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Full-scale implementation of an advanced control system on a biological wastewater treatment plant

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Abstract: The implementation of a multivariable control package for the real-time control and supervision of a biological wastewater treatment plant is reported and discussed. The goal is to improve the plant operation in terms of effluent quality and operational costs. A dynamic matrix control algorithm is put into operation for controlling the ammonia concentration at the end the biological reactor in the activated sludge process. The status of the plant instrumentation is continuously monitored by multivariate statistical technology based on moving windows principal component analysis. Results of the first six months of continuous operation show the ability of the designed predictive control in reducing the aeration energy consumption whilst keeping the ammonia concentration in the effluent within the limits.

Keywords: Activated sludge process, Biological wastewater treatment, Dynamic matrix control, Principal component analysis.

1. INTRODUCTION

Until very recently, the lack of adequate and reliable instrumentation was considered one of the major obstacles for the implementation of control and automation systems in wastewater treatment plants (WWTPs, Olsson, 2012). This barrier is now slowly starting to engulf offering new challenges and opportunities to the modern plants. WWTPs are aiming to achieve efficient and safe operations with high-quality effluents, while optimising operating costs through the use of real-time automation technologies, such as model predictive control (MPC) and multivariate statistical process control (SPC) tools.

MPC has been an attractive control strategy for a considerable number of WWTP applications over the last decades, mainly due to its ability to deal with multivariate constrained control problems in an optimal way (Maciejowski, 2002). Examples of successful applications are given *inter alia* by Steffens and Lant (1999); Rosen et al. (2002); Corriou and Pons (2004); Vrečko et al. (2004); Stare et al. (2007); Ekman (2008); Ostace et al. (2011). Few works relate to pilot plants (e.g., Marsili-Libelli and Giunti, 2002; Vrečko et al., 2011) and very few with full-scale plants. For instance, Weijers (2000) applied a linear MPC on the calibrated model of a wastewater treatment plant of the carrousel type in the Netherlands. O'Brien et al. (2011) detailed the real-time implementation of predictive control and a plant monitoring system for a wastewater treatment process in the United Kingdom. Mulas et al. (2015) compared different predictive control configurations on an activated sludge plant in Finland, aiming at decreasing the energy costs and reducing the effluent nitrogen compounds.

Reliability of the on-line measurements is fundamental for the successful implementation of the predictive control. Multivariate data analysis is an advanced statistical approach that has been applied for monitoring the data collected in biological WWTPs (see Haimi et al. (2013), for references). Considerable efforts in the development of multivariate techniques, as for instance principal component analysis (PCA), were made since the pioneering works of Rosen (2001) and Lennox (2002). Full-scale applications on municipal plants are proposed by Baggiani and Marsili-Libelli (2009) for real-time fault detection and isolation and by Corona et al. (2013) for detecting outliers in the measurement data of a biological post-filtration unit.

The purpose of this work is to present the testing outcomes of the real-time implementation of predictive and statistical process control tools on a full-scale wastewater treatment plant. The tools are combined in a single control package, the advanced control system (ACS) developed as part of the 2-year EU-funded project DIAMOND ("AdvanceD data management and InformAtics for the

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optimuM operatiON anD control of wastewater treatment plants"). The project represented a multidisciplinary effort for optimising the global operation of wastewater systems by adequately managing and using all the information available. This paper discusses the results of the first six months of continuous operation of ACS in the full-scale testing plant, the Mussalo WWTP located in the district of Kotka on the east coast of the gulf of Finland.

The paper is organised as follows. After an introductory description of the testing site and the available instrumentation (Section 2), the set-up of ACS is introduced in Section 3 and its building modules detailed in Section 3.1 and Section 3.2. The results are discussed in Section 4 and some preliminary conclusions drawn in Section 5.

2. ACTIVATED SLUDGE PROCESS AT THE FULL-SCALE TEST-PLANT

The Mussalo WWTP has a treatment capacity of 40000 m^3/d. It receives wastewater from four municipalities (Kotka, Pyhtää, Anjalankoski and Hamina) and from industries such as board mills, glass-fibre and food (bakery and sweeteners) production. Being industry the major share with around 55% of incoming organic load, the plant is designed to treat wastewater of 200000 population equivalent with an estimation of 93000 inhabitants from the four municipalities. A total revamp and renewal of the plant were carried out in 2009.

