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Control of Nitrate Flow in Pre-Denitrification Systems using Long-Range Identification for Predictive Control

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Abstract— **This paper is concerned with long-range adaptive predictive control of the biological nitrogen removal process in a pre-denitrification activated sludge plant. A control-oriented identification procedure is used for modelling a multi-step ahead (long-range) predictor using a reduced model of the nitrate concentration at the plant anoxic zone, in the range required by the predictive controller. The optimal structure of the reduced model and its parameters are identified by an advanced regression orthogonal estimator, based on the Modified Gram-Schmidt algorithm. The proposed controller controls the internal nitrate recirculation flow in order to maintain a desired nitrate concentration set-point at the anoxic zone. Simulation results, using a benchmark model, compare the performance of the proposed adaptive predictive controller against the performance of a well tuned PI controller, showing that the proposed controller presents much better external process disturbances attenuation and equivalent set-point tracking ability.**

I. INTRODUCTION

It is known that high concentrations of nitrogen in the effluent wastewater may cause several problems: nitrogen stimulates the growth of aquatic plants and algae; can cause a severe depletion of dissolved oxygen due that a large quantity of oxygen should be consumed by the bacteria during degrading process. Nitrogen is present in wastewater in several forms such as: ammonia (NH_3), ammonium (NH_4^+), nitrate (NO_3^-) and organic compounds. To avoid these and other problems caused by high nitrogen concentration in the incoming wastewater, the amount of nitrogen must be reduced.

The biological nitrogen removal process in a wastewater treatment plant can be performed by a pre-denitrification activated sludge plant. When pre-denitrification is applied, the denitrifying bacteria can better use the organic material of the incoming wastewater. Since the nitrification takes place in the aerated zones, located after the anoxic ones, water with high concentration of nitrate must be recirculated from the end of the aerobic zones back to the beginning of the anoxic zones, in order to assure the necessary presence of nitrate. Conversely, this wastewater treatment plant configuration allows the control problem to be decomposed into the control of the nitrification process in the aerobic zones and the control of the denitrification process in the anoxic ones, based on the fact that both processes can be influenced in a medium time scale (hours and days) [1], [2]. The nitrification process can be controlled manipulating the Dissolved Oxygen (DO) set-point in order to regulate the required concentration of ammonium in the effluent (ammonium controller) [3]. The denitrification process, scope of this paper, is primarily influenced by the internal nitrate recirculation flow and external carbon dosage (if necessary).

In adaptive model predictive controllers, such as Generalized Predictive Controller (GPC) [4], an explicit model and measures obtained from the process must be used to predict the process future behavior. This model is typically identified using some variant of the recursive least-square method (RLS), which minimizes the sum of the one-step ahead predictions errors. It is known that the standard least-square method tends to emphasize high frequencies [5]. So, if RLS is used with GPC to identify reduced order models, the fitting possibly restricted to high frequency region, will cause structural model-plant mismatch.

This paper is concerned with long-range adaptive predictive control of the biological nitrogen removal process in a pre-denitrification activated sludge plant. A reduced model of the nitrate concentration at the anoxic zone is obtained from available on-line measurements of the nitrate and internal recirculation flow. To avoid structural model-plant mismatch, the long range identification approach (LRPI) of Shook *et al.* [6] is used to obtain a model that best predicts the nitrate concentration, not for just one-step ahead, but for multi-steps ahead in the range required by the predictive controller. This control method will be called here predictive controller based on long-range predictive identification (GPC-LRPI).

The paper is organized as follows. In section II, the simulation benchmark model ASWWTP-USP [7] is presented. In section III, the reduced model of the nitrate concentration with an optimal structure is identified, using a control-relevant multi-level pseudo-random excitation signal based on prior process knowledge [8]. The GPC-LRPI formulation is derived in section IV. In section V, a four different scenarios simulation study is carried out using the benchmark model, showing the controller effectiveness to track the nitrate concentration set-point and to reject external disturbances.

