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Static and dynamic set point optimization techniques for optimal operation of wastewater treatment plants

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Abstract—**Optimization and control strategies are necessary to keep wastewater treatment plants operating in the best possible conditions with the minimum consumption of energy. In this paper static and dynamic set point optimization strategies to improve the operation of the plant in order to achieve the economically optimal conditions are studied. Different objective function formulations are compared and the overall performance of the plant operating in a rain weather scenario is evaluated to determine the most adequate operation strategy.**

I. INTRODUCTION

In Wastewater Treatment Plants (WWTPs), the nitrogen removal (N-removal process) is carried out by means of the nitrification and denitrification processes in the activated sludge process (ASP). The nitrification is the biological conversion of ammonium to nitrates in aerobic conditions, while denitrification is the biological reduction of nitrates to nitrogen gas (N_2) in anoxic conditions.

Wastewater treatment is considered a non-productive process; therefore WWTPs are enforced to improve their facilities and their operation strategies in order to meet the stringent effluent quality standards in the presence of large disturbances. Optimization and control strategies are necessary to keep the plant operating in the best possible conditions with the minimum consumption of energy.

The most important control variable is the dissolved oxygen concentration (DO) in the aerobic reactors; it is regulated by the aeration system. Therefore, most of the control strategies focus in DO control [1]. Another typical control variable is the nitrate concentration in the anoxic zone which is regulated with the internal recycle flow [2].

Several authors have proposed different strategies for the optimization of the operation of the plant. Yamanaka et al. (2006) evaluate a cost minimization control scheme using the Benchmark Simulation Model. The control structure is hierarchical where a higher level controller provides the set-points of the process based on optimization using a simplified process model and genetic algorithms. The lower level controller follows the set-points. In the case of aeration control, the optimizer determines an appropriate ammonia set point which the lower level PI controller follows.

In [4] and [5] a hierarchical control structure is applied for DO control, which is divided into the supervisory control layer, optimising control layer and follow-up control layer. In [4], the structure involves integrated control of a treatment plant and sewer system and the optimizing control layer involves slow, medium and fast time scales. In [5], the low level DO controller in the follow-up layer consists of a simple proportional controller; however, the authors argue that a much better solution would be to apply an MPC (Model Predictive Controller). The simulations in the report are based on real data from the Katurzy UCT (University of Cape Town) treatment system in Poland.

Machado et al. [6] used a hierarchical structure for optimizing the operation of a nutrient removal WWTP, consisting on three cost controllers (linear PI) that dynamically send set points to the process PI controllers to minimize the difference between the cost measurement and the cost set point. A reduction of 13% of cost index was achieved.

This paper considers the activated sludge process in a typical municipal wastewater plant to study different strategies to improve the operation of the plant in order to achieve the economically optimal conditions. The proposed methods are the set point optimization based on stationary models and the dynamical optimization using a hierarchical control scheme. The optimal operation strategies will be tested in a reduced plant, considering only the N-removal process.

The paper is organized as follows: first, the model of the process is described in section 2, the static and dynamic set point optimization problem is described in section 3 and the results are presented in section 4. Finally, conclusions and different projections of this work are included.

II. N-REMOVAL PROCESS

The main goal of the activated sludge process is to remove the nutrients and organic matter in wastewater treatment plants to meet the stringent concentration requirements over Chemical Oxygen demand (COD) and nutrients as ammonium and other nitrogen compounds in the effluent discharged to receiving waters.

The efficiency of the biological nitrification depends on the Dissolved Oxygen (DO) concentration that is regulated by the aeration system. The DO concentration in the aerobic zone should be sufficiently high to supply enough oxygen to the microorganisms in the sludge. However, high air flow rates can produce an excess in DO concentration in the aerobic zone that affect negatively the denitrification process

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through the internal recycle and increases unnecessarily the energy consumption. Hence, the control of the DO concentration is crucial for the satisfactory operation of the activated sludge process.

