Event-based control for dissolved oxygen and nitrogen in wastewater treatment plants

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

M. Barbu
Dept. Automatic Control and Electrical Eng.
Dunarea de Jos University of Galati.
800008 Galati, Romania
Marian.Barbu@ugal.ro

***Abstract*—This paper addresses the problem of basic control loops in wastewater treatment plants. By basic control loops we are referring to the traditional dissolved oxygen and nitrates. In a usual activated sludge process based wastewater treatment plant, these controls are located, respectively, at the aerated and anoxic sections. They are the basic controls more sophisticated control solutions can be based upon. Therefore it is important that these loops perform in an efficient way. The problem is addressed here within the framework provided by the Benchmark Simulation Model Number 1 (BSM1) and by the use of an event-based solution. As far as to the knowledge of the authors, no solution based on this kind of controllers has been proposed already in the literature. The controllers are taken as of similar complexity as the ones provided as default control strategy in the BSM1, therefor being the main difference, the possibilities provided by the event-based implementation. It will be verified that the solution can slightly improve the performance of the already exiting controllers both at loop level as well as at plant operation level.**

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

I. Introduction

The increasing human activities have generated the need of using appropriate methods to reduce their impact on the environment. One of the essential components of this effort is the implementation of wastewater treatment plants in order to bring the effluent to acceptable pollutant concentration limits before it is discharged into natural recipients (lakes, rivers etc.). 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 in WWTPs is playing an important role in research in recent years [1] and [2].

An efficient solution to improve the efficiency of wastewater treatment plants is to adopt automatic control methods. [3]–[5]. Their adoption for these systems is slow in the case of wastewater treatment plants, the main reasons being, on one hand, the fact that they are extremely complex processes and the lack or the high cost of the measurement equipment, and on the other hand, the significant reticence of the industry to allow the testing of the control solutions on real plants, given the potential environmental risks [6]. Nevertheless, a few cases of plant automation, made possible by new monitoring instrumentation, [7] have been recently cited in the literature, [8] and more are being gradually implemented in full-size facilities.

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Another proposed solution is to build some benchmark models which allow different users to test their control structures and algorithms on the same platform. A first model is the Benchmark Simulation Model No. 1 (BSM1) [9] which includes only water processing units and defines three scenarios for the influent, based on the rain conditions that may arise. BSM1 includes a control strategy that is called Default Control Strategy (DCS). This is based on PI controllers in order to control the dissolved oxygen in the fifth tank ($DO5$) and the nitrate in the second tank ($NO2$) by manipulating the oxygen transfer coefficient in the fifth tank (KLa_5) and the internal recycle flow rate ($Qrin$) respectively. Obtaining a satisfactory control performance of these variables is of great importance, especially when applying more complex control strategies that vary the set-points of the default control loops. In these cases, with better performance of the default control loops, effluent quality is improved with lower costs. In this way, for several years and still recently there are many works that focus on the objective of improving the performance of $DO5$ and $NO2$ control, as in [10] and [11].

The present work is based mainly on the application of event-based control in order to improve the performance of DCS. Event-based control is a technique already used in other areas such as in [12] for pH control for the effective use of flue gases or in [13] for greenhouse production processes. However, it is a novelty in the literature related to Wastewater Treatment Plant control. In common control techniques, the control signal is actualised based on time. In the case of event-based controllers, the verification of events is regularly carried out, but the control signal is only actualised when one or more events occur.

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The rest of te paper is as follows. First of all, the simulation scenario is presented. The BSM1 layout, performance indexes and default control strategy is presented. Secondly, in section 3, the event-based control strategy based on the internal model control formulation is outlined. This generic structure was first presented in [14] in more detail, so just the basic structure and design principles are outlined here. It follows section 4 with the definition of the event based controllers for the BSM1 basic loops and presentation of the simulation results, The paper ends with concluding remarks and suggestions for further work.

