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Performance Comparison of Predictive Controllers in Optimal and Stable Operation of Wastewater Treatment Plants

Hasanlou, H.[1], Torabian, A.[1], Mehrdadi, N.[1], Kosari, A. R.[2] and Aminzadeh, B.[1*]

1. School of Environment, College of Engineering, University of Tehran, Tehran, Iran

2. Department of Aerospace, Faculty of New Sciences and Technologies, University of Tehran, Tehran, Iran

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ABSTRACT: Any proper operation could be translated as a constrained optimization problem inside a WWTP, whose nonlinear behavior renders its control problems quite attractive for performance of multivariable optimization–based control technique algorithms, such as NMPC. The main advantage of this control technique lies in its ability to handle model nonlinearity as well as various types of constraints on the actuators and state variables. The current study presents the process of BSM1 building, step by step, proposing appropriate numerical methods are creating the simulation model in MATLAB environment. It also makes a detailed comparison of the proposed NMPC with five recent predictive control schemes, namely LMPC, hierarchical MPC+ff, EMPC, and MPC+fuzzy, along with the default PI. The performance of predictive control schemes is much better than the default PI; however, something of highest importance is the ability to use the proposed control scheme in real systems, for a real application faces several limitations, especially in terms of the equipment. Finally, in order to compare predictive controllers, it is necessary to determine the same conditions so that results from more days can be used, and, if needed, more than 28 days have to be simulated. MOI index can help determine which of the proposed control scheme is really applicable.

Keywords: Stable Operation, Predictive Control, BSM1, Wastewater Treatment Plant, Unconventional Loading.

INTRODUCTION

A closer look at current operation of WWTPs reveals that automation is still minimal even in a scientific community. The importance of automation and control processes, related to various types of industries, has now been recognized for almost 40 years (Olssen et al., 2005) as it is marginal to treatment processes and considers WWTPs a non-profit industry. Therefore, automation, process control, and operating systems have all been labelled costly and out of the process design. In general, a control system aims at making the process output behave in a desired way by manipulating the plant's inputs. From a control engineering point of view, controlling WWTPs is a complex topic for several reasons. For instance, the response to changes in air flow rate is nearly instantaneous, while dissolved oxygen affects the treatment process in minutes.

So far various works have dealt with the way a linear model can be reduced (e.g., Smets et al., 2003; Jeppsson et al., 1993;

* Corresponding Author, Email: bamin@ut.ac.ir

Julien et al., 1998; Hahn and Edgar, 2002; and Lee et al., 2002), showing that balancing linear systems is a powerful technique, easy to implement. However, especially when model-based control methods like nonlinear model predictive control are needed, a nonlinear model can provide a more accurate description of process dynamics. However, due to the increased complexity introduced by model nonlinearity, nonlinear controllers show some drawbacks when compared to linear ones.

The main goal of this project is to maintain the quality of the plant effluent in given limits in terms of flow rate and composition, whatsoever the variations of the incoming wastewater. This can be used in two approaches: controlling various concentrations (nitrate, oxygen, etc.) at specific locations within the reactors or in a direct scheme, where the set points are the effluent quality indicators. The difficulty here is that they are given as constraints, not as set points (Shen et al., 2008).

In the literature, one can see works that propose various methods to control and model WWTPs, even though their evaluations and comparisons are difficult (Chachuat et al., 2001; Olsson and Newell, 2002; Mulas, 2005; Weijers, 2000). Most papers have used the Benchmark Simulation Model No.1 (BSM1) as the working scenario, their control objectives usually based on improving the effluent quality and/or cost indices. There is not a vast amount of literature to cover control in WWTPs. In some cases a direct control of the effluent variables were used to avoid violations of the effluent limits. Qin and Badgwell (2003) made a good overview of both linear and nonlinear commercially-available MPC technologies, while Francisco et al. (2011) and Han et al. (2014) presented a procedure for tuning of MPC of WWTPs and a nonlinear multi-objective MPC control scheme. Shen et al. (2009) implemented three different forms of feedback MPC, i.e., DMC, QDMC, and a modified version of QDMC, incorporating feed forward. In addition, direct addressing of effluent quality as well as operating costs in a control design was expected in some works, e.g., Zeng and Liu (2015), to be capable of obtaining significantly-improved results, where economic MPC was adapted to a WWTPs and the performance of the EMPC was compared with a PI control scheme. This method could have a practical application if and only if the process model, occurring in the clarifier, is available; otherwise, no satisfactory performance can be expected. The reason behind using the LMPC is that linearized model requires less computational effort and time to simulate. This will of course have limited applicability.

Other works have given a trade-off between operational costs and effluent quality, though not tackling effluent violations. They usually propose hierarchical control structures. For instance, Santin et al. (2015) proposed a control strategy with the aim of eliminating violations of effluent pollutants by using fuzzy and MPC controllers. Another work proposed a two-level compensated hierarchical control strategies (MPC+FF) to control $S_{NO,2}$ and $S_{O,5}$ in the lower level, with the higher one modifying $S_{O,5}$ set point of lower level, in accordance with the working conditions (Santin et al., 2015). A more recent work in this area can be found in Revollar et al. (2017) who compared five different control schemes of EMPC in dry weather condition.

Motivated by the success of different schemes of MPC in various applications and the fact that more and more severe regulations are imposed to WWTPs, themselves inherently multi-variable processes, the present work takes full advantage of NMPC control scheme to optimize effluent quality, while minimizing the costs, which is at the same time the main objective of treatment plants. In this control approach the control action, based on the prediction of future dynamics of the system, allows early control action to be taken in order to accomplish the control performance based on the expected future behavior.

What makes this work significant can be listed as below:

1. Its identification of the nonlinear predictive model of the process along with simulation and on-line control of NMPC controllers is performed via MATLAB direct coding instead of MPC toolbox.
2. It determines the initial conditions of the reactors as well as the 10^{th} layer settler.
3. It applies more than one numerical solution in different steps of simulation, thus reducing the amount of additional calculation and time significantly especially for non-advanced computers . This becomes very important in predictive controlling systems.
4. It makes a detailed comparison among five control techniques include for trajectory tracking under external disturbances: classical linear MPC, hierarchical MPC with feed forward action, Economic MPC (EMPC), MPC+fuzzy, default PI, and a more advanced nonlinear MPC (NMPC). The main aim of this comparison is to determine both the benefits and drawbacks of considering the full system dynamics in terms of computation effort, performance improvement, and disturbance rejection.
5. The method of building the BSM1 simulation model is presented step by step.

After introducing the steps of building BSM1 model, the article compares the proposed NMPC in details with five recent predictive control schemes as well as the default PI controllers of benchmark model.