II. SIMULATION BENCHMARK MODEL

The simulation model used by the identification experiment and controller evaluation is the ASWWTP-USP benchmark [7], depicted in Fig. 1. This model is adopted because it is based on the IAWQ Activated Sludge Model No. 1 (ASM1) [9] and its pre-denitrification configuration. The pre-denitrification configuration includes an anoxic zone, two aerobic zones and a secondary settler. The DO concentration

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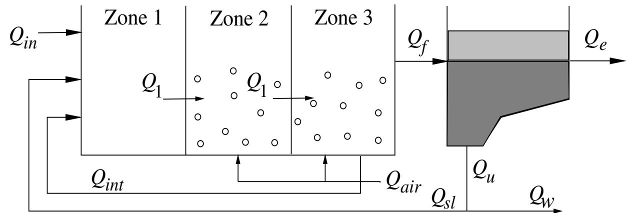

Fig. 1. Layout of the benchmark ASWWTP-USP model.

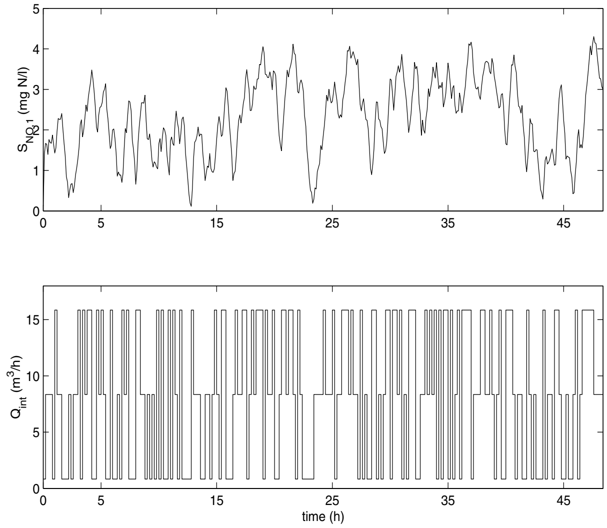

Fig. 2. Output signal (nitrate concentration) and 3-level MLPRS input signal (internal recycle flow) for identification.

of the two aerobic zones are regulated in 2 mg/l by PI controllers (not included in the layout). The influent flow rate is $Q_{in} = 4.17$ m^3/h, with total COD of 224 mg/l and total nitrogen of 45.88 mg/l. The internal recirculation flow is $Q_{int} = 2Q_{in}$. The external recirculation flow is $Q_{sl} = 0.5Q_{in}$. The sludge wastage flow is $Q_w = 0.0258$ m^3/h. The inflow wastewater conditions, the parameter values for the anoxic and aerobic zones and initial concentrations for the model are given in [7].

III. Reduced model identification of the nitrate concentration

In this section, a reduced order linear model of the nitrate concentration at the anoxic zone (Zone 1) $S_{NO,1}$ related to the nitrate internal recirculation flow Q_{int} (see Fig. 1) is obtained using the Modified Gram-Schmidt (MGS) orthogonal algorithm [10]. As input signal, it is used a Multi-level pseudo random signal (MLPRS) designed to satisfy the process bandwidth relevant for control, persistence of excitation and the minimal signal length based on process *a priori* knowledge.

A. Input signal design

The design parameters of MLPRS signal are obtained according the guidelines provided by Braun and coworkers [8]. In particular, this signal can be designed to exhibit inverse repeat characteristic, useful to identify linear behavior in the presence of non-linearities. Mappings of inverse-repeat MLPRS signals (signals with harmonics multiples of 2 suppressed) are given in [11].

The *a priori* knowledge about the process is obtained applying a sequence of positive and negative steps in the nitrate recirculation flow Q_{int}. The fastest and the slowest dominant time-constants obtained are $\tau^L_{dom} = 0.23$ h and $\tau^H_{dom} = 1.12$ h, respectively. It is adopted $\alpha_s = 3$ for the closed-loop dynamics be three times faster than open-loop. It is adopted $\beta_s = 5$, related to 99% settling time, to satisfy the low frequency contents. Hence, the resulting excitation signal bandwidth is $0.1784 \leq w_s \leq 13.06$ rad/h. A MLPRS signal with 3 levels, switching time $T_{sw} = 0.2$ h and harmonics multiples of 2 suppressed, is chosen satisfying the low frequency requirement with maximum number of harmonics present in the required bandwidth (uniform power) and minimal length (cycle time of 48.4 h). The designed MLPRS sinal is generated using the MLPRS generator [12], implemented in Simulink® platform. Fig. 2 shows the nitrate concentration output signal $S_{NO,1}$ and the internal recycle flow MLPRS input signal Q_{int} with 3 levels and harmonics multiples of 2 suppressed.

