that store the empirical knowledge of the experts about the operation of the process. The fuzzy logic computes the grade of membership of each if condition of a rule and aggregates the partial results of each condition using fuzzy set operator. The inference engine combines the results of the different rules to determine the actions to be carried out, and the defuzzifier converts the control actions of the inference engine into numerical variables, determining the final control action that is applied to the plant. There are two different methods to operate these modules: Mamdani (Mamdani (1976)) and Sugeno (Takagi & Sugeno (1985)). Mamdani system aggregates the area determined by each rule and the output is determined by the center of gravity of that area. In a Sugeno system the results of the $if-then$ rules are already numbers determined by numerical functions of the input variables and therefore no deffuzifier is necessary. The output is determined weighting the results given by each rule with the values given by the if conditions.

For example, Fig. 6 shows three triangular membership functions ($mf1$, $mf2$ and $mf3$) with a range of input values from 0 to 5. Thus, an input of 1.5 can be transformed into fuzzy expressions as 0.25 of $mf1$ and simultaneously 0.5 of $mf2$. Fig. 7 shows the three membership functions ($mf4$, $mf5$, $mf6$) of the Mamdani defuzzifier with a range of outpu values from 0 to 5. The $if-then$ rules implemented are:

if ($Input$ is $mf1$) **then** ($Output$ is $mf4$)
if ($Input$ is $mf2$) **then** ($Output$ is $mf5$)
if ($Input$ is $mf3$) **then** ($Output$ is $mf6$)

The output is the result of the aggregation of two rules, one that gives 0.25 of $mf4$ and other that gives 0.5 of $mf5$.

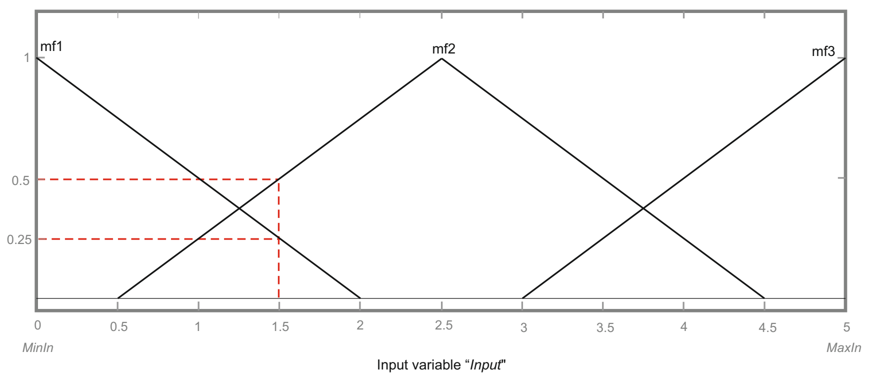


Figure 6: Example of membership functions of fuzzifier

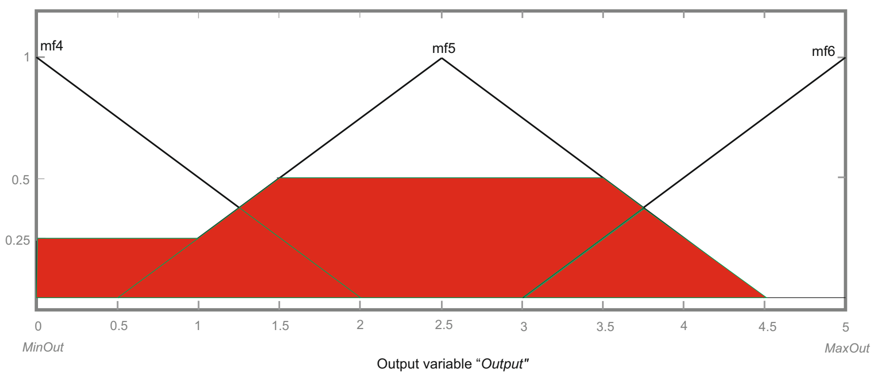


Figure 7: Example of membership functions of defuzzifier

4. Control configurations for the proposed objectives

The control configurations proposed in this work are based on MPC+FF, fuzzy control and ANN. MPC+FF controllers are used in order to keep the $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ at the given set-point. Fuzzy control is applied, on one side, as higher level controller in a hierarchical structure to vary the S_O references to be tracked by the MPC controllers, and, on the other hand, to remove $S_{N_{tot,e}}$ and $S_{NH,e}$ violations by determining $q_{EC,1}$ and Q_a values. 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, and the violations removal of $S_{N_{tot,e}}$ and $S_{NH,e}$. 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 and thus to choose the control strategy to be applied (see Fig. 8).

MPC, FCs and ANNs are implemented using Matlab® for the simulation and on-line control. Specifically, MPC controllers have been designed with MPC toolbox, FCs with FIS editor and ANNs with Neural Network Fitting toolbox. The prediciton models of MPC controllers have been identified with System Identification toolbox. To solve the quadratic objective of MPC in equation (23), the Quadratic Dynamic Matrix Control solver (Garcia & Morshedi (1986)) with hard linear constraints in the inputs provided by Matlab® MPC toolbox has been used.

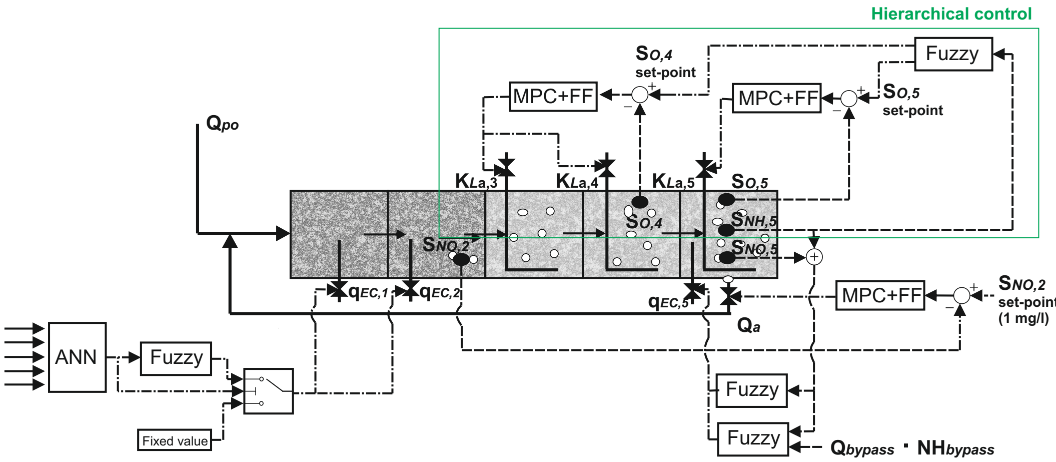
4.1. $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ tracking

Two MPC+FF controllers are proposed for the aerated zone, to control $S_{O,5}$ by manipulating K_La_5 and to control $S_{O,4}$ by manipulating K_La_3 and K_La_4 based on Nopens et al. (2010). The aim of these MPC+FF controllers is to improve the set-points tracking regarding the PI controllers of defCL. Also, an MPC+FF is applied to control $S_{NO,2}$ at a reference value of 1mg/l by manipulating Q_a, based on the default strategy of BSM1.

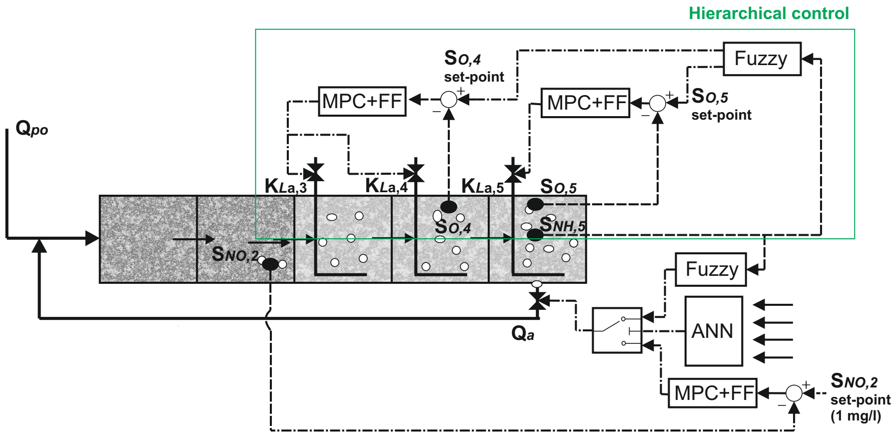
Different variables have been considered for the feedforward action in the referred works, but in our case Q_{po} has been selected for its better results. Any change in Q_{po} affects directly the flow rates of all the tanks, modifying their hydraulic retention time. Therefore, it is necessary to adjust the manipulated variables immediately to compensate the Q_{po} disturbances.

In this work, unlike the defCL, $S_{O,4}$ and $S_{O,5}$ references are not maintained at a fixed value. Instead of this, a FC varies the set-point, adapting it based on the conditions of the nitrification process. Due to this reason, it should be noted the importance of the MPC+FF controllers performance to ensure that the $S_{O,4}$ and $S_{O,5}$ values are as close as possible to the set-point given by the FC.

The variables of the state-space model (24) for the three MPC+FF controllers are described following: $u_1(k)$ is K_La4 and K_La3, $u_2(k)$ is Q_{po} and $y_1(k)$ is $S_{O,4}$ in the MPC+FF for $S_{O,4}$ control; $u_1(k)$ is K_La5, $u_2(k)$ is Q_{po} and $y_1(k)$ is $S_{O,5}$ in



(a) Proposed control strategy for $S_{N_{tot,e}}$ violations removal



(b) Proposed control strategy for $S_{NH,e}$ violations removal

Figure 8: Proposed control strategies for $S_{N_{tot,e}}$ or $S_{NH,e}$ violations removal with a simultaneously EQI and OCI reduction

the MPC+FF for $S_{O,5}$ control; $u_1(k)$ is Q_a, $u_2(k)$ is Q_{po} and $y_1(k)$ is $S_{NO,2}$ in the MPC+FF for $S_{NO,2}$ control.

The tuning parameters are: $\triangle t$, m, p, $\Gamma_{\triangle \mathbf{u}}$, $\Gamma_{\mathbf{y}}$ and the overall estimator gain.

- $\triangle t$ has a significant effect on the effectiveness of the controller. High values of $\triangle t$ can give less controller performance, mainly when there are important input disturbances, and low values of $\triangle t$ can produce changes too quickly in the actuators and also high energy consumption. Therefore, it is recommended to chose $\triangle t$ as the lowest one that allows achieving a successful tracking of the controlled variables, without abrupt changes in the actuators and without a significant aeration cost increase.

- To decrease $\Gamma_{\triangle \mathbf{u}}$ or to increase $\Gamma_{\mathbf{y}}$ give better performance of the controlled variable, otherwise they could produce strong oscillations in the actuators that must be avoided.

- m and p should be adjusted in each case depending on the control system. However, values that are too high can increase the computational time in excess, and on the other hand, values that are too small may result in oscillatory responses or may not work at all.

- At each $\triangle t$ the controller compares the measured values of the outputs with the expected values. The difference can be due to noise, to measurements errors and to unmeasured disturbances. With the overall estimator gain parameter it is determined the percentage of this difference that is attributed to unmeasured disturbances and the calculation matrix is consequently adjusted. Higher overall estimator gains improve the results, but too high values can make the controller unfeasible.

The identification of the linear predictive models of the MPC+FF controllers was performed using Matlab® System Identification toolbox. The data of the output variables ($S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$) are obtained by making changes to the input variables (K_La3, K_La4, K_La5 and Q_a) with a maximum variation of 10% regarding its operating point, which is the value of K_La necessary to obtain 2 mg/l of $S_{O,4}$, 1 mg/l of $S_{O,5}$ and the value of Q_a necessary to obtain 1 mg/l of $S_{NO,2}$. Specifically, the working points are 120 day $^{-1}$, 60 day $^{-1}$ and 61944 m^3/day for K_La3 / K_La4, K_La5 and Q_a respectively. Prediction error method (PEM) was selected to determine the model with the obtained data. Therefore the following second order state-space models are obtained:

- $S_{O,4}$ control

$$\begin{aligned}
\mathbf{A} &= \begin{bmatrix} 0.9768 & 0.1215 \\ 0.09664 & 0.2635 \end{bmatrix} \\
\mathbf{B} &= \begin{bmatrix} 0.002984 & -3.673 \cdot 10^{-6} \\ -0.01796 & 8.318 \cdot 10^{-6} \end{bmatrix} \\
\mathbf{C} &= \begin{bmatrix} 3.682 & -0.4793 \end{bmatrix} \\
\mathbf{D} &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned} \tag{25}$$

- $S_{O,5}$ control

$$\begin{aligned}
\mathbf{A} &= \begin{bmatrix} 0.9794 & 0.1109 \\ 0.0976 & 0.3544 \end{bmatrix} \\
\mathbf{B} &= \begin{bmatrix} 0.001836 & -1.259 \cdot 10^{-5} \\ -0.01153 & 7.04e-005 \end{bmatrix} \\
\mathbf{C} &= \begin{bmatrix} 8.412 & -0.1429 \end{bmatrix} \\
\mathbf{D} &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned} \tag{26}$$

- $S_{NO,2}$ control

$$\begin{aligned}
\mathbf{A} &= \begin{bmatrix} 0.8301 & 0.2828 \\ 0.0578 & 0.8674 \end{bmatrix} \\
\mathbf{B} &= \begin{bmatrix} 3.264 \cdot 10^{-6} & -1.358 \cdot 10^{-5} \\ -1.767 \cdot 10^{-6} & -2.87 \cdot 10^{-6} \end{bmatrix} \\
\mathbf{C} &= \begin{bmatrix} 5.035 & 0.2777 \end{bmatrix} \\
\mathbf{D} &= \begin{bmatrix} 0 & 0 \end{bmatrix}
\end{aligned} \tag{27}$$

The selected values to tune the MPC+FF controllers are m = 5, p = 20, $\triangle t$ = 0.00025 days (21.6 seconds), Γ_y = 1 and $\Gamma_{\triangle u} = 1 \cdot 10^{-5}$ and overall estimator gain = 0.8 for $S_{O,4}$ control; m = 5, p = 20, $\triangle t$ = 0.00025 days (21.6 seconds), Γ_y = 1 and $\Gamma_{\triangle u} = 5 \cdot 10^{-4}$ and overall estimator gain = 0.8 for $S_{O,5}$ control; m = 5, p = 50, $\triangle t$ = 0.00025 days (21.6 seconds), Γ_y = 1 and $\Gamma_{\triangle u} = 1 \cdot 10^{-5}$ and overall estimator gain = 0.9 for $S_{NO,2}$ control.

4.2. 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 using FCs (explained in the next subsection) are applied to avoid them. When a risk of SNH;e violation is detected, Q_a is manipulated based on $S_{NH,5}$ to reduce $S_{NH,e}$ peak, instead of being manipulated to control $S_{NO,2}$, as it occurs the rest of the time. Regarding $S_{N_{tot,e}}$, when a risk of violation is detected (the value of $S_{N_{tot,ep}}$ exceeds the limit), q_EC is manipulated based on this prediction, instead of being kept at a fixed value as usual.

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 necessary 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, 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.

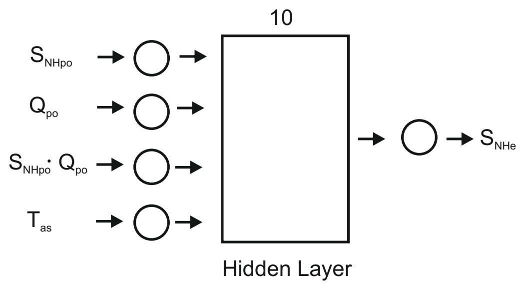
Therefore, the inputs of ANNs have been determined according to the mass balance equations (10 and 11) explained in Section 2.1. The variables used to perform the prediction for both ANNs are Q_{po}, Z_{po} and T_{as}. The variable Q_a has also been used as an input for the ANN that predicts $S_{N_{tot,e}}$, 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.

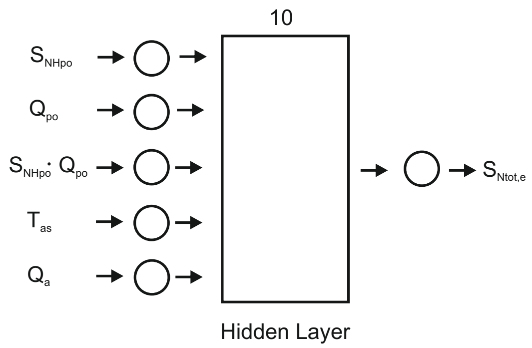
Finally, due to the mentioned reasons, the inputs for the ANNs are:

- 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 without the control strategies for avoiding $S_{N_{tot,e}}$ and $S_{NH,e}$ violations. 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.9.



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



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

Figure 9: Structures of the proposed ANNs

4.3. Manipulation of S_O set-points, q_{EC} and Q_a

Four FCs have been implemented in the proposed control strategies with three objectives: to reduce EQI and OCI, to remove $S_{N_{tot,e}}$ violations and to eliminate $S_{NH,e}$ violations. They are based on the biological processes given by ASM1 explained in Section 2.1.

For the four FCs applied, Mamdani (Mamdani (1976)) is the method selected to defuzzify. The design of the FCs was based on the observation of the simulations results obtained by operating the plant with the default control of BSM2.

Fuzzy Controller for EQI and OCI reduction

A FC is applied as higher level controller to manipulate $S_{O,4}$ and $S_{O,5}$ set-points based on the $S_{NH,5}$ with the aim to reduce EQI and OCI. Specifically, it is based on the nitrification process, improving it or making it worse based on a trade-off between the values of S_{NH} and S_{NO}. The idea of this control is to improve the nitrification process by increasing $S_{O,4}$ and $S_{O,5}$ references (6) when there is an $S_{NH,5}$ increase caused by the influent, reducing thus $S_{NH,e}$ peaks. Conversely, to reduce the XB,H growth when the $S_{NH,5}$ level is low, in order to produce less S_{NO} (6) and (2) and at the same time to reduce operational costs (15).

For the high level FC, three triangular membership functions for input and for output are used (*low*, *medium* and *high*). The implemented $if - then$ rules are:

if ($S_{NH,5}$ is *low*) **then** ($S_{O,4}$ set is *low*)
if ($S_{NH,5}$ is *medium*) **then** ($S_{O,4}$ is *medium*)
if ($S_{NH,5}$ is *high*) **then** ($S_{O,4}$ is *high*)

The range of the input values is from 0.2 to 4, and the range for the output values is from -0.75 to 4.5. $S_{O,5}$ set-point is equal to the half value of $S_{O,4}$.

Fuzzy Controllers for $S_{N_{tot,e}}$ violations removal

The idea of this control strategy is to add q_{EC} only when there is a risk of violation in order to reduce operational costs, unlike the default control strategy, which keeps $q_{EC,1}$ at 2 m^3/d continuously. Three FCs are proposed. One FC is used as predictive control, adding $q_{EC,1-2}$ when a violation is predicted, based on $S_{N_{tot,ep}}$ value given by the ANN (explained above). This control strategy is necessary, because acting only when a high $S_{N_{tot}}$ value in the reactors is detected could not be enough if $S_{N_{tot}}$ is quite high. The second FC adds q_{EC} in the fifth tank ($q_{EC,5}$) based on $S_{NH,5}$ plus S_{NO} in the fifth tank ($S_{NO,5}$), which are the contaminants with more influence on $S_{N_{tot}}$. This control acts when, in spite of the predictive control, $S_{NH,5}$+$S_{NO,5}$ increases excessively. As the biological process is designed to treat a maximum flow rate of 60420 m^3/d, when the flow rate coming from the primary treatment surpasses this value, the excess is bypassed directly to the effluent without being treated. In state of bypass, the third fuzzy control manipulates $q_{EC,5}$ based on the bypass flow rate (Q_{bypass}) multiplied by S_{NH} in the bypass ($S_{NH,bypass}$), in order to compensate the increase of $S_{NH,e}$ due to the flow rate that cannot be treated.