MATERIAL AND METHODS

Benchmark of wastewater treatment plants: From a practical point of view, it is not possible to assess all control strategies, provided in research works, either in real life or in a laboratory context, thus making any attempt of simulation a cost-effective tool for this purpose. However, one should consider to compare different operation strategies, for which a standard instruction has to be followed in order to create the system model. The present section gives the BSM1 model employed in the controllers' formulation in details. BSM1 is a simulation environment, defining a plant layout, a simulation model, influent loads, test procedure, and evaluation criteria for both the evaluation and comparison of different control strategies. Figure1 demonstrates a common and relatively-simple plant layout, combining nitrification with pre-denitrification. The plant is consisted of five bioreactors, connected in series, followed by a 10-layer secondary settler, the 6^{th} layer of which (counting from bottom to top) is the feed layer, itself. Also Table 1 offers the main characteristics of BSM1 benchmark model.

The current research used the IWA Activated Sludge Model No.1 (ASM1) (Henze et al., 2000) to describe and simulate eight different biological processes, taking place in the reactors. Double-exponential settling velocity model (Takacs et al., 1991) was also used to simulate vertical transfers between the settler layers. Both models are internationally accepted.

The three scenarios used for this study entailed typical feed disturbances for three influential data (Alex et al., 2008), namely dry weather, rainy weather, and stormy weather, for 14 days of the influential data with sampling intervals of 15 minutes. Such a multivariable process should operate under those constraints that concern the outputs along with the manipulated variables. Table 2 presents the effluent constraints. In order to ensure that the results were obtained under very same conditions and could be compared, a simulation protocol got established. Figure 2 demonstrates the BSM1 building process step by step.

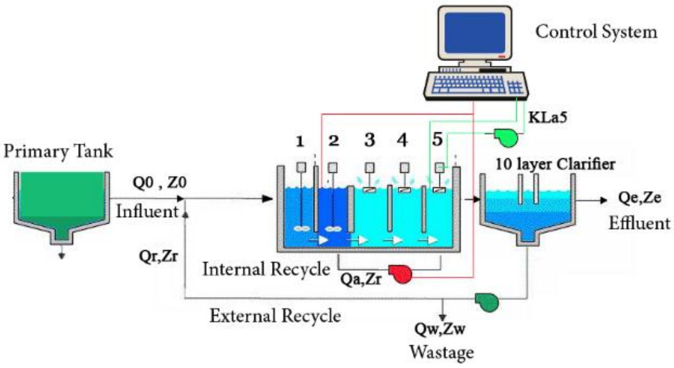

Fig. 1. BSM1 benchmark layout

Table 1. Characteristics of BSM1 model (Alex et al., 2008)

Process Parameter	Value
Total volume of bioreactors	5999 m^3
Non-aerated compartments volume (reactor 1 &2)	1000 m^3
Aerated compartments volume (reactors 3 to 5)	1333 m^3
Fixed oxygen transfer coefficient (K_La)	1 h^{-1}
Saturation concentration for oxygen	8 g/m^3
Settler volume	6000 m^3
Internal recycle flow rate	55338 m^3/d
Average influent flow rate	18446 m^3/d
Wastage flow rate	385 m^3/d
External recycle flow rate	18446 m^3/d

Table 2. Effluent quality limits (Alex et al., 2008)

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 $BOD.m^3$

Step 1. Predicting the initial values of the steady state for aeration reactors and secondary settler.

↓

Step 2. Simulating the plant in open loop for 150 days under constant inputs of the 1st column of Table 3 by using ODE15s solver and comparing the results to appendix 2 of ref (Alex et al., 2008).

↓

Step 3. Simulating the plant in closed loop for 150 days first under constant inputs of the 1st column of Table 3 by using ODE15s solver, then under dry weather conditions for 14 days via ODE45 as suggested in ref (Alex et al., 2008), and saving the results as the initial values of dynamic simulation.

↓

Step 4. Simulating the plant under different weather conditions with default PI controllers and the results of the last 7 days to be used for evaluation of the performance of the control scheme.

↓

Step 5. Performing step 4 with NMPC

Fig. 2. Flowchart of building BSM1 with different controllers

Table 3 demonstrates the initial values of steady state solution of the equation matrix inversion and state variables of raw influent wastewater. As shown in Table 4, the initial values for use in the numerical integration routine can be obtained from the steady state solution for each completely-mixed reactor. The process of treatment can be described by the following equations matrix:

Table 3. Results of performing step 1 of the flowchart.

State variable	Input (mg/L)	Initial concentrations of state variables (mg/L)				
		Reactor 1	Reactor 2	Reactor 3	Reactor 4	Reactor 5
S_I	30.00	30.00	30.00	30.00	30.00	30.00
S_S	69.50	2.81	1.46	1.15	1.00	0.89
X_I	51.20	1149.13	1149.13	1149.13	1149.13	1149.13
X_S	202.32	82.13	76.39	64.85	55.70	49.31
X_{BH}	28.17	2551.80	2553.39	2557.13	2559.18	2559.34
X_{BA}	0.00	148.39	148.31	148.94	149.53	149.8
X_P	0.00	448.85	449.53	450.52	451.31	452.21
S_O	0.00	0.00	0.00	1.72	2.43	0.49
S_{NO}	0.00	5.37	3.66	6.54	9.30	10.42
S_{NH}	31.56	7.92	8.34	5.55	2.97	1.73
S_{ND}	6.95	1.22	0.88	0.83	0.77	0.69
X_{ND}	10.59	5.28	5.03	4.39	3.88	3.53
S_{ALK}	7.00	4.93	5.08	4.67	4.29	4.13
TSS	211.27	3285.20	3282.55	3277.85	3273.63	3269.84

Table 4. Steady state solution of mixed aeration reactors equations

	State variables vector													
	1	2	3	4	5	6	7	8	9	10	11	12	13	
	S_I	S_S	X_I	X_S	X_{BH}	X_{BA}	X_P	K_La	S_{NO}	S_{NH}	S_{ND}	X_{ND}	S_{ALK}	**Input vector**
1	$-D_h$	0	0	0	0	0	0	0	0	0	0	0	0	$-D_hS_{I,1}$
2		$v_{21}K_1 - D_h$		$v_{27}K_7$										$-D_hS_{s,1}$
3			$-D_x$											$-D_hX_{I,1}$
4				$v_{47}K_7-D_x$	$v_{44}b_H$	$v_{45}b_A$								$-D_hX_{s,1}$
5					$v_{54}b_H-D_x$									$-D_hX_{BH,1}$
6						$v_{65}b_A-D_x$				$v_{63}K_3$				$-D_hX_{BA,1}$
7					$v_{74}b_H$	$v_{75}b_A$	$-D_x$							$-D_hX_{P,1}$
8		$V_{81}K_1$						$O_{2sat}-S_O$		$v_{83}K_3$				$-D_h(S_{o,1}-S_o)$
9									$-D_h$	$v_{93}K_3$				$-D_hS_{NO,1}$
10		$V_{101}K_1$								$v_{103}K_3-D_h$	$v_{106}K_6$			$-D_hS_{NH,1}$
11											$v_{116}-D_h$	$v_{118}K_8$		$-D_hS_{ND,1}$
12					$v_{124}b_H$	$v_{125}b_A$						$v_{128}K_8-D_x$		$-D_hX_{ND,1}$
13		$V_{131}K_1$								$v_{133}K_3$	$v_{136}K_6$		$-D_h$	$-D_hS_{ALK,1}$
	State-state matrix													

