Decentralized Model Predictive Control for N and P removal in wastewater treatment plants

X. Hongyang, C. Pedret, I. Santin, R. Vilanova
Department of Telecomunications and Systems Engineering.
School of Engineering. Universitat Autonoma Barcelona
08193 Bellaterra, Barcelona, Spain
{Ramon.Vilanova, Carles.Pedret}@uab.cat

***Abstract*—Due to the complex and non linear character, wastewater treatment process is difficult to be controlled. And the demand for removing the pollutant, especially for nitrogen (N) and phosphorus (P), as well as reducing the cost of wastewater treatment plant (WWTP) is an important research topic. This paper applies PI control and decentralised model predictive control control to the combined phosphorus removal Benchmark Simulation Model 1 (BSM1-P) wastewater treatment process to enhance the P removal. A default control strategy which contains two control loops and is similar to the one given by the original version of BSM1 was tested on BSM1-P. In addition, linear models have been identified and model predictive controllers implemented for each one of these loops. The simulation results showed that the MPC controllers are able to the controller performance in all the three weather conditions.**

***Index Terms*—Nutrient removal, Wastewater treatment plants**

I. Introduction

Over the past decades, as the human society has developed rapidly, the demand for water resources has increased considerably. However, the wastewater of industrial and civil activity has not always been treated adequately. The natural aquatic systems have a certain ability to recover from the pollutants, but this is not always sufficient nowadays. In Europe, the implementation of the Council Directive 91/271/EEC of 21 May 1991 concerning urban wastewater treatment, has lead to new requirements for wastewater treatment plants (WWTPs). Wastewater treatment plants (WWTPs) are used worldwide to ensure the suitable water quality for the receiving environment. Some of the pollutants are reduced to allowed levels by the default WWTP structure without applying any automatic control. However, other pollutants are more difficult to be reduced. For this reason and also to restrict operational costs, the application of control engineering inWWTPs is playing an important role in research in recent years [1] and [2].

Water quality parameters such as chemical oxygen demand (COD), concentration of ammonia nitrogen (NH4), total nitrogen (N) and total phosphorus (P) as long as general effluent quality index (EQI) are the most important components to represent the efficiency of a WWTP. The total phosphorus and the total nitrogen are important pollution component which are responsible for the eutrophication. Then, to get a good balance between P removal and N removal a precise control method is highly required because, for one hand the P removal procedure is more complicated than COD removal and N removal. On the other hand, the conditions that benefit P removal and N removal are contradictory.

Different control strategies such as dissolved oxygen (DO) control, model based control, sludge inventory control, advanced nutrient removal control and respire meter based control have been proposed to improve plant performance, to optimise the energy costs and to reduce environmental contamination. Authors in [3] show that by combining PI control loops for DO, internal recycle and waste sludge, a well balanced of effluent quality and operational cost is achieved. And besides fuzzy control is also applied on BSM1-P to reduce the general quality and the concentration of phosphorus of effluent [4].In addition, by applying model predictive control (MPC) and feedforward control, Santin et al in [6] improved by more than 90% of the control performance of nitrate concentration and dissolved oxygen under three weather conditions as well as the effluent quality. In [7], a fuzzy model-based predictive control paradigm achieved satisfactory benefits in terms of both transient and steady performances for the DO control. And in [8], an adaptive predictive expert controllers to dissolved oxygen (DO) control in the aerobic reactors of a wastewater treatment plant resulted in more precise and stable DO control with a reducing energy consumption. According to the control methods mentioned before, we can see that present researches of applying automatic control on wastewater treatment systems mostly focus on certain system state like DO or nitrate nitrogen concentration to improve the effluent quality, or avoiding unnecessary costs. However, because of the complexity, nonlinear of WWTPs, as well as many parameters contribute to the quality and costs, it is difficult to find a direct solution to improve these two overall indexes simultaneously.

Although the BSM1 modelling tool has been widely used in the WWTP research community, it has a structural limitation that it does not involve the P removal that should be taken into account for achieving a more realistic simulation model. To fill this gap, Gernaey and Jorgensen [5] developed a

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simulation benchmark which models the combined biological P and N removal suitable for the anaerobic-anoxic-oxic (AAO) processes, which could be regarded as benchmark simulation model no.1 including P removal (BSM1-P). Two PI controllers have been designed and tested for this process and defined as the default control (DC).