In the denitrification process that takes place in the anoxic zone, the key variable is the nitrates concentration. A typical control strategy is to maintain a low nitrates concentration at end of the anoxic zone. Here, the internal recycle flow is used as manipulated variable to regulate the nitrates removal. This control action affects the pumping energy consumption.

The Benchmark Simulation Model (BSM1) has been widely applied to test control strategies for the Activated Sludge Process (ASP) in wastewater treatment plants. A schematic representation of the activated sludge process represented by the BSM1 is presented in Figure 1. It consists of 5 bioreactors: 2 anoxic and 3 aerobic.

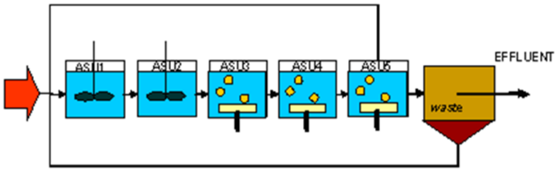

Figure 1. Schematic representation of the BSM1 plant.

In this work, a simplified model is considered, where only the significant variables on a medium scale of time are taken into account. The processes with slow variations in time (the growth of autotrophic and heterotrophic microorganisms and hydrolyse processes) are neglected. The BSM1 representation is reduced to one anoxic and one aerated reactor. The volumes of the two tanks are 2000 m^3 and 3999 m^3, to make them equivalent to total volumes of the anoxic and the aerobic compartments in the BSM1.

The simplification reduces the biological processes and the state variables, therefore the considered biological processes are described by the following equations:

$$\rho_{1i} = \mu_H \cdot \left(\frac{S_{Si}}{K_s + S_{Si}} \right) \cdot \left(\frac{S_{Oi}}{K_{O,H} + S_{Oi}} \right) X_{B,H} \tag{1}$$

$$\rho_{2i} = \mu_H \cdot \left(\frac{S_{Si}}{K_s + S_{Si}} \right) \cdot \left(\frac{K_{O,H}}{K_{O,H} + S_{Oi}} \right) \left(\frac{S_{NOi}}{K_{NO} + S_{NOi}} \right) n_g X_{B,H} \tag{2}$$

$$\rho_{3i} = \mu_A \cdot \left(\frac{S_{NHi}}{K_{NH} + S_{NHi}} \right) \cdot \left(\frac{S_{Oi}}{K_{O,A} + S_{Oi}} \right) X_{B,A} \tag{3}$$

where i:1,2. The index 1 refers to the anoxic tank and the index 2 to the aerobic one.

The differential equations describing the model are the following:

$$\frac{dS_{NH1}}{dt} = \frac{1}{V_1} \begin{bmatrix} Q_{in} \cdot S_{NHin} + Qr \cdot S_{NH2} - (Q_{in} + Q_a) \cdot S_{NH1} - i_{Xb} \cdot \rho_{11} \\ -i_{Xb} \cdot \rho_{21} - \left(i_{Xb} + \frac{1}{Y_A} \right) \cdot \rho_{31} \end{bmatrix} \tag{4}$$

$$\frac{dS_{NO1}}{dt} = \frac{1}{V_1} \left[Qr \cdot S_{NO1} - (Q_{in} + Qr) \cdot S_{NO1} - \frac{1 - Y_H}{2.86 Y_H} \rho_{21} + \frac{1}{Y_A} \cdot \rho_{31} \right] \tag{5}$$

$$\frac{dS_{S1}}{dt} = \frac{1}{V_1} \left[Q_{in} \cdot S_{Sin} + Qr \cdot S_{S2} - (Q_{in} + Qr) \cdot S_{S1} - \frac{1}{Y_H} \rho_{11} - \frac{1}{Y_H} \rho_{21} \right] \tag{6}$$

$$\frac{dS_{O1}}{dt} = \frac{1}{V_1} \left[Qr \cdot S_{O2} - (Q_0 + Qr) S_{O1} \right] - \left[\frac{1 - Y_H}{Y_H} \rho_{11} + \left(\frac{4.57}{Y_A} + 1 \right) \rho_{31} \right] \tag{7}$$