For instance the 6th row can be obtained as follow:

$$v_{65}b_A\ X_{BA} - D_x\ X_{BA} + v_{63}K_3\ S_{NH} = -D_h\ X_{BA,1}$$

The initial values for different layers of secondary settler were equal to the 5th column of the table. For the purpose of complementary explanations about the processes, occurring in an activated sludge reactor, one can refer to Henze et al. (2000). The initial conditions, from steps 2 and 3 of the flowchart, can be found in Zeng, J .and Liu, J .(2015).

Finding a suitable control structure; that is to find the actual implementation of the optimum policy in the plant, is an important step in controlling of a WWTP. It makes definition of the optimal operation for the process a critical and important task. Model-based predictive control has been considered recently due to its capacity to deal with multivariable systems and constraints. Continuing research activities in the field of Nonlinear Model Predictive Control has resulted in various contemporary developments, with NMPC predicting the trajectory of the system on a prediction horizon by means of the process' model, also computing an optimal control sequence on a control horizon (Muller et al., 2014). It is quite beneficial to use the non-linear model of the plant as a nonlinear state estimator with two PID controllers, instead of the default PI controller of BSM1. This is pertinent as popular PI controller may be hard to tune or becomes ineffective when a multivariable system with actuators is to be controlled. Two benefits of MPC control technique implementation include its integration of constraints into the optimization of the cost function and handling multivariable control problems (Rossiter, 2003). A detailed discussion on the construction of the estimator can be found in Alvares (2000) and Lopez (2000).

PI/PID Controller or three-term controller is a control loop feedback mechanism, widely used in industrial control systems, whose distinguishing feature is its ability to use the three control terms of proportional, integral, and derivative influence on the controller output in order to apply accurate and optimal control. The form of the PID controller, encountered in industry most often than not, can be expressed mathematically as below:

$$u_j(t_k) = K_{pj}\left[\left(y_j^{set} - y_j(t_k)\right) + \frac{T_{tj}}{T_{ij}}\sum_{m=0}^{k}\left(y_j^{set} - y_j(t_m)\right) + T_{dj}\left(y_j(t_{k-1}) - y_j(t_k)\right)\right] \quad (1)$$

$$Ki = Kp / Ti$$

$$Kd = Kp \times Td$$

$$j = 1,\ 2$$

where y_1^{set} and y_2^{set} are the set points of $S_{NO,2}$ and $S_{O,5}$, respectively. Since set points are constant, their derivatives get eliminated. K_{p1}, T_{t1}, T_{i1}, and T_{d1} are the proportional gain, the anti-windup time constant, integral time constant, and derivative time constant of the controller associated with $S_{NO,2}$, respectively, with K_{p2}, T_{t2}, T_{i2}, and T_{d2} being corresponding parameters of the controller, associated with $S_{O,5}$, Ki, and Kd, all being non-negative and denoting the coefficients for integral and derivative terms, respectively (Astrom and Hagglund, 1995). The first control loop involves the control of DO,5 via manipulating K_La5 to the set point of 2 mg/L. The second one has to maintain NO,2 at a set point of 1 mg/L by manipulating Qr. Table 5 summarizes the needed parameters of PI/PID controllers. By setting the Kd coefficient to zero, the default PI controllers of BSM1 could be achieved.

Table 5. Parameters of PI/PID controller

	$S_{NO,2}$controller	**unit**	**$S_{O,5}$ controller**	**unit**
Sensor class	B0	-	A0	-
Measurement range	0-20	gN/m^3	0-10	$g(-COD)/m^3$
Measurement noise	0.5	gN/m^3	0.25	$g(-COD)/m^3$
Kp	10000	$m^3/d/(gN/m^3)$	25	$m^3/d/(gCOD/m^3)$
Ti	0.025	days	0.002	days
Tt	0.015	days	0.001	days
Td	0.015	days	0.001	days
Set point	1	gN/m^3	2	$g(-COD)/m^3$
MV	Qr	m^3/d	K_La5	1/h
MV range*	0 to 5 of Q0	m^3/d	0-10	1/h

*MV: Manipulating Variable

The idea of MPC, whether linear or nonlinear, is to utilize a model of the process in order to predict and optimize the future system behavior. In linear MPC, system operation is approximated in the vicinity of the working point by a discrete-time state-space linearized model. Nonlinear MPC fits with the nonlinear nature of the system's operational problems. The chief argument is that it is much more challenging to use nonlinear models than linear ones, with most natural systems using a nonlinear model to express the relations among their parameters. Yet, most of the time, a linearized model is used to design the process control system. Once correct functioning of the control system is ensured, the designed controller is applied to the real system with a nonlinear model. Thus, in practice one will encounter some errors. The use of a nonlinear model to design the control system is only preferable for systems with slow dynamics. Yet, on the contrary, using linearized model is the first choice in fast dynamics systems. In what follows, a continuous nonlinear time MPC control method will be explained.

The highly nonlinear nature of the treatment process' operational problems is the major reason why Nonlinear Model Predictive Control (henceforth abbreviated as NMPC) is worth substantial investigation. An optimization-based method to control nonlinear systems, NMPC is primarily applied for stabilization and tracking problems, being widely used in process industry, in particular, thanks to its applicability on large scale processes along with capability to handle the constraints (Shen et al., 2008). The idea for an MPC, whether linear or nonlinear, is to utilize a model of the process in order to predict and optimize the future system behavior. The additional term nonlinear indicates that model (2) needs not to be a linear map. Model, constraints, and performance index are three main components of an MPC scheme and a nonlinear model in form of (2) is the first important element:

$$\dot{x}=f(x(t),u(t)),\ x(0)=x0 \tag{2}$$

In generic notation, the NMPC problem can be expressed as quadratic function, often the first choice for the cost function. The NMPC algorithm relies on calculating optimal control actions over a control horizon (hc), which minimizes the impact of system input on the cost function (J) of the system over a prediction horizon (hp) and satisfying constraints. Variables are predicted with regard to the system model, defining their relations to the system. Although a vector on hp optimal control actions is calculated at every sampling time, only the first element of the vector is implemented to the real system, upon which the system status is updated to form an updated cost function in order to be optimized and able to find the optimal controlling parameters vector for the next step and so on. The NMPC scheme shown in Figure 3, repeatedly solves the following Optimal Control Problem (OCP): At each sampling step n, the predicted future behavior of the system over a finite time horizon k=0,…,N-1 of length N≥2 is optimized and only the first element of the resulting optimal control sequence is used as a feedback control value for the next sampling interval. Now the optimal control problem (OCP) can be defined as follows:

$$\min_{U,X} \int_{t=0}^{T} (x(t)-x_{ref,k}(t)_{Q_x}^2 + u(t) - u_{ref,k}(t)_{R_u}^2)dt + x(T)-x_{ref,k}(T)_P^2 \tag{3}$$