II. Materials and Methods

This paper relies on a specific control scenario and controller configuration approach. As the scenario is the well known Benchmark Simulation Model #1 (BSM1), a very synthetic presentation will be introduced here. For a more complete and detailed presentation the reader is referred to the relevant literature such is [15], [16]. For what matters to the event-based control approach, the general design principles where presented in [14]. Therefore, the main ideas will be outlined here and a more detailed analysis can be found on such reference.

1) Benchmark Simulation Model #1 (BSM1): The BSM1 scenario is a simulation environment defining a plant layout, a simulation model, influent loads, test procedures and evaluation criteria. The plant layout jointly with the provided default control strategy is shown in Fig. 1. This control strategy is commonly used as a comparison source for other control proposals. It is defined in [9] ans involves the use of two Proportional-Integral controllers. The first one involves the control of the dissolved oxygen, $S_{O,5}$, by acting on the oxygen transfer coefficient K_La in the fifth tank (K_La_5). The set-point for this loop is fixed to $S_{O,5} = 2$ mg/l. The purpose of the other controller is to keep the nitrates level at the second tank at a set-point of 1 mg/l by manipulating the recirculating flow rate, Q_a.

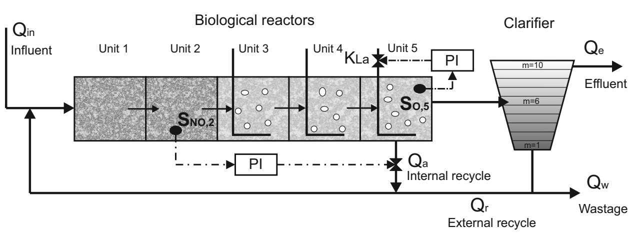

Fig. 1. Default control strategy of BSM1

2) Event-based Internal Model Control (IMC): The Internal Model Control (IMC) approach is very well known among the process control community. it was presented in [17] and extended to discrete time and multivariable systems in [18].

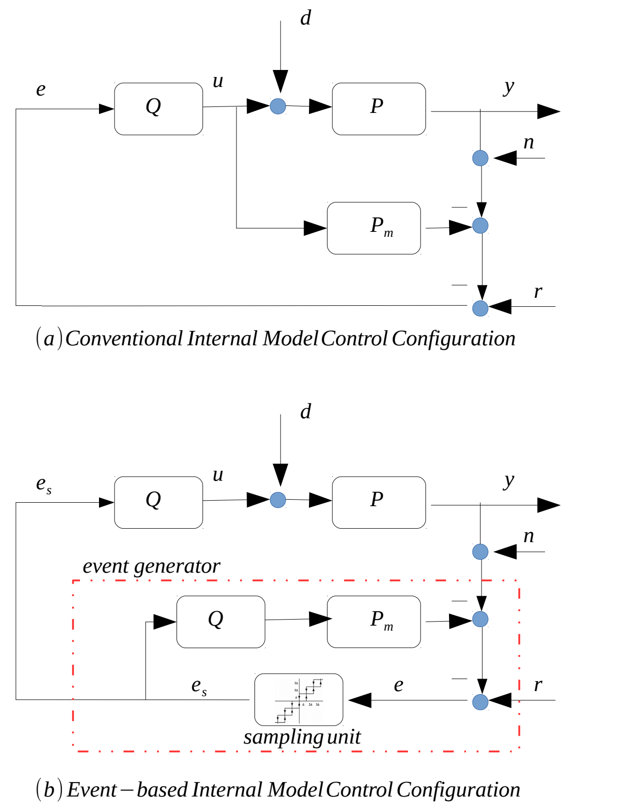

Fig. 2. Conventional and event-based Internal Model Control configurations

The essential point of the IMC is to generate a feedback signal that is built up as an aggregate of the plant model mismatch and the eventual presence of disturbances. The conventional and event-based IMC schemes are depicted in Fig. (2(a)) and (2(b)) respectively.