$$\frac{dS_{NH2}}{dt} = \frac{1}{V_2} \begin{bmatrix} (Q_{in} + Qr) S_{NH1} - (Q_{in} + Qr) S_{NH2} \\ -i_{xb} \cdot \rho_{12} - \left(ix_b + \frac{1}{Y_A} \right) \cdot \rho_{32} \end{bmatrix} \tag{8}$$

$$\frac{dS_{NO2}}{dt} = \frac{1}{V_2} \begin{bmatrix} (Q_{in} + Qr) S_{NO1} - (Q_{in} + Qr) S_{NO2} \\ -\frac{1 - Y_H}{2.86 Y_H} \rho_{22} + \frac{1}{Y_A} \cdot \rho_{32} \end{bmatrix} \tag{9}$$

$$\frac{dS_{S2}}{dt} = \frac{1}{V_2} \left[(Q_{in} + Qr) \cdot S_{S1} - (Q_{in} + Qr) \cdot S_{S2} - \frac{1}{Y_H} \rho_{12} - \frac{1}{Y_H} \rho_{22} \right] \tag{10}$$

$$\frac{dS_{O2}}{dt} = \frac{1}{V_2} \begin{bmatrix} (Q_{in} + Qr) \cdot S_{O1} - (Q_{in} + Qr) \cdot S_{O2} - \left[\frac{1 - Y_H}{Y_H} \rho_{12} + \frac{4.57 - Y_A}{Y_A} \rho_{32} \right] \\ +K_L a \left(S_{O,sat} - S_{O2} \right) \end{bmatrix} \tag{11}$$

The values of the kinetic and physical parameters are assumed to be the same of BSM1 [2]. The state variables in equations are: the ammonium concentration (S_{NHi}), the nitrate concentration (S_{NOi}), the carbonaceous compounds concentration (S_{Si}), and the oxygen concentration (S_{Oi}).

Control problem

The controlled variables are the oxygen concentration (DO) in the aerated zone S_{O2} and the nitrate concentration in the anoxic zone S_{NO1}. The manipulated variables are: the internal recycle flow (*Qr*) and the oxygen transfer coefficient (*KLa*).Note that it is not straightforward to follow the effect of the manipulated variables in the outputs because of the coupled dynamics and multivariable features of the process.

The disturbances are: the influent flow (Q_{in}), the carbonaceous compounds ($S_{S,in}$) and the ammonium concentration ($S_{NH,in}$) in the influent. The BSM1 profiles are used in this study to characterize the influent disturbances, specially the rain weather profile where a strong and long-term variation is observed during the day 8 to 11.

III. PROBLEM FORMULATION

The implementation of adequate control techniques and optimization strategies are the key issue to improve the operation of the WWTPs. Some measures are necessary to characterize the effluent quality and energy use. The performance indices have been used extensively for evaluation of WWTP to determine its optimality. In [2] are presented performance indices for the evaluation of control strategies based on simulations in the Benchmark Simulation Model. The indices include the Effluent Quality Index (*EQ*) which integrates the total amount of pollutants for the process with different weights depending on their severity, Aeration Energy (*AE*) and Pumping Energy (*PE*).

These indices are considered in the different strategies proposed here to optimize the operation of the plant, specifically a Static Set Point Optimization and Dynamic Optimization by means of a hierarchical control scheme.

A general description of the method and the formulation of the optimization problem for each one of the mentioned strategies are presented as follows.

A. Static Optimization

A Real Time Optimization (RTO) system is a model-based, upper-level control system that is operated in closed loop and provides set points to the lower-level control systems in order to maintain the process operation as close as possible to the economic optimum. The introduction of an RTO system provides a clear separation of concerns and time-scales between the RTO system and the process control system. The RTO system optimizes the plant economics on a medium time-scale while the control system provides tracking and disturbance rejection on shorter time-scales from seconds to hours [7].