The first FC, which is based on the $S_{N_{tot,ep}}$, has one input and one output, with three membership functions for each (*low*, *medium* and *high*). The implemented $if-then$ rules are:

if ($S_{N_{tot,ep}}$ is *low*) **then** ($q_{EC,1-2}$ is *low*)
if ($S_{N_{tot,ep}}$ is *medium*) **then** ($q_{EC,1-2}$ is *medium*)
if ($S_{N_{tot,ep}}$ is *high*) **then** ($q_{EC,1-2}$ is *high*)

If $q_{EC,1-2}$ value is less than the maximum value of q_{EC} set in each reactor (5 m^3/d), it is only added to the first reactor. If q_{EC} is greater than 5 m^3/d, $q_{EC,1}$ is equal to 5 m^3/d and $q_{EC,2}$ is equal to the value of $q_{EC,1-2}$ minus 5. The range of the input values of the fuzzifier is from 17 to 19.5, and the range for the output values is from 4 to 15. Therefore, $q_{EC,1-2}$ is added when $S_{N_{tot,ep}}$ is over 17 mg/l instead of 18 mg/l which is the limit value, thus a margin of error of 5.5% in the prediction is established.

Since a situation of risk is detected ($S_{N_{tot,ep}} > 17$ mg/l), the predict control is kept running until the three following conditions are met to ensure that the risk has disappeared: $S_{N_{tot,ep}}$ is lower than 16 mg/l, $S_{NH,5}$ plus $S_{NO,5}$ is lower than 13.5 mg/l and the controller has been operating 6 hours at least. The controller calculates a $q_{EC,1-2}$ value at each sample time, but the true value applied to the plant is the maximum of all the previous samples, in order to ensure that the effluent violation is avoided.

The second FC, which manipulates $q_{EC,5}$ based on $S_{NH,5}$+$S_{NO,5}$, has one input and one output, with three membership functions for each input and output (*low*, *medium* and *high*). The range of the input values is from 15.3 to 15.9, and the range of the output values is from -1 to 6. The implemented $if-then$ rules are:

if ($S_{NH,5}$+$S_{NO,5}$ is *low*) **then** ($q_{EC,5}$ is *low*)
if ($S_{NH,5}$+$S_{NO,5}$ is *medium*) **then** ($q_{EC,5}$ is *medium*)
if ($S_{NH,5}$+$S_{NO,5}$ is *high*) **then** ($q_{EC,5}$ is *high*)

The third FC, which manipulates $q_{EC,5}$ based on $S_{NH,5}$+$S_{NO,5}$ and $Q_{bypass} \cdot S_{NH,bypass}$, has two inputs and one output, with three membership functions for each input and output (*low*, *medium* and *high*). The range of the $S_{NH,5}$+$S_{NO,5}$ input values is from 12 to 12.5, the range of the $Q_{bypass} \cdot S_{NH,bypass}$ input values is from 0 to $1.4{\cdot}10^5$ and the range for the output values is from $-1{\cdot}10^4$ to $6{\cdot}10^5$. The implemented $if-then$ rules are:

if ($S_{NH,5}$+$S_{NO,5}$ is *low* and $Q_{bypass} \cdot S_{NH,bypass}$ is *low*) **then** ($q_{EC,5}$ is *low*)
if ($S_{NH,5}$+$S_{NO,5}$ is *medium* and $Q_{bypass} \cdot S_{NH,bypass}$ is *medium*) **then** ($q_{EC,5}$ is *medium*)
if ($S_{NH,5}$+$S_{NO,5}$ is *high* and $Q_{bypass} \cdot S_{NH,bypass}$ is *high*) **then** ($q_{EC,5}$ is *high*)

This controller works while there is bypass. As in the first FC, the $q_{EC,5}$ value applied to the plant by the second and third FCs is the maximum of all the previous calculated values during the situation of risk.

Fuzzy Controller for S_{NH_e} violations removal

A FC is proposed to eliminate $S_{NH,e}$ violations by manipulating Q_a based on $S_{NH,5}$. This control strategy is applied only when a $S_{NH,e}$ violation is predicted by the ANN, explained in Section 4.2. The rest of the time Q_a is manipulated to control $S_{NO,2}$.

When a risk of violation is detected ($S_{NH,ep} > 4$ mg/l), the proposed FC is applied, first to dilute $S_{NH,po}$ and subsequently to reduce the hydraulic retention time when the increase of S_{NH} reaches the reactors. Thus, according to the mass balance equation in the first reactor (10), when $S_{NH,po}$ increases, Q_a is incremented to reduce the rise of $S_{NH,1}$, 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. When, in spite of this control, $S_{NH,5}$ reaches the value of 3.5 mg/l, a complementary action is applied and the $S_{O,4}$ ans $S_{O,5}$ set-points are increased by multiplying its value by 1.5.

The FC has one input and one output, with three membership functions for each (*low*, *medium* and *high*). The implemented $if-then$ rules are:

if ($S_{NH,5}$ is *low*) **then** (Q_a is *high*)
if ($S_{NH,5}$ is *medium*) **then** (Q_a is *medium*)
if ($S_{NH,5}$ is *high*) **then** (Q_a is *low*)

The tuning parameters are set looking for a great variation in Q_a. Thus, the range of the input values is from 3 to 4.1, and the range for the output values is from $-3{\cdot}10^4$ to $2{\cdot}10^5$.

This control is interrupted when the risk of violation disappears ($S_{NH,ep} <$ 4 mg/l and $S_{NH,5} <$ 3.5 mg/l). When it happens, the MPC+FF controller needs time to recover a successfully $S_{NO,2}$ control. In order to avoid abrupt changes in the manipulated variable, variations of Q_a are limited during one day after of the control strategy application.

5. Simulation Results

In this section the control configurations proposed in the previous section are tested and compared. Ideal sensors have been considered. The simulation protocol is established in Jeppsson et al. (2007): First, a steady state simulation of 200 days, and next a dynamic simulations of 609 days. Nevertheless, only the data generated during the final 364 days of the dynamic simulation are used for plant performance evaluation.

In Table 3 the results obtained with the proposed control strategies are shown. The chosen indicators to show the results obtained are based on the proposed objectives: EQI to evaluate the quality of effluent, OCI to evaluate costs, and the percentages of time of $S_{NH,e}$ and $S_{N_{tot,e}}$ violations.

The results have been compared with the default control strategy provided in Jeppsson et al. (2007), and with the two control strategies presented in the finalization of the plant layout in Nopens et al. (2010). In addition, the results of Kim & Yoo (2014) and Flores-Alsina et al. (2011) are also shown for illustrative purposes. However, it should be noted that the comparison in these cases is not completely fair. In the case of Flores-Alsina et al. (2011), the applied EQI equation increase the EQI result because it includes the different oxidized nitrogen forms, and the simulation in Kim & Yoo (2014) is carried out using only 275 days of influent data, what results in lower EQI and OCI. On the other hand, the comparison with the referenced works Flores-Alsina et al. (2010); Benedetti et al. (2009); Flores-Alsina et al. (2013) is not possible. The reason is that Flores-Alsina et al. (2010) and Benedetti et al. (2009) use an earlier version of BSM2 (instead of the modified version in Nopens et al. (2010)), and Flores-Alsina et al. (2013) presents EQI and OCI graphs, but they do not provide numeric values.

As shown in Table 3, the results of the proposed strategies are obtained for various fixed $q_{EC,1}$ values. Obviously, when the control strategy for $S_{N_{tot,e}}$ violations removal is applied, the $q_{EC,1}$ value is modified. Logically, as $q_{EC,1}$ is increased, EQI is reduced but OCI is increased. In comparison with defCL, Kim

		EQI	OCI	$S_{N_{tot,e}}$ violation (% of time)	$S_{NH,e}$ violation (% of time)
Jeppsson et al. (2007)	defCL	5577.97	9447.24	1.18	0.41
Nopens et al. (2010)	CL1	5447	9348	N/A	0.29
	%	2.35	1.05	N/A	29.27
	CL2	5274	8052	N/A	0.23
	%	5.45	14.77	N/A	43.9
Kim & Yoo (2014)	S1	5249	7154	N/A	N/A
(different simulation time)	%	5.9	24.27	N/A	N/A
	S2	5927	8773	N/A	N/A
	%	-62.6	7.14	N/A	N/A
	S3	5530	8072	N/A	N/A
	%	0.86	14.56	N/A	N/A
	S4	5593	7442	N/A	N/A
	%	0.27	21.22	N/A	N/A
Flores-Alsina et al. (2011)	A1	6239	13324	2.17	19.44
(different EQI equation)	%	-11.85	-41.04	-83.9	-4641.46
	A2	6172	13323	1.09	20.83
	%	-10.65	-41.02	7.63	-4980.49
	A3	5995	13580	1.35	5.4
	%	-7.48	-43.74	-14.4	-1217.07
Proposed control strategy for	$q_{EC,1}$=0	5318.95	6289.59	0.046	0.15
$S_{N_{tot,e}}$ violations removal	%	4.64	33.42	96.1	63.41
	$q_{EC,1}$=0.5	5197.49	6873.65	0.037	0.14
	%	6.82	27.24	96.86	65.85
	$q_{EC,1}$=1	5069.51	7573.34	0.037	0.14
	%	9.11	19.83	96.86	65.85
	$q_{EC,1}$=2	4852.49	9196.59	0.028	0.13
	%	13	2.65	97.63	68.29
Proposed control strategy for	$q_{EC,1}$=0	5387.81	5942.77	2.39	0
$S_{NH,e}$ violations removal	%	3.41	37.09	-102.54	100
	$q_{EC,1}$=0.5	5217.9	6680.66	1.027	0
	%	6.45	29.28	12.97	100
	$q_{EC,1}$=1	5112.01	7399.13	0.69	0
	%	8.17	21.68	41.52	100
	$q_{EC,1}$=2	4875.14	9066.01	0.25	0
	%	12.6	4.03	78.81	100

Table 3: Comparative results of the proposed control strategy for S_{NH_e} violations removal and the proposed control strategy for $S_{N_{tot,e}}$ violations removal

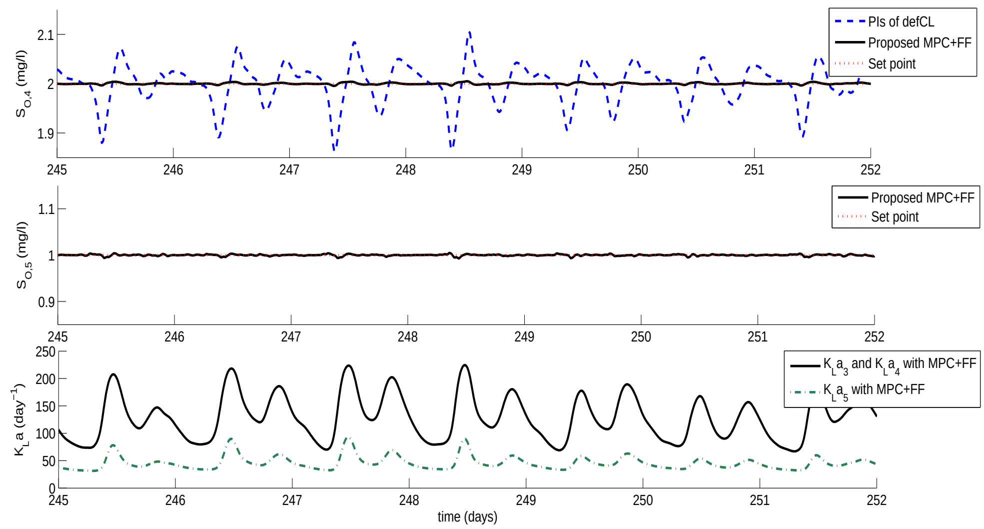
& Yoo (2014) and Flores-Alsina et al. (2011), applying $q_{EC,1}$ = 0.5, both OCI and EQI are reduced, while the percentage of time of $S_{N_{tot,e}}$ and $S_{NH,e}$ violations is lower and sometimes zero. EQI and OCI reduction is mainly achieved with the hierarchical control structure. Important aspects to be considered in this hierarchical control are: first to get a good tracking through the lower level MPC+FF controllers and, on the other hand, to give a suitable S_O set-points by the higher level FC.

Regarding the tracking of the lower level control, Fig. 10 shows one week evolution of $S_{O,4}$ control, where the improvement of MPC+FF controller compared to the PI controllers of defCL can be observed. Table 4 shows the numerical results of the performance of both controllers, including the percentage of improvement of MPC+FF for the $S_{O,4}$ control. The results of $S_{O,5}$ and $S_{NO,2}$ control obtained in this work are also shown. To the best knowledge of the authors, the performance results of the lower level control in other works of the literature based on BSM2 are not shown. Therefore they can not be compared.

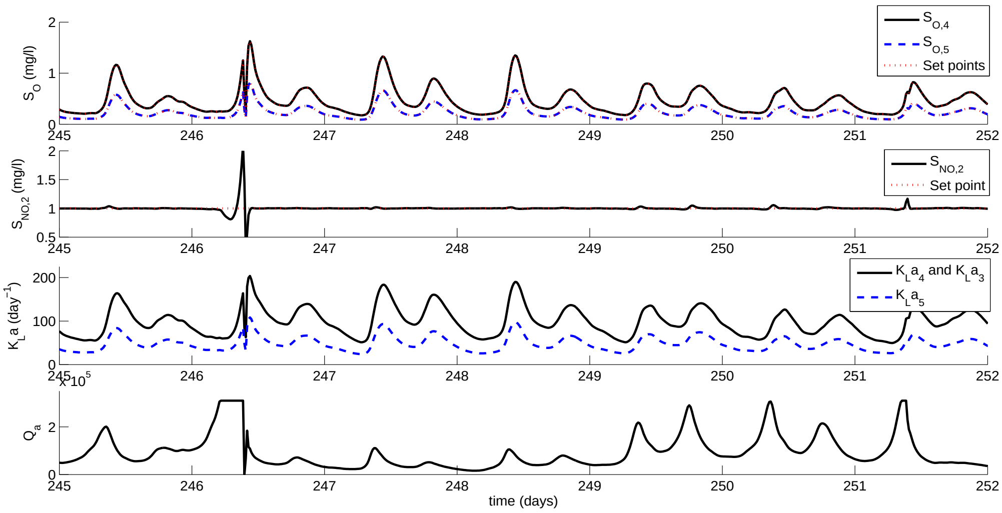
	Fixed S_O set-points and fixed Q_a				Hierarchical control and $S_{NO,2}$ control		
	$S_{O,4}$ control			$S_{O,5}$ control	$S_{O,4}$ control	$S_{O,5}$ control	$S_{NO,2}$ control
	PI of defCL	MPC+FF	%	MPC+FF	MPC+FF	MPC+FF	MPC+FF
IAE	9.079	0.33	96.36	0.44	0.44	0.37	3.91
ISE	0.4	0.0005	99.87	0.001	0.0049	0.0011	2.76

Table 4: Control performance results with fixed $S_{O,4}$ and $S_{O,5}$ set-points (2 mg/l and 1 mg/l respectively) and fixed Q_a (61944 m^3/d) and with $S_{NO,2}$ control at a set-point of 1 mg/l and varying $S_{O,4}$ and $S_{O,5}$ set-points with hierarchical control

One reason of the EQI and OCI reduction obtained with the proposed control strategies, in comparison with the referred works of Table 3, is the way how the controllers of the higher level work. The referred papers try always to control S_{NH} at a fixed reference, but always with a very large error. This is not the case of the FC of the present work, which modifies the S_O set-points based on the biological processes, but without trying to maintain $S_{NH,5}$ at a fixed reference as in Santín et al. (2015a). It is also important to note that the referred works only vary the S_O set-point of one aerobic reactor, whereas in the present work $S_{O,4}$ and $S_{O,5}$ set-points are modified. Fig. 11 shows one week evolution of the most important variables when there are $S_{NH,5}$ peaks. It shows the comparison between hierarchical control and the control strategy with fixed S_O set-points. In the case of hierarchical control, when $S_{NH,5}$ increases, $S_{O,4}$ and $S_{O,5}$ set-points are also



(a) Control performance with fixed S_O set-points and fixed Q_a



(b) Control performance with $S_{NO,2}$ control and varying S_O set-points with hierarchical control

Figure 10: Simulation of the first evaluated week of the control performance of the MPC+FF controllers with fixed $S_{O,4}$ and $S_{O,5}$ set-points (2 mg/l and 1 mg/l respectively) and fixed Q_a (61944 m^3/d) (a); and with $S_{NO,2}$ control at a set-point of 1 mg/l and varying $S_{O,4}$ and $S_{O,5}$ set-points with hierarchical control (b)

increased and $S_{NH,e}$ peaks are reduced, and when $S_{NH,5}$ decreases, $S_{O,4}$ and $S_{O,5}$ are also decremented generating less S_{NO} and reducing operational costs.

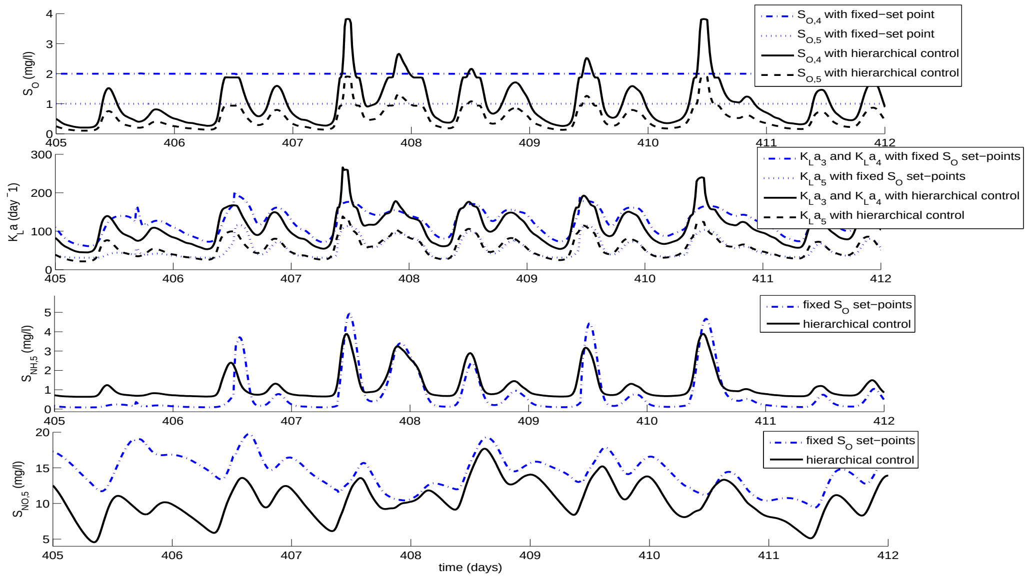


Figure 11: One week simulation comparison between control strategy with fixed S_O set-points and varying S_O set-points with hierarchical control

Regarding the effluent violations, Table 4 shows that all $S_{NH,e}$ violations are removal, while the vast majority of $S_{N_{tot,e}}$ violations are also eliminated. There are a few special cases where the $S_{N_{tot,e}}$ violation is not possible to be avoided. Specifically, it happens three times in the simulation year in the cases of $q_{EC,1}$ is equal to 0, 0.5 and 1; and one time in the simulation year in the case of $q_{EC,1}$ is equal to 2. These violations are due to an increased flow rate just when peaks of pollutants are in the last reactors, possibly due to a heavy rain. Furthermore, in two of these three times, the influent flow rate exceeds the capacity of the plant and is partially led directly to the effluent through the bypass, without being treated. Therefore, although the FC acts adding $q_{EC,5}$, there is not enough time in advance to avoid the violation. Fig. 13 and Fig. 12 show some cases where $S_{N_{tot,e}}$ and $S_{NH,e}$ violations are eliminated, unlike what happens only with hierarchical control. Fig. 13 (c) shows one case where $S_{N_{tot,e}}$ violation removal is not possible.