In this event-based configuration, the essential parts of the IMC controller, Q, are distributed and replicated on both, the sensor (including the event-generator) and the controller. On that basis, the event generator includes the plant model, P_m, as well as another implementation for the IMC controller. The event generator receives the IMC error as an input with the purpose to detect uncertainty levels up to some threshold. The Simmetric-Send-On-Delta (SSOD) sampling algorithm [19] has been considered. The output of this sampling unit is computed on the basis of two predefined parameters $\Delta \in \mathbb{R}^+$, and the internal state of the algorithm $j \in \mathbb{Z}^+$. If $e(t)$ is the input signal to the sampling unit, its output is computed according to $e_s(t) = j\Delta$.The events are triggered when consecutive levels are crossed by the error signal, which means that the sampled signal changes its value to the upper or lower quantization level when the input signal $e(t)$ increases or decreases more than Δ. More details on the event-based internal model control approach and its application to another domain can be found in [14] and [20] respectively.

III. SIMULATION RESULTS

In this section, we present the application if the event-based IMC control to the two basic control loops defined in the BSM1 scenario. For such purpose, in what follows, the design of the controller is presented first, followed by its implementation under an event-based strategy. The motivation in showing this application is also to show the fact that the design of the controller can be addressed in a complete independent way from its event-based implementation. This is one of the main advantages of this method that allows the independent (re)adjustment of both parts of the control system .

A. Internal Model Controllers

The design of the IMC controllers follow the usual process design approach. First of all a linear, low order model, is derived for each one of the loops to control. Then, the usual, straight, IMC design approach based on model inversion plus filtering is followed. Therefore. we will face now the design of the DO controller for the fifth aerated tank, DO_5, as well as for the nitrate on the second tank, NO_2.

As usual in process control, whenever possible, the design models will be reduced to the usual First-Order-Plus-time-Delay (FOPTD) or even just First-Order (FO) in order to facilitate the application of simple controller tuning rules. The following procedure is followed in order to derive the open loop models: drive the system to a steady state situation and to apply a 10% step change in the manipulated variables. The resulting data is collected and used for identification. The algorithm employed was N4SID [21], which exhibits robust numerical properties and relatively low computational complexity. The following first order models, $P_{DO_5}(s)$ and $P_{NO_2}(s)$ have been obtained for the for the relation from the KLa_5 to the DO_5 and between Q_{rin} and NO_2, respectively:

$$P_{DO_5}(s) = \frac{K_{DO5}}{T_{DO5}s+1} = \frac{0.0163}{0.01s+1} \tag{1}$$

$$P_{NO_2}(s) = \frac{K_{NO2}}{T_{NO2}s+1} = \frac{7.9145\ 10^{-5}}{0.02s+1} \tag{2}$$

As it can be observed, the models have been reduced to the minimum complexity. No higher order models are needed. As a side benefit, the corresponding controllers will also be very simple from both the design point of view as well as the implementation one. The design of the corresponding IMC controllers, follows the usual procedure. In IMC control, if $P(s)$ denotes the process model, the IMC controller $Q(s)$ is expressed as:

$$Q(s) = P(s)^{-1}F(s) = P(s)^{-1}\frac{1}{(\lambda s+1)^n} \tag{3}$$

where $F(s)$ is the well known IMC filter. The λ parameter, determines the closed-loop time constant. This time constant can be selected on the basis of the open-loop time constant, T, as $\lambda = \tau_c T$, where τ_c expresses the speed of response of the closed-loop with respect to the open-loop. Here, we select the desired closed-loop tome constant as ten times faster. Therefore, for both loops, $\tau_c = 0.1$. The resulting IMC controllers read as:

$$Q_x(s) = P_x(s)^{-1}F_x(s) = \frac{(T_x s+1)}{K_x}\frac{1}{(T_x\tau_c s+1)^2} \tag{4}$$

where x stands for $DO5$ and $NO2$ in each case.