B. Identification procedure

The MGS orthogonal algorithm [10] selects an optimal structure and estimates the parameters for non-linear autoregressive with external input (NARX) models:

$$y(t) = b + f^{\ell}[\, y(t-1), ..., y(t-N_y), u(t-1), ..., u(t-N_u), d(t), ..., d(t-N_d)] + e(t) \quad (1)$$

where y, u and d are output, input and measured disturbance, respectively. b is a bias and N_y, N_u and N_d are the maximum lags for the output, input and measured disturbance, respectively. The ℓ index denotes the model nonlinearity degree and e is a modelling error or model uncertainty. The goal using this identification algorithm, with MLPRS control-relevant excitation signals, is to obtain parsimonious models for control purposes.

For the identification experiment, the signals were previously scaled and normalized. The selected initial sampling time is $T_s = 0.04$ h, but, after data decimation, it is addopted a sampling time $T_s = 0.1$ h according [13]. The nitrate sensor is assumed to be a first-order linear dynamic system with a time constant of 5 minutes and a white noise disturbance with zero mean and variance 0.01 [2].

Using the MGS orthogonal algorithm with $\ell = 1$ (linear model), $N_y = 3$, $N_u = 3$ and $N_d = 2$, the following linear model is obtained:

$$S_{NO,1}(t) - 1.468 S_{NO,1}(t-1) + 0.187 S_{NO,1}(t-2) + 0.295 S_{NO,1}(t-3) = 0.003 - 0.038 Q_{int}(t-3) - 0.053 Q_{int}(t-4) \quad (2)$$

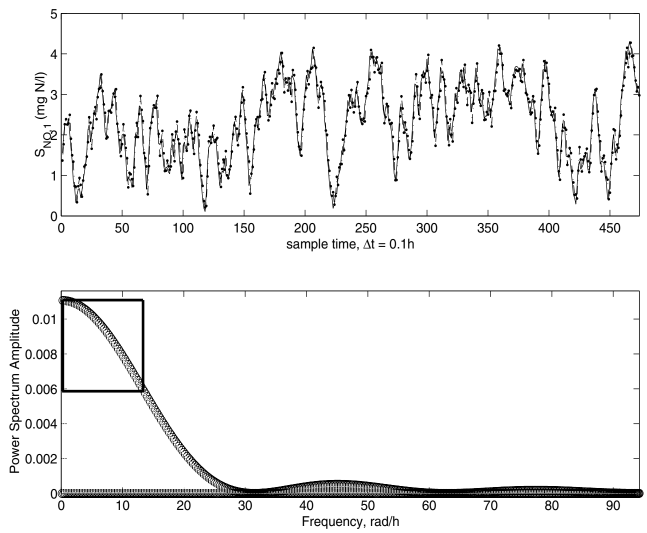

Fig. 3. Validation of the identified model (upper graph) and power spectrum with control-relevant region emphasized (lower graph).

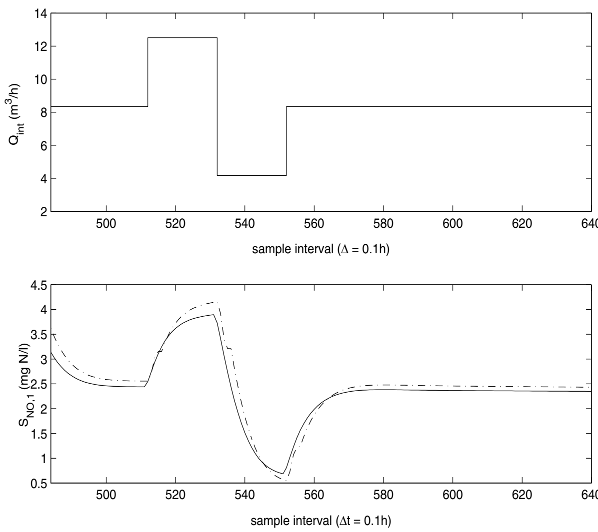

Fig. 4. Validation of the identified model after trends removal.