The wastewater treatment line includes bar screening, sand removal, primary sedimentation, aeration basins and secondary sedimentation. The sludge, coming from primary sedimentation and aerations basins, is treated in drying tanks with polymer addition before the spin-dryer.

The biological removal process is achieved in four activated sludge process (ASP) lines, of which three were introduced in the renovation process in 2009. The configuration and arrangement of "old" and "new" ASPs is slightly different but for all of them nitrogen removal is accomplished in the bioreactor in presence of a high concentration of activated sludge. In the design configuration, a large share of the bioreactor is always aerated with fine bubble diffusers located at the bottom of the basin. Each line begins with an anoxic (i.e., the dissolved oxygen (DO) concentration is low) zone (Z_1) where the pre-settled wastewater, return sludge from the secondary sedimentation basin and an internal recycle from the degassing basin are fed. Two zones (Z_2 and Z_3) follow for further empowering the denitrification or nitrification processes and three subsequent aerobic zones (Z_4-Z_6) are always highly aerated in order to achieve nitrification. The last zone (D) is devoted to the degasification of the mixed liquor. The first three zones are equipped with agitators and are either aerated or anoxic, non-aerated (and mechanically mixed) depending on the aeration mode in use. The internal recycle flow-rate is regulated by a set of rules based on the influent flow-rate and the upper and lower limits of the pumps. The external sludge recycle from the secondary settler is kept proportional to influent flow-rate with a constant ratio.

ACS involves the control and supervision of the four ASP lines in Mussalo. We here present and discuss only the implementation of ACS on the reactors line 4 (R_4), even though similar reasoning is adopted and implemented for the other lines. For R_4, the available on-line instrumentation employed by ACS is described in Table 1 and its location is depicted in Figure 1 and Figure 2. Although not directly involved in ACS, analysers available at the plant effluent channel are inspected for verifying the effects of the advanced controllers, in terms of nitrate, phosphate and turbidity before discharging the treated water.

Table 1. On-line measurements selected for the activated sludge process line R_4 in Mussalo.

Name	Description	Unit
IR_4_Qin	Influent flow-rate to the ASP	m^3/h
IR_4_Qri	Internal recycle to ASP	m^3/h
IR_4_Qre	External recycle to ASP	m^3/h
R_4_DO_2	Dissolved Oxygen in ASP in Z_2	mg/l
R_4_DO_3	Dissolved Oxygen in ASP in Z_3	mg/l
R_4_DO_4	Dissolved Oxygen in ASP in Z_4	mg/l
R_4_DO_5	Dissolved Oxygen in ASP in Z_5	mg/l
R_4_DO_6	Dissolved Oxygen in ASP in Z_6	mg/l
R_4_145_Qair	Cumulative airflow in Z_1, Z_4 and Z_5	Nm^3/h
R_4_236_Qair	Cumulative airflow in Z_2, Z_3 and Z_6	Nm^3/h
ER_4_Qw	Excess sludge from ASP	m^3/h
ER_4_SS	Suspended solids from ASP	g/l
ER_4_NH4	NH4-N from ASP	mg/l
ER_4_pH	pH from ASP	

3. ACS ARCHITECTURE SET-UP

The ACS package provides tools for the control and supervision of wastewater treatment operations in terms of critical process parameters and energy usage on unit- and plant-wide scale. In general terms, ACS aims at the optimisation of operational costs of WWTPs, while guaranteeing compliance with the environmental regulations. In more specific terms, ACS achieves these goals through two modules: The so-called optimal process control module (OPCM) and the statistical process control module (SPCM). At the Mussalo WWTP, the main scope of the OPCM is to control ammonia concentration at the exit of the biological reactor (ER_4_NH4), while minimising the operational costs of the unit. This is achieved by providing the set-points for the low-level DO controllers in the anoxic zones of the reactor and the internal recycle flow-rate with a MPC strategy. The main scope of the SPCM is to prepare, select and complement plant data and information, before it is internally transmitted to the OPCM. In this first implementation of the ACS at the Mussalo WWTP, the two modules are working independently.