As explained in previous sections, the most important novelty of this work is the application of ANNs to predict the values of $S_{N_{tot,e}}$ and $S_{NH,e}$. As seen in Fig. 12 and Fig. 13, the prediction made by the ANNs allows to apply the appropriate

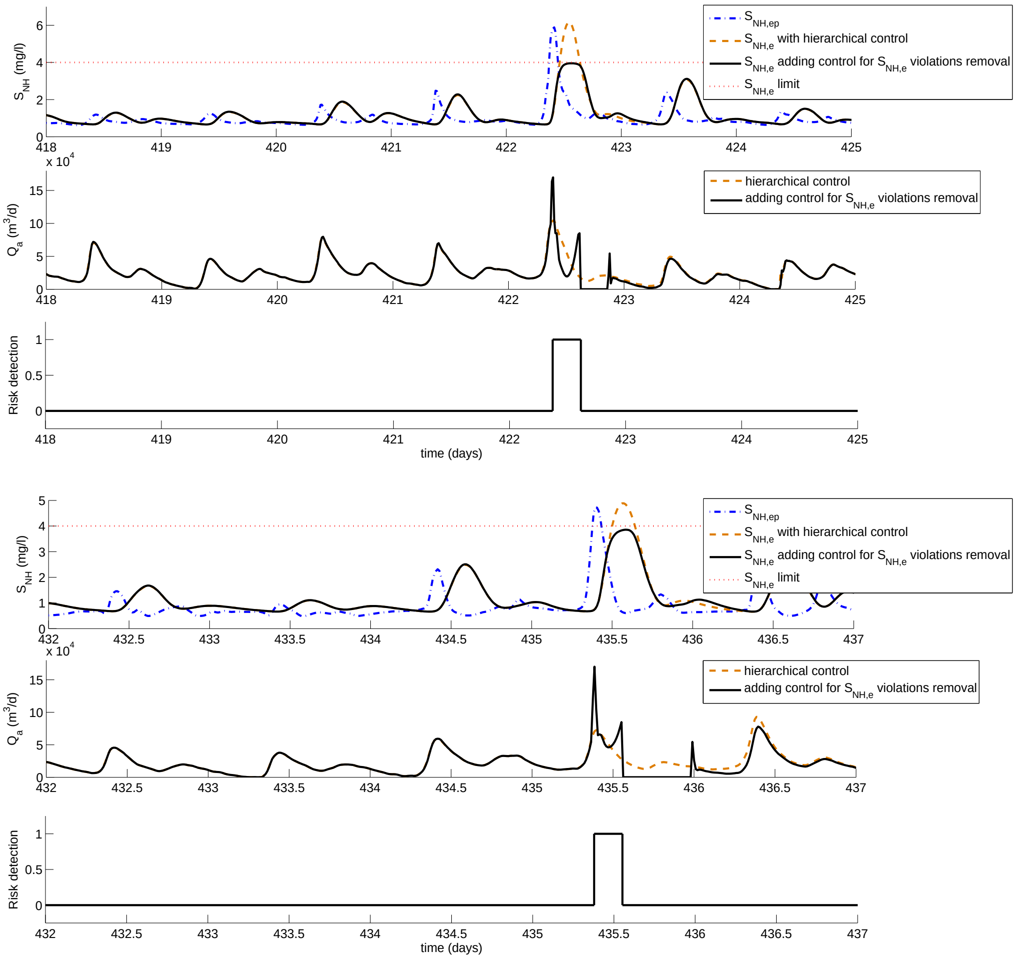


Figure 12: Simulation of two cases of the proposed control strategy for $S_{NH,e}$ violations removal aplication and its comparison with hierarchical control alone

control strategy enough in advance to prevent violations. In case that a violation of $S_{NH,e}$ is predicted, Q_a is increased by a FC to dilute S_{NH}, and when the increasing of S_{NH} reaches the fifth reactor, Q_a is decreased to reduce the hydraulic retention time and thus to improve the nitrification process. In the case that a violation of $S_{N_{tot},e}$ is predicted, $q_{EC,1-2}$ is added according to the calculated value by a FC.

6. Conclusion

In this paper, the application of advanced control techniques in BSM2 has been presented with the goals of avoiding $S_{NH,e}$ and $S_{N_{tot,e}}$ violations while improving water quality and reducing operational costs.

Satisfactory $S_{O,4}$, $S_{O,5}$ and $S_{NO,2}$ control performance by the MPC+FF controllers have been achieved. Due to this tracking and the regulation of $S_{O,4}$ and $S_{O,5}$ set-points by a FC, based on biological processes, it has been shown that the OCI and EQI indexes can be improved compared to defCL and the literature.

In order to apply the appropriate control strategy with sufficient time, ANNs have been used to obtain effluent predictions. Several FCs are responsible for implementing the control strategy when a risk of $S_{N_{tot,e}}$ or $S_{NH,e}$ violation is detected. The simulation results have shown the complete elimination of $S_{NH,e}$ violations. Regarding $S_{N_{tot,e}}$ violations, they have been avoided except one time in a simulation year, in which a large increase of flow rate coincides with a peak of pollutants in the last reactor and with a situation of bypass.

Acknowledgment

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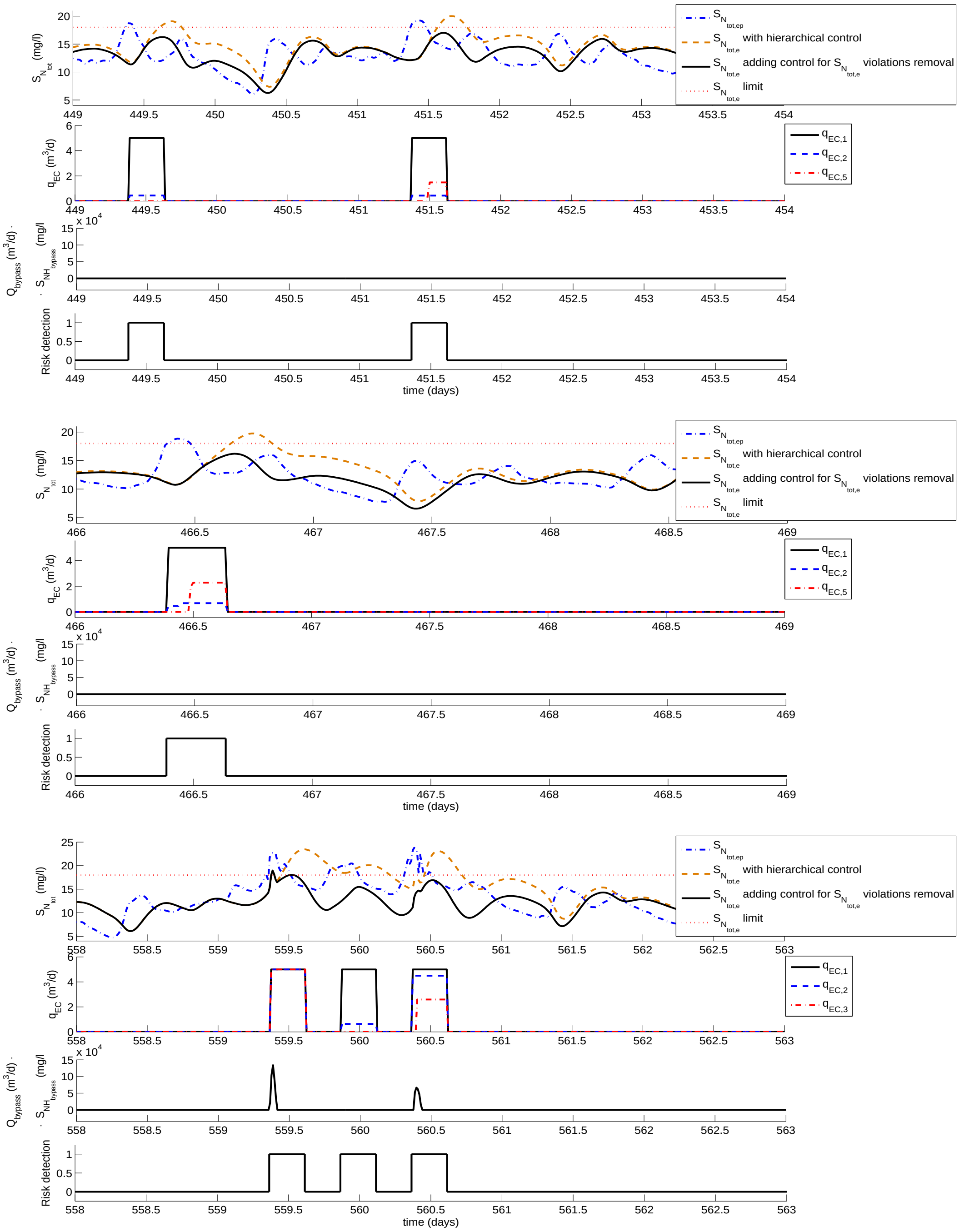

Figure 13: Simulation of some cases of the proposed control strategy for $S_{N_{tot,e}}$ violations removal aplication and its comparison with hierarchical control alone

Model Predictive Control and Fuzzy Control in a hierarchical structure for wastewater treatment plants

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***Abstract*—This paper presents a hierarchical two-level control structure for a biological wastewater treatment plant (WWTP), with the goal of simultaneously improving the effluent quality and reducing operational costs. The Benchmark Simulation Model No.1 is used as working scenario.**

The idea is to adjust the dissolved oxygen in the fifth tank (DO5) according with the present working conditions, instead of keeping it in a fixed value. Thus is concreted by a hierarchical structure. MPC with inlet flow rate feedforward control (MPC + FF) is proposed for the lower level to control nitrate nitrogen concentration of the second tank (NO2) and DO5. The high level is the responsible for adjusting the DO setpoint in the fifth tank (DO5 setpoint) of the controller of the low level, according with the ammonium and ammonia nitrogen concentration in the fifth tank (NH5). The controller for the high level is based on a Fuzzy control. A tuning region has been determined for the high level controller, in which the results show a simultaneously improvement of the effluent quality and operational cost.

I. Introduction

Biological wastewater treatment plants (WWTPs) are complex, nonlinear systems with very different time constants. The intricate behaviour of the micro-organisms and the large disturbances in concentrations and flow rates of the influent makes the control of the WWTP a complex task. In addition, there are effluent requirements defined by the European Union (European Directive 91/271 Urban wastewater) with economic penalties. The purpose of this work is to operate WWTPs with the aim of improving the effluent quality and reduce operational costs.

Many control strategies have been proposed in the literature but their evaluation and comparison, either practical or based on simulation is difficult. This is due to the variability of the influent, the complexity of the biological and biochemical phenomena, the large range of time constants (varying from a few minutes to several days), and the lack of standard evaluation criteria (among other things, due to region specific effluent requirements and cost levels). In order to face this complexity, the evaluation and comparison of the different strategies can be based on the Benchmark Simulation Model 1 (BSM1), developed by the International Association on Water Pollution Research and Control ([1]; [2]). This benchmark includes a plant layout, influent loads, test procedures and evaluation criteria.

For the challenging task of controlling WWTPs, Model Predictive Control (MPC) has demonstrated to be efective: [3] tried an indirect control, with the dissolved oxygen concentration in the fifth tank (DO5) as controlled variable; [4] tested a direct control, with the quality indices as controlled variables, with feedforward control of the influent flow rate to reject disturbances; [5] applied also quality indices as controlled variables with feedforward control of the influent ammonium and ammonia nitrogen concentration (NH) and flow rate, and in addition experimented with hard constraints in the manipulated variables and soft constraints in the controlled variables; [6] employed a multivariable control strategy with two controlled variables, DO5 and nitrite and nitrate nitrogen concentration of the second tank (NO2), with feedforward control of nitrite and nitrate nitrogen (NO) and dissolved oxygen (DO) concentrations in the inlet flow of the first anoxic reactor, improving the performance of NO2 control, but not of DO5 control in comparison with default PI controllers.

Other works have experimented in the NH5 control by manipulating DO5 set point. [7] tested with PI controllers and [8] with PI controllers and a MPC. Both references worked with a variation of BSM1.

This paper proposes first an MPC with inlet flow rate feedforward (MPC + FF) to control NO2 and DO5 by manipulating the oxygen transfer coefficient (K_La) in the fifht tank and the internal recirculation flow rate (Q_{rin}), based upon the work [6]. However, in this work, a different feedforward control is proposed and an improvement of DO5 and NO2 performance control is achieved in comparison with default PI controllers.

Next, a two-level hierarchical control strategy is investigated, in which the lower level is MPC + FF, and the higher level modifies DO5 set point of the lower level according with the working conditions of the plant. For the higher level is tested a Fuzzy controller, obtaining a tuning region by trade-off representations, in which the results show a simultaneously improvement of the effluent quality and operational costs for the three weather conditions: dry, rain and storm.

II. Control strategies

The original BSM1 definition includes the so called default control strategy that is commonly used as a reference ([1]; [2]). This strategy uses two PI control loops as it can be seen in Fig. 1. The first one involves the control of DO5 by manipulating K_La. The set point for DO5 is 2 mg/l. The second control loop has to maintain NO2 to a set point of 1 mg/l by manipulation of Q_{rin}. In this work, the following alternatives are proposed. First, the two PI controllers are replaced by MPC + FF with the objective to get a better DO5 and NO2 set points tracking. Subsequently, a higher level control is added to manipulate DO5 set point based on NH concentration in

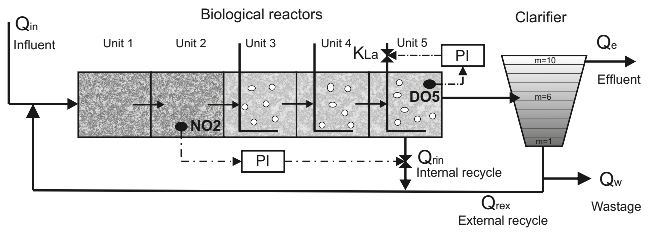

Fig. 1. Benchmark Simulation Model 1

the fifth tank (NH5). A Fuzzy controller is proposed for this higher level.

A. MPC + FF configuration

The two PI controllers of the default BSM1 control strategy are replaced by an MPC with two inputs (DO5 and NO2) and two outputs (K_La and Q_{rin}). Due to the presence of strong disturbances on WWTPs, MPC has difficulties in keeping the controlled variables at their reference level. To compensate the disturbances, a feedforward control is added, as in [9], [4], [5] and [6] (see Fig. 2). Different variables have been considered for the feedforward action in those works, but in our case the influent flow rate has been selected for its better results. The MPC algorithm requires a state-space

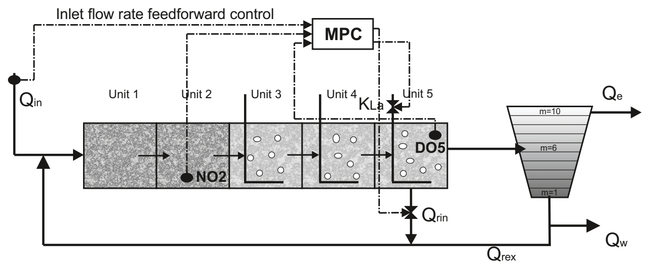

Fig. 2. BSM1 with MPC + FF instead of default PI controllers

linear model to foresee how the plant outputs, $y(k)$, react to the possible variations of the control variables, $u(k)$, and to compute at each $\triangle t$ the control moves. WWTPs are nonlinear systems, but his operation can be approximated in the vicinity of a working point by a continuous-time state-space model as:

$$
\begin{aligned}
x(k+1) &= Ax(k) + Bu(k) \\
y(k) &= Cx(k) + Du(k)
\end{aligned}
\tag{1}
$$

where $x(k)$ is the state vector, and A, B, C and D are the state-space matrices. In concrete terms, $u_1(k)$ is Q_{rin}, $u_2(k)$ is K_La, $u_3(k)$ is Q_{in} and $y_1(k)$ is NO2 and $y_2(k)$ is DO5.

The tuning parameters are: $\triangle t$, m, p, $\Gamma_{\triangle u}$, Γ_y and the overall estimator gain.

- $\triangle t$ has a significant effect on the effectiveness of the controller. High $\triangle t$ can give less controller performance, mainly when there are important input disturbances, and low $\triangle t$ can produce too rapid changes in the actuators and high energy consumption.
- Lower $\Gamma_{\triangle u}$ or higher Γ_y give better performance of the controlled variable, otherwise could produce strong oscillations in the actuators that must be avoided.
- m and p should be adjusted depending of system control in each case. However too high values can increase the computational time too much, and on the other hand, too small values may results in oscillatory responses or may not work at all.
- At each $\triangle t$ the controller compares the real value of the outputs with the expected values. The difference can be due to noise, to measurements errors and to unmeasured disturbances. Regarding the overall estimator gain parameter it is determined the percentage of this difference that is attributed to unmeasured disturbances and the calculation matrix is consequently adjusted. Higher overall estimator gains improve the results, but too high values can make the controller unfeasible.

B. Two Level Hierarchical Control configuration

In this section a two-level hierarchical control scheme is proposed. The lower level controller is responsible of following the set points by manipulating K_La and Q_{rin}. The higher level controller has to manipulate DO5 set point of the lower level controller according with NH5 (see Fig. 3). When NH is higher, more DO is needed for nitrification. On the contrary, when NH is lower, less DO is required, producing less NO. Other works have experimented in the NH5 control by manipulating DO5 set point ([7], [8]). Nevertheless, these investigations use default PI controllers at the lower level. [7] tested a higher level PI controller, and [8] experienced with PI and MPC controllers as higher level (working with a variation of BSM1, with one anoxic tank and four aerobic tanks). The proposed configuration of this paper uses the MPC + FF as lower level control explained before (section II-A). As the purpose of the high level is to adjust the DO set point of the low level control depending on NH5 values, and not to keep NH5 to a set point value, a Fuzzy controller is tested for the high level, and a range of tuning parameters is proposed.