C. Validation of the nitrate model

The upper graph of Fig. 3 shows the validation results of the identified model of nitrate concentration at the outlet of the anoxic zone. The lower plot of Fig. 3 shows the input signal power spectrum after ZOH. It can be verified that 77% of the total power is contained in the control-relevant frequency region $0.1784 \leq w \leq 13.06$ rad/h, emphasized by a rectangle.

An additional validation is performed, to verify the prediction ability of the control reduced model with new independent input data (from 48.4 to 64 h), as shown in the upper graph of the Fig. 4. The presence of trends, detected using the procedure of Mann-Kendall, were removed using a procedure recommended in [2]. The lower graph of Fig. 4 shows the nitrate concentration compared with its one-step ahead prediction given by the identified model.

IV. Predictive controller based on Long-range identification

Consider the cost function for N measures [6]:

$$V_N(\theta) = \frac{1}{N}\sum_{t=1}^{N}\frac{1}{N_2-N_1+1}\sum_{j=N_1}^{N_2}\left[y(t)-\hat{y}(t/t-j),\theta\right]^2 \tag{3}$$

where $y(t)$ is the measured output, $\hat{y}(t/t-j)$ is the j-step ahead predicted output, N_1 and N_2 are the minimal and maximum prediction horizon, respectively.

Consider also the CARIMA model of the GPC adaptive controller [4]:

$$A(q^{-1},\theta)y(t) = B(q^{-1},\theta)u(t-1) + C(q^{-1})\xi(t) \tag{4}$$

where $\xi(t)$ is a white noise, A, B are polynomials in the back-shift operator q^{-1} with the following structure:

$$\begin{aligned} A(q^{-1},\theta) &= 1 + a_1 q^{-1} + \cdots + a_m q^{-m} \\ B(q^{-1},\theta) &= b_0 + b_1 q^{-1} + \cdots + b_n q^{-n} \end{aligned} \tag{5}$$

and C is a polynomial given by:

$$C(q^{-1}) = T(q^{-1})/\Delta \tag{6}$$

where T is a known polynomial and $\Delta = 1 - q^{-1}$ is the differencing operator.

The Long Range Predictive Identification (LRPI) corresponds to the minimization of (3) with respect to parameters θ of model (4). This minimization can be performed using the following procedure.

Procedure 1:

Estimate parameters of polynomials A, B (4), (5), solution of LRPI.

1) Set $L_1 = 1$.
2) Filter input/output data with $\tilde{G}$:

$$\tilde{G} = \frac{L_1(q^{-1})\Delta}{T(q^{-1})}\ ;\ \tilde{y} = \tilde{G}y\ ;\ \tilde{u} = \tilde{G}u \tag{7}$$

where T is a known polynomial considered as a controller tuning parameter to ensure convergence [6].

3) Using standard least square method, estimate the parameters θ of the model:

$$A(q^{-1},\theta)\tilde{y}(t) = B(q^{-1},\theta)\tilde{u}(t-1) + \xi(t) \tag{8}$$

where $\xi(t)$ is a white noise and A, B are given in (5).

4) Solve using a spectral factorization routine

$$L_1(q^{-1})L_1(q) = \left(\sum_{j=N_1}^{N_2} E_j(q^{-1})E_j(q)\right) \tag{9}$$

where E_j is obtained, jointly with F_j, as solutions of the next Diophantine equation

$$T(q^{-1}) = E_j(q^{-1})A(q^{-1})\Delta + q^{-1}F_j(q^{-1}) \tag{10}$$

of degrees $j-1$ and m (5), respectively.

5) Return to step 2 until convergence of the estimate is achieved.

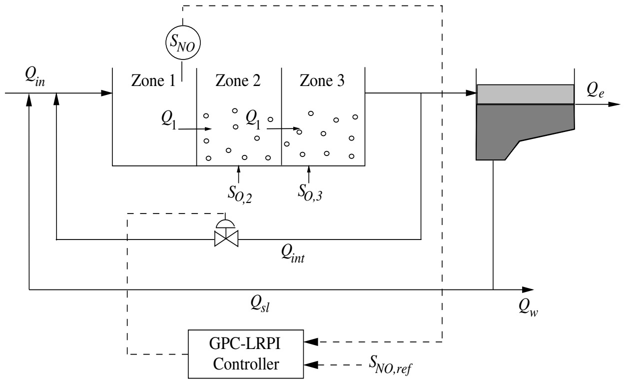

Fig. 5. Nitrate flow control schematic.