ACS is further reinforced by dedicated support routines for the cleaning of the raw on-line data. That is, unfeasible zeros and constant process values associated with saturated measurements as well as obviously wrong data are removed, prior conveying the data to the two modules.

3.1 Optimal process control module

Given the prime concern of an easy and straightforward solution to solve the optimisation problem, the dynamic matrix control (DMC) algorithm is selected among the several MPC methods. The use of the linear DMC controller satisfies the requisite of simplicity which makes it more attractive for the full-scale application. As shown in Figure 1, the OPCM control structure for the Mussalo's

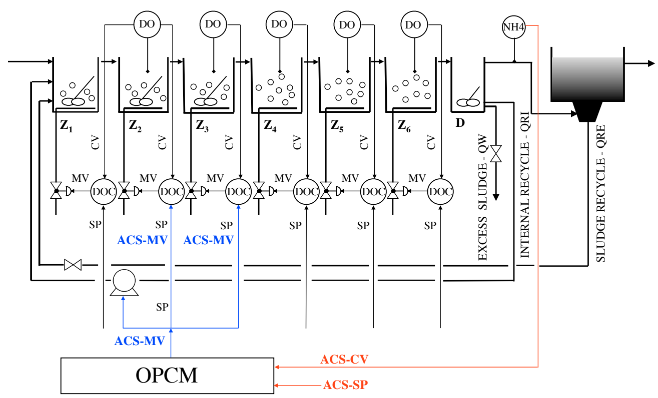


Fig. 1. Activated sludge process at the Mussalo WWTP: Inputs (in red) and outputs (in blue) for OPCM.

WWTP ASP line consists of one controlled variable (the ammonia concentration at the end of the ASP line, ACS-CV) and three manipulated variables (ACS-MVs): the DO set-points in the anoxic zones (Z_2 and Z_3) and internal recycle flow-rate, namely, R_4_DO_2-SP, R_4_DO_3-SP and IR_4_Qri. To ensure compliance with the environmental regulation, the set-point for the controlled variable (ACS-SP) is set at 1 mg/l. Given its modularity, the OPCM configuration can be easily expanded for further improving the effluent quality and minimising the operative costs. For instance, the dissolved oxygen in aerobic zones (Z_4, Z_5 and Z_6) and the external recirculation flow rate could be included in the control structure as manipulated variables. The suspended solids and the nitrate measurements, when available, could be further considered as controlled variables. In this work, the configuration in Figure 1 was mainly selected because of its straightforward applicability. It represents the most appropriate configuration for the status of the available instrumentation in the plant and a reasonable starting point for the future developments.

The DMC is selected as the building-block technology of the OPCM. Its main idea, as for every predictive control algorithm, is to calculate at each control step a control sequence that minimises a certain objective function. The control sequence is calculated based on a simplified model of the process and measured outputs. For a prediction horizon H_p and a control horizon H_u, the DMC of a system with m inputs and n outputs finds the vector $\Delta\mathbf{u}(k) \in \mathbb{R}^{mH_u}$ of future control moves that minimises the sum of squared deviations of the predicted control variables from a time-varying reference trajectory, while constraining the magnitude of the manipulated variables $\mathbf{u}(k)$ and their rates $\Delta\mathbf{u}(k)$. That is, the DMC optimises the following objective function:

$$J[\Delta\mathbf{u}(k)] = \left[\mathbf{e}(k+1) - \mathbf{A}\Delta\mathbf{u}(k)\right]'\left[\mathbf{e}(k+1) - \mathbf{A}\Delta\mathbf{u}(k)\right] + \left[\Delta\mathbf{u}(k)\right]^T \mathbf{R}_{\boldsymbol{\Delta}\mathbf{u}}\left[\Delta\mathbf{u}(k)\right]. \tag{1}$$