II. Plant description and performance indexes

A. Plant description

The processes in the WWTPs are simulated by two internationally accepted models: the Activated Sludge Model No. 2d (ASM2d) for biological processes in the reactors and the double-exponential settling velocity model for the vertical transfers between layers in the settler. Nineteen componenets and twenty one biological processes are designed in the ASM2d. ASM2d divide the components into two sets: soluble components (S_i) and particulate components (X_i). The conceptual components covers the essential biological subtance to describe the wastewater treatment behavior: the microbiologies to acomplish the pollutant removal (X_A, X_H and X_{PAO}); the carbon, nitrogen and phosphorus resource for their growth; the unbiodegradable but plant performace affeted components (S_I, X_I and X_{MeP}); the oxygen concentration that determines the growth environment (S_{O_2}); and other performance criteria related components such as X_{TSS}. The bioprocess 1-3 represent the hydrolysis process in the aerobic, anoxic and anaerobic conditions respectively; bioprocess 4-9 describe the processes of facultative heterotrophic organisms; 10-17 represent the growth of phosphorus accumulating organisms; 18-19 explain the nitrification behavior; and 20-21 describe the chemical precipitation of phosphates. The secondary settler is modeled as a ten-layer unit, and to be realistic it is assumed that biological reactions also occur here. In each layer the concentration of all components, no matter the soluble ones or the particulate ones, are assumed to be evenly ditributed, and the transfer of particulate components only happens between two layers. The calculation of particulate components concentration is achieved by performing a solics balance around each layer.

The benchmark simulation model no.1 with phosphorus removal (BSM1-P) [5] used in this paper consists of seven bioreactors followed by one secondary settler, as showed in Fig. 1. The bioreactors consist of two anaerobic tanks ($S_O \approx 0$ and $S_{NO} \approx 0$), two anoxic tanks ($S_O \approx 0$ and $S_{NO} > 0$) and three aerobic tanks ($S_O > 0$ and $S_{NO} > 0$) where air explosion occurs (see table I). In the first two tanks, the phosphorus accumulating organisms (PAO) release phosphate, S_{PO_4} from poly-phosphate, X_{PP}, and utilize the energy which is from the hydrolysis of X_{PP} to store cell external fermentation products S_A in the form of cell internal organic storage material X_{PHA} under the anaerobic condition. Meanwhile, the process of denitrification in which the bacteria use nitrite (S_{NO}) as electron acceptor for growing and consequently converse nitrite to dinitrogen happens in the following two anoxic tanks. In the last three aerobic tanks the bactetia oxidize ammonium to nitrite to obtain the energy necessary for growth. It should be mentioned that both in the two anoxic tanks and in the three aerobic tanks, PAO realize the growth by consuming PHA as well as the storage S_{PO_4} to X_{PP}.

TABLE I
List of State Variables of BSM1-P

notation	definition	unit
S_O	dissolved oxygen	g(-COD)/m^3
S_F	fermentable, readily biodegradable organic substrates	g COD/m^3
S_A	fermentation products, considered to be acetate	gCOD/m^3
S_I	inert soluble organic material	gCOD/m^3
S_{NH}	ammonium plus ammonia nitrogen	g N/m^3
S_{N_2}	dinitrogen	g N/m^3
S_{NO}	nitrate plus nitrite nitrogen	g N/m^3
S_{PO_4}	inorganic soluble phosphorus,	g P/m^3
S_{ALK}	alkalinity of the wastewater	mol HCO$_3$/m^3
X_I	inert particulate organic material	g COD/m^3
X_S	slowly biodegradable substrates	g COD/m^3
X_H	heterotrophic organisms	g COD/m^3
X_{PAO}	phosphate-accumulating organisms	g COD/m^3
X_{PP}	poly-phosphate	g P/m^3
X_{PHA}	a cell internal storage product of PAO	g COD/m^3
X_A	nitrifying organisms	g COD/m^3
X_{TSS}	total suspended solids, TSS	g SS/m^3
X_{MeOH}	metal-hydroxides	g SS/m^3
X_{MeP}	metal-phosphate	g SS/m^3