Although a steady state model is used for RTO, when connected to a plant, the resulting system is dynamic. This operation scheme can be compared with a single step, model-based controller with a future horizon (control and prediction) of just one point. Specific disturbances related to changes in economics or process efficiency that occur at lower frequencies but accommodated in real time could be considered [8].

Because RTO is supported by a static model, the plant must be sufficiently steady to reliably update the plant model. Steady-state detection methods typically incorporate statistics such as the mean, variance, or slope for selected signals over a moving window. Filters and averages of plant measurements are used to remove high frequency disturbances and suppress dynamic effects [8].

The static optimization proposed here, it is not strictly an RTO, because the plant is under high frequency disturbances and it is not possible to reach the steady operation. In addition, the exact simulation model of the process is used to optimise the set points and, therefore, it is not necessary to compare the outputs of process and model to update the optimization model.

Formulation of the Static Optimization problem for the N-removal process

In the set point optimization formulation, the objective is to find the steady state working point (equilibrium point) that minimizes the energy costs given by the Pumping Energy (*PE*) and the Aeration Energy (*AE*). Additional validation of the methodology is performed optimizing the Effluent Quality (*EQ*) index together with costs. The decision variables are *KLa* and *Qr*, which are used to calculate the S_{NO1} and S_{O2} values in steady state: S_{NO1ss}, S_{O2ss}.

The objective function is:

$$\boldsymbol{cost} = w_1 \cdot \left(PE_{ss} + AE_{ss}\right) + w_2 \cdot EQ_{ss} \qquad (12)$$

where w_1 and w_2 are user defined weights that are selected to evaluate different objective function formulations.

The Pumping Energy (*PE*) that represents the energy consumption due to pumping of the internal recycle is given by:

$$PE=0.004 \cdot Q_{rss}\ [kWh/d] \qquad (13)$$

The Aeration Energy (*AE*) is calculated from oxygen transfer coefficient (K_{La}) according to the following relation:

$$AE = \frac{S_{O,sat}}{1.8 \cdot 1000} \cdot V_2 \cdot K_{La}\ \left[{}^{kWh}\!/\!{}_{d}\right] \qquad (14)$$

that takes into account parameters as the type of diffuser, bubble size, depth of submersion.

The Effluent Quality is averaged over the period of observation, based on weighting of the effluent loads of compounds data that have a major influence on the quality of the receiving water:

$$EQ = \frac{1}{1000}\left[2 \cdot SS_e + COD_e + 30 \cdot Nt + 10 \cdot S_{NO,e} + 2 \cdot BOD_e\right]Q_e \left[{}^{Kg}\!/\!{}_{d}\right] \qquad (15)$$

where:

$$BOD_e = 0.25 \cdot \left(\left(1-0.08\right)\left(X_{B,Ae} + X_{B,He}\right)\right) g/m^3 \qquad (16)$$

$$COD_e = \left(S_{Se} + X_{B,Ae} + X_{B,He}\right) g/m^3 \qquad (17)$$

$$Nt = S_{NOe} + S_{NHe} + i_{XB}\left(X_{B,He} + X_{B,Ae}\right) g/m^3 \qquad (18)$$

In the effluent: S_{NHe}=S_{NH2ss}, S_{NOe}=S_{NO2ss}, S_{Se}=S_{S2ss}. It is supposed that the separation in the settler produces: $X_{B,Ae}$=0.0038·$X_{B,A}$ and $X_{B,He}$=0.0038·$X_{B,H}$.