At this point it is worth to notice that, even the design of the controller is presented within the IMC framework, the presented controllers are, in fact, filtered PI controllers. Therefore, the same kind of control law as the ones implemented in the benchmark.

Effectively, the feedback controller $K_x(s)$ associated to $Q_x(s)$ reads

$$\begin{aligned} K_x(s) &= \frac{T_x s+1}{K_x}\frac{1}{\lambda_x^2 s^2+2s\lambda_x} \\ &= \frac{2T_x}{K\lambda_x}\left(1+\frac{1}{T_x s}\right)\frac{1}{\lambda_x/2s+1} \end{aligned} \tag{5}$$

This is a PI controller with parameters $K_p = (2T_x/K_x\lambda_x)$, $T_i = T_x$ and filtered with a low pass filter with time constant $\lambda_x/2$. Therefore, at the end, it can be seen either as a PI or as an IMC.

B. Event-based implementation

For the event-based implementation, we just need to specify the sampling time of the event generator and the precision interval that will determine the event quantisation. As the order of magnitud of both loops is the same, the precision interval for event detection has been chosen as $\Delta_{DO5} = \Delta_{NO2} = \Delta = 0.01$. Also, the the sampling time of for event detection has been fixed to 1min. This means that a process measurement will be taken every minute and the event-detection will be executed. If no event is detected then no signal will be transmitted to the actuator.

These settings arise quite naturally from the dynamics of the loops under consideration. The selection of these parameters will determine the track following capabilities of the corresponding loop. Notice whereas the controllers defined in the default control strategy do operate in continuous time here the manipulated variable moves are driven by the generation of the corresponding events.

As a matter of comparison, the PI controller parameters that would result from translating the IMC designs into its PI form are compared with the PI tuning specified in the benchmark. Table (I) shows both tunings. It is observed that the event-based implementation allows higher controller gains that are traduced into better tracking and faster disturbance attenuation.

C. Simulation results

The time responses as well as quantitative metrics that show the performance of the proposed controllers in comparison with the default controllers included in the benchmark. It is

TABLE I
PI CONTROLLER TUNINGS

Loop	*Proposed*		*Benchmark*	
	K_p	T_i	K_p	T_i
$DO5$	1.227	0.01	25	0.002
$SNO2$	25.2700	0.02	10.000	0.025

worth to highlight that in the literature, the improvement in these two loops is usually addressed by the use of other , more advanced, control approaches such as model predictive control [22]. Here we show that there is still room for improvement if what is introduced is not a change in the computation of the control law itself but in its implementation. Here as event-driven controllers.

As with the established benchmark, one week of evolution is considered. Figures (3) and (4) show the evolution of fifth tank dissolved oxygen and second anoxic tank nitrates concentrations along with the corresponding manipulated variables. It can be seen that the tracking performance of the event-based controllers is superior to that one of the PI controllers provided by the benchmark. The benefits are remarkably better in the $NO2$ loop, where more accurate tracking is achieved. In the $DO5$ control loop, quite high precision is already achieved by the benchmark controller. In the solution provided here, in addition with the slight tracking error reduction, there is the fact that DO measures are needed with just one minute sampling. This point will allow, for example, the use of modern smart sensors with wireless communication capabilities by imposing lower data transmission needs.

The main impact of the event-based implementation can be seen in the manipulated variables. Whereas for the dissolved oxygen control loop, the control signal follows a very similar pattern (with very slight differences), the internal recirculation flow rate has higher bandwidth as the major responsible for the tracking improvement.

Figures (5) and (6) show a more detailed view of the operation of both loops during day 8th. As expected, the number of events is much more dense when the disturbance enters into effect and the controlled variable is driven away from the reference value. In both cases, it can be appreciated that when the controlled variable suffers high deviation from the reference value, an higher number of events are generated that corresponds to a more continuous control action (always within the established sample times) that is slightly anticipated with respect to the benchmark one.