From Fig. 1 we can see wastewater enters the plant at flow rate Q_{in}; and there is an internal recycle (Q_a) and a sludge recycle (Q_r). Q_a brings back the wastewater flow which contains suffucient nitrite back to the first anoxic tank to realize the denitrification as well as supply electron acceptor for PAO. Q_r brings back particial concentrated sludge back to the first anaerobic tank as well as the whole WWTP system. Besides, a waste sludge flow (Q_w) is pumped continuously from the underflow of the sedimentation tank. In addition, the flow from bioreactor No.7 to the secondary settler is designed to feed the 6th layer. The parameters of BSM1-P are presented in Table. II. In addition, the oxygentranster coefficients of aerobic bioreactors that represnt the aeration rate are denoted as K_La_5 K_La_6 and K_La_7, respectively.

In this work, the controlled inputs are the internal recycle flow rate Q_a and the oxygen transfer coefficient in the last tank K_La_7.

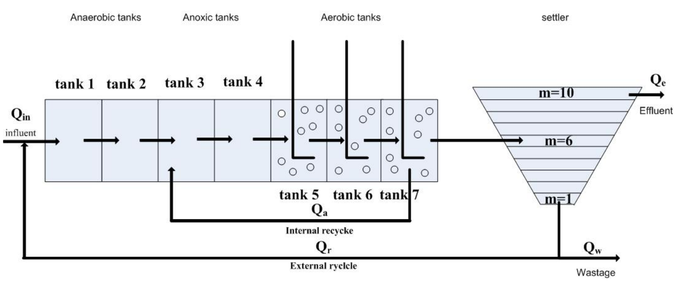

Fig. 1. Layout of BSM1-P

TABLE II
BSM1-P PARAMETERS

volume of tank1 (V_1)	500 m^3
volume of tank2 (V_2)	750 m^3
volume of tank3 (V_3)	750 m^3
volume of tank4 (V_4)	750 m^3
volume of tank5 (V_5)	1333 m^3
volume of tank6 (V_6)	1333 m^3
volume of tank7 (V_7)	1333 m^3
volume of settler	6000 m^3
Q_a under the dry weather condition	55338 m^3/d
Q_r under the dry weather condition	18446 m^3/d
Q_w	400 m^3/d

B. Performance indexes

Different criteria are stablished to evaluate and compare the performance of the proposed control configurations. The proposed indexes measure the settler effulent quality, the overall operation costs as well as the set-poit tracking performace of the controler

To evaluate the general quality of the effluent, the effluent quality index (EQI) is defined. This index is designed to include most of the important pollutant components and could be related with the fines to be paid according to the discharge of pollution. The way to calculate EQI is:

$$\begin{aligned} EQI = & \frac{1}{1000 \cdot T} \int_{t_0}^{t_f} (B_{TSS} \cdot TSS(t) + B_{COD} \cdot COD(t) \\ & + B_{NKj} \cdot S_{NH}(t) + B_{NO} \cdot S_{NO}(t) \\ & + B_{BOD_5} \cdot BOD_5(t) + B_{P_{tot}} \cdot P_{tot}(t)) \cdot Q(t) \cdot dt \end{aligned} \tag{1}$$

where, B_i are weighting factors (expressed in g pollution unit g^{-1}) which are showed in Table III, T is the total time (7 days), t_0 and t_f are starting and ending time respectively. TSS is total suspended solid, COD is chemical oxygen demand, BOD_5 is biological oxygen demand and P_{tot} is total phosphorus.