Process constraints:

The optimization constraints are given by the effluent regulations and process characteristics:

$$S_{NH2} \le 4\,[mg/l] \qquad (19)$$

$$S_{Ntot} \le 22[mg/l] \qquad (20)$$

$$COD_e \le 100\ [mg/l] \qquad (21)$$

$$S_{O2} \ge 1.5\ [mg/l] \qquad (22)$$

$$EQ_{\max} \le 6200\ [Kg/d] \qquad (23)$$

$$0 \le KLa\ [1/h] \le 1.5 \qquad (24)$$

$$0 \le Qr\ [m^3/h] \le 3850 \qquad (25)$$

The optimization problem is solved in order to obtain the stationary working point: KLa_{ss}, Qr_{ss}, S_{O2ss} and S_{NO1ss} containing the manipulated variables, oxygen and nitrates set points that optimize the cost function (12) that contemplates Aeration Energy, Pumping Energy and Effluent Quality indices.

The set point optimization is performed each T_{opt} considering the average of the values of Q_{in}, $S_{S,in}$ and $S_{NH,in}$ in the operation window defined by T_{opt}/4.

B. *Dynamic Optimization - Hierarchical control*

Multilayer control structures are extensively used to controllarge scale systems. This can be useful at least in two cases: when the overall process under control is characterized by different dynamic behaviour or in plantwide optimization when optimization and control algorithms working at different rates compute both the optimal targets and the effective control actions to be applied [9].

In these schemes, the regulator at a higher layer computes its desired control inputs, which are the reference signals of the immediately lower layer.

In these hierarchical structures, in order to guarantee that references computed at the higher layer are feasible for the lower layer dynamics and constraints, as well as to consider the presence of disturbances acting at the lower layer, some additional information has often to be transmitted bottom-up.

In this case, the optimization problem described above is solved dynamically considering a Non Linear Model Predictive Control (NLMPC) paradigm to obtain the control signal corresponding to the optimal references for the lower level controller. The predictions of the dynamic response of the plant in a time horizon N are used to calculate the corresponding performance indices.

Different static and hierarchical set point optimization strategies are evaluated in this work. The analysis of results of the different set point optimizations are presented in section 4.

IV. RESULTS

The proposed static and dynamic set point optimization strategies are tested in the WWTP Activated Sludge Process described in section II. The lower layer is comprised by two decentralized PI controllers tuned by dynamic optimization of the controller parameters in a typical operation scenario. The obtained values for the proportional gain and integral time are K_p=68.3, T_i=10.5 for the KLa-S_{O2} loop, and K_p=91, T_i=47 for the Qr-S_{NO1} loop, respectively.

The proposed strategies are evaluated considering the operation under rain weather influent profile (Figure 2). A simulator of the plant developed in Matlab® is used to represent such operation scenario during 14 days and the set point optimization is carried out online with T_{opt}=1 day.

The static set point optimization is performed considering two different formulations of the objective function:

- Static Opt. 1 with w_1=1 and w_2=2, to take into account the cost and the effluent quality in the optimization.
- Static Opt. 2 with w_1=1 and w_2=0, considering only the economic objectives.

The NLMPC upper level controller is evaluated considering different objective functions:

- Hierarchical1 with w_1=1 and w_2=2.
- Hierarchical2 with w_1=1 and w_2=0.
- Hierarchical3 with w_1=1 and w_2=2 and including a term to penalize the set point movements.

$$\boldsymbol{cost}_{\Delta U} = w_3 \cdot \left(PE_k + AE_k - \left(PE_{k+1} + AE_{k+1} \right) \right) \qquad (26)$$

- Hierarchical4 with w_1=1 and w_2=2 and including a term to penalize the set point movements that are not favorable to costs.

$$\boldsymbol{cost}_{\Delta U} = w_3 \cdot \min\left(\left(PE_k + AE_k - \left(PE_{k+1} + AE_{k+1} \right) \right), 0 \right) \qquad (27)$$

The weights in the objective functions have been selected according to the purpose of each case. Their magnitudes have been chosen by a trial and error procedure in order to validate the methodology, but for future work more realistic values could be used.

In order to compare the set point optimization strategies to reference case study, a fixed optimal set point is calculated considering the average values of the inputs in the evaluated operation scenario.