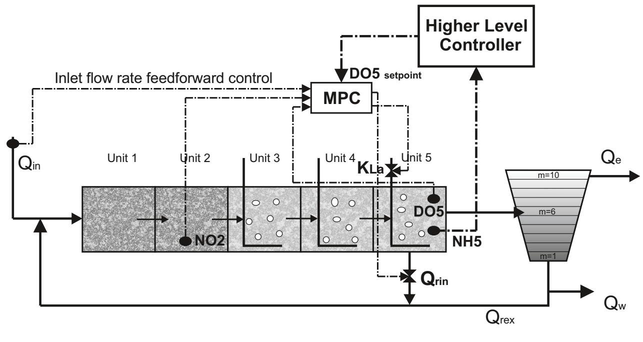

Fig. 3. BSM1 with MPC + FF and Hierarchical control

III. Simulation Results

In this section the control configurations proposed in the above section are tested and compared. Ideal sensors have been considerated for the simulations. Results of effluent quality and operational costs are measured with the Effluent Quality Index (EQI) and the Overall Cost Index (OCI) ([1]; [2]):

$$EQI = \frac{1}{1000 \cdot T} \int_{t=7days}^{t=14days} (2 \cdot TSS(t) + COD(t)$$

$$+30 \cdot NK_j(t) + 10 \cdot NO(t) + 2 \cdot BOD_5(t)) \cdot Q_e(t) \cdot dt \quad (2$$

where T is the total time, TSS is the Total Suspended Solids COD_t is the Total Chemical Oxygen Demand, NKj is th Kjeldahl Nitrogen, BOD_5 is the Biological Oxygen Demanc and Q_e(t) is the effluent flow rate.

$$OCI = AE + PE + 5 \cdot SP + 3 \cdot EC + ME \quad (3$$

where AE is the aeration energy, PE is the pumping energy, S is the sludge production to be disposed, EC is the consumptio of external carbon source and ME is the mixing energy.

A. MPC + FF configuration

DO5 and NO2 values to get the linear model have been obtained by varying K_La around $\pm 10\%$ of 131.6514 day^{-1} and Q_{rin} around $\pm 10\%$ of 16486 m^3/day and applying a step of $+50\%$ to Qin.

By using Matlab System Identification Toolbox with prediction error method, the following third order state-space model (1) is obtained:

$$A = \begin{bmatrix} 0.8748 & 0.04463 & 0.1314 \\ 0.04091 & 0.7331 & 0.1796 \\ 0.2617 & -0.1318 & 0.3007 \end{bmatrix}$$

$$B = \begin{bmatrix} 7.641 \cdot 10^{-6} & 0.004551 & -2.749 \cdot 10^{-5} \\ -2.631 \cdot 10^{-5} & 0.006562 & -4.551 \cdot 10^{-6} \\ -9.63 \cdot 10^{-6} & -0.02161 & 2.447 \cdot 10^{-5} \end{bmatrix} \quad (4)$$

$$C = \begin{bmatrix} 0.8812 & -0.5948 & 0.02114 \\ 1.187 & 0.9893 & -0.3754 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

The selected values to tune the MPC are m=5 and p=20. It should be noted that these values are not critical and they can slightly be changed with similar results. $\triangle t$ is 0.00025 days (21.6 seconds). The followings weights have been used for DO5 control: $\Gamma_y = 1$, $\Gamma_{\triangle u} = 0.01$, and for NO2 control: $\Gamma_y = 1$, $\Gamma_{\triangle u} = 0.0001$. The selected overall estimator gain value is 0.8. Trial-and-error method was used for the identification of these parameters.

Fig. 4 shows DO5 and NO2 for the dry weather case compared with the default PI control. Table I shows that MPC + FF reduces ISE of NO2 control more than 99% and ISE of DO5 control more than 97% in comparison with the default PI controllers. This control performance improvement results in a 1.1% of EQI reduction, keeping a similar OCI (increase of 0.0063%).

This comparison is also done for the rain (see Fig. 5) and storm influents (see Fig. 6), obtaining similar percentages of improvement (see Table I): ISE 99.6% (rain) and 99.5% (storm) for NO2 control and 92.02% (rain) and 90.8% (storm) for DO5 control, and reducing EQI with MPC + FF 1.03% for rain and 1.09% for storm. OCI is similar, increasing a 0.037% for rain and 0.044% for storm; nevertheless this difference is not significant.

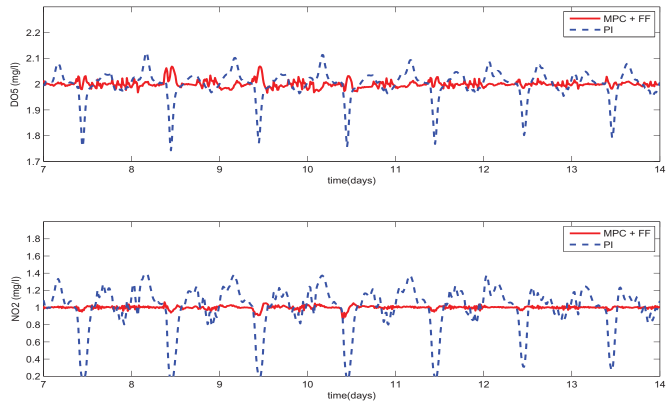

Fig. 4. Dry influent: Performance control of DO5 and NO2 with default PI controllers and with MPC + FF

	PI	MPC + FF	%
Dry weather			
ISE (NO2 control)	0.47	0.0013	-99.7%
ISE (DO5 control)	0.022	0.00067	-96.9%
EQI (kg pollutants/d)	6115.63	6048.25	-1.1%
OCI	16381.93	16382.97	+0.0063%
Rain weather	PI	MPC + FF	%
ISE (NO2 control)	0.69392	0.002819	-99.6%
ISE (DO5 control)	0.016362	0.0013026	-92.02%
EQI (kg pollutants/d)	8174.98	8090.29	-1.03%
OCI	15984.85	15990.85	+0.037%
Storm weather	PI	MPC + FF	%
ISE (NO2 control)	0.69392	0.002819	-99.6%
ISE (DO5 control)	0.016362	0.0013026	-92.02%
EQI (kg pollutants/d)	8174.98	8090.29	-1.03%
OCI	15984.85	15990.85	+0.037%

TABLE I. ISE, EQI AND OCI RESULTS USING DEFAULT PI CONTROLLERS AND MPC + FF FOR DRY, RAIN AND STORM INFLUENTS

B. Two Level Hierarchical Control configuration

For the hierarchical control structure, OCI and EQI trade-off representations have been implemented for the three weather conditions. OCI and EQI results are obtained assessing the extreme points where the best EQI without increasing OCI and the best OCI without increasing EQI are achieved compared to MPC + FF alone.

For the implementation of high level Fuzzy controller three triangular membership functions for input and for output are used (low, medium and high). The rules implemented are:

if (NH5 is *low*) **then** (DO5 is *low*)
if (NH5 is *medium*) **then** (DO5 is *medium*)
if (NH5 is *high*) **then** (DO5 is *high*)
Mamdani ([10]) has been the method to defuzzify. The

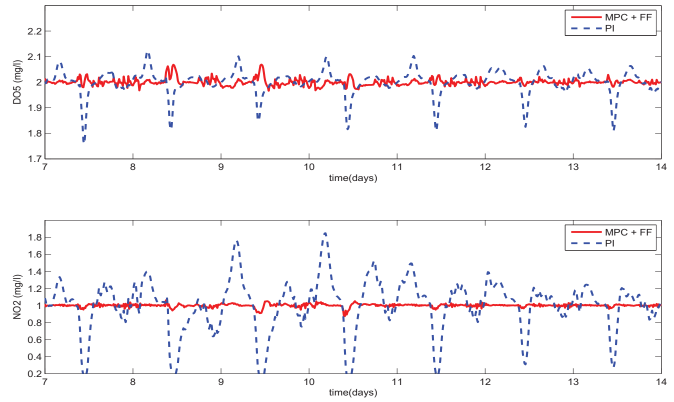

Fig. 5. Rain influent: Performance control of DO5 and NO2 with default PI controllers and with MPC + FF

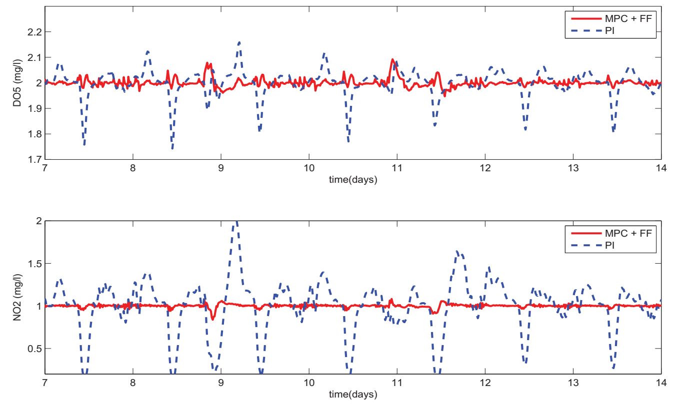

Fig. 6. Storm influent: Performance control of DO5 and NO2 with default PI controllers and with MPC + FF

minimum value for the range of input and output membership function is 0.1. Maximum values of the input in the membership functions (maxin) and maximum values of the output in the membership functions (maxout) have been determined with OCI and EQI trade-off representations (Fig. 7, Fig. 8, and Fig. 9). Each one of the lines corresponds to the results obtained with different maxin (3, 5, 7, 9), and each of the points marked with crosses are the results for different maxout (2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5). The results obtained with MPC + FF alone and with default PI controllers alone are also shown. Taking into account the trade-off representations (see Fig. 7, Fig. 8, and Fig. 9), Table II shows the maxin and maxout values for the extreme cases of lowest EQI without increasing OCI and lowest OCI without worsening EQI in comparison with MPC + FF alone and default PI controllers alone for the three influents. In order to improve EQI, NH and NO concentrations have to be reduced because they are the pollutants with largest influence in the effluent quality. Fig. 10 shows NH5, NO5 and DO5 for dry influent with the tunning parameters where the best EQI without increasing OCI is obtained. As it is shown in Fig. 10, by varying DO5 set point with two level hierarchical control, NH5 peaks and NO5 are reduced. In the case of

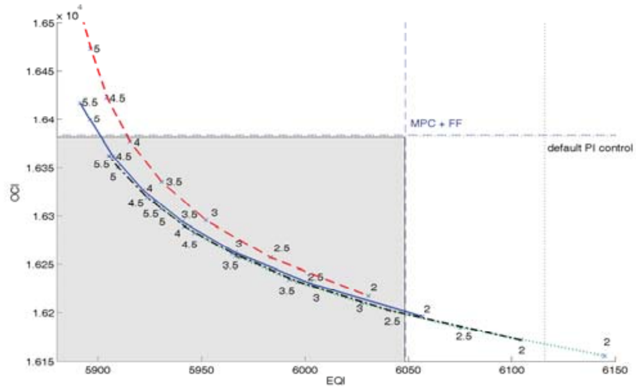

Fig. 7. Dry influent: OCI and EQI trade-off with higher level Fuzzy controller for a range of maxout values (points marked with crosses) and maxin = 3 (dashed line), 5 (solid line), 7 (dash-doted line) and 9 (doted line)

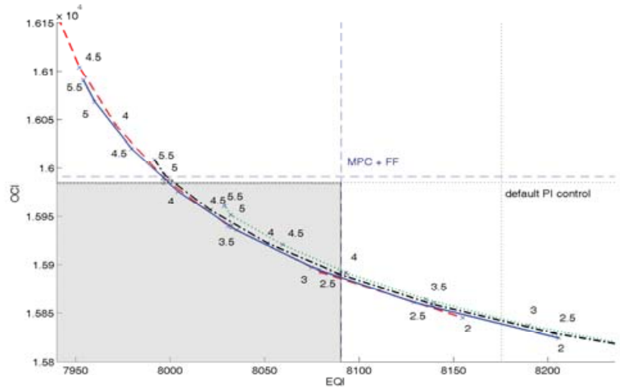

Fig. 8. Rain influent: OCI and EQI trade-off with higher level Fuzzy controller for a range of maxout values (points marked with crosses) and maxin = 3 (dashed line), 5 (solid line), 7 (dash-doted line) and 9 (doted line)

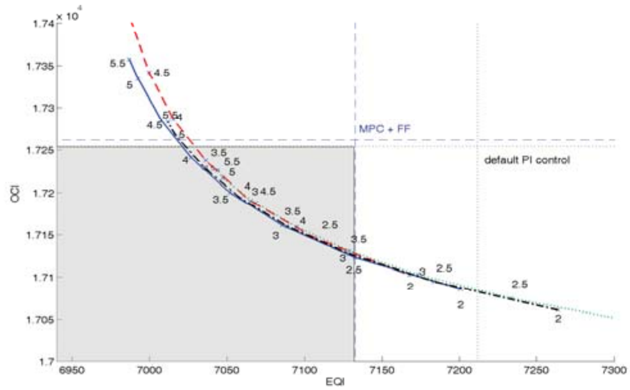

Fig. 9. Storm influent: OCI and EQI trade-off with higher level Fuzzy controller for a range of maxout values (points marked with crosses) and maxin = 3 (dashed line), 5 (solid line), 7 (dash-doted line) and 9 (doted line)

higher level Fuzzy controller, when NH5 is over the fixed set point, DO5 reference of the lower level control is increased, which produces more oxidation of NH5 and consequently softens his peaks, while NO5 and the aeration costs grow. In opposition, when the NH5 is under the fixed set point, DO5

	dry		rain		storm	
	lowest EQI	lowest OCI	lowest EQI	lowest OCI	lowest EQI	lowest OCI
maxin	5	9	5	3	5	5
maxout	4.78	2.76	4.1	2.41	4.14	2.5

TABLE II. HIGHER LEVEL FUZZY CONTROLLER TUNING: MAXIN AND MAXOUT VALUES

reference is decreased, NH5 goes up and NO5 and aeration costs go down. The final balance from day 7 to day 14 is a reduction of 2.4% of EQI in comparison with MPC + FF alone, (Table III).

The same concentrations (NH5, NO5 and DO5) for rain and storm influents are shown in Fig. 11 and Fig. 12 respectively. Within 7 days of simulation (day 7 to 14), two days are shown coinciding with a rainfall (Fig. 11) and a storm (Fig. 12) events. As it is observed, during the rain and storm events, the differences of NH5 peaks and NO5 for higher level Fuzzy controller and MPC + FF are lower compared with dry weather. This has a direct consequence on the EQI results shown in Table III. As it can be seen, there is also an improvement by working with higher level Fuzzy controller in comparison with MPC + FF alone, but with a lower percentage compared with dry weather. For the rain influent case, EQI is decreased by 1.1% and for the storm influent case, EQI is decreased by 1.5%.

In the opposite point of the trade-off representations (see Fig. 7, Fig. 8, and Fig. 9) (best OCI without worsening effluent quality), OCI results are compared for the different control structures. Fig. 13 shows K_La in the fifth tank for the higher level Fuzzy controller and MPC + FF. The aeration costs depend directly on the K_La values. Fig. 13 shows that the values of K_La with higher level Fuzzy controller are most of the time lower than those obtained with MPC + FF alone, proving that costs can be reduced without increasing EQI with a better optimization of KLa. This reduction of K_La results in a reduction of 1.1% of OCI (Table III).

The results value evolution of K_La is also shown for rain and storm influents (Fig. 14 and 15 respectively), obtaining also an OCI reduction when working with the higher level Fuzzy controller in comparison with MPC + FF alone. In this case, with less percentage in comparison with dry influent results (see Table III): For rain influent, higher level Fuzzy controller reduces OCI by 0.6%, and for storm influent the reduction is 0.8%.

IV. CONCLUSION

In this paper different control techniques for the BSM1 with the aim of reducing EQI and OCI are evaluated and compared, with the aim of reducing EQI and OCI.

First, MPC + FF was proposed to control NO2 and DO5 by manipulating Q_{rin} and K_La. The performance control of NO2 and DO5 was improved by more than 90 % for the three weather conditions (dry, rain and storm) in comparison with default PI controllers. This performance enhancement resulted in a slight improvement in EQI with similar OCI. MPC + FF was based on [6]. However, in the referred work a feedforward control of NO and DO concentrations in the inlet flow of the first anoxic reactor was implemented, improving the performance of NO2 control, but not of DO5 control in comparison with default PI controllers.

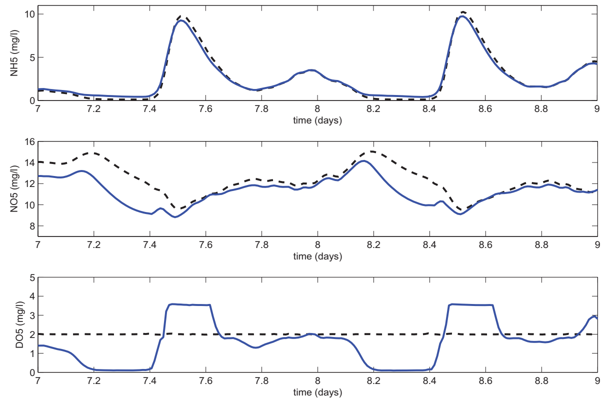

Fig. 10. Dry influent: Comparison of NH5, NO5 and DO5. MPC + FF (dashed line) and hierarchical control (solid line)

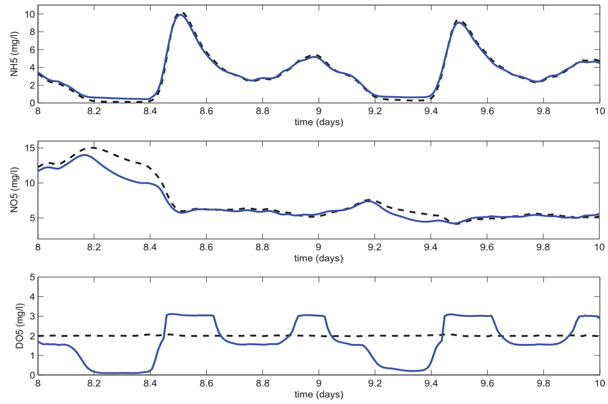

Fig. 11. Rain influent: Comparison of NH5, NO5 and DO5. MPC + FF (dashed line) and hierarchical control (solid line)

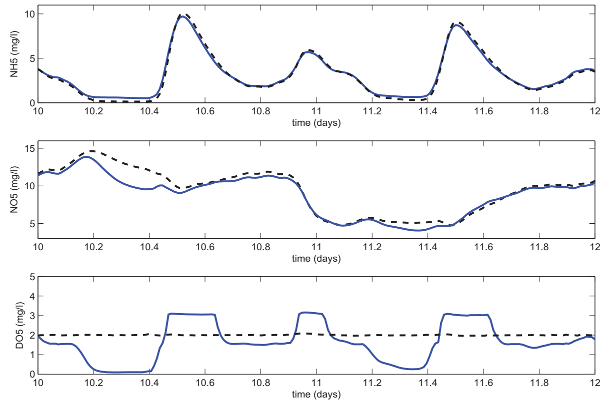

Fig. 12. Storm influent: Comparison of NH5, NO5 and DO5. MPC + FF (dashed line) and hierarchical control (solid line)

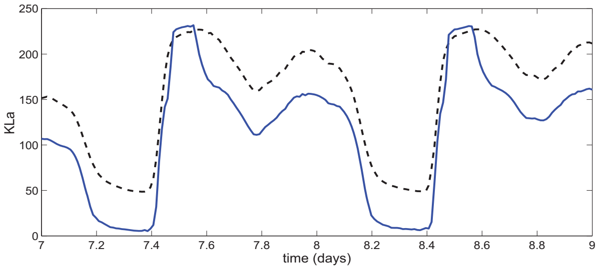

Fig. 13. Dry influent: Comparison of K_La in the fifth tank. MPC + FF (dashed line) and hierarchical control (solid line)

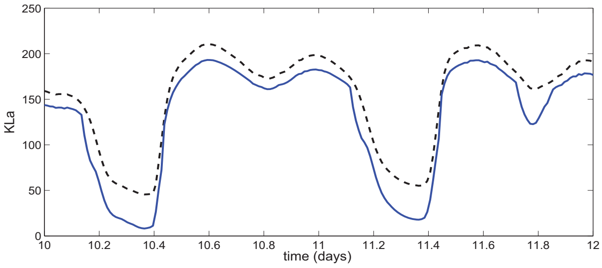

Fig. 14. Rain influent: Comparison of K_La in the fifth tank. MPC + FF (dashed line) and hierarchical control (solid line)

Next, a two level hierarchical control strategy was proposed, where the lower level controls NO2 and DO5 by manipulating Q_{rin} and K_La respectively, and the higher level controller regulates the DO5 set point of the lower level controller according to the NH5. For the lower level, MPC + FF was used. For the higher level, a Fuzzy controller was proposed. It was tested in the three weather conditions: dry, rain and storm. In each case, a set of different tuning parameters was determined. As a result, EQI and OCI were reduce significatively with respect to MPC + FF alone. These improvements have been greater in dry weather conditions.