TABLE III
B_i VALUES

Factor	B_{TSS}	B_{COD}	B_{NKj}	B_{NO}	B_{BOD_5}	$B_{P_{tot}}$
Value	2	1	30	10	2	20

The operational cost is also an important aspect to be concerned when the control strategy is evaluated. The overall operational cost index (OCI) is defined as:

$$OCI = AE + PE + 5 \cdot SP + 3 \cdot EC + 1.5 \cdot EM + ME \tag{2}$$

where AE (kWh/d) is the aeration energy of aerobic tanks, PE (kWh/d) is the pumping energy for the recycles and wastewater transfer between tanks, SP (kg/d) is the sludge production to be disposed, EC (kg/d) is external carbon source, EM (kg/d) is the external metal source and ME (kWh/d) is the mixing energy. In this paper, we have considered that there are neither external carbon source nor external metal source, thus EC and EM are equal to 0.

The aeration energy AE is calculated as:

$$AE = \frac{S_o^{sat}}{1800T} \int_{t_0}^{t_f} \sum_{i=5}^{7} V_i \cdot K_L a_i(t) \cdot dt \tag{3}$$

where S_o^{sat} denotes the saturation concentration for oxygen whose value is 8g/m^3, and $K_L a_i$ (i=1,...,7) denotes the oxygen transfer coefficient in the i-th bioreactor.

The pumping energy PE is calculated as:

$$PE = \frac{1}{T} \int_{t_0}^{t_f} (0.004 Q_a(t) + 0.008 Q_r(t) + 0.05 Q_w(t)) dt \tag{4}$$

The sludge production SP includes the total suspended solid from wastage and the solids accumulated in the system over the estimated time:

$$\begin{aligned} SP = & \frac{1}{T} \cdot (TSS_a(t_f) - TSS_a(t_0) + TSS_s(t_f) - TSS_s(t_0) \\ & + \int_{t_0}^{t_f} TSS_w \cdot Q_w \cdot dt) \end{aligned} \tag{5}$$

where TSS_a is the concentration of suspended 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.

The mixing energy ME is a function of the bioreactor volumes and oxygen transfer coefficients to avoid the solid components settling in the anaerobic and anoxic tanks:

$$ME = \frac{1}{T} \int_{t_0}^{t_f} ME(t) dt \tag{6}$$

where

$$ME(t) = 24 \sum_{i=1}^{5} \begin{cases} 0.005 \cdot V_i & if \quad K_L a_i(t) < 20 d^{-1} \\ 0 & if \quad K_L a_i(t) \geq 20 d^{-1} \end{cases} \tag{7}$$

There are several ways to evaluate the output set-point tracking performance of the controllers. In this paper, we choose the Integral of the Squared Error (ISE) as the criterion:

$$ISE = \int_{t_0}^{t_f} (S_i^{set} - S_i)^2 dt \tag{8}$$

where S_i is the measured value of concerned component (DO and S_{NO} in this paper), and S_i^{set} is the set-point.

III. CONTROL STRATEGIES

In this work, we propose to compare the basic default PI based control algorithms with a decentralised MPC algorithm for phosphorus removal by using the BSM1-P. First, we give a class of nonlinear system in the general compact form to describe BSM1-P:

$$\begin{aligned} \dot{x}(t) &= f(x(t)) + g(x(t))u(t) \\ y(t) &= h(x(t)) \end{aligned} \tag{9}$$

where x is the vector of process states variables, $u = [u_1 \ u_2]^T = [K_L a_7 \ Q_a]^T$ denotes the controlled input values, $y = [y_1 \ y_2]^T = [S_{O,7} \ S_{NO,3}]^T$ denotes the controlled outputs vector.

We assume that the entire process variables are sampled at time instants t_k, where $t_k \geq 0$, such that $t_k = t_0 + k\Delta t$, t_0 is the initial time and Δt is the sampling time interval and k is a positive integer. At each time instant t_k, the vector of process states is denoted as $x(t_k)$, the vector of manipulated inputs is denoted by $u(t_k)$ and the vector of controlled outputs is dented as $y(t_k)$.