Subjected to $\dot{x}=f(x,u)$;
u(t) ϵ U & x(0)=x(t_0).

where Qx≥0, Ru>0 and P≥0 are the penalty on the state error, the penalty on control input error, and the terminal state error penalty, respectively, while $x_{ref,k}$ and $u_{ref,k}$ are the target state vector and target control input at time k (Grune and Pannek, 2010). U indicates the control input constraint and finally **f** stands for the state equations of the process, demonstrated in Table 4, related to BSM1.

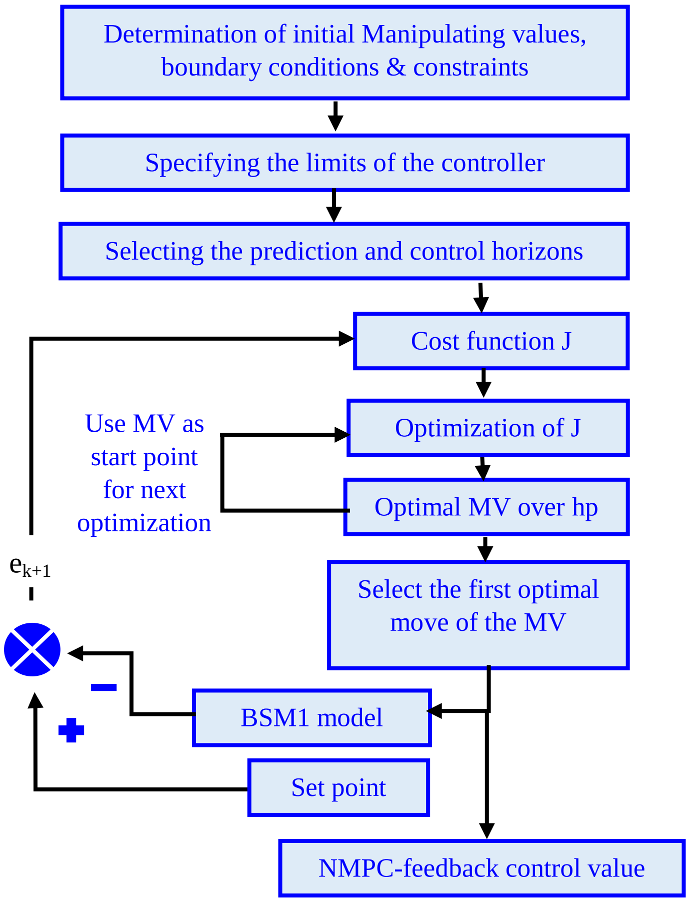

Fig. 3. Flowchart of NMPC algorithm

Due to slow dynamics of the process, there is more time to compute control commands. Therefore, the performance criterion is considered the least control effort. According to Equation (3), sum of the three positive terms is the smallest value, each inclined towards zero and one should keep both x and u variations around this value, meaning that the system state is near the equilibrium point and the actuators are used as little as possible to consume less energy. Therefore, the system cost function is composed of two parts, one trying to maintain the state of the system around the balance point which preserves it with the least control effort, while the other's concept in Equation (3) is a way of energy optimization. The aforementioned OCP needs to be solved repeatedly by means of implicit approaches. Direct methods techniques such as Runge-Kutta or Euler have attracted particular attention to address OCPs. Hybrid implicit Runge-Kutta order 4 and Euler are employed to forward simulation of the system dynamics along the interval. In this way, the computation time can be improved (Hasanlou et al., 2018). Furthermore, Genetic Algorithm (GA) method is used to solve the optimization process.

RESULTS AND DISCUSSION

This section compares the implemented control configurations, proposed in the previous section, with the results from other related works. Here, the results were obtained, through MATLAB implementation, described in Alex et al. (2008) and the NMPC controllers got identified, using direct coding in this software. Such controllers consider more general optimal control problems (OCPs) than the ones, penalizing the distance to a desired reference solution (Grune and

Pannek, 2010). The WWTP, illustrated in Figure 1, was represented by a nonlinear model in the state-space form with 145 state variables. The same sensors and actuators, defined within the BSM1, were also applied, though it was assumed that the dissolved oxygen sensors were ideal with no delay and noise. Prediction horizon (hp) and control horizon (hc) proved to be the significant factors, affecting NMPC performance, with the selected values for tuning the controllers being hp = 7 and hc = 3. It should be noted that only a slight change might be noted in the results with different values of hp and hc, since these values were not critical and could be slightly changed with similar results. The assessment took place in two levels. The first one concerned the control performance, serving as evidence for proper application of the proposed control strategy, assessed by the Integral of the Square Error (ISE) criterion. The second one, however, provided the measures for the impact of the control strategy on plant performance, and included the Effluent Quality Index (EQI) and Overall Cost Index (OCI). Table 6 gives the performance assessment criteria definition with the used indices being as follows:

$$\mathrm{OCI} = \mathrm{AE} + \mathrm{PE} + 5.\mathrm{SP} + 3.\mathrm{EC} + \mathrm{ME} \tag{4}$$

$$\mathrm{EQI} = \frac{1}{T \times 1000} \int_{t=21\,days}^{t=28\,days} \left(B_{SS}.TSS_e(t) + B_{COD}.COD_e(t) + B_{BOD5}.BOD5_e + B_{Nkj}.TKN_e(t) + B_{NO}.S_{NOe}(t) \right) Q_e(t).dt \tag{5}$$

$$\mathrm{PE} = \frac{1}{T} \int_{t=21\,days}^{t=28\,days} \left(0.004.Q_a(t) + 0.008.Q_r(t) + 0.05.Q_w(t) \right).dt \tag{6}$$

$$\mathrm{AE} = \frac{S_O^{sat}}{T.1.8.1000} \int_{t=21\,days}^{t=28\,days} \sum_{i=1}^{5} V_i.K_L a_i(t).dt \tag{7}$$

$$\mathrm{SP} = \frac{1}{T}\left(TSS_a(14days) - TSS_a(7days) + TSS_s(14days) - TSS_s(7days) + \int_{7days}^{14\,days} TSS_w.Q_w.dt \right) \tag{8}$$

$$\mathrm{EC} = \frac{COD_{EC}}{T.1000} \int_{7days}^{14days} \left(\sum_{i=1}^{n} q_{EC} \right).dt \tag{9}$$

$$\mathrm{ME} = \frac{24}{T} \int_{7days}^{14days} \sum_{i=1}^{5} \left[0.005.V_i \;\; if K_L a_i(t) < 20d^{-1} \;\; otherwise 0 \right] \tag{10}$$