Here, k denotes the time index and $\mathbf{e}(k+1)$ is the nH_p-dimensional error vector representing the difference between the desired input trajectory $\mathbf{r}(k+1) \in \mathbb{R}^{nH_p}$ and current output prediction in the absence of further control actions $\mathbf{y}^0(k) \in \mathbb{R}^{nH_p}$. The error is corrected by the measured outputs $\mathbf{d}(k) \in \mathbb{R}^{nH_p}$ available at the sampling instant k. In Equation 1, $\mathbf{u}(k) = \mathbf{u}(k-1) + \Delta\mathbf{u}(k)$ denotes the mH_u-dimensional input vector and the simplified model of the process is represented by the dynamic matrix $\mathbf{A} \in \mathbb{R}^{nH_p \times mH_u}$. The dynamic matrix is obtained by arranging nm blocks of coefficients between pairs of inputs and outputs, each for a prediction horizon H_p and a control horizon H_u. $\mathbf{R}_{\boldsymbol{\Delta}\mathbf{u}} \in \mathbb{R}^{mH_p \times mH_p}$ is a diagonal weighting matrix that is used to penalise changes in the control signals and avoid excessive effort on the manipulated variables.

A careful identification of the process is a key step in the development of the predictive controller and in the construction of the dynamic matrix $\mathbf{A}$. Linear predictive models are developed and implemented in the DMC algorithm (Ogunnaike and Ray, 1994). The matrix $\mathbf{A}$ coefficients are obtained "off-line" by studying the plant historical data. To this end, the responses of the controlled variable ER_4_NH4 to the step changes in the manipulated variables R_4_DO_2, R_4_DO_3 and IR_4_Qri are analysed during selected representative periods.

For each ASP line, the parameters related to the DMC development, such as prediction and control horizon, sampling time and weights, are found by analysing the dynamic response of the process, considering the frequency of the inputs variations and by tuning. For every line, a sampling time of 15 minutes, a control horizon of 4 hours and a prediction horizon of 4 hours are set. The upper value of the DO set-points is further constrained to a maximum of 2.5 mg/l. For line R_4, in particular, to allow an adequate DO profile and account for the practical requirements of the recirculation pumps the weights of the matrix $\mathbf{R}_{\boldsymbol{\Delta}\mathbf{u}}$ are selected as [0.081 0.095 0.02].

3.2 Statistical process control module

Being principal component analysis (PCA, Jolliffe, 2007) the leading method applied to multivariate data, it represents also the building-block technology of SPCM in ACS.

SPCM detects out-of-control observations according to two measures of fit based on the residuals of a PCA model: The Hotelling's T^2 statistic and the Q statistic (Jackson and Mudholkar, 1979). The former measures the (normalised) distance of a projected observation from the origin of the subspace and the latter measures the (orthogonal) distance of an observation from its reconstruction on the principal subspace. For control purposes, acceptable magnitudes of these distances are quantified by two cut-off values, T^2_{lim} and Q_{lim} (Atkinson et al., 2004; Nomikos and MacGregor, 1995, respectively). The limits are estimated using only training data and can be calculated for different confidence values: usually, the 97.5% confidence limits are used. Based on the two cut-offs, three types of anomalous observations can be defined and the corresponding samples flagged as out-of-control. The PCA model (together with T^2 and Q) is recalculated as time evolves, in a moving-window type of implementation.

The SPCM structure validated for the Mussalo WWTP is identical for all of its four lines and it acquires the following 12 raw process measurements (in Figure 2 for line R_4): Influent flow-rate, internal recycle flow-rate, external recycle flow-rate, DO in Z_2, DO in Z_3, DO in Z_4, DO in

Table 2. Line R_4 - Monthly averages during January–June 2014 and 2015.

	Total airflow per unit Qin [Nm^3/m^3]		**Airflow in Z_1-Z_4-Z_5 per unit Qin** [Nm^3/m^3]		**Airflow in Z_2-Z_3-Z_6 per unit Qin** [Nm^3/m^3]		**Internal recycle** [m^3/h]		**Effluent Ammonia** [mg/l]	
	2014	2015	2014	2015	2014	2015	2014	2015	2014	2015
January	5.81	6.41	3.04	3.74	2.77	2.67	885	799	1.34	1.71
February	7.73	6.39	4.70	3.71	3.03	2.68	883	763	0.97	1.40
March	5.64	3.95	3.08	2.37	2.46	1.58	737	739	0.99	1.23
April	6.50	4.99	4.95	3.14	2.35	1.85	823	740	0.86	1.37
May	6.46	6.88	4.86	5.61	1.60	1.27	610	654	0.27	0.63
June	8.64	10.97	6.96	9.02	1.68	1.95	597	593	0.35	0.22

Z_5, DO in Z_6, airflow rate to ASP Line (Zones 1 to 6), pH, suspended solids and ammonia at the end of the bioreactor.