A. Proportional-Integral control

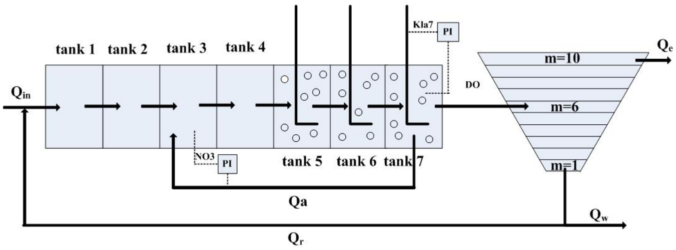

Fig. 2. Description of DF control strategy of BSM1-P

We present a PI control strategy which contains two control loops (see Fig. 2): the first one is a DO controller to regulate $S_{O,7}$ at a set-point by manipulating $K_L a_7$, and the second one is to maintain $S_{NO,3}$ at a set-point by manipulation of Q_a. The two PI controllers are designed by means of the following equations:

$$u_1(t_k) = K_{p1}[(y_1^{set}(t_k) - y_1(t_k)) + \frac{1}{T_{i1}} \sum_{j=0}^{k} (y_1^{set}(t_j) - y_1(t_j))] \tag{10}$$

$$u_2(t_k) = K_{p2}[(y_2^{set}(t_k) - y_2(t_k)) + \frac{1}{T_{i2}} \sum_{j=0}^{k} (y_2^{set}(t_j) - y_2(t_j))] \tag{11}$$

where $y_1^{set}(t)$ and $y_2^{set}(t)$ are the set-point trajectories of $S_{O,7}$ and $S_{NO,3}$, respectively. K_{p1} and T_{i1} are the proportional gain and the integral time constant of the controller associated with $S_{O,7}$; K_{p2} and T_{i2} are the corresponding parameters of the controller associated with $S_{NO,3}$.

B. Model Predictive Control

Model Predictive Control (MPC) refers to a large class of computer control methods which make an explicit use of a process model to predict the future response of the plant. An algorithmic principle for MPC is described as followed: at each time instant t_k, an error $e(t_k)$ between the process real output $y(t_k)$ and the predicted output $\widetilde{y}(t_k)$ based on past inputs is calculated. The trajectories for $\widetilde{y}(t_k)$ and $e(t_k)$ are also calculated. Then the MPC control law is generated for making the predictive future output to match with the reference trajectory $y^{set}(t_k)$.

For any calculated set of present and future control moves $u(t_k)$, $u(t_{k+1})$, ... , $u(t_{k+m-1})$ the future behavior of the process outputs computed at the time instant t_k are denoted as $y(t_{k+1}|t_k)$, $y(t_{k+2}|t_k)$, ? , $y(t_{k+p}|t_k)$ and can be predicted by a horizon p.The sequence of future control signals is calculated by minimizing an objective function $J(y(t_k), u(t_k))$ as follows:

$$\min_{\Delta u(t_{k+1}|t_k), i=0,1,\ldots,m-1} J(y(t_k), u(t_k)) \tag{12}$$

where

$$J = \sum_{i=k}^{k+p} (y^{set} - y(t_i))^T \Gamma_y (y^{set} - y(t_i)) \tag{13a}$$

$$+ \sum_{j=k}^{k+m} \Delta u(t_j) \Gamma_u \Delta u(t_j) \tag{13b}$$

$$s.t. \quad \dot{\widetilde{x}}(t) = f(\widetilde{x}(t)) + g(\widetilde{x}(t) \cdot u(t)) \tag{13c}$$

$$\widetilde{y} = h(\widetilde{x}(t)) \tag{13d}$$

$$\Delta u(t_k) = u(t_k) - u(t_{k-1}) \tag{13e}$$

$$u(t) \in U \tag{13f}$$

$$y(t) \in Y \tag{13g}$$

where Γ_y, $\Gamma_u \geq 0$ are weighting matrices. Equations 13b and 13c represnt the model of the plant used for the predictions. $\widetilde{x}(t)$ and $\widetilde{y}(t)$ are the predicted state trajectory and the predicted output, respectively, for the input trajectory cumputed by the optimization problem. Equation 13d denotes the control increment at time interval t_k. Equation 13e and 13f represent the constraints of the manipulated imputs and the constaints of the outputs, respectively.

It has to be noticed that although m control moves $u(t_k)$, $u(t_{k+1})$, ... , $u(t_{k+m-1})$ are computed, only the first one ($u(t_k)$) is applied to the WWTP. Then, in the next control step, the same calculations are repeated according to the new measured (real) system outputs to obtain the manipulated variables for this time instant. The predicted process outputs depend on the identified model, i.e., equations (1b) and (1c). and the current measurements, as well as the unmeasured disturbances if are considered.