Table 6. Criteria definitions, used in the performance assessment formula and B_i values

Definition	Formula
Total effluent suspended solids (TSSe)	$0.75(X_{Se}+X_{BH,e}+X_{BA,e}+X_{P,e}+X_{I,e})$
Required effluent Chemical oxygen demand (CODe)	$S_{S,e}+S_{I,e}+X_{S,e}+X_{I,e}+X_{BH,e}+X_{BA,e}+X_{P,e}$
Required effluent Biochemical oxygen demand (BOD_5)	$0.25(S_{S,e}+X_{S,e}+(1-f_P).(X_{BH,e}+X_{BA,e}))$
Total kjeldahl nitrogen content (TKNe)	$S_{NH,e}+S_{ND,e}+X_{ND,e}+i_{XB}(X_{BH,e}+X_{BA,e})+i_{XP}(X_{P,e}+X_{I,e})$
Effluent nitrate nitrogen (NO_e)	$S_{NO,e}$
Total effluent nitrogen ($N_{tot,e}$)	$TKN_e+S_{NO,e}$
Total sum of suspended solids of reactors and settler	TSS_a+TSS_s
Weighting factor of B_{SS}	2
Weighting factor of B_{COD}	1
Weighting factor of B_{BOD5}	2
Weighting factor of B_{TKN}	30
Weighting factor of B_{NO}	10

Most environmental issues, caused by wastewater, are related to its nitrogen and phosphorus contents. BSM1 suffers from an anaerobic reactor; therefore, the effect of one of the most important parameters of wastewater, phosphorus, was not studied at all. Consequently, the control system focused on nitrogen-containing parameters. Taking full advantage of the process model in the structure of the control system played a significant role in maintaining the standard of discharge to receptive bodies. The more accurate the model, the better the results.

To compare the trajectory tracking of each controller, Figure 4 shows the performance of the two control schemes under three external disturbances. As it can be seen, there was no significant difference between PI controllers' performance in the three weather conditions and the NMPC outperformed the default PI. Clearly, the set point tracking, implemented in the NMPC or other predictive controllers, greatly improved the performance of the proposed control strategies.

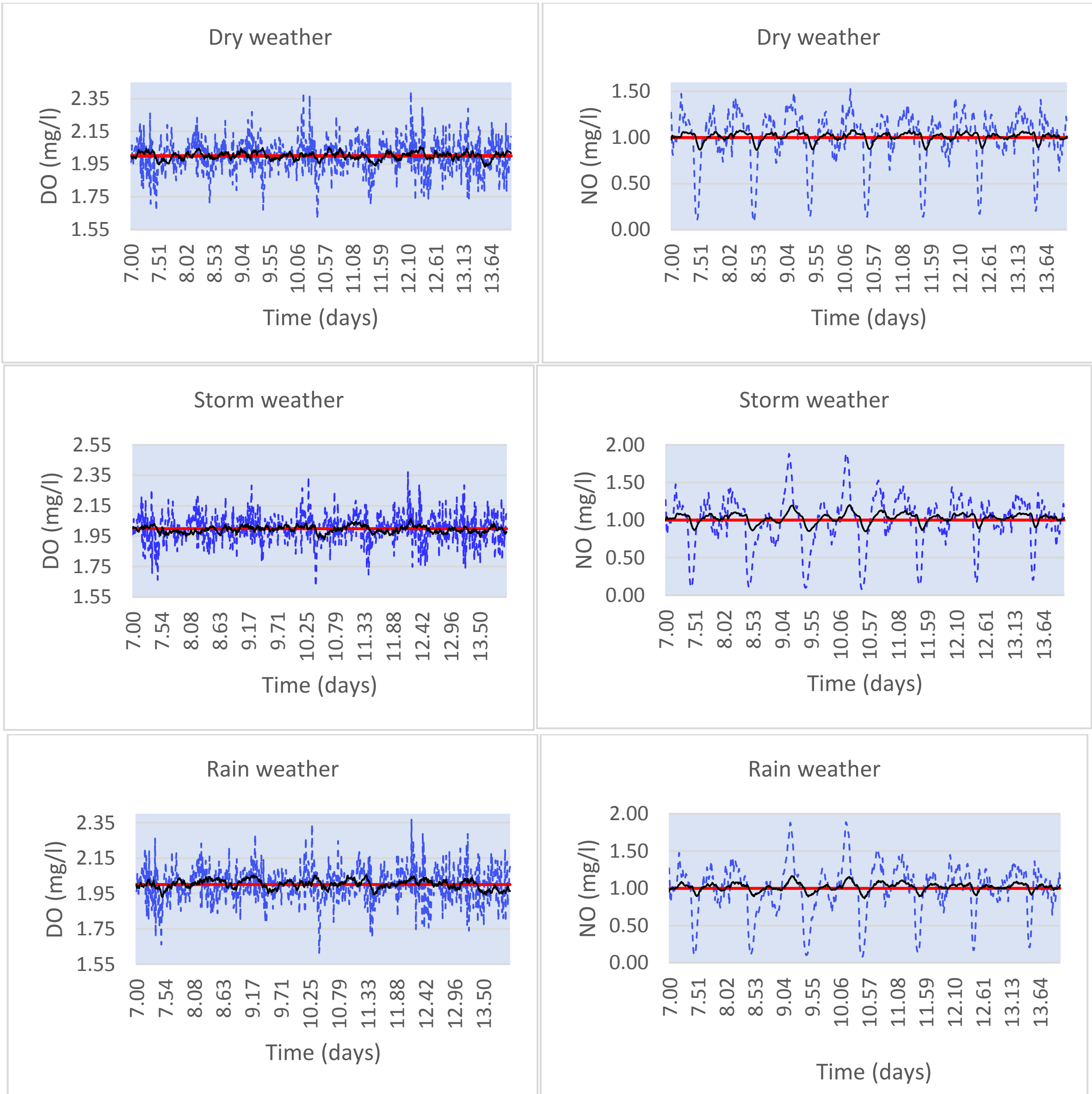

Fig. 4. Performance of NMPC (solid black line) and default PI (blue dashed line) controllers in different weather conditions for $S_{O,5}$ and $S_{NO,2}$ control; the red line is the set point.