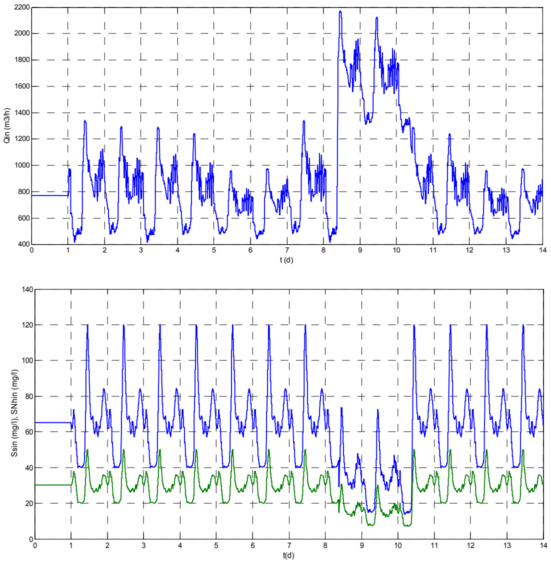

Figure 2: Rain weather influent profiles

Table 1: Performance indices in the last 7 operation days with rain weather influent profile

	EQ (Kg/d)	*OCI* (EUR/d)	*PE* (Kwh/d)	*AE* (Kwh/d)
Fixed static optimized SP	7212.1	1759.8	78.61	1681.2
Static Opt. 1	7331.1	1510.1	73.81	1436.3
Static Opt. 2	7383.4	1521.8	66.47	1455.4
Hierarchical1	7379.7	1546.6	66.67	1479.9
Hierarchical2	7411.5	1531.1	66.21	1464.9
Hierarchical3	7330.4	1723.7	67.59	1656.1
Hierarchical4	7547.8	1531.2	65.90	1465.3

In table 1 are presented the performance indices obtained for the different set point optimization strategies during the last 7 days of rain weather operation. The economics is measured using the Overall Cost Index (*OCI*).

$$OCI(EUR/d) = PE_{7\,days} + AE_{7\,days} \tag{28}$$

It is observed a clear improvement (14%) in the operation costs respect to fixed set point operation when the references are optimized even static or dynamically.

It was expected a better performance with the hierarchical methodology, because dynamic optimization seemed to be the best scheme for a process operating under frequently variations in the inputs. However, the static optimization performed better in the evaluated scenarios, and high prediction horizons, that increased computer time, were necessary to obtain good results with the hierarchical MPC controller.

Among the different objective function formulations for the static and dynamic optimization, the best combination of weights for the objectives resulted in w_1=1 (*OCI*) and w_2=2 (*EQ*) and no penalizations for set point movements. However, in this case, the set point optimization seems to be only slightly influenced by the relative weighting of the costs and effluent quality in the objective function. In the scenario "Hierachical3" an important increase in the *OCI* is observed evidencing the effect of the control movement penalization, and in the scenario "Hierarchical4" the penalization of the set point movements that are not favorable to costs seems to affect slightly the effluent quality.

Static optimization:

a) Scenario Static Opt. 1, w_1=1 and w_2=2.