The sampling time interval Δt, the control horizon m, the prediction horizon p, the input rate weight Γ_u and the output rate weight Γ_y can be used as tunning parameters for the process to perform as required. Δt has a significant effect on the controler operation. High values of Δt can give poor control performance, mainly when there are important input disturbances. On the contrary, low values of Δt can produce fast changes in the actuators with the consequent high energy consumption. Γ_u is the parameter to avoid too quick changes of input or strong oscillations in the actuators, however a higher Γ_u will lead to a slower response of the actuators and hence a worse control performance. Γ_y is the weight for reducing the errors of controlled variables which is most important for a controller, thus Γ_y should be high enough to assure the control performance. The prediction horizon p has the following efect: if a high value of p is taken it will originate a smooth response of the process and an increase of the computational time; on the other hand, small values reduce the computational effort at espenses of a possible oscillatory process response. The control horizon m imporves the performance of the precess output as the value of m increases, at the espense of additional computation time; on the other hand, small values may result in oscillatory responses.

In this work, we design two seperate single input single output MPC on BSM1-P: the first one is DO controller to regulate $S_{O,7}$ by manipulating K_La_7, and the second one is to maintain $S_{NO,3}$ at a set-point by manipulation of Q_a (see Fig 3).

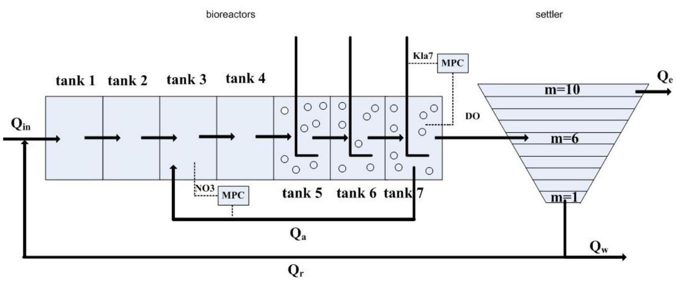

Fig. 3. Model predictive control of BSM1-P

IV. Simulation Results

In this section we apply the control methods explained in the previous section on BSM1-P under three weather conditions (dry, rain and storm weather) and we compare the simulation results. The control objects are: by applying PI and MPC, we regulate $S_{O,7}$ and $S_{NO,3}$ at the set point. The plant is simulated for 2 weeks and the results of the last week is used to evaluate the performance of the controllers and the plant. Ideal sensors are considered in the simulation process.

In the design of PI, there are two control loops: the DO controller for bioreactor 7 manipulates K_La_7 to maintain the dissolved oxygen ($S_{O,7}$) at the set-point $S_{O,7}^{set}$=2 g(-COD)/m^3, and the internal recycle controller to maintain the nitrate concentration of the third bioreactor $S_{NO,3}$ at the set-point $S_{NO,3}^{set}$=1gN/m^3.

The MPC is designed as two separate single input single out MPC controllers as shown in Figure 3. The models (13) for the MPC are developed using identification techniques based on process response data [17]. To obtain the identified model for DO MPC controller, we use a random signal input of K_La_7, with a mean value of 240 d^{-1} and a variance of 10%; to get the identified model for NO3 controller, we also chose a random signal input of Q$_{intr}$ with a mean value of 55338 m^3/d and 10% of variance. The second order state-space model for DO is as follows:

$$\begin{aligned} A &= \begin{bmatrix} -0.1322 & 0.3086 \\ 1.286 & -3.372 \end{bmatrix} \\ B &= \begin{bmatrix} 0.009144 & -1164 \\ -0.1014 & 13230 \end{bmatrix} \\ C &= [1.849 \ -0.3041], \\ D &= \mathbf{0} \end{aligned} \tag{14}$$

similarly, the identified model for NO3 obtained is:

$$\begin{aligned} A &= \begin{bmatrix} -0.002024 & 0.004699 \\ 0.02789 & -1.331 \end{bmatrix} \\ B &= \begin{bmatrix} 3.902 \times 10^{-6} \\ -0.001099 \end{bmatrix} \\ C &= [9.062 \ -0.01557], \\ D &= \mathbf{0} \end{aligned} \tag{15}$$