For each ASP line and for a given degree of the confidence, SPCM returns a cumulative unit status. In addition, as secondary output signals, SPCM provides the individual status (OK and Not-OK) of the 12 input variables and the total number of Not-OK variables. When one or more variables are detected to be contributing to a not-in-control state, it only means that their measurements are likely to differ from what expected, when considered together with measurements of all other variables. These calculations are updated at fixed intervals of one week, with a memory interval of one month.

In the current configuration of ACS operation in Mussalo, OPCM and SPCM are working independently. The two modules should be linked in the next step of implementation. In this way, SPCM provides support information for a more efficient operation of OPCM, by authorising the low-level controllers to use the calculated ACS-MVs as set-points only when SPCM reports an in-control state. Otherwise, the last available set-point should be used.

3.3 ACS architecture implementation

The ACS application is implemented in a stand-alone machine at Aalto University with Mathworks Matlab R2013b. The main ACS routine is implemented as a single Matlab script that performs the communication tasks and part of the calculations. The OPCM and SPCM subroutines are called by the main routine and perform ACS calculations. The raw data are received every 15 seconds and, after calculations, the ACS outputs are returned to the plant every 15 minutes.

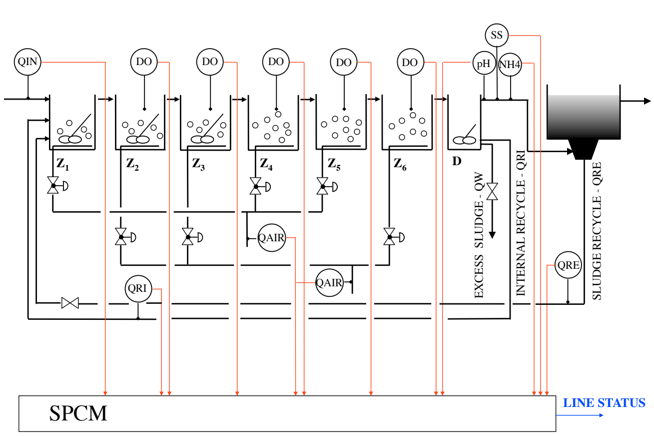


Fig. 2. Activated sludge process at the Mussalo WWTP: Input (in red) and outputs (in blue) for SPCM.

4. RESULTS OF THE FIRST SEMESTER OF REAL-TIME OPERATION

In this section the preliminary results for the first six months of continuous operation in 2015 of the ACS are presented and discussed for the ASP line R_4.

Given time differences in the ACS implementation on the four ASP lines during 2015 and the slightly dissimilar operational configurations of the lines, comparing their behaviour during the same periods in 2015 is not possible. For this reason, the performances of line R_4 in January-June 2015 are discussed against the same period in 2014 when ACS was not operative yet. Although the correspondence between two years of operation is not completely fair due to all the possible differences in plant operation, here we consider this comparison as a mere starting point for discussing the ACS performances. Being the main assumption that R_4 has been subjected to a reasonably similar influent load in the first six months of 2014 and 2015.

Table 2 reports the monthly average results in terms of airflow rate per influent flow-rate, internal recycle and ammonia concentration at the exit of the bioreactor. Noticeably, the overall airflow consumption diminished by 3% over the first six months in 2015, while the effluent ammonia slightly increased, nevertheless it was kept within the limits. The effect of the OPCM module is evident from the average airflow R_4_236_Qair per influent flow-rate in the line. In fact, in zones Z_2, Z_3 and Z_6 the overall airflow decreased by 14% and in particular, R_4_DO_2 and R_4_DO_3 diminished by 33% and 11% during the period under study. On the other hand, the dissolved oxygen in zones Z_4, Z_5 and Z_6 was kept close to the constant set-points of, respectively, 3 mg/l, 2.5 mg/l and 2 mg/l by the low-level controllers during 2014 and 2015. Furthermore, the internal recirculation flow-rate decreased by 5%. It must be stressed out that these figures refer to the sole R_4 line and that similar results can be achieved for each ASP line in Mussalo.