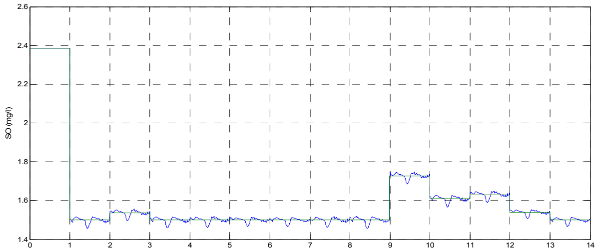

Figure 3: Static Opt. 1-Oxygen concentration in the aerobic tank

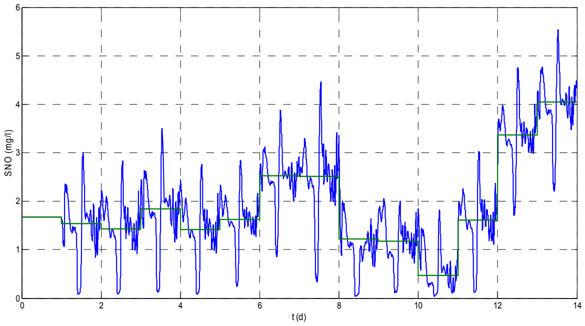

Figure 4: Static Opt. 1-Nitrate concentration in the anoxic tank

The dynamic responses applying the most adequate operation strategies are presented in figures 3 to 13. In the figures are shown the evolution of the controlled variables S_{O2} and S_{NO1}, the constrained operation variables S_{NH2} and S_{Ntot} and the evolution of the Effluent Quality (*EQ*) and *OCI*. The set point tracking is particularly good in the case of S_{O2}, while in the case of S_{NO1} larger deviations are observed due to its slower dynamics. Moreover, some constraint violations are reported for S_{NH2} and S_{Ntot} in the corresponding figures. This is only a consequence of using PI controllers in the lower level, which do not consider constraints, and it could be improved by using an advanced controller, e.g. an MPC.

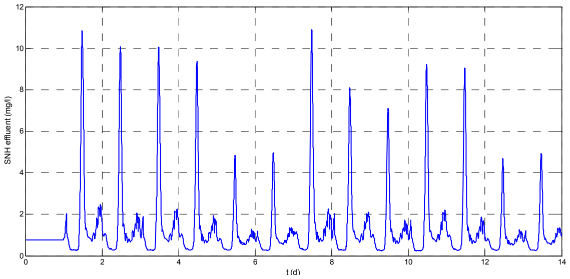

Figure 5: Static Opt. 1-Ammonium concentration in the effluent

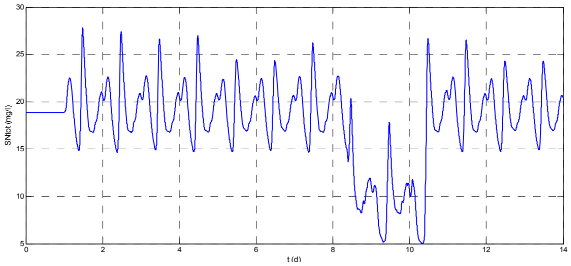

Figure 6: Static Opt. 1-Total Nitrogen in the effluent

In figures 5 and 6, it is shown the evolution of the constrained variables S_{NH2} and S_{Ntot}, which cannot meet the bounds imposed with PI schemes. A MPC or NLMPC, that includes constraints in the control law formulation could be useful to maintain that variables around the desired variables.

It is important to notice that in the economical optimization Static Opt. 2 the reference for the oxygen concentration in the aeration tank (S_{O2}) is always in the lower bound. It only changes when disturbances in the inputs are important. In general, the set point optimization performance can be improved including some techniques to avoid unnecessary set point changes.