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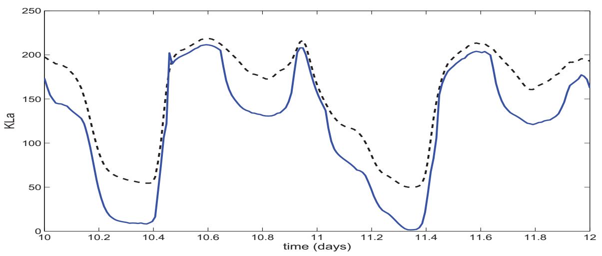

Fig. 15. Storm influent: Comparison of K_La in the fifth tank. MPC + FF (dashed line) and hierarchical control (solid line)

Dry weather				
	MPC + FF	Higher level Fuzzy controller		
		lowest EQI	lowest OCI	%
EQI (kg pollutans/d)	6048.31	5900.73	6047.95	-2.4%
OCI	16382.97	16382.67	16197.86	-1.1%
Rain weather				
	MPC + FF	Higher level Fuzzy controller		
		lowest EQI	lowest OCI	%
EQI (kg pollutans/d)	8090.29	7998.78	8090.27	-1.1%
OCI	15990.85	15984.23	15884.21	-0.6%
Storm weather				
	MPC + FF	Higher level Fuzzy controller		
		lowest EQI	lowest OCI	%
EQI (kg pollutans/d)	7132.60	7020.83	7132.25	-1.5%
OCI	17261.39	17252.6	17123.01	-0.8%

TABLE III. EQI AND OCI RESULTS WITH MPC + FF AND HIGHER LEVEL FUZZY CONTROLLER FOR DRY, RAIN AND STORM INFLUENTS

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Control strategies for ammonia violations removal in BSM1 for dry, rain and storm weather conditions

Ignacio Santín[1], Carles Pedret[1] and Ramon Vilanova[1]

Abstract— **This paper presents a proposal with the objective of eliminating violations of ammonia nitrogen in the effluent (NH$_e$) of a wastewater treatment process. Furthermore, improving effluent quality and reducing operating costs and the percentage of violations of total nitrogen in the effluent (N$_{tot,e}$) are also considered. The evaluation of control strategies are conducted with the Benchmark Simulation Model Nº 1 (BSM1). Several controllers have been proposed: Model Predictive Control (MPC) with inlet flow rate feedforward compensation (MPCFF), Fuzzy controller and Exponential, Linear and Affine Functions. MPCFF and Fuzzy controller are applied in a hierarchical structure to improve effluent quality, to reduce operational costs and to decrease NH$_e$ peaks. Exponential, Linear and Affine Functions are implemented, along with the hierarchical control structure, to avoid NH$_e$ violations. The results are presented and compared with the default control strategy of BSM1 for dry, rain and storm weahter conditions. They show that the NH$_e$ violation removal is achieved for the three weather conditions. For dry influent also an improvement of effluent quality and a reduction of operational cost are acquired. For the rain and storm cases, an increment of operational cost is required.**

I. INTRODUCTION

The control of biological wastewater treatment plants (WWTPs) is not an easy task due to the complexity of its biological and chemical processes, the disturbances of the influent and the legal requirements established for the effluent (European Directive 91/271 Urban wastewater).

The Benchmark Simulation Model Nº 1 (BSM1), developed by the International Association on Water Pollution Research and Control ([1], [2], [3]) is the selected benchmark for the evaluation and comparison of the different control strategies in a wastewater treatment process. This benchmark defines a plant layout (see Fig. 1), influent loads, test procedures and evaluation criteria.

Many works can be found in the literature that propose different methods for controlling WWTPs using BSM1. Some of them apply a direct control on the effluent variables, mainly ammonium and ammonia nitrogen (NH) and total nitrogen (N$_{tot}$) ([4], [5], [6]). The difficulty in this method is that the fixed values for the effluent variables are constraints and not set points to be tracked. Other studies deal with the basic control strategy (control of dissolved oxygen concentration (DO) in the fifth tank (DO5) and nitrate nitrogen concentration (NO) of the second tank (NO2)), but testing with different controllers such Model Predictive Controller (MPC) and Fuzzy controller ([7], [8], [9]). These methods provide an acceptable balance between quality and costs. Finally other investigations propose a hierarchical control that regulates the DO set points, depending on some states of the plant, usually NH and NO concentration values in any tank or in the influent ([10], [11], [12], [13]) or DO in other tanks ([14]). Other works in the literature have presented proposals for avoiding effluent violations ([4], [5], [6]), with the quality indices as controlled variables. However, [4] do not provide costs results, and [5], [6] present a high cost increase.

This work proposes a control strategy with the goal of eliminating violations of NH in the effluent (NH$_e$) for dry, rain and storm weather conditions, while taking into account effluent quality and operational costs compared to the default control of BSM1. The control objectives of previous works are usually based on achieving an improvement in the effluent quality and / or costs indices. However, it is of significant importance to avoid violations of pollution in the effluent, regarding the quality of the water from a legal point of view, and certainly in terms of cost, as these violations involve fines to be paid.

The proposed approach is implemented by making use of Fuzzy logic, MPC controllers and Exponential, Linear and Affine Functions. MPC and Fuzzy controllers are used to improve effluent quality and operational costs in a two-level hierarchical control structure. The lower level is composed by three MPC with feedforward compensation (MPCFF) ([15]) of the influent flow rate (Q$_{in}$), to control DO in the third tank (DO3), DO in the fourth tank (DO4) and DO5. The higher level is built with a Fuzzy controller that adjusts the DO set points according to NH in the fifth tank (NH5). A combination of Exponential and Linear Functions are proposed, along with the hierarchical structure, for avoiding NH$_e$ violation, by manipulating the internal recirculation flow rate (Q$_{rin}$) based on NH5, NH in the influent (NH$_{in}$) and Q$_{in}$. It is worth to say, that the days after the rain and storm events the plant presents also specific problems due to the fact that during those events the bacteria population is strongly reduced. For these cases, an Affine Function is added to manipulate external carbon flow rate (q$_{EC}$) in the fourth and fifth tank (q$_{EC_{4-5}}$).

II. CONTROL STRATEGIES

The BSM1 provides a default control strategy that includes two Proportional-Integral (PI) control loops: control of the DO5 at a set point value of 2 g/m^3 by manipulating the oxygen transfer coefficient (K$_L$a) in the fifth tank (K$_L$a5),

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and control of the NO2 at a set point value of $1 g/m^3$ by manipulating Q_{rin} (see Fig. 1).

The main control objective of this work is to eliminate violations of NH_e. However, this objective should not be fulfilled at any price. For this reason, this work also takes into account the operational costs and the effluent quality, comparing them with those obtained applying the default control strategy of BSM1.

Thus, two control strategies based on two objectives are applied: on the one hand, to improve effluent quality and to reduce operational costs and, moreover, the NH_e violations removal. To improve effluent quality and to reduce operational costs, a two-level hierarchical control structure based on MPCFF controllers and a Fuzzy controller is proposed. To eliminate violations of NH_e a control strategy based on Exponential and Linear functions is applied to manipulate Q_{rin} based on NH5 and NH_{in}, and it is proposed along with the hierarchical structure. Dry, rain and storm weather conditions have been taken into account. In the cases of rain and storm influents, an Affine Function is added to manipulate $q_{EC_{4-5}}$ based on NH_{in} mean of two days before ($NH_{inmean,2}$). These control strategies are shown in Fig. 2, and they are described below.

A. Two-level hierarchical control structure

The aim of the two-level hierarchical control structure is to improve effluent quality and to reduce operational costs by improving the nitrification process in the aerated zone. The biological treatment of NH and NO, that takes place in the reactors, is the result of several processes given by Activated Sludge Model Nº 1 (ASM1) ([16]).

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

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

$$\rho_1 = 4\left(\frac{S}{10+S}\right)\left(\frac{DO}{0.2+DO}\right)X_{B,H} \tag{3}$$

$$\rho_2 = 4\left(\frac{S}{10+S}\right)\left(\frac{0.2}{0.2+DO}\right)\left(\frac{NO}{0.5+NO}\right)0.8\cdot X_{B,H} \tag{4}$$

$$\rho_3 = 0.5\left(\frac{NH}{1+NH}\right)\left(\frac{DO}{0.4+DO}\right)X_{B,A} \tag{5}$$

$$\rho_6 = 0.05\cdot ND\cdot X_{B,H} \tag{6}$$

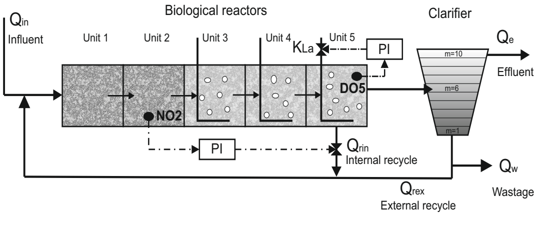

Fig. 1. Benchmark Simulation Model 1: Default control strategy

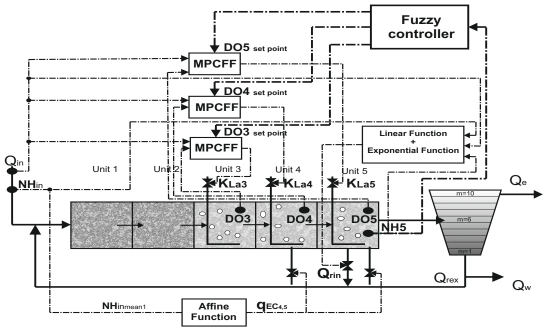

Fig. 2. Proposed control strategy for BSM1

where r_{NH} is the reaction rate of NH, r_{NO} is the reaction rate of NO, S is the readily biodegradable substrate, ND the soluble biodegradable organic nitrogen, $X_{B,H}$ the active heterotrophic biomass and $X_{B,A}$ the active autotrophic biomass. The biological parameter values used in the BSM1 correspond approximately to a temperature of 15 ºC.

The nitrification process is performed by $X_{B,A}$ whose growth is obtained by ρ_3 (5). As it can be observed, higher NH and DO produce a greater NH removal. However, increasing the DO value also increases NO (2) and operational costs (13). For this reason it is important to increase DO when NH increases to reduce NH peaks, and decrease DO when NH decreases, producing less NO and reducing costs.

The lower level of this hierarchical control structure is composed of three MPC controllers to track the DO set points values of the three aerated tanks, given by the higher level controller, by manipulating K_La of each of these three tanks. Thus, each of MPC is composed of one input (DO3 set point, DO4 set point and DO5 set point respectively) and one output (K_La in the third tank (K_La3), K_La in the fourth tank (K_La4) and K_La5 respectively). The higher level controller regulates the DO set points of the lower level based on NH5. A Fuzzy controller is proposed for this higher level control. It must be said that similar results could be obtained with an Affine Function in the higher level control as it is shown in [12].

The importance of the controllers performance of lower level should be noted in order to track the optimal DO value of the three aerated tanks, given for the higher level Fuzzy controller. To improve this DO set points tracking is the reason why MPCFF controllers are used instead of default PI controllers as it is shown in [12]. Due to the presence of strong disturbances in WWTPs, MPC has difficulties in keeping the controlled variables at their reference level. To compensate the disturbances, a feedforward control is added, as in [4], [5], [7], [6]. MPC provides options for the feedforward compensation of the measured disturbances, in the same way as for the reference signals. Different variables have been considered for the feedforward action in those works, but in our case the influent flow rate has been selected for its better results.

B. Control for NH_e violations removal

An Exponential Function and a Linear Function are proposed with the aim of eliminating NH_e violations by manipulating Q_{rin} based on NH5, Q_{in} and NH_{in}. Also $q_{EC_{4-5}}$ is added based on NH5, Q_{in} and NH_{in} during the rainfall or storm event, and based on $NH_{inmean,2}$ using an Affine Function for the days after rain or storm. NH_e violations removal is achieved for dry, rain and storm weather conditions.

The behavior of NH can be explained by the mass balance equation in the first reactor:

$$\begin{aligned} \frac{dNH1}{dt} &= \frac{1}{V1}(Q_{rin} \cdot NH_{rin} + Q_{rex} \cdot NH_{rex} + Q_{in} \cdot NH_{in} + \\ &\quad + r_{NH1} \cdot V1 - Q1 \cdot NH1) \qquad (7) \\ Q1 &= Q_{rin} + Q_{rex} + Q_{in} \end{aligned}$$

where NH_{rin} is NH in the internal recirculation, NH_{rex} is NH in the external recirculation, r_{NH1} is r_{NH} in the first tank and Q1 is the flow rate in the first tank.

When NH_{in} increases, Q_{rin} is incremented to reduce the rise of NH in the first tank (NH1), and when the increase of NH arrives to the fifth tank, Q_{rin} is reduced to increase the retention time and so to improve the nitrification process.

According to this Q_{rin} regulation, a combination of Exponential Function and Linear Function is applied for this control strategy. When there are peaks of $NH_{in} \cdot Q_{in}$ ($NH_{in} \cdot Q_{in} > 10^6$), the following Exponential Function is applied until NH5 is decreased (NH5<3.75 mg/l):

$$\mathrm{Q}_{rin} = \frac{a}{exp(\mathrm{NH5} \cdot b)} \qquad (8)$$

The rest of the time the following Linear Function is applied:

$$\mathrm{Q}_{rin} = \frac{\mathrm{NH}_{in}}{\mathrm{NH5}} \cdot c \qquad (9)$$

where a, b and c are constants used as tuning parameters.

However, for rain and storm events the reduction of NH_e using this control strategy is not enough to eliminate violations. This is due to that, during rain and storm periods, the $Q_{in} \cdot NH_{in}$ relationship is similar to that of dry weather, but Q_{in} increases and NH_{in} decreases. This NH_{in} reduction decreases the growth of $X_{B,A}$ and therefore the nitrification process (5) is worsened. For this reason $q_{EC_{4-5}}$ is added when there is a peak of $NH_{in} \cdot Q_{in}$ until NH5 is decreased and also when there is a rain or storm event. Normally, $q_{EC_{4-5}}$ is added to reduce NO, nevertheless in r_{NH} equation (1) it is observed that although the elimination of NH largely depends on nitrification (5), NH is also reduced with the growth of $X_{B,H}$ (3, 4). Thus adding $q_{EC_{4-5}}$, besides applying the Exponential Function, NH_e violation removal is achieved for rain and storm weathers.

The days after the rain and storm events present also problems with NH_e limits violations due to the fact that the $X_{B,A}$ population decreases during those periods and does not recover its normal level until some days later. During those days $q_{EC_{4-5}}$ is added. As $X_{B,A}$ reduction is due to a NH_{in} decrease, the addition of $q_{EC_{4-5}}$ is based on $NH_{inmean,2}$, using the following Affine Function:

$$q_{EC_{4-5}} = NH_{inmean,2} \cdot d + e; \qquad (10)$$

where d and e are constants used as tuning parameters.

III. Controllers tuning

In this section, the tuning parameters of the controllers applied for the proposed strategy are indicated. The controllers are: MPCFF of the low level control of the hierarchical structure, Fuzzy controller of the higher level of the hierarchical structure and Exponential, Linear and Affine Functions of the control for NH_e violations removal.

A. MPCFF: Lower level control of the hierarchical structure.

The MPC algorithm requires a state-space linear model to foresee how the plant outputs, $y(k)$, react to the possible variations of the control variables, $u(k)$, and to compute the control moves at each $\triangle t$. WWTPs are nonlinear systems, but their operation can be approximated in the vicinity of a working point by a discrete-time state-space model.

DO3, DO4 and DO5 values to get the linear models of the MPCFF controllers have been obtained by varying K_La3, K_La4 and K_La5 in a range of $\pm 10\%$ around 264.09 day^{-1}, 209.23 day^{-1} and 131.65 day^{-1} respectively and applying a step of $+10\%$ to Q_{in} (measured variable for the feedforward compensation).

The tuning parameters are: sampling time ($\triangle t$), control horizon (m), prediction horizon (p), the output weight (Γ_y), the input rate weight ($\Gamma_{\triangle u}$), and the overall estimator gain.

By trial error method, the following values have been selected to tune the MPCFF: m = 5, p = 20, $\triangle t$ = 0.00025 days (21.6 seconds), Γ_y = 1 and $\Gamma_{\triangle u}$ = 0.01 for DO3, DO4 and DO5 control and Γ_y = 1 and $\Gamma_{\triangle u}$ = 0.0001 for NO2 control and overall estimator gain = 0.8.

B. Fuzzy Controller: Higher level control of the hierarchical structure.

The typical architecture of a Fuzzy controller, consists of: a fuzzifier, a fuzzy rule base, an inference engine and a defuzzifier ([17]).

The implementation of the Fuzzy controller is based on the observation of the simulations results obtained by operating the plant with the default control of BSM1.

The input of the Fuzzy controller is NH5. Three triangular membership functions are applied to the input to fuzzify. The following Fuzzy sets have been used: *low*, *medium* and *high*. The minimum value of the input is 0.8 and the maximum value of the input is 3.

The output is the DO5 setpoint of the lower level control. Also three triangular membership functions have been applied to the output with the same Fuzzy sets: *low*, *medium* and *high*. The minimum value of the output is 0.1 and the maximum value of the output is 5.5.

The if-then Fuzzy rules that relate the input and output are:

if (NH5 is *low*) **then** (DO set point is *low*)
if (NH5 is *medium*) **then** (DO set point is *medium*)
if (NH5 is *high*) **then** (DO set point is *high*)

The DO set point of the output is the same for the three aerated tanks.

The Mamdani method ([18]) has been chosen to defuzzify the results of the if-then Fuzzy rules and thereby obtain a single value of the DO5 set point based on the value of NH5.

C. Exponential, Linear and Affine Functions: Control for NH_e violations removal.

For the control of NH_e violations removal, when there are peaks of $NH_{in} \cdot Q_{in}$ until NH5 is decreased, the Exponential Function (8) is applied. The rest of the time the Linear Function (9) is used. A trade-off analysis of OCI and percentage of operating time of N_{tot} in the effluent ($N_{tot,e}$) violation is made by varying the tuning parameters a and c of the Exponential and Linear Functions, reflecting only the results that avoid the NH_e violations. It is obtained an area where OCI and the operating time of $N_{tot,e}$ violation are decreased compared to default PI controllers (see Fig. 3). The value of b is fixed at 6, and a and c values are chosen according to the Nash Solution ([19]): a = $2.5 \cdot 10^{14}$ and c = $7 \cdot 10^{-4}$.