To improve the overall computational efficiency of Procedure 1, it is recommended to adopt for polynomials A, B the order and structure of a control relevant reduced model obtained according the methodology in Section III.

A recursive version of Procedure 1 can be obtained making the following modifications:

- In step 1, set L_1 equal to L_1 of the previous sample;
- In step 2, use a recursive standard least square method;
- Bootstrap the procedure with a control relevant reduced model.

Considering the reduced model given by LRPI, the GPC-LRPI formulation corresponds to determination of control input u which minimizes the partially restricted long-range cost function given by:

$$\begin{aligned} J(u,t) = E\{ \sum_{j=N_1}^{N_2} [y(t+j/t) - r(t+j)]^2 + \\ \lambda_u \sum_{j=1}^{N_c} [\Delta u(t+j-1)]^2 \} \\ s.a.: \Delta u(t+j) = 0, \quad j = N_c, \cdots, N_2. \end{aligned} \tag{11}$$

where N_c is the control horizon, $r(t+j)$ represent the future set-point sequence and λ_u weights the control input.

V. Simulation results

Considering the model of nitrate concentration in Section III, the LRPI and GPC-LRPI formulations presented in Section IV, a GPC-LRPI adaptive controller is designed for regulation of the nitrate concentration at the outlet of the anoxic zone of the pre-denitrification activated sludge plant, using the internal nitrate recirculation flow Q_{int} as control variable. See Fig. 5.

Based on extension of the tuning strategy proposed in [14], the parameters of the GPC-LRPI formulation are:

- prediction horizon $N_p = 8$ (also used for the LRPI estimator);
- control horizon $N_c = 4$;
- minimum prediction horizon $N_1 = 1$;
- input weighting $\lambda_u = 8$;
- controller sampling time $T_{s,c} = 3$ min based on initial $T_{s,c} \geq 1.38$ min and according guidelines in [14];
- polynomial T of LRPI estimator pre-filter:

$$T(q^{-1}) = 1 - 0.8q^{-1}$$

Given the reduced rate of the anoxic growth of heterotrophs, the denitrification reaction dynamics can be fairly considered in the time frame of hours to days, as mentioned in Section I. The parameters of the denitrification reaction can be assumed slowly time-variant if compared with other wastewater reactions. Hence, parameter estimation can be performed by a recursive least square algorithm with an exponential forgetting factor to discount old data. However, this recursive algorithm must be modified to avoid an eventual wind-up effect due lack of persistent excitation data. Such estimator can be implemented using a factored form of the covariance matrix P, updating the factors rather than the full matrix, as shown in [15].

Based on the mentioned considerations, the adaptive form of the LRPI estimator uses an exponential forgetting factor of 0.98 with initial covariance magnitude of 1000. The parameter values of the reduced model (2) are used to bootstrap the recursive identification algorithm and to eliminate singularities.

A. Set-point choice

Current nitrogen removal control strategies, based on nitrate measurements, are motivated by the continuous improvements in reliability, accuracy and easy maintenance of nitrate sensors [16], [17].

The nitrate concentration measured at the outlet of the anoxic zone is a good indicator of the denitrification reaction completion in the biological nitrogen removal process [2]. Changes on denitrification rate will lead to changes on effluent nitrate total concentration. In [1] it is showed that a nitrate set-point choice between 1 to 3 mg N/l leads to close to a maximum nitrogen removal in the anoxic zone, if the internal recirculation nitrate flow Q_{int} is used as control variable. According to [18], the nitrate set-point in the anoxic zone can be twice the nitrate half-saturation coefficient for denitrifying heterotrophs, which is $K_{NO} = 0.5$ g NO_3-N/m^3 for the ASWWTP-USP model. Hence, the nitrate concentration $S_{NO,1}$ set-point of the GPC-LRPI controller is selected constant, equal to 1 mg N/l, at the outlet of the anoxic zone. This choice, besides leading to near maximum nitrogen removal for a wide range operational conditions [1], it also satisfies the operational condition of keeping the anoxic zone "anoxic".