The parameters of PI controllers are: 1) for DO controller K_p=500 and T_i=0.0001; 2) for $S_{NO,3}$ controller, K_p=15000 and T_i=0.05. And The parameters chosen for tuning MPC are $m = 5$ and $p = 20$, $\Delta t = 0.00025 days$ (21.6s). The weights for MPC controller are: $\Gamma_y = 1$ and $\Gamma_u = 0.0001$.

The simulation results provided by the PI and the MPC designs under dry weather, rain weather and storm weather are shown in Fig.4, Fig.5 and Fig.6. The numeric comparison are shown in Table IV. It can be observed that by applying MPC controller, in a dry weather scenario, the ISE of SNO3 reduces 99.8% and ISE of DO7 reduces 98.98%. The control performance results in a marginal 0.093% OCI reduction at the expense of a 0.26% EQI increment. Under rain and storm weather conditions, the similar improvements are also obtained: ISE reduces in 99.4% (rain) and 99.8% (storm) for $S_{NO,3}$ control and reduces in 93% (both rain and storm) for $S_{O,7}$ control. A marginal 0.02% (rain) and 0.017% (storm) OCI reduction is obtained at the expense of a 0.1% (rain) and

0.14% (storm) EQI increment.

In view of the above comparison, it can be concluded that the designed MPC does not entail significant improvements in performance compared to the PI controller, if we look at the aggregated indexes. However, if we look at the effluent concentrations for the major components of interest: P, NH_e and N_tot, e we can observe that with the MPC it is possible to improve a little bit the N related compounds concentrations while keeping the P levels at similar values. At least not worse. Therefore, achieving better tradeoff. An example for the rein influent case is shown in figures (7), (8) and (9).

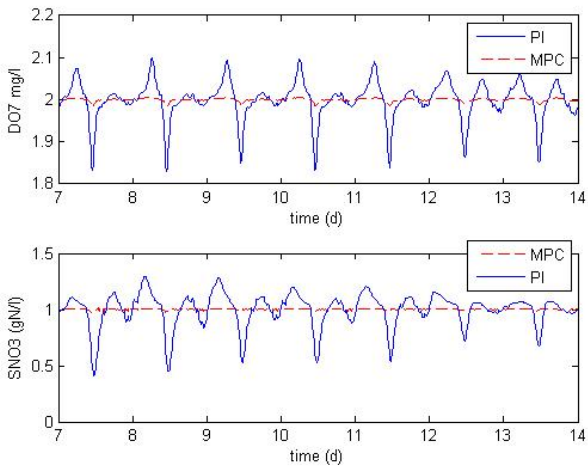

Fig. 4. Control performance of PI and MPC under dry weather

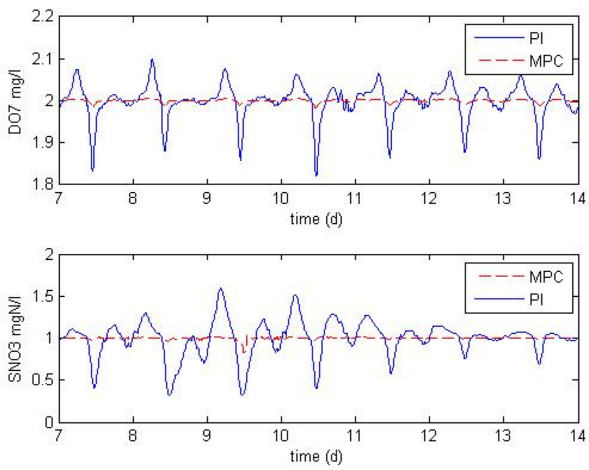

Fig. 5. Control performance of PI and MPC under rain weather

V. CONCLUSIONS

In this work, model predictive control is implemented on BSM1-P, and the results are evaluated and compared with PI and MPC. First, we propose PI and MPC to regulate dissolved oxygen of bioreactor 7 and nitrate nitrogen of bioreactor 3 at the set point.The simulation results show that both of them are able to achieve the control purpose, and further, the MPC controllers are able to improve more than 95% of the controller performance in all the three weather conditions.