During a rain or storm event, when there is a peak of $NH_{in} \cdot Q_{in}$ until NH5 is decreased, a dosage of 5 m^3/d of $q_{EC_{4-5}}$ is added, which is the maximum limit value. For the days after a rain or storm event, the Affine Function (10) is applied. The tuning parameters d and e are defined by two experimental cases, which correspond to the extreme cases of highest and lowest dosage of $q_{EC_{4-5}}$ that is needed to eliminate violations of NH_e:

$$\begin{aligned} 0.25 &= 25.3 \cdot d + e \\ 3 &= 15 \cdot d + e \end{aligned} \tag{11}$$

Therefore, solving this system of equations, the d and e tuning parameters are -0.2667 and 7 respectively.

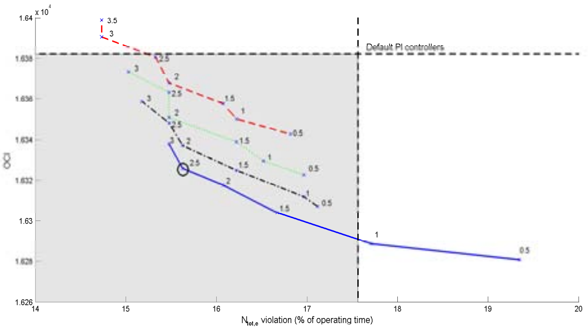

Fig. 3. Trade-off representation of OCI and the percentage of operating time of $N_{tot,e}$ violations for a range of a values from 0.5 to 4 with increments of 0.5 (points marked with crosses) and c values = 7 (solid line), 6 (dash-dotted line), 5.5 (dotted line), 5 (dashed line)

IV. SIMULATION RESULTS

In this section the control strategy proposed is tested and compared with the default control strategy of BSM1. Ideal sensors have been considered for the simulations. Three influent disturbances, representative of different weather conditions, have been defined in BSM1, [20], [21], and evaluated in this paper: dry weather, rain weather and storm weather. Each scenario contains 14 days of influent data with sampling intervals of 15 minutes. A simulation/experiment protocol is established to assure that results and performance data are collected under the same conditions and can be compared. First, a 150 days period of stabilization in a closed-loop using constant influent data with no noise on the measurements has to be completed to drive the system to a steady-state, next running a dynamic simulation by using the dry weather file (14 days) and finally testing the desired influent data (dry, rain or storm). A week is evaluated from day 7 to day 14. Analyses of time response of the controlled and manipulated variables are shown. The percentages of operating time of NH_e and $N_{tot,e}$ limits violations are indicated. Results of effluent quality and operational costs are measured with the Effluent Quality Index (EQI) and the Overall Cost Index (OCI) ([1], [2], [3]):

$$EQI = \frac{1}{1000 \cdot T} \int_{t=7days}^{t=14days} (2 \cdot TSS(t) + COD(t)$$

$$+30 \cdot NK_j(t) + 10 \cdot NO(t) + 2 \cdot BOD_5(t)) \cdot Q_e(t) \cdot dt \tag{12}$$

where T is the total time, TSS is the Total Suspended Solids, COD_t is the Total Chemichal Oxygen Demand, NKj is the Kjeldahl Nitrogen, BOD_5 is the Biological Oxygen Demand, and Q_e(t) is the effluent flow rate.

$$OCI = AE + PE + 5 \cdot SP + 3 \cdot EC + ME \tag{13}$$

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 and ME is the mixing energy.

Fig. 4, Fig. 5 and Fig. 6 show the time evolution of the controlled and manipulated variables of the proposed control strategy and its comparison with the default control strategy of BSM1.

As it can be observed, for the dry influent (see Fig. 4), two major changes have been introduced in comparison with the default control strategy of BSM1. First, DO5 setpoint is regulated by a Fuzzy controller based on NH5 instead of being kept at a fixed value of 2 mg/l. This regulation of the DO setpoint is also applied to the third and fourth tanks. After, Q_{rin} is manipulated based on NH5, NH_{in} and Q_{in} to improve the nitrification process, instead of aiming to control NO2. These changes result in a large reduction of NHe peaks and the elimination of NH_e limits violations. It is also worth to note the successful DO tracking achieved by MPCFF controllers.

In Fig. 5 and Fig. 6 the rain and storm events can be observed, in which there is a Q_{in} increase and a NH_{in}

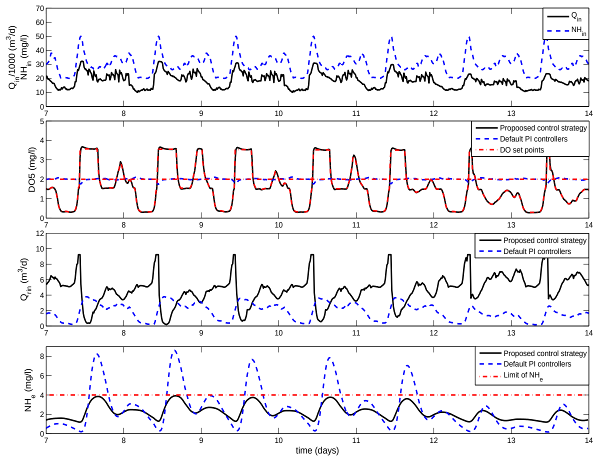

Fig. 4. Dry influent: time evolution of the most important variables with the proposed control strategy and with the default control strategy of BSM1.

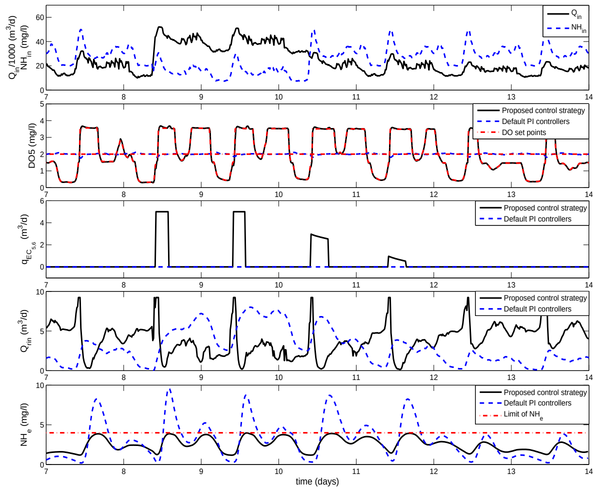

Fig. 5. Rain influent: time evolution of the most important variables with the proposed control strategy and with the default control strategy of BSM1.

reduction. The time evolution of the product of Q_{in} and NH_{in} remains the same as with dry influent, but the NH_{in} reduction does decrease the population of $X_{B,A}$. Due to this cause, $q_{EC_{4-5}}$ is added at its maximum value of $5m^3/d$ when a rain or storm event and an NH peak are matched. For the days after rain or storm events, the $q_{EC_{4-5}}$ value is regulated by the Affine Function based on $NH_{inmean,2}$, which determines the recovery of the $X_{B,A}$ population.

Table I shows the results of EQI, OCI and percentage of time over the limits of NH_e and $N_{tot,e}$, with dry, rain and storm influents.

The results for dry influent show an improvement in all the specified data compared to the default control strategy of BSM1. The elimination of NH_e violations is completely achieved with the proposed control strategy and, in addition, a reduction of EQI and the percentage of time of $N_{tot,e}$ violation is achieved by varying DO based on NH5 with the hierarchical control structure.

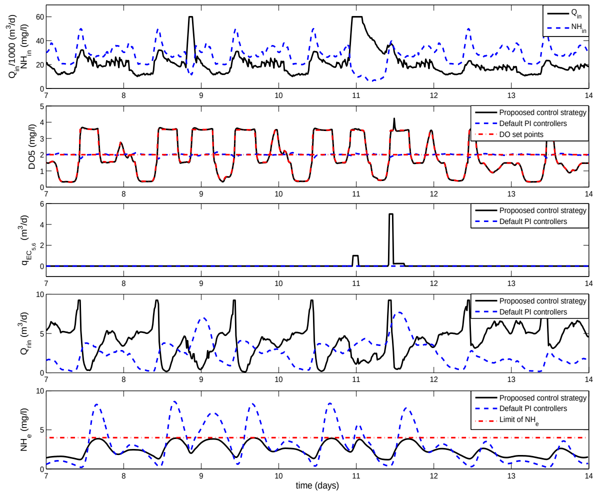

Fig. 6. Storm influent: time evolution of the most important variables with the proposed control strategy and with the default control strategy of BSM1.

For cases of rain and storm influents, there is an increase of costs due to the necessary addition of $q_{EC_{4-5}}$. OCI and percentage of operating time of $N_{tot,e}$ violation are influenced by $q_{EC_{4-5}}$ value and therefore by the intensity and the duration of the rainfall. For storm influent, the percentage of the cost increase is lower than in the case of rain influent because less $q_{EC_{4-5}}$ is needed for the NH_e removal. Furthermore, when there is rain or storm event, greater nitrification is performed by Q_{rin} manipulation, therefore increases NO and also $N_{tot,e}$. However, adding $q_{EC_{4-5}}$ also decreases the value of NO and thus $N_{tot,e}$. Therefore, as in the case of rain influent the dosage of $q_{EC_{4-5}}$ is greater, there is a reduction in the percentage of operating time of $N_{tot,e}$ violation, unlike what happens with the storm influent where a lower $q_{EC_{4-5}}$ addition is necessary.

V. CONCLUSIONS

In this paper, different control strategies based on MPC, Fuzzy controller and Exponential, Linear and Affine Functions have been used in a WWTP with the aim to eliminate NH_e violations, improving, at the same time, the results of OCI and EQI in comparison with the default control strategy of BSM1. They have been tested with dry, rain and storm weather conditions.

A two-level hierarchical control structure is implemented to perform an EQI and OCI improvement. The lower level of this hierarchical structure is composed by three MPCFF controllers that control DO3, DO4, DO5 by manipulating K_La3, K_La4, K_La5. In the higher level, a Fuzzy controller is implemented to manipulate DO set points of the lower level based on NH5 and NH_{in}.

The removal of NH_e violations is carried out by manipulating Q_{rin} according to NH5, NH_{in} and Q_{in}, by an Exponential Function when there are peaks of NH and a Linear Function

TABLE I

RESULTS WITH THE PROPOSED CONTROL STRATEGY AND WITH THE DEFAULT CONTROL STRATEGY OF BSM1

Dry influent			
	Default PI controllers	Control for NH_e violations removal	% of improvement
EQI (kg pollutants/d)	6115.63	5823.76	-4.77%
OCI	16381.93	16374.01	-0.048%
$N_{tot,e}$ violations (% of operating time)	17.56	15.48	-11.85%
NH_e violations (% of operating time)	17.26	0	-100%
Rain influent			
	Default PI controllers	Control for NH_e violations removal	% of improvement
EQI (kg pollutants/d)	8174.98	7799.91	-4.59%
OCI	15984.85	17643.79	+10.38%
$N_{tot,e}$ violations (% of operating time)	10.86	8.93	-17.77%
NH_e violations (% of operating time)	27.083	0	-100%
Storm influent			
	Default PI controllers	Control for NH_e violations removal	% of improvement
EQI (kg pollutants/d)	7211.48	6924.15	-3.98%
OCI	17253.75	17636.44	+2.2%
$N_{tot,e}$ violations (% of operating time)	15.03	20.23	+34.66%
NH_e violations (% of operating time)	26.79	0	-100%

the rest of the time. This control strategy is applied along with the hierarchical structure. During rain and storm events, the combination of the Exponential and Linear Functions is not sufficient to eliminate limit violations of NH_e, for this reason the addition of $q_{EC_{4-5}}$ to its maximum allowed value is required to reduce more the NH_e peaks and avoid violations of the effluent limits. The days after rain or storm periods, the addition of $q_{EC_{4-5}}$ is also necessary, due to the fact that the population of $X_{B,A}$ decreases during those events and some time is needed to its recovery. In this case, an Affine Function manipulates $q_{EC_{4-5}}$ based on $NH_{inmean,2}$.

The results show that with dry weather, it is possible to eliminate NH_e violations without increasing costs, to reduce simultaneously EQI and the percentage of time of $N_{tot,e}$ violation. However, with rain and storm influents, a costs increase is required in order to remove NH_e violations due to the necessary addition of $q_{EC_{4-5}}$.

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Process Based Control Architecture for avoiding effluent pollutants quality limits violations in wastewater treatment plants

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Abstract*—This paper presents a hierarchical control architecture for operation of biological wastewater treatment plants. The main goal of this control architecture is conceived being that of avoiding violations of effluent pollution limits while, at the same time, keeping reasonable values for effluent quality and operational costs. The Benchmark Simulation Model No.1 (BSM1) is used for evaluation. A hierarchical structure regulates the dissolved oxygen (DO) of the three aerated tanks based on the ammonium and ammonia nitrogen concentration (NH) in the fifth tank (NH5). The proposed architecture is a two layer cascaded control where the lower level deals with the goal of keeping the process variables to the desired set-points that are determined by the upper layer. The main contribution of the paper is to operate the upper layer under the idea of not keeping a fixed set-point but following simple rules dictated by the process reaction equations. While an MPC with feedforward compensation is used for the lower level, an affine function is selected for the higher level. To eliminate violations of total nitrogen in the effluent ($N_{tot,e}$), an affine function, implemented with a sliding window, adds external carbon flow rate in the first tank based on nitrate nitrogen in the fifth tank (NO5) plus NH5. To avoid violations of NH in the effluent (NH_e), a combination of a linear function and an exponential function that manipulates the internal recirculation flow rate based on NH5 and NH in the influent is proposed. As a result, $N_{tot,e}$ violations and NH_e violations are avoided.

I. INTRODUCTION

The growth of cities and industry during the last centuries brought in parallel an increase in water use for different human needs such as drinking, cleaning, washing and for the production of goods, therefore increasing the production of waterborne wastes. During several years those wastes have been discharged to the rivers and oceans without any further consideration, producing large damages in the ecosystems, affected still today. Also, overexploitation and contamination of underground water by human activities has resulted in the scarcity of this resource, with its functionality limited by the amount of contaminants present in it, with the increase of the diseases caused by consumption of contaminated water, affecting the life quality of the human beings themselves.

In Europe, the implementation of the Council Directive 91/271/EEC of 21 May 1991 concerning urban wastewater treatment, mandates new concepts in management and operation from the adaptation of existing plants, that lack robustness and flexibility, to adapt to the new requirements. In order to solve the main problems of wastewater management, researchers' efforts have been focused, during last years, in objectives such as to improve the water quality by also minimizing the operational costs in order to achieve sustainable treatments.

Automatic control has been used as a support to achieve the proposed objectives. In the literature there are several papers working on modelling of wastewater treatment plants (WWTPs) as (Rojas et al., 2011, 2012; Vrecko et al., 2003, 2006). In these works the evaluation and comparison of the different control strategies is based on Benchmark Simulation Model No.1 (BSM1), developed by the International Association on Water Pollution Research and Control (Alex et al. (1999, 2008); Copp (2002)). This benchmark defines a plant layout, influent loads, test procedures and evaluation criteria. On this respect, WWTP operation is usually conducted on the basis of the usual cost/performance tradeoff, measured in terms of the usual Operation Costs Index (OCI) and Effluent Quality Index (EQI). In fact this is the orientation of the usual WWTP control and operation studies, where effluent quality is one of the major concerns (Guerrero et al., 2011; Santin et al., 2015). Due to implementation of control the general performance of WWTPs has been improved, but the analysis from the environmental point of view will not be complete if the imposed pollutant limits are not taken into account.

There are several works in the literature that propose different methods for controlling WWTPs. Some of them apply a direct control of the effluent variables, mainly ammonium and ammonia nitrogen (NH) and total nitrogen (N_{tot}) Corriou and Pons (2004); Shen et al. (2008, 2009). The difficulty in this method is that the fixed values for the effluent variables are constraints and not set points. Other studies deal with the basic control strategy (Dissolved Oxygen (DO) of the aerated tanks and Nitrate Nitrogen (NO) of the last anoxic tank), but testing with different controllers such as Model Predictive Controller (MPC) and fuzzy controller Cristea et al. (2008); Holenda et al. (2008); Belchior et al. (2012); Han et al. (2014). These methods provide an acceptable balance between quality and costs.

Unlike the referred articles, the present work deals with the avoidance of N_{tot} in the effluent ($N_{tot,e}$) and NH in the effluent (NH_e) violations but without forgetting about the effluent quality and operational costs. The proposed control strategies are based on improving the nitrification process by oxidizing

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the aerated tanks (Liu et al. (2013)) and by manipulating the internal recirculating flow rate (Q_{rin}) (Zhou et al. (2013)), and on improving the denitrification process by adding external carbon flow rate (q_{EC}) (Ruhl et al. (2014)). Other important innovation is the introduction of a sliding window to dosage the minimum q_{EC} in the first tank (q_{EC1}) necessary for the N_{tot} violations removal in order to minimize operational costs. A hierarchical control structure is implemented for this purpose. The lower level is composed by three MPC controllers with feedforward compensation of the influent flow rate (MPC + FF) (Ferramosca et al. (2013)), to control NO2, DO in the third tank (DO3), DO in the fourth tank (DO4) and DO in the fifth tank (DO5). Afterwards higher level is described next. One contribution of this work is not just to propose the controller upper-layer to monitor pollutants limit violation in the effluent but to determine the rationale of such upper-layer on the basis of the process reactions, which describe the biological phenomena that takes place into the reactors.

The higher level adjusts the DO set-points according to NH in the fifth tank (NH5), and an affine function is proposed for this level. Next, two controls are added in order to eliminate effluent violations. NH_e and $N_{tot,e}$ are the pollutants that present more difficulties for being kept under the established limits. For reducing peaks of $N_{tot,e}$, q_{EC1} is added based on NO in the fifth tank (NO5) plus NH5. An Affine function is proposed for this control, with a sliding window for its implementation. And for reducing peaks of NH_e, Q_{rin} is manipulated based on NH5, and the control of NO2 is removed. A combination of linear function and exponential function is proposed for this control.

II. Benchmark Simulation Model #1

This section provides a brief description of the working scenario provided by the BSM1. This is a simulation environment defining a plant layout, a simulation model, influent loads, test procedures and evaluation criteria.

A. Plant layout and Influent loads

The schematic representation of the WWTP is presented in Fig.1. The plant consists in five biological reactor tanks connected in series, followed by a secondary settler. The first two tanks have a volume of 1000 m^3 each and are anoxic and perfectly mixed. The rest three tanks have a volume of 1333 m^3 each and are aerated. The settler has a total volume of 6000 m^3 and is modeled in ten layers, being the 6th layer, counting from bottom to top, the feed layer. Two recycle flows, the first from the last tank and the second from the underflow of the settler, complete the system. The plant is designed for an average influent dry-weather flow rate of 18446 m^3/d and an average biodegradable chemical oxygen demand (COD) in the influent of 300 g/m^3. Its hydraulic retention time, based on the average dry weather flow rate and the total tank and settler volume (12000 m^3), is 14.4 h. The default wastage flow rate (Q_w) is fixed to 385 m^3/d that determines, based on the total amount of biomass present in the system, a biomass sludge age of about 9 days. The nitrogen removal is achieved using a denitrification step performed in the anoxic tanks and a nitrification step carried out in the aerated tanks. The internal recycle is used to supply the denitrification step with NO.

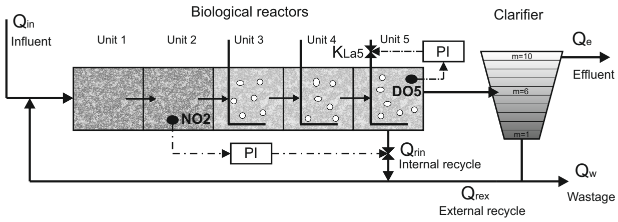

Fig. 1. Benchmark Simulation Model 1

BSM1 defines three different influent data Copp (1999); Vanhooren and Nguyen (1996): dry weather, rain weather and storm weather. Each scenario contains 14 days of influent data with sampling intervals of 15 minutes.