A more quantitative performance comparison is shown in table (II) where the metrics provided by the BSM1 scenario are employed. Performance at both control loop and plant level are used. Effectively the tracking performance of both loops is clearly superior in absolute and aggregated terms. However, it is well known that sometimes, to achieve this increment in tracking performance at loop level, has small repercussions at plant level or event it may increase the overall costs at the expenses of not improving the plant treatment efficiency. In this case, the proposed controllers achieve a non despreciable improvement on the plant treatment capacity at the expenses of practically the same overall cost. Clearly, the average of effluent nutrient concentrations as well as effluent limit violations are slightly improved.

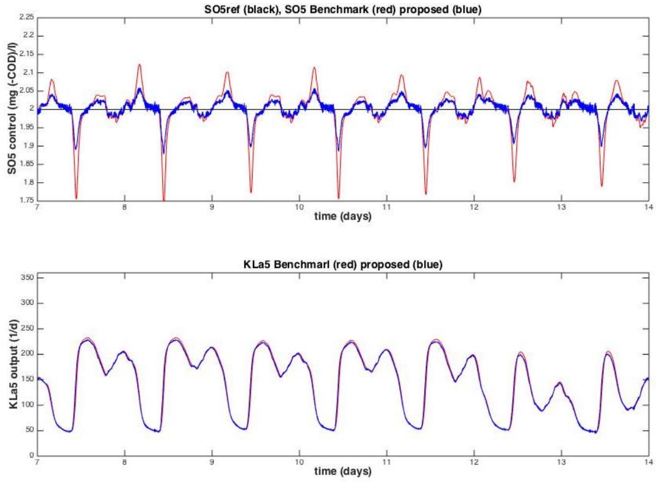

Fig. 3. SO_5 control loop performance and KLa_5 manipulated variable

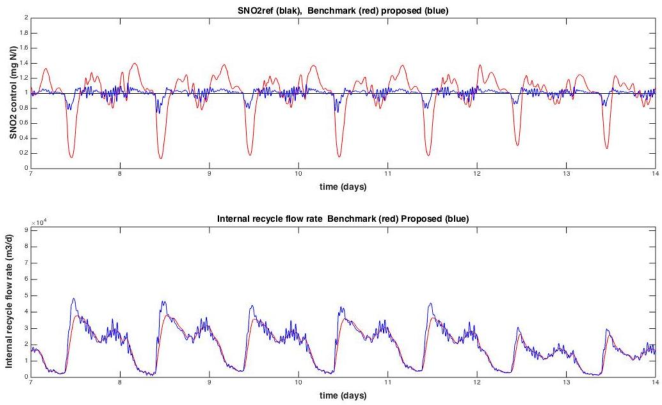

Fig. 4. SNO_2 control loop performance and Q_{intr} manipulated variable

IV. CONCLUSIONS

Analyse the control scheme within a real-time control scenario where data transmission is also implemented and issues such as sensor/actuator power energy consumption, packed losses, etc are also taken into account.

The introduction of the proposed event-based scheme is also to be introduced at higher level control solutions where the problem of variable set-point following is also an issue. This is the case, for example, of the usual cascade control configuration where the ammonia concentration in the last aerated tank drives the DO concentration of te aerated section.

As the problem tackled in this paper is, basically, a regulation problem where the controllers task is basically to attenuate the effect of influent load input disturbances, it would also be interesting to study the use of other solutions rather

TABLE II
BENCHMARK DEFAULT C ONTROL (DC) AND EVENT-BASED (EB) CONTROL COMPARISON.