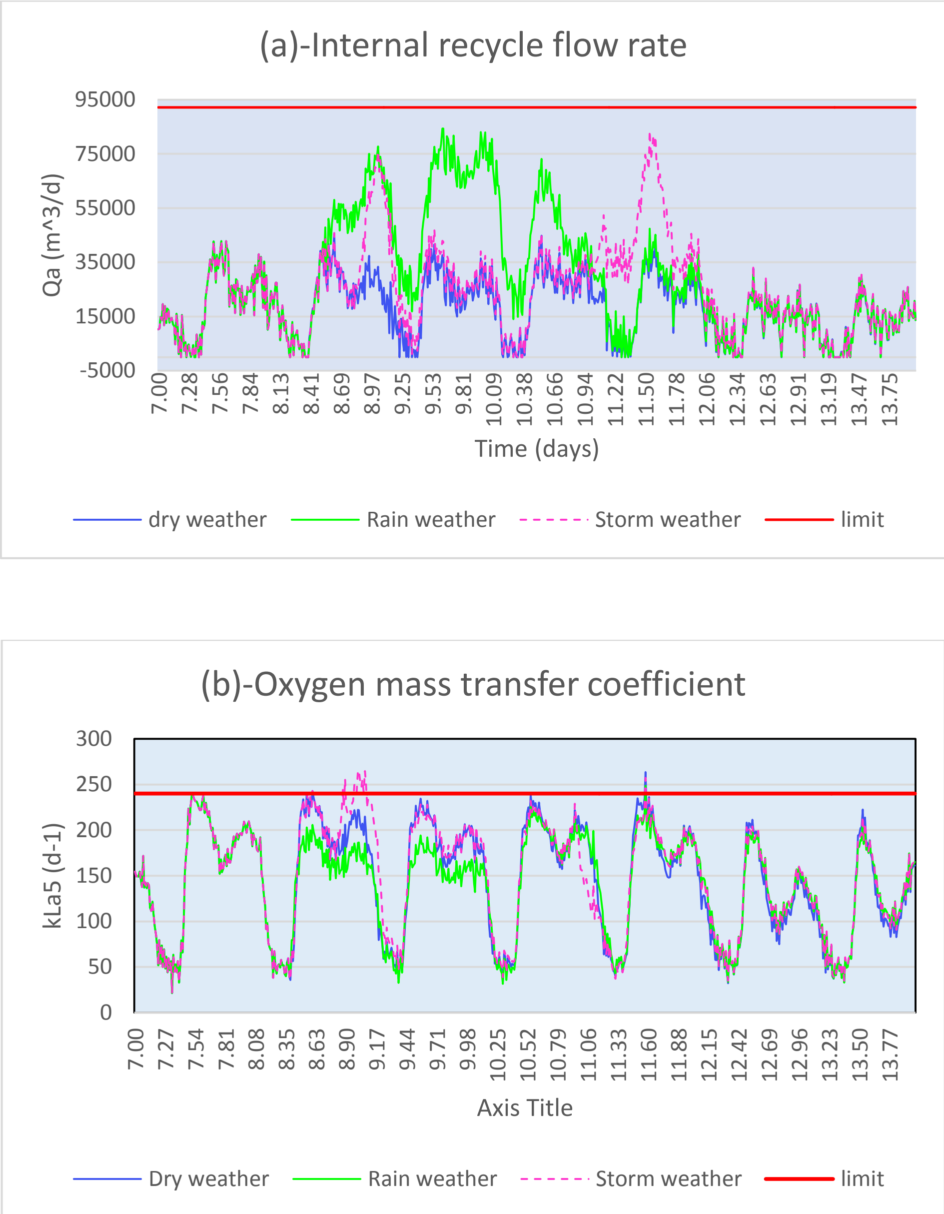

Fig. 5. Manipulated inputs in different weather conditions

What is quite noticeable from Figure 5-a, is the wide range of changes in the internal recycle flow rate values at the presence of system disturbances. The maximum flow rate under normal operating conditions was about 45000 (m^3/d), while in rainy weather conditions this amount was approximately twice the normal rate. Although a large range of variation was considered for this variable, the saturation limit was reached more often than not. From a practical point of view, the capacity of the sludge transmission line and pumping system was somewhat clear; to overcome this problem a backup transmission line can be considered in parallel with the main line. The more frequently is the equipment turned on and off, the longer they work efficiently. In spite of the wide range of changes in this control parameter, this large domain got significantly reduced and confined.