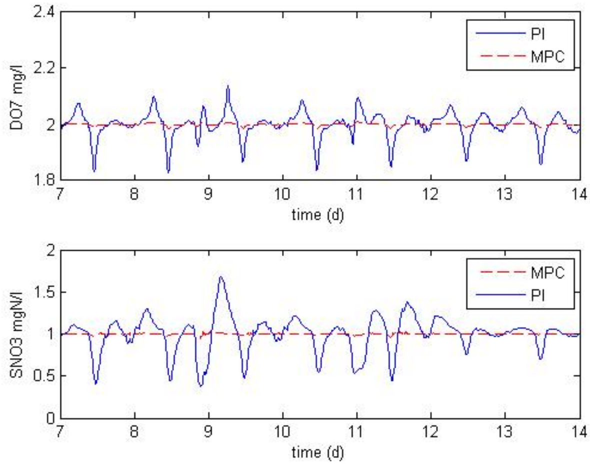

Fig. 6. Control performance of PI and MPC under storm weather

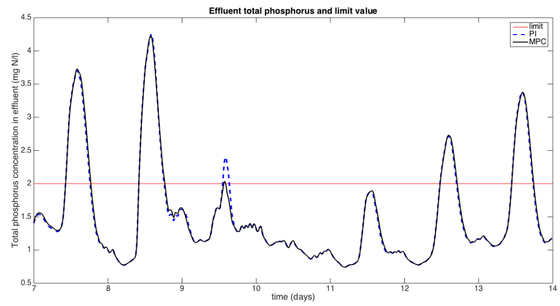

Fig. 7. Comparison of effluent concentration regarding P for rain influent

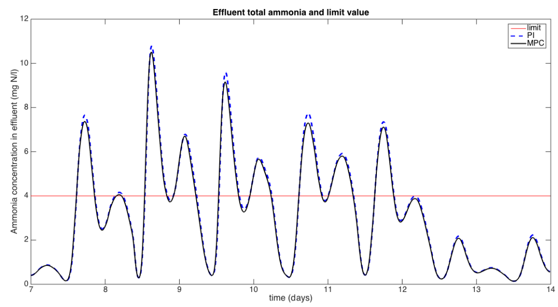

Fig. 8. Comparison of effluent concentration regarding NH_e for rain influent

TABLE IV
COMPARISON OF ISE, EQI, OCI WITH PI AND MPC UNDER DRY, RAIN AND STORM WEATHER

	PI	MPC	%
Dry weather			
ISE(SNO3)	0.159	0.000194	-99.8%
ISE(DO7)	0.00948	0.0000963	-98.98%
EQI	4495.64	4507.182	+0.26%
OCI	20628.88	20609.62	-0.093%
Rain weather			
ISE(SNO3)	0.325	0.00187	-99.4%
ISE(DO7)	0.0119	0.0000803	-99.3%
EQI	4919.16	4914.16	+0.1%
OCI	20187.22	20191.18	-0.02%
Storm weather			
ISE(SNO3)	0.323	0.000623	-99.8%
ISE(DO7)	0.0144	0.000102	-99.3%
EQI	4695.01	4701.69	+0.14%
OCI	21632.73	21628.98	-0.017%

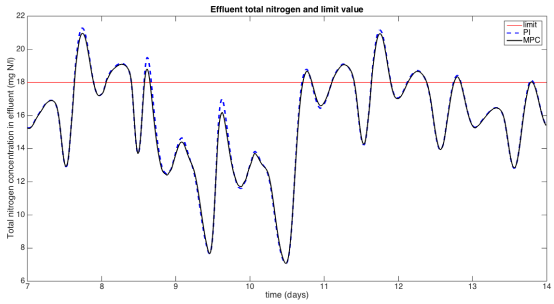

Fig. 9. Comparison of effluent concentration regarding $N_{tot,e}$ for rain influent

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