B. Test procedures

A simulation protocol is established to assure that results are got under the same conditions and can be compared. So first a 150 days period of stabilization in closed-loop using constant influent data has to be completed to drive the system to a steady-state, next a simulation with dry weather is run and finally the desired influent data (dry, rain or storm) is tested. Only the results of the last seven days are considered.

C. Evaluation criteria

In order to compare the different control strategies, different criteria are defined.

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. It is assessed by Integral of the Squared Error (ISE) criterion. The second level provides measures for the effect of the control strategy on plant performance. It includes Effluent Quality Index (EQI) and Overall Cost Index (OCI).

The evaluation must include the percentage of time that the effluent limits are not met and the number of violations. This last term is defined as the number of crossings of the limit, from below to above the limit.

1) Effluent limits: The effluent concentrations of N_{tot}, Total COD (COD_t), NH, Total Suspended Solids (TSS) and Biological Oxygen Demand (BOD_5) should obey the limits given in Table I.

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

TABLE I. Effluent quality limits

N_{tot} is calculated as the sum of NO and Kjeldahl nitrogen (NKj), being this the sum of organic nitrogen and NH.

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2) Effluent Quality Index: EQI is defined to evaluate the quality of the effluent. It is related with the fines to be paid due to the discharge of pollution. EQI is averaged over a 7 days observation period and it is calculated weighting the different compounds of the effluent loads.

$$EQI = \frac{1}{1000 \cdot T} \int_{t=7days}^{t=14days} (B_{TSS} \cdot TSS(t) + B_{COD} \cdot COD(t) +$$

$$B_{NKj} \cdot NK_j(t) + B_{NO} \cdot NO(t) + B_{BOD_5} \cdot BOD_5(t)) \cdot Q(t) \cdot dt \quad (1)$$

where B_i are weighting factors (Table II) and T is the total time.

Factor	B_{TSS}	B_{COD}	B_{NKj}	B_{NO}	B_{BOD_5}
Value (g pollution unit g^{-1})	2	1	30	10	2

TABLE II. B_i VALUES

3) Overall Cost Index: OCI is defined as:

$$OCI = AE + PE + 5 \cdot SP + 3 \cdot EC + ME \quad (2)$$

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 and ME is the mixing energy.

AE is calculated according to the following relation:

$$AE = \frac{S_o^{sat}}{T \cdot 1.8 \cdot 1000} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} V_i \cdot K_L a_i(t) \cdot dt \quad (3)$$

where V_i is the volume of the tank i and $K_L a_i$ is the oxygen transfer coefficient in tank i.

PE is calculated as:

$$PE = \frac{1}{T} \int_{7days}^{14days} (0.004 \cdot Q_{in}(t) + 0.008 \cdot Q_{rin}(t) + 0.05 \cdot Q_w(t)) \cdot dt \quad (4)$$

where Q_{in} is the influent flow rate. SP is calculated from the TSS in the flow wastage (TSS_w) and the solids accumulated in the system:

$$SP = \frac{1}{T} \cdot (TSS_a(14days) + TSS_s(14days) - TSS_a(7days)$$

$$-TSS_s(7days) + \int_{t=7days}^{t=14days} TSS_w \cdot Q_w \cdot dt) \quad (5)$$

where TSS_a is the amount of solids in the reactors and TSS_s is the amount of solids in the settler.

EC refers to the carbon that could be added to improve denitrification.

$$EC = \frac{COD_{EC}}{T \cdot 1000} \int_{t=7days}^{t=14days} \left(\sum_{i=1}^{i=n} q_{EC,i} \right) \cdot dt \quad (6)$$

where $q_{EC,i}$ is q_{EC} added to compartment i, COD_{EC} = 400 $gCOD.m^{-3}$ is the concentration of readily biodegradable substrate in the external carbon source.

ME is the energy employed to mix the anoxic tanks to avoid settling and it is a function of the compartment volume:

$$ME = \frac{24}{T} \int_{t=7days}^{t=14days} \sum_{i=1}^{5} \left[0.005 \cdot V_i \; if \; K_L a_i(t) < 20 d^{-1} \; otherwise \; 0 \right] \cdot dt \quad (7)$$

III. PROCESS MODEL BASED CONTROL ARCHITECTURE

As mentioned in the introduction, one of the main concerns of wastewater plant operation is that of dealing with effluent limit violations. This is the goal kept in mind when conceiving the control architecture that will be used. One of the constants that are observed in the WWTP control literature is that of presenting alternative control loops (being operated by, probably, different control techniques such as PI/PID, MPC, Fuzzy, etc) with the main goal of keeping some effluent concentrations of interest at some prescribed values. Also with some concentrations in, for example, the second (anoxic) or fifth (aerated) reactor tanks. It should be noted here that the constraint imposed by the effluent limits is a kind of inequality constraint. What it matters is not to croose over the specified value and not to keep the effluent concentrations at fixed values. On the other hand, by attempting to keep the concentrations at some prescribed levels there is the chance to make the system operate in order to produce higher effluent levels than it will do because of the influent concentration levels. This is one of the more severe drawbacks of maintaining, for example, ammonia in the last aerated tank at a concentration of 4 g $N.m^{-3}$. If the actual levels are, for example, around 3 g $N.m^{-3}$, the plant operation will try to push the ammonia to higher levels. Therefore generating higher effluent contamination.

In this work, we propose to use a predictive control for the control at the lower level: to control the DO at the three aerated tanks and the NO2. A higher level is now defined in order to determine the appropriate set-points for these base-layer loops with the purpose of avoiding effluent limits violation. The predictive control layer will not be described here as it is along the lines of Santín et al. (2015) and Santín et al. (2014). Whereas in Santín et al. (2015) a Fuzzy control approach is proposed for dealing with effluent limit violations, here we analyze the main process reactions described by the process model and it is on that basis that we define and configure the upper control layer. With the goal of avoiding $N_{tot,e}$ violations, an affine function that manipulates q_{EC1} based on NO5 plus NH5 is added. A sliding window is also implemented with the goal of adding the minimum q_{EC} necessary to avoid $N_{tot,e}$ violations. In order to avoid the limit violations of NH_e, a controller that regulates Q_{rin} based on NH5 and NH_{in} is proposed, and NO2 control is eliminated. For this control, a combination of an affine function and a exponential function is used. These control strategies for removing violations of the effluent pollution are implemented keeping the hierarchical control structure, because the goal includes also the reduction of EQI and OCI.

A. *Process model motivation*

The biological phenomena of the reactors are simulated by the Activated Sludge Model no. 1 (ASM1) Henze et al. (1987) that considers eight different biological processes. The vertical transfers between layers in the settler are simulated by the double-exponential settling velocity model Tackacs et al. (1991). None biological reaction is considered in the settler. The two models are internationally accepted and include thirteen state variables. The proposed control strategies in this work are based on the conversion rates of NH (r_{NH}) and NO (r_{NO}). The referred processes are as follows:

$$r_{NH} = -0.08\rho_1 - 0.08\rho_2 - \left(0.08 + \frac{1}{0.24}\right)\rho_3 + \rho_6 \quad (8)$$

$$r_{NO} = -0.1722\rho_2 + 4.1667\rho_3 \quad (9)$$

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:

$$\rho_1 = 4\left(\frac{S}{10+S}\right)\left(\frac{DO}{0.2+DO}\right)X_{B,H} \quad (10)$$

$$\rho_2 = 4\left(\frac{S}{10+S}\right)\left(\frac{0.2}{0.2+DO}\right)\left(\frac{NO}{0.5+NO}\right)0.8\cdot X_{B,H} \quad (11)$$

$$\rho_3 = 0.5\left(\frac{NH}{1+NH}\right)\left(\frac{DO}{0.4+DO}\right)X_{B,A} \quad (12)$$

$$\rho_6 = 0.05\cdot ND\cdot X_{B,H} \quad (13)$$

where S is the readily biodegradable substrate, ND the soluble biodegradable organic nitrogen, $X_{B,H}$ the active heterotrophic biomass and $X_{B,A}$ the active autotrophic biomass. The biological parameter values used in the BSM1 correspond approximately to a temperature of 15 ^{o}C.

The values of NH and NO depend largely on their reaction rate, which is the result of several processes (8),(9),(10),(11),(12),(13) given by ASM1, which describes the biological phenomena that take place in the reactors. When NH increases, more DO is needed for nitrification.

B. *$N_{tot,e}$ violations removal*

For removing $N_{tot,e}$ violations, q_{EC1} is manipulated based on NH5 plus NO5. The variables with the highest influence in N_{tot} are NO and NH. Further efforts to reduce more NH increasing nitrification results also in an increment of NO and consequently $N_{tot,e}$ is not decreased. According to the biological processes of ASM1 (13, 15), an increase of substrate produces a growth of $X_{B,H}$ and therefore the denitrification process and the consequently reduction of NO are improved. Therefore, $N_{tot,e}$ is reduced with the dosage of EC in the first tank (EC1). However dosing EC1 results in an increase of operational costs (2), so it is important to dosage EC1 only when a violation of $N_{tot,e}$ could take place. Consequently, the control strategy is based on the manipulation of q_{EC1} according to NH5 plus NO5.

Due the large disturbances, it is not possible to maintain NH5 at a fixed reference value by manipulating DO set points of the lower level controllers. For this reason, the controller proposed for the higher level is a simple affine function, that varies DO3, DO4 and DO5 set points based on NH5, but without keeping NH5 at a reference level. The following affine function is proposed:

$$DO5_{set\,point}(t) = NH5(t) - k \quad (14)$$

where k is a constant that is used as a tuning parameter. Also a constraint for the maximum DO3, DO4 and DO5 values has been considered. The values of k and DO3, DO4 and DO5 maximum values are determined by an OCI and EQI trade-off analysis.

On the other hand, NH and NO are the pollutants present in N_{tot} that contribute with more weight. For this reason, in order to eliminate violations of $N_{tot,e}$, q_{EC1} is added based on NO5 plus NH5 (see Fig. 2). The following affine function is proposed for this control:

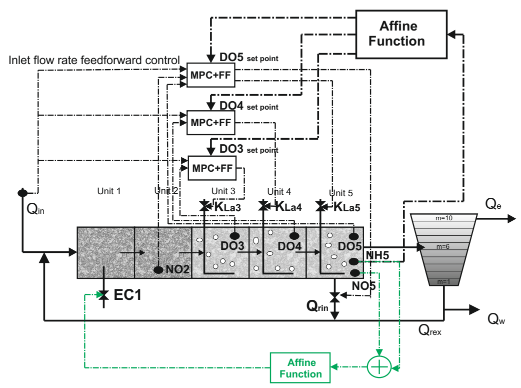

Fig. 2. BSM1 with a control strategy for $N_{tot,e}$ removal

$$q_{EC1} = ((NH5 + NO5) - a)\cdot b \quad (15)$$

where a and b are used as tuning parameters whose values are set depending on the maximum value of $N_{tot,e}$ given by a sliding window, which is shift at each sample time and presents only the values measured the day one week before. Specifically, following are shown the chosen equations for a and b values:

$$b = M_d\cdot 2 - 35.5 \quad (16)$$

$$a = 34.25 - M_d \quad (17)$$

where M_d is the maximum value of the day, one week before. This approach tries to dosage the minimum of q_{EC1} to remove $N_{tot,e}$ violations. The maximum q_{EC1} value was limited to $5m^3/d$.

C. *NH_e violations removal*

For removing NH_e violations, Q_{rin} is manipulated based on NH5 and NH in the influent (NH_{in}). The mass balance that matters in this case reads as:

$$\begin{aligned}\frac{dNH1}{dt} &= \frac{1}{V1}(Q_{rin} \cdot NH_{rin} + Q_{rex} \cdot NH_{rex} + Q_{in} \cdot NH_{in} + \\ &+ r_{NH1} \cdot V1 - Q1 \cdot NH1) \qquad (18)\\ Q1 &= Q_{rin} + Q_{rex} + Q_{in}\end{aligned}$$

where NH_{rin} is NH in the internal recirculation, NH_{rex} is NH in the external recirculation, r_{NH1} is r_{NH} in the first tank and Q1 is the flow rate in the first tank. According to the mass balance equation in the first reactor (18), when NH_{in} increases, Q_{rin} is incremented to reduce the rise of NH in the first tank (NH1), and when the increase of NH arrives to the fifth tank, Q_{rin} is reduced to increase the retention time and so to improve de nitrification process.

With the goal of removing NH violations, Q_{rin} is manipulated based on NH5 and NH_{in}. Therefore, the MPC of the lower level that controls DO5 and NO2 by manipulating K_La in the fifth tank (K_La5) and Q_{rin} is replaced by a MPC with one input (DO5) and one output (K_La5) (see Fig. 3).

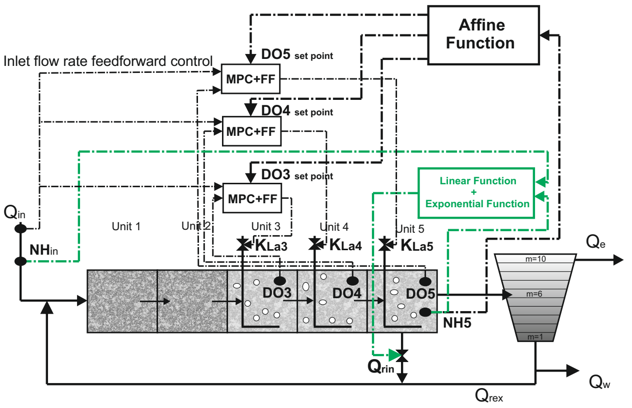

Fig. 3. BSM1 with a control strategy for NH_e removal

The NH5 controller is designed to act in two different ways, depending on NH peaks. When the peaks are present in the influent, it is convenient to increase Q_{rin} for diluting them, and when the peaks are already in the aerated tanks, it is convenient to reduce Q_{rin} for increasing the retention time.

A combination of exponential function and linear function is proposed for this control strategy. When there are peaks of NH_{in} or NH5, the following exponential function is applied:

$$Q_{rin} = \frac{c}{exp(\text{NH5} \cdot d)} \qquad (19)$$

Otherwise the following linear function is applied:

$$Q_{rin} = \frac{\text{NH}_{in}}{\text{NH5}} \cdot e \qquad (20)$$

where c, d and e are used as tuning parameters, whose values are determined by a trade-off analysis of OCI and percentage of operating time of $N_{tot,e}$ violation, reflecting only the results that avoid NH_e violations.

IV. Simulation Results

In this section the control configurations proposed in the above section are tested and compared. Ideal sensors have been considered for the simulations. Dry influent has been applied to evaluate the proposed control strategies.

A. $N_{tot,e}$ violations removal

The control strategy to remove $N_{tot,e}$ violations also takes into account not to worsen the percentage of NH_e above the limits, not to increase operational costs and to improve EQI in comparison with the default control strategy of BSM1. To get this, a trade-off analysis has also been conducted considering the percentage of operating time that NH_e and $N_{tot,e}$ is over the limits. This is done with hierarchical control strategy and without adding q_{EC1}. Tuning parameters are chosen for the point where the percentage of operating time of NH_e over the limits is the same as with the default control strategy (17.26%). The tuning parameters of the higher level affine function are k = 1.07 and DO maximum = 3, and the percentage of operating time of $N_{tot,e}$ violation with these parameters is 6.35%. With these parameters selected for the higher level, the affine function (15) is added to manipulate q_{EC1}. The solid lines of Fig. 4 correspond to the evolution of q_{EC1}, $N_{tot,e}$ and NH_e from day 7 to 14. It is observed that $N_{tot,e}$ violations are removed. As it is shown, q_{EC1} dosage varies every day, while $N_{tot,e}$ peaks are very similar. It proves that the minimum necessary q_{EC1} is added. It is due to the fact that the affine function for $N_{tot,e}$ violations removal is based on the M_d given by the sliding window. For this reason and with the correct selection of the tuning parameters of the higher level affine function by the trade-off analysis shown in Fig. 7, the removal of $N_{tot,e}$ violations without increasing OCI is possible. The choice of the right tuning parameters of the higher level affine function also makes possible to reduce the time of NH_e violation.

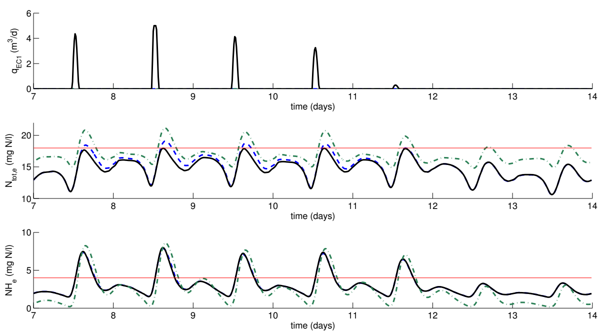

Fig. 4. q_{EC1}, NH_e and $N_{tot,e}$ evolution form day 7 to day 14 with default PI controllers (dash-doted line), with hierarchical control without adding q_{EC1} (dashed line) and with hierarchical control adding q_{EC1} (solid line)

Table III presents the results for EQI and OCI as well as the percentage of operating time out of the limits of $N_{tot,e}$ and NH_e obtained with the hierarchical control adding q_{EC1} and compared to the default control strategy of BSM1. It is shown that by adding q_{EC1} and applying a hierarchical control of DO in the three aerated tanks, the violations of $N_{tot,e}$ can be avoided. Moreover, the results of EQI and OCI as well as the

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operating time percentage of NH_e violations are also improved in comparison with the default PI controllers. This is achieved for the three influents provided by the BSM1 scenario. During a rain or storm event, Q_{in} increases and NH_{in} decreases. The Q_{in} increment has the effect of reducing the hydraulic retention time and the NH_{in} reduction decreases the growth of $X_{B,A}$ and therefore the nitrification process (12) is worsened. Due to this this reason, there is an increase of NH without incrementing the generation of NO (9 and 12). Therefore, the resulting $N_{tot,e}$ is lower than for dry weather. In the periods after the rain or storm events, the Q_{in} reduction has an immediate effect on the hydraulic retention time, but $X_{B,H}$ and $X_{B,A}$ need more time to recover their normal levels and it causes a small $N_{tot,e}$ increase. To compensate this, q_{EC1} is incremented. Even so, OCI is reduced for the three influents with the proposed control strategy. Nonetheless, it has to be said that that the reduction of costs would be greater if the savings obtained by avoiding effluent violations were considered.