Although not directly involved in ACS, it is worth noticing that the nitrate concentration at the effluent of the Mussalo plant decreased by 12% during the first semester of 2015. The effluent phosphate diminished by 9% and the turbidity increased by 9%.

In order to appreciate the dynamic behaviour of the ACS control module, about 2 weeks of operation in April 2014 and April 2015 are plotted and discussed in the following. During this period, line R_4 was subjected to a rather similar dynamics of the influent flow-rate (Figure 3).

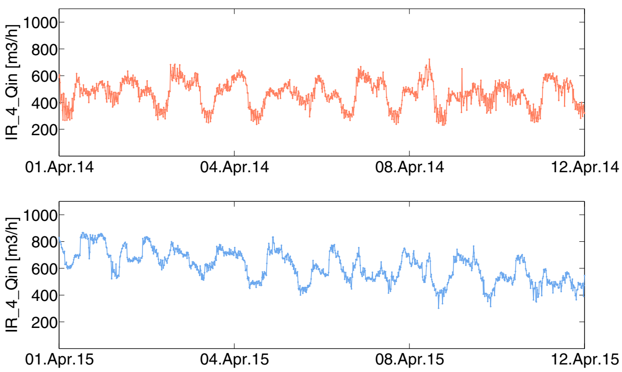
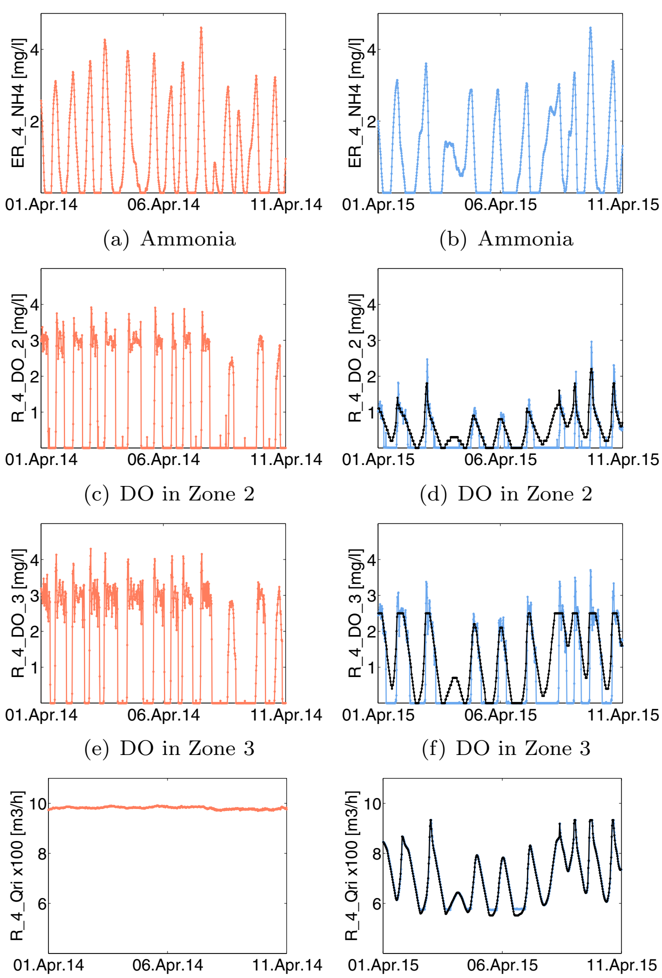


Fig. 3. Line R_4 - Influent wastewater flow-rate in April, 2014 (top) and 2015 (bottom).