B. Evaluation scenarios

The proposed control strategy is evaluated by a simulation study where the benchmark ASWWTP-USP [7] plays the role of the activated sludge wastewater treatment plant. The nitrate sensor dynamics is the same one used in section III for model identification. The raw wastewater flow, recirculation flows and its concentrations are assumed equal to their

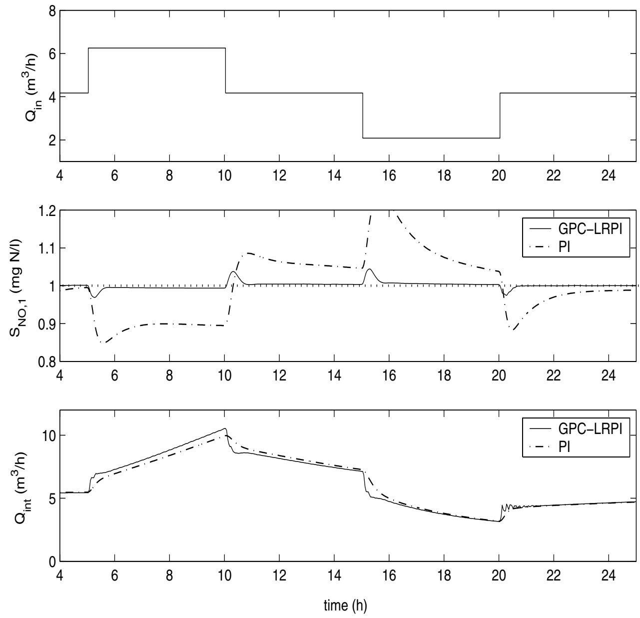

Fig. 6. GPC-LRPI and PI controllers performance when disturbances are added to Q_{in}.

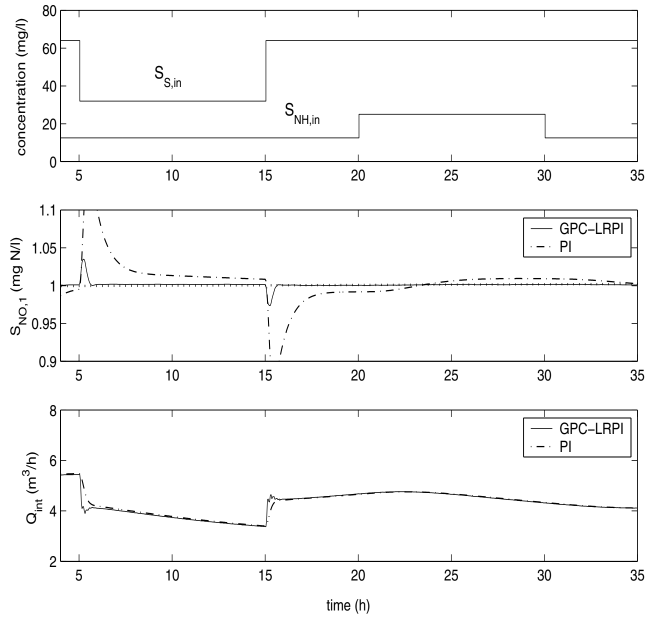

Fig. 7. GPC-LRPI and PI controllers performance when disturbances are added to concentrations of S_S and S_{NH} in influent flow.

corresponding steady state default values of the benchmark model.

For comparison purposes, a PI nitrate controller from benchmark model is fairly tuned with parameters $K_P = 0.2361$ and $K_I = 0.3543$.

Four different simulation scenarios are investigated for performance evaluation of the controllers GPC-LRPI and PI:

1) Addition of an external disturbance to the input flow rate Q_{in}, corresponding to a staircase function with values ranging from 50% to -50% of Q_{in} nominal value, as shown in the upper graph of Fig. 6.
2) Addition of external disturbances to the concentrations of substrate rapidly biodegradable S_S and ammonium S_{NH} in the input flow rate, corresponding to staircase functions with values ranging from 0 to -50% and 0 to 100% of the nominal values, respectively, as shown in the upper graph of Fig. 7.
3) Addition of an external flow of carbon Q_{ext}, corresponding to staircase function with values ranging from 0 l/h to 4 l/h, as shown in the upper graph of Fig. 8. The carbon source is composed of pure methanol as a 33%-solution with a concentration of 80,000 mg COD/l.
4) $S_{NO,1}$ set-point variations corresponding to a square function with values ranging from 1 mg N/l to 2 mg N/l, as shown in the upper graph of Fig. 9, to test the controllers set-point tracking ability.