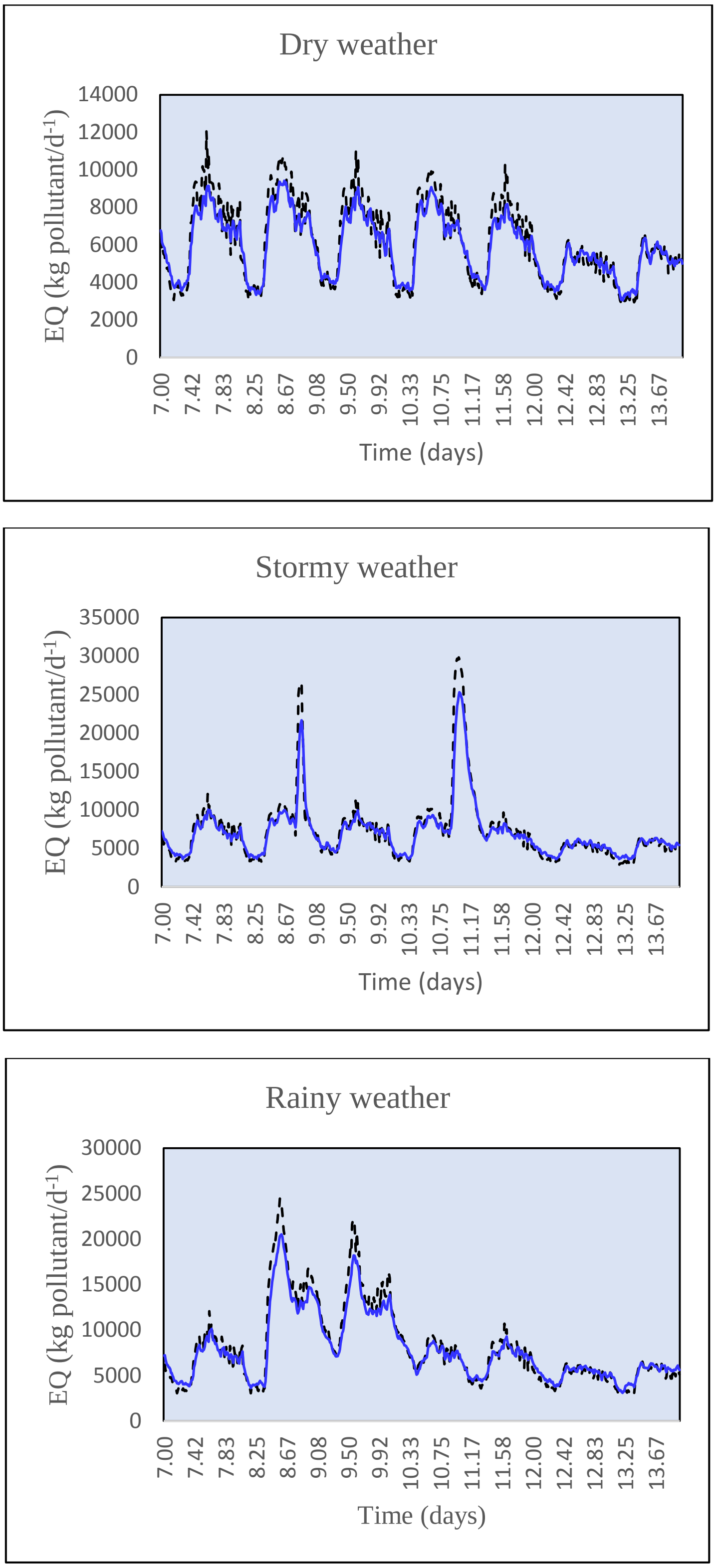

Fig. 6. Instantaneous EQ, given by NMPC (solid line) and PI (dashed line) in three weather conditions

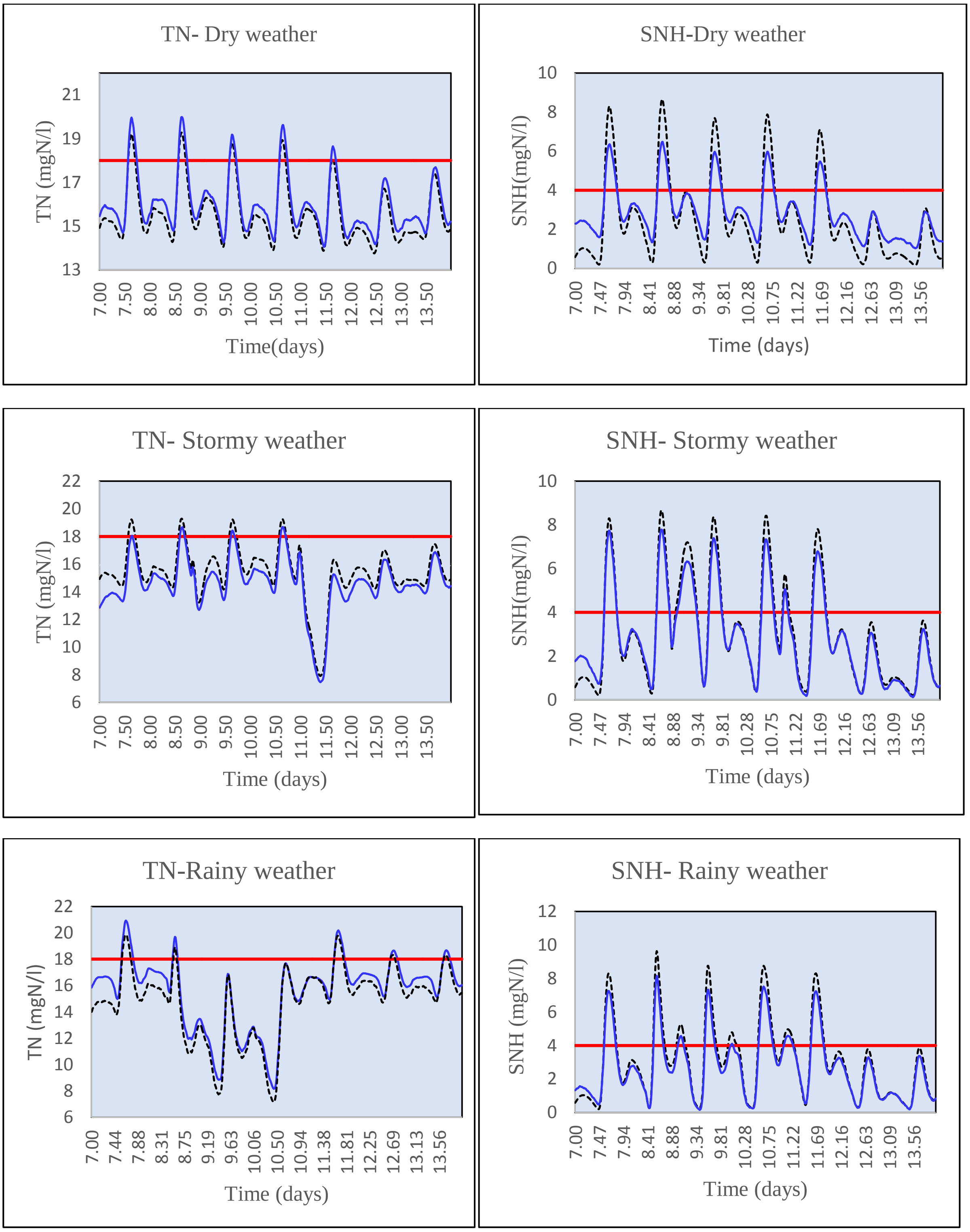

Fig. 7. Effluent parameters concentration in different weather disturbances for NMPC (solid line) and PI (dashed line)

By means of the proposed NMPC scheme, the specified limit was never reached. Unlike Qa, the k_La5's values were approximately close to one another in various weather conditions, except for the stormy condition, in which the bound was never reached during the same period (Figure 5-b). As a result, aeration equipment were not in any serious trouble.

The Effluent Quality (kg pollution unit/d) is defined as the daily average of weighted summation of compounds that have a major influence on the quality of the receiving water (Copp et al., 2002). This index is typically considered as an important indicator of the performance of control systems. Figure 6 compares trajectories of the instantaneous EQ given by the NMPC and the PI control under different weather conditions. From this figure, it can be seen that the NMPC gives better EQ under external disturbances but changing the type of the controller will not change this index much.

According to figure 7, the concentrations of total nitrogen and ammonia nitrogen have oscillating state. This is due to changes in the characteristics of the input sewage during over a week or even in a day. Three parameters including: COD, BOD5 and TSS meet the related standard limits by default PI controllers (Hasanlou et al., 2018). In addition to reducing the concentration of parameters at the courier points, the number of violations of the standard limits is also reduced. This trend is visible in all three weather disturbances. As expected, the exact tracking of the set points has put its impact on the process outputs. The comparison aims to highlight the benefits of full system dynamics consideration and its effect on the WWTP performances. The detailed results of controller performance assessment comparison and total WWTP performance assessment are shown in Table 7 and Table 8.

Table 7. Results of different control schemes for three weather conditions.