(a) Ammonia (b) Ammonia

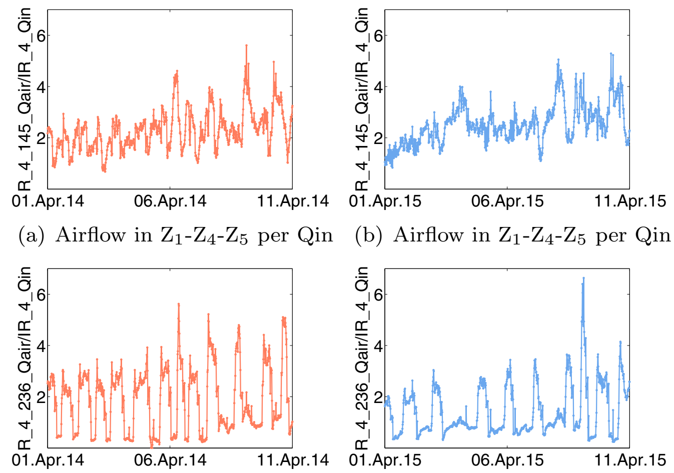
(c) DO in Zone 2 (d) DO in Zone 2

(e) DO in Zone 3 (f) DO in Zone 3

(g) Internal recycle (h) Internal recycle

Fig. 4. Line R_4 - Process operation comparison without (left column) and with (right column) the OPCM, in terms of effluent ammonia from the bioreactor, (a) and (b), dissolved oxygen in zone Z_2 (c) and (d), in zone Z_3, (e) and (f) and internal recycle, (g) and (h). The black line is the control action given by OPCM.

Figure 4 shows the operation of Line R_4 in April 2014, in red on the left column, and April 2015, in blue on the right column. The black lines in Figure 4(d), Figure 4(f) and Figure 4(h) represent the set-points that the OPCM returns as control actions to the low-level controllers: R_4_DO_2-SP, R_4_DO_3-SP and R_4_Qri.



(a) Airflow in Z_1-Z_4-Z_5 per Qin (b) Airflow in Z_1-Z_4-Z_5 per Qin

(c) Airflow in Z_2-Z_3-Z_6 per Qin (d) Airflow in Z_2-Z_3-Z_6 per Qin

Fig. 5. Line R_4 - Process operation comparison without (left column) and with (right column) the OPCM, in terms of the cumulative airflow per influent flow-rate in the zones Z_1, Z_4, Z_5, (a) and (b), and in the zones Z_2-Z_3-Z_6, (c) and (d).

The airflow rates given by R_4_145_Qair and R_4_236_Qair are plotted in Figure 5 per unit of influent flow-rate during April 2014 (left column) and April 2015 (right column). Compared to the normal operation in 2014, the ACS predictive control module led to a reduction in the dissolved oxygen demand. From Figure 5(d), in particular, it is possible to notice the effect of the ACS control module on the airflow to the 2nd and 3rd zone of the bioreactor.

The status of line R_4, represented by a flag {OK, Not OK} calculated in real-time, is shown in Figure 6 for the first six months of 2015. The line is considered in OK conditions if and only if both the T^2 and the Q do not violate the respective limits T^2_{lim} or Q_{lim}, whereas violations of either limit led to observations flagged as Not OK.

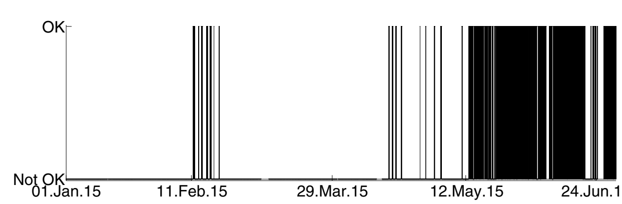


Fig. 6. Line R_4 - Status in the first six months of 2015.

5. CONCLUSIONS ON THE FIRST SEMESTER OF REAL-TIME OPERATION

This paper presented the first results of the real-time operation of an advanced control system to a full-scale biological wastewater treatment plant. The system involves two main modules for the control and supervision of the plant and aims at reducing the operational costs while improving or maintaining the process performances.

The first months of continuous operation show:

- The successful applicability of real-time multivariable predictive control on a full-scale wastewater treatment plant.
- The potential of the OPCM module in reducing the aeration energy consumption in the bioreactor.
- The ACS control policy would lead to further savings in the energy consumptions, if expanded to include the aerobic zones in the bioreactor.
- The proposed advanced control structure can be further enhanced by linking OPCM and SPCM. That is, by allowing the low-level controllers to adopt the set-points calculated by OPCM only when the unit has been flagged as in-control by SPCM.

Summarising, the real-time operation of the proposed control architecture demonstrates the benefits of advanced control for wastewater treatment plant. It shows that stricter regulations and operative cost reduction can be effectively enforced through the use of multivariable controllers and that the status of the plant can be successfully monitored through the use of multivariate statistical tools.

6. ACKNOWLEDGMENTS

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