Dry influent			
	Default PI controllers	Control for NH_e violations removal	% of reduction
EQI (kg pollutants/d)	6115.63	5910.83	3.3%
OCI	16381.93	16242.97	0.8%
$N_{tot,e}$ violations (% of operating time)	17.56	0	100%
NH_e violations (% of operating time)	17.26	16.81	2.6%

TABLE III. RESULTS WITH DEFAULT PI CONTROLLERS AND WITH CONTROL FOR $N_{tot,e}$ VIOLATIONS REMOVAL FOR DRY INFLUENT

B. NH_e violations removal

For the higher level affine function (14), in this case the chosen parameters are: k = 0.1 and DO maximum = 4.5. For the control of NH_e violations removal, when there are peaks of NH_{in} or NH5, the exponential function (19) is applied. The rest of the time the linear function (20) is used. A trade-off analysis of OCI and percentage of operating time of $N_{tot,e}$ violation is also conducted here by varying the tuning parameters c and e of the Exponential and Linear Functions, reflecting only the results that avoid the NH_e violations. The value of d is fixed at 6, and c and e values are chosen as: $c = 2.5 \cdot 10^{14}$ and $e = 7 \cdot 10^{-4}$. Q_{rin}, $N_{tot,e}$ and NH_e evolutions from day 7 to 14 are shown in Fig. 5. The results with default PI controllers are also shown. It can be observed that, with this control strategy, NH_e peaks are reduced under the limits established. This fact is due to the increment of DO by the hierarchical control (explained in the previous section) and mainly to the Q_{rin} manipulation. As shown in Fig. 10, Q_{rin} evolution is very different from the one obtained with the default control strategy. When a NH_{in} peak is detected, Q_{rin} is increased to its maximum allowed value (92280 m^3/d) in order to dilute NH, and when this increase of NH arrives to the fifth tank, the exponential function rapidly reduces Q_{rin} in order to decrease also the hydraulic retention time and so to improve the nitrification process. As a result, a large decrease of NH_e peaks is achieved and limits violations are avoided. The correct choice of the tuning parameters of the higher level affine function results also in obtaining a decrease in OCI and time of $N_{tot,e}$ violation.

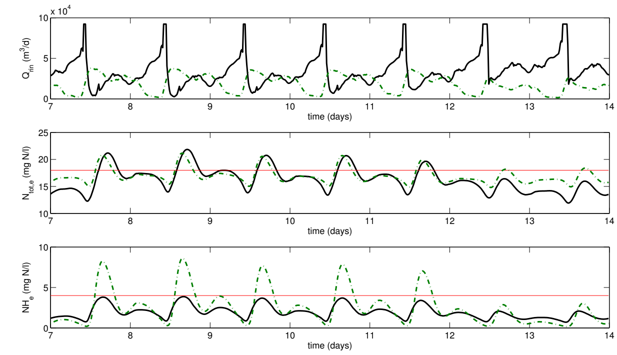

Fig. 5. Q_{rin}, NH_e and $N_{tot,e}$ evolution from day 7 to day 14 with default PI controllers (dash-doted line) and with the control for NH_e violations removal (solid line)

Table IV shows the results of EQI, OCI and percentage of time over the limits of NH_e and $N_{tot,e}$ for the three weather conditions. It can be seen that with the regulation of Q_{rin} based on NH5 and NH_{in} applying alternatively an exponential function and a linear function, and also with the hierarchical control of DO in the three aerated tanks, it is possible to avoid NH_e violations. In addition, an improvement of 5.5% of EQI and 0.6% of OCI in comparison with the default control strategy of BSM1 is achieved for dry influent. However, for rain and storm events an increase of costs is required. This is due to the fact that, during rain and storm periods, the nitrification process (12) is worsened as explained in the previous section. For this reason, extra addition of q_{EC} is needed when there is a rain or storm event, generating an increase of costs. Normally, q_{EC} is added to reduce NO. Nevertheless, in r_{NH} equation (8) it is observed that although the elimination of NH largely depends on nitrification (12), NH is also reduced with the growth of $X_{B,H}$ (10 and 11). Thus adding q_{EC}, besides applying the exponential function, NH_e violation removal is achieved for rain and storm scenarios. It should be noted that costs saved due to avoid violations are not reflected in the OCI equation and therefore the cost comparison is not completely fair.

Dry influent			
	Default PI controllers	Control for NH_e violations removal	% of reduction
EQI (kg pollutants/d)	6115.63	5760.95	5.8%
OCI	16381.93	16323.48	0.4%
$N_{tot,e}$ violations (% of operating time)	17.56	15.62	11.04%
NH_e violations (% of operating time)	17.26	0	100%

TABLE IV. RESULTS WITH DEFAULT PI CONTROLLERS AND WITH CONTROL FOR NH_e VIOLATIONS REMOVAL FOR DRY, RAIN AND STORM INFLUENTS

C. $N_{tot,e}$ and NH_e violations removal

Finally, both control strategies for $N_{tot,e}$ and NH_e violations removal have been tested together. Table V shows the results obtained by applying the control strategies to eliminate both $N_{tot,e}$ and NH violations for the three weather conditions. As it can be observed, the $N_{tot,e}$ and NH violations removal is possible for dry, rain and storm weather conditions. However, removing the two pollutants simultaneously gives rise to an increase of OCI. It is due to the fact that the reduction of NH peaks by the exponential function is based on an improvement in the nitrification process, what causes a great generation of NO (9 and 12) and also a $N_{tot,e}$ increase. To counteract it, the dosage of q_{EC} is increased, and q_{EC} in the second tank ($q_{EC,2}$) is also added, as shown in Fig. 6. This q_{EC} increase results in the total elimination of $N_{tot,e}$ and NH violations and an EQI reduction, but also in an OCI increase. However, as explained in the previous section, the OCI equation does not take into account the reduction of costs of avoiding violations and thus, the cost comparison is not completely fair.

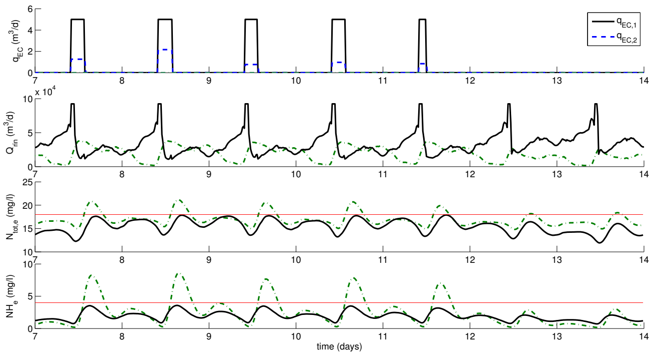

Fig. 6. q_{EC}, Q_{rin}, NH_e and $N_{tot,e}$ evolution form day 7 to day 14 with default PI controllers (dash-doted line) and with the control strategies for NH_e and $N_{tot,e}$ violations removal (solid line)

Dry influent			
	Default PI controllers	Control for NH_e violations removal	% of reduction
EQI (kg pollutants/d)	6115.63	5624.41	8.03%
OCI	16381.93	17494.44	-6.8%
$N_{tot,e}$ violations (% of operating time)	17.56	0	100%
NH_e violations (% of operating time)	17.26	0	100%

TABLE V. RESULTS WITH DEFAULT PI CONTROLLERS AND WITH CONTROL STRATEGIES FOR $N_{tot,e}$ AND NH_e VIOLATIONS REMOVAL FOR DRY INFLUENT.

V. CONCLUSIONS

In this paper different control strategies have been tested in a biological wastewater treatment process with the aim of avoiding effluent violations. The improvement of the denitrification process, by adding q_{EC1}, achieves the complete elimination of $N_{tot,e}$ violations. The implemented affine function with a sliding window allows to dosage the minimum q_{EC1} necessary for this aim. Finally, the improvement of the nitrification process by manipulating Q_{rin} with the combination of a linear function and an exponential function makes possible the NH_e violations removal.

Simulation results show that $N_{tot,e}$ and NH_e violations are removed for the dry influent case. In the cases of $N_{tot,e}$ violations removal for the three weather conditions and NH_e violations removal for dry weather, a simultaneous reduction of EQI and OCI is achieved in comparison with the default control strategy. The NH_e violations removal for rain and storm influents is considered as a natural extension of the results presented here.

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Artificial Neural Network for Nitrogen and Ammonia effluent limit violations risk detection in Wastewater Treatment Plants

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***Abstract*—One of the major concerns in Wastewater Treatment Plant (WWTP) operation is that of satisfying the legal requirements that impose maximum allowable concentration levels for effluent pollutants. Not meeting these requirements may generate economic punishment in terms of fines in addition, of course, to the environmental consequences. The effluent limit violations is usually measured as a side performance measure to existing WWTP control and operation approaches. However no explicit way of tackling this issue is found. In this paper a first step towards this direction is proposed in terms of a prognostication of the situations of risk. This is to say when the effluent is close to generate a limit violation for some of the limiting components. This is accomplished by means of effluent pollutants concentration prediction by using Artificial Neural Networks (ANN). The prediction is applied to a controlled plant and it is shown how a logical signal (therefore amenable for monitoring and decision) can be generated at the instants where such a risk is detected.**

I. 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 (among others, the European Directive 91/271 Urban wastewater established by the European Union). 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 Alex et al. (2008). This benchmark was extended in a new version, Benchmark Simulation Model No.2 (BSM2), in (Jeppsson et al. (2007)) which was updated in Nopens et al. (2010). 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 (Vilanova and Visioli (2012)). 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 ($S_{N_{tot}}$) (Corriou and Pons (2004); Shen et al. (2008, 2009)). 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 ($S_{NO,2}$)) (Cristea et al. (2008); Holenda et al. (2008); Belchior et al. (2011)), 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 (Vrecko et al. (2006); Stare et al. (2007); Ostace et al. (2010, 2011); Vilanova et al. (2011); Santín et al. (2014)) or S_O in other tanks (Ekman et al. (2006)).

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 manipulating the wastage flow rate (Q_w) (Flores-Alsina et al. (2010); Benedetti et al. (2009); Flores-Alsina et al. (2011); Kim and Yoo (2014)). 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. It 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 Santín et al. (2015).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.

The paper is organized as follows: In the following section the BSM2 working scenario is presented. Next, Artificial Neural Networks (ANN) as used tool for prediction are presented followed, in the fourth section, by the control plant scenario that will be used to train the ANN. Fifth section present the effluent violation risk detection showing the prediction ANN are capable of doing. Next section show simulation results where limit violations are detected therefore showing the usefulness of the method. Finally, the most important conclusions are drawn.

II. Benchmark Simulation Model No. 2

The simulation and evaluation of the proposed control strategy is carried out with BSM2 (Jeppsson et al. (2007)) which was updated by Nopens et al. (2010).

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.

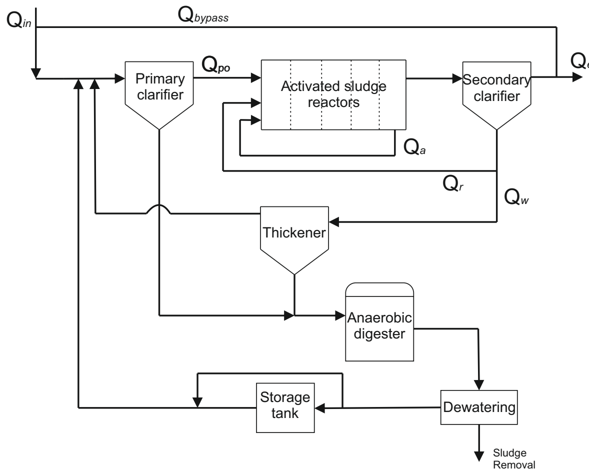


Fig. 1. BSM2 plant with notation used for flow rates

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.

A. *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) Henze et al. (1987) 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:

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

$$r_{NO} = -0.1722\rho_2 + 4.1667\rho_3 \quad (2)$$

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:

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

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

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

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

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

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}

B. 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 I. $S_{N_{tot}}$ is calculated as the sum of S_{NO} and Kjeldahl nitrogen (S_{NKj}), being this the sum of organic nitrogen and S_{NH}.

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 I. EFFLUENT QUALITY LIMITS

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.

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

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

where B_i are weighting factors (Table II) and T is the total time.

Factor	B_{TSS}	B_{COD}	B_{NKj}	B_{NO}	B_{BOD_5}
Value(g pollution unit g^{-1})	2	1	30	10	2

TABLE II. B_i VALUES

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.

III. 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 Santín et al. (2015) 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 set-point. 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

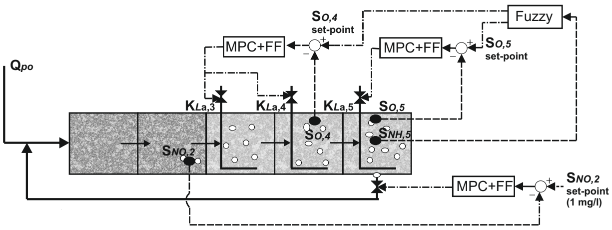


Fig. 2. BSM2 Hierarchical control for ANN training and risk prediction

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 .

IV. ARTIFICIAL NEURAL NETWORK

ANNs are inspired by the structure and function of nervous systems, where the neuron is the fundamental element (Yegnanarayana (2009)). 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 (Wang and Adeli (2015); Przystalka and Moczulski (2015)). 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.

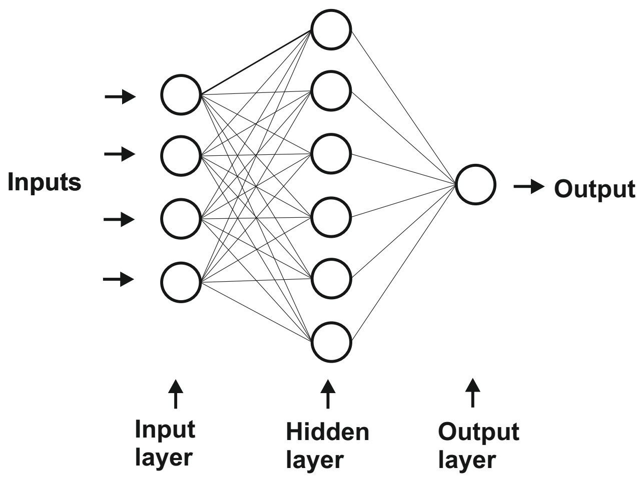


Fig. 3. Structure of Artificial Neural Network layers

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 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 (Karunanithi et al. (1994)).

V. 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 necessary 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.

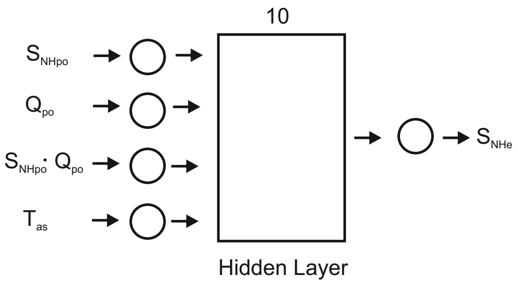
Therefore, the inputs of ANNs have been determined according to the mass balance equations (10 and 11) explained in Section II-A. The variables used to perform the prediction for both ANNs are Q_{po}, Z_{po} and T_{as}. The variable Q_a has also been used as an input for the ANN that predicts $S_{N_{tot},e}$, 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.

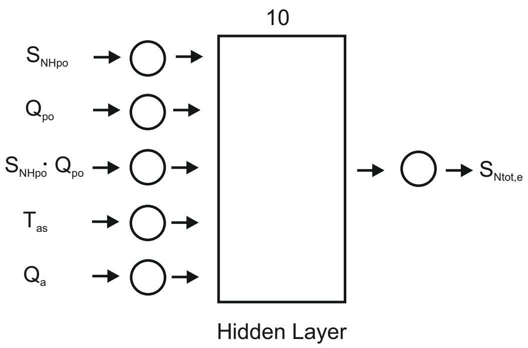
Finally, due to the mentioned reasons, the inputs for the ANNs are:

- 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



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



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

Fig. 4. Structures of the proposed ANNs

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. 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

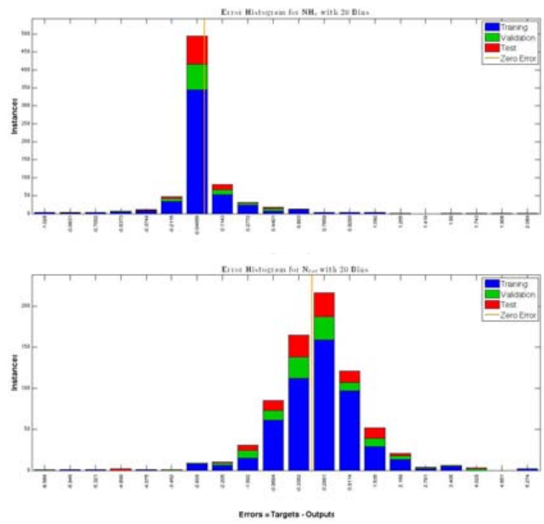


Fig. 5. ANN training error histograms.

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.

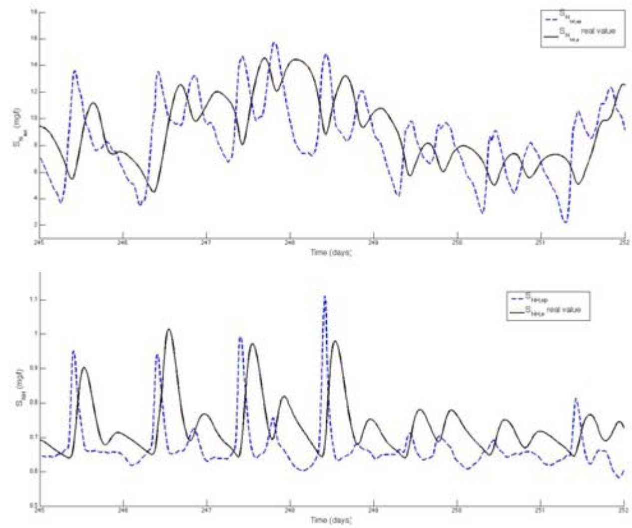


Fig. 6. ANN Effluent prediction for $S_{NH,e}$ and $S_{N_{tot,e}}$

VI. 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 7 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 stintuitions are detected. Therefore it is on such time instants where supplementary control actions will be needed.

In order to better show how risk detection works, figures 8 and 9 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 9, 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.

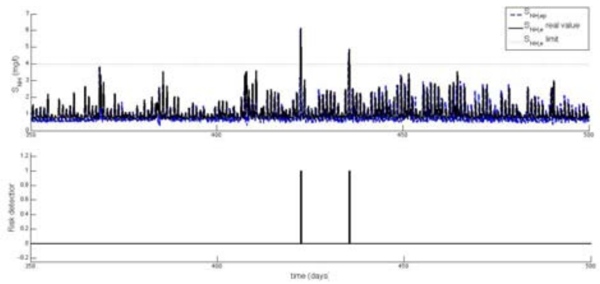


Fig. 7. $S_{NH,e}$ limit violation risk detection. Long time window.

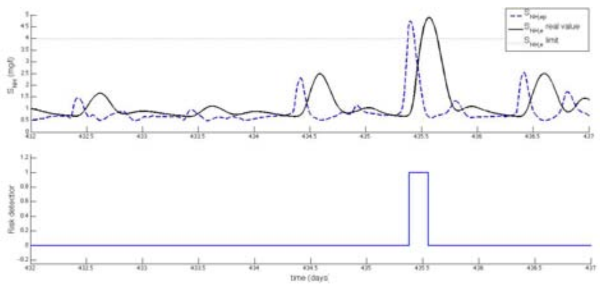


Fig. 8. $S_{NH,e}$ limit violation risk detection

VII. Conclusions

This paper ha 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.

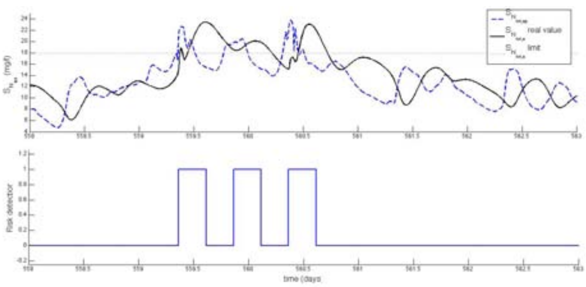


Fig. 9. $S_{N_{tot,e}}$ limit violation risk detection

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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