	PI (Henze et al. 2008)	**NMPC**	**MPC (Muller et al. 2014)**	**Hierarchical MPC+ff (Santin et al. 2015)**	**EMPC (Muller et al. 2014)**	**MPC+fuzzy (Santin et al. 2015)**
Dry weather						
AE (kWh/d)	3698.34	3691.04	3692.93	-	3690.73	-
PE (kWh/d)	241.03	289.15	243.83	-	307.01	-
SP for disposal (kg/d)	2440.61	2439.75	2439.97	-	2441.37	-
EQI (kg pollutants/d)	6123.02	5938.29	6022.64	6048.25	5671.86	5910.83
OCI	16382.40	16418.94	16376.59	16382.97	16493.88	16242.97
Storm weather						
AE (kWh/d)	3720.92	3709.81	3715.15	-	3791.25	-
PE (kWh/d)	265.20	317.36	271.07	-	322.33	-
SP for disposal (kg/d)	2605.49	2606.51	2606.49	-	2609.14	-
EQI (kg pollutants/d)	7220.72	6904.59	7173.62	7132.60	6819.67	7022.25
OCI	17253.57	17299.72	17258.66	17261.39	17438.11	17243.73
Rain weather						
AE (kWh/d)	3671.35	3708.12	3667.87	-	3808.71	3044.92
PE (kWh/d)	285.26	303.53	291.39	-	333.17	298.34
SP for disposal (kg/d)	2357.59	2358.01	2357.03	-	2359.1	2439.26
EQI (kg pollutants/d)	8184.73	7978.45	8233.04	8090.29	7895.52	8072.5
OCI	15984.55	16041.7	15984.41	15990.85	16212.37	15780.83

Table 8. Performance comparison of $S_{O,5}$ and $S_{NO,2}$ control indifferent control schemes for three weather conditions.

	$S_{O,5}$ control			**$S_{NO,2}$ control**		
	ISE (mg(-COD)/l)^2*d	**IAE ((mg(-COD)/l)*d)**	**mean(|e|) (mg(-COD)/l))**	**ISE (mg N/l)^2*d)**	**IAE (mg N/l)*d)**	**mean(|e|) (mg N/l)**
Dry Weather						
NMPC	0.0033	0.1192	0.0177	0.0152	0.2536	0.0377
PI (Henze et al. 2008)	0.083975	0.58831	0.084044	0.56897	1.4348	0.20497
Hierarchical MPC+ff* (Santin et al. 2015)	0.00067	0.047	0.0068	0.0013	0.067	0.0096
EMPC (Muller et al. 2014)	-	7.72791	-	-	8.07046	-
MPC (Muller et al. 2014)	-	0.01314	-	-	0.02758	-
MPC+fuzzy (Santin et al. 2015)	-	-	-	-	-	-
Storm weather						
NMPC	0.0033	0.1222	0.0182	0.0347	0.3995	0.0594
PI (Henze et al. 2008)	0.0789	0.5660	0.0809	0.7880	1.6785	0.2398
Hierarchical MPC+ff* (Santin et al. 2015)	-	-	-	-	-	-
EMPC (Muller et al. 2014)	-	-	-	-	-	-
MPC (Muller et al. 2014)	-	-	-	-	-	-
MPC+fuzzy (Santin et al. 2015)	-	-	-	-	-	-
Rain weather						
NMPC	0.0041	0.1369	0.0203	0.0208	0.2976	0.0442
PI (Henze et al. 2008)	0.0747	0.5567	0.0795	0.7944	1.7349	0.2478
Hierarchical MPC+ff* (Santin et al. 2015)	-	-	-	-	-	-
EMPC (Muller et al. 2014)	-	-	-	-	-	-
MPC (Muller et al. 2014)	-	-	-	-	-	-
MPC+fuzzy (Santin et al. 2015)	-	-	-	-	-	-

* The units of the criteria are not mentioned in the article.

As it is clear in Table 7, the five MPC schemes have remarkable improvement and very comparable in the results in comparison with the default PI. It should be noted that the results of all predictive control schemes are close to each other and there is no significant difference between them. This item is visible in all three disturbances results and no control scheme has absolute superiority.

For a more comprehensive comparison, some related referenced papers have been compared with the proposed NMPC control scheme for different weather disturbances in

Table 8. Three statistical criteria have been considered in addition to allow the comparison with more papers that use the original version of BSM1. Integral of Square Error (ISE), Integral of absolute error (IAE) and average of the absolute error (mean (|e|)) (Alex et al., 2008). The performance of NMPC in all weather conditions is better than the default PI. Unfortunately, these three criteria have not been calculated in related works and only the results of the dry weather disturbance are available. An important issue to be considered is some control schemes are justified only theoretically, although they have good results. As long as the range of mechanical equipment performance is limited, they will have a longer lifespan, less depreciation and operation and maintenance and operation costs will be lower. Also, the frequency of switching on and off the mechanical equipment has a significant effect on the energy consumption and lifetime of the devices. For instance pumps, which are one of the most important mechanical devices in a treatment plants, have limited range of performance. This issue can be solved by defining an Index which includes factors such as: hours of operation, range of performance, life span and depreciation in calculation of OCI.

CONCLUSION

Finding the optimal operation conditions for the activated sludge process is the main goal of controlling urban wastewater treatment plants. Taking full advantage of process model plays a significant role to achieve this goal. In this study, the steps of building BSM1 were presented clearly and two of the most important ambiguities of the model, initial values inside the reactors and the clarifier layers for starting the static simulation and appropriate solvers for numerical methods in different simulation steps were answered. Applying more than one numerical solution to solving the simulation model reduces the amount of additional calculus and time significantly which is very important in predictive controlling systems.

Due to slow dynamics of the treatment process, model based predictive control systems are an appropriate option for applying process control strategies. So the NMPC control procedure was defined and compared with four recent predictive control schemes and the default PI controllers of BSM1. Exploiting of full dynamic of the process helps to more precisely examine the process control behavior. Moreover, the damper property of predictive control schemes against external disturbances plays an effective role in meeting the standard wastewater discharge. The results of the simulations indicate that the proposed control strategies do not necessary have a positive effect on all effluent process parameters and in some cases they also have reverse effects. It's almost impossible to control all process parameters simultaneously.

In spite of the mentioned theoretical developments and real applications of predictive control systems in various processes; no successful practical application of this kind of controllers have been reported in urban treatment plants. So, one cannot definitely comment on the superiority of the particular type of them. To evaluate the effectiveness of the proposed control scheme in real application, it is suggested that an index be defined as Maintenance & Operation Index (MOI) including factors such as: hours of operation, range of performance, life span and depreciation be considered in the OCI calculation.

The performances of all predictive control schemes are much better than the default PI but, what is more important than anything else is the ability to use the proposed control scheme in real systems. Due to the fact that there are several limitations in real application especially the constraints associated with the equipment. Finally, it should be noted that in default PI controllers, from 28 days of simulation, we only have access to the results of the last seven days, from the 21st to 28th day. Consequently, in order to compare predictive controllers, it's necessary to determine the same conditions so that the results of more days can be used and if it is needed to simulate more than 28 days, can be acted as specified instruction.

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