	Dry		*Rain*		*Storm*	
	DC	EB	DC	EB	DC	EB
			$NO2$ loop			
IAE (gN/m^3d)	1.25	0.26	1.57	0.40	1.52	0.40
ISE $(gN/m^3)^2d$	0.47	0.02	0.70	0.06	0.70	0.07
Max deviation gN/m^3	0.86	0.22	0.90	0.52	1.0	0.60
			$DO5$ loop			
IAE $g(-COD)/m^3d$	0.25	0.14	0.21	0.12	0.24	0.13
ISE $(g(-COD)/m^3)2d$	0.02	0.005	0.02	0.003	0.02	0.005
Max deviation $g(-COD)/m^3$	0.26	0.11	0.24	0.1	0.26	0.11
			Effluent average concentrations			
SNH (limit = 4 gN/m^3)	2.53	2.45	3.21	3.35	3.05	3.07
TSS (limit = 30 gSS/m^3)	13,0	13.0	16.17	16.09	15.27	15.28
Total N (limit = 18 gN/l)	16,89	16.74	14.71	14.65	15.83	15.70
Total COD (limit = 100 $gCOD/m^3$)	48,22	48.21	45.43	45.32	47.65	47.66
BOD5 (limit = 10 g/m^3)	2,75	2.75	3.45	3.45	3.20	3.20
			Quality / Cost variables			
EQI (kg poll.units/day)	6115,63	6058.26	8174.98	8216.17	7211.48	7190.45
OCI	16381,93	16382.24	15984.5	16035.06	17253.75	17250.39
			Effluent violations			
95% percentile of ef. SNH (gN/m^3)	7.36	7.02	8.03	8.0	7.76	7.62
95% percentile of ef. total (gN/m^3)	15.77	15.73	19.07	18.6	20.03	19.61
95% percentile of ef. TSS $(gCOD/m^3)$	20.18	19.70	21.70	21.6	20.78	20.76

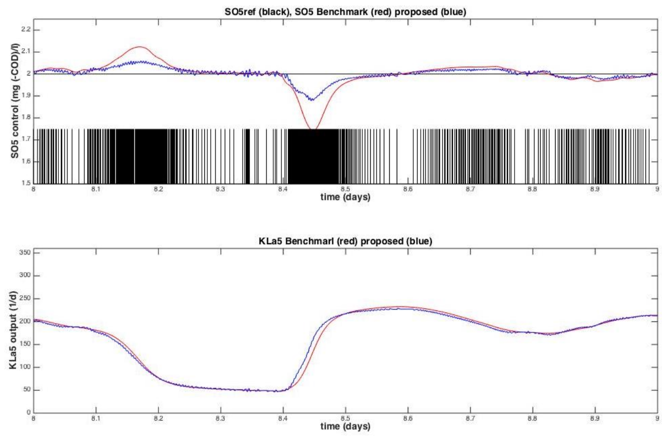

Fig. 5. SO_5 control loop performance and KLa_5 for one day showing event generation

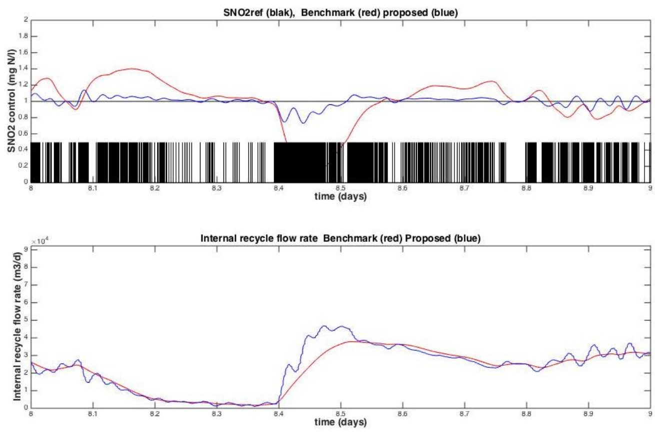

Fig. 6. SNO_2 control loop performance and Q_{intr} for one day showing event generation

than the usual IMC approach that us more aimed at set-point following. To this end, the direct-synthesis approach for load disturbance will result promising as it also shares the same design principles as the IMC controller.

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