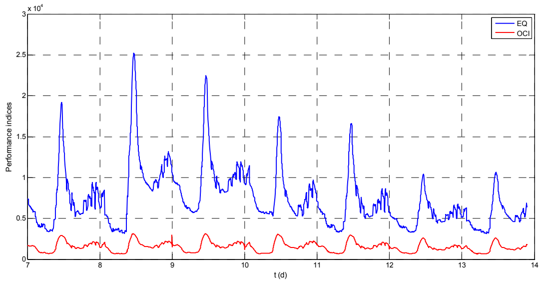

Figure 7: Static Opt. 1- Performance indices evolution

b) Scenario Static Opt. 2, w_1=*1* and w_2=*0*

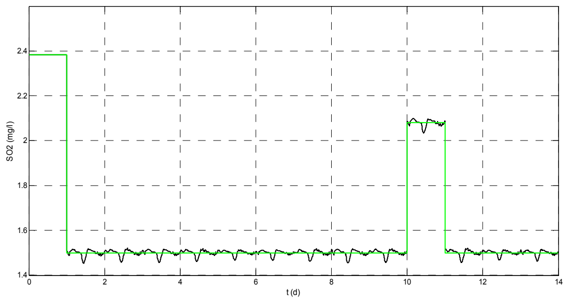

Figure 8: Static Opt. 2-Oxygen concentration in the aerobic tank

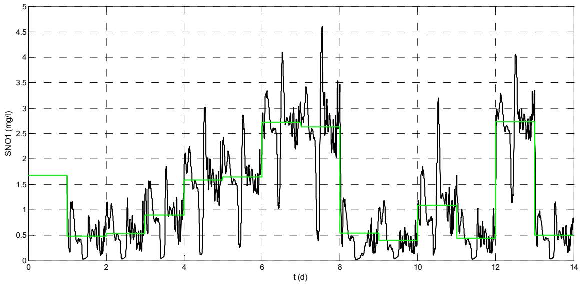

Figure 9: Static Opt. 2-Nitrate concentration in the anoxic tank

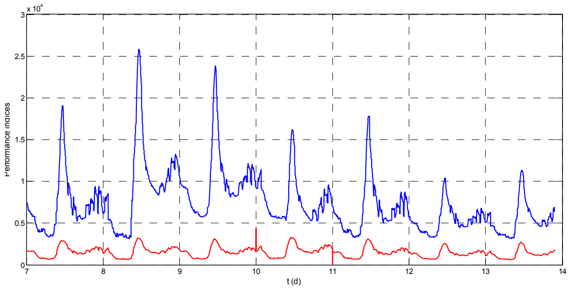

Figure 10: Static Opt. 2- Performance indices evolution

Dynamic optimization:

a) Hierarchical1: $w_1=1$ and $w_2=2$

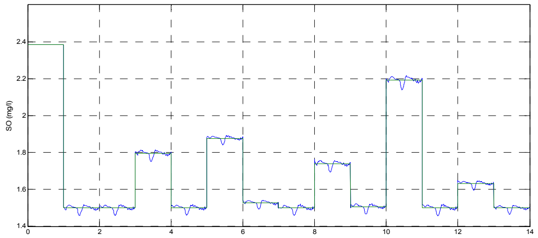

Figure 11: Hierarchical1 -Oxygen concentration in the aerobic tank

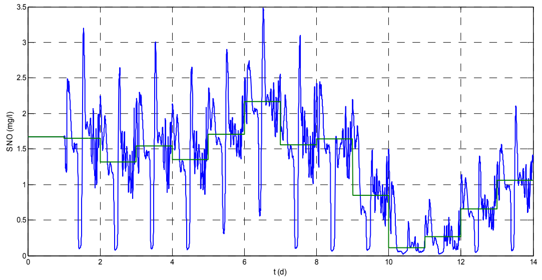

Figure 12: Hierarchical1-Nitrate concentration in the anoxic tank

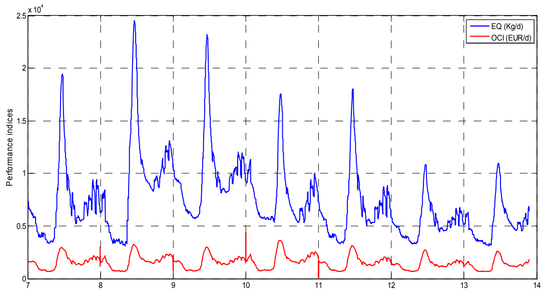

Figure 13: Hierarchical1-Performance indices evolution

V. CONCLUSIONS

In this paper, static and dynamic set point optimization strategies for improving the operation of a wastewater treatment plant has been evaluated. Different objective function formulations were compared and the overall performance of the plant operating in a rain weather scenario was evaluated to determine the most adequate operation strategy.

In the future work, some strategies to avoid unnecessary set point changes will be studied in order to improve the performance of the optimization methods and more complex controller as MPC in the lower level will be used. Another issue to be considered will be the model uncertainty associated to the biological parameters of the differential equations of the model, by using robust approaches at both levels of optimization.

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