It can be verified in the middle graphs of Figures 6, 7, 8, that the GPC-LRPI controller presents much better external disturbances attenuation performance than the PI controller, for all types of disturbances in scenarios 1 to 3. It can be also verified for GPC-LRPI controller that the the variation of $S_{NO,1}$ is less than $\pm 5\%$ of its set-point.

It can be verified in the upper graph of Fig. 9 that the GPC-LRPI and the PI controllers show equivalent tracking performance. The choice of λ_u makes a trade-off between the required control energy and the tracking ability of the GPC-LRPI controller. So, if better tracking performance is desirable for the GPC-LRPI controller, it can be obtained taking a smaller λ_u value, respecting, however, the amplitude and rate limits of the control variable.

VI. Conclusion

An adaptive predictive controller based on long-range identification model (GPC-LRPI) has been designed to regulate on-line the nitrate concentration at the anoxic zone of a pre-denitrification activated sludge wastewater treatment plant, using the nitrate internal recirculation flow as control variable.

The Guidelines for design of control-relevant excitation signals showed to be effective for identification of reduced models for control, using the orthogonal Modified Gram-Schmidt algorithm. It was also shown that the plant model-mismatch, due to model reduction, can be significantly attenuated using the long-range predictive identification technique.

Control tuning is particularly complex for nitrate control, because its stiff nonlinear dynamical behavior. Despite this, it was shown that the extended tuning strategy can be directly applied to GPC-LRPI design. The four-scenarios simulation study showed the performance and the effectiveness of the proposed GPC-LRPI controller for set-point tracking, with small overshoot, and external disturbances attenuation.

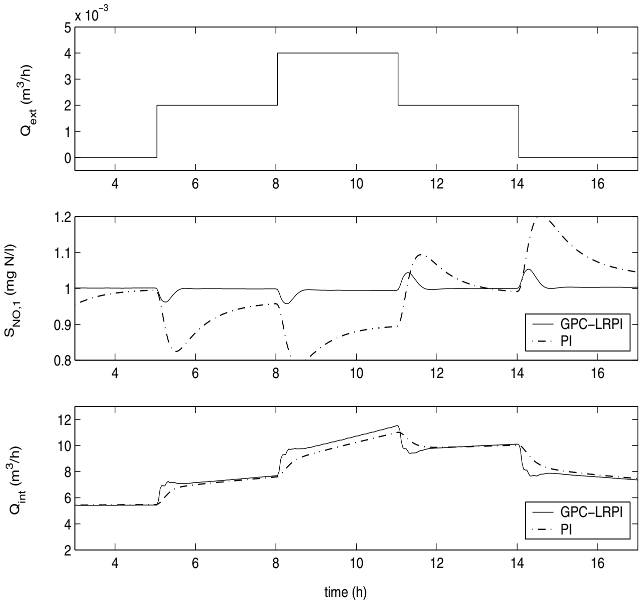

Fig. 8. GPC-LRPI and PI controllers performance when disturbances are added to the external flow rate Q_{ext}.

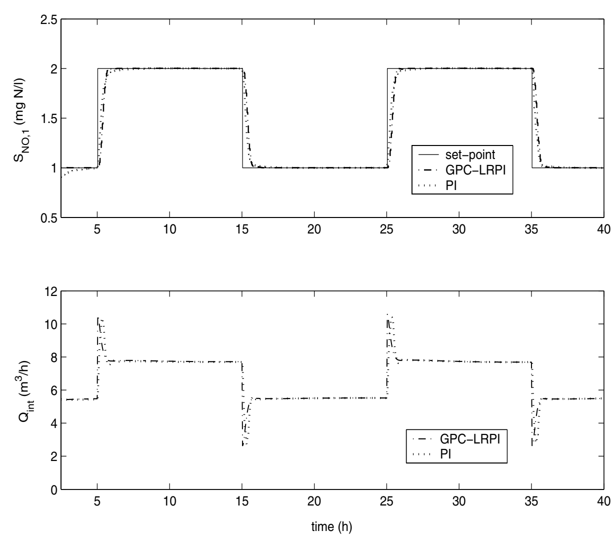

Fig. 9. GPC-LRPI and PI controllers performance tracking the set-point of nitrate concentration $S_{NO,1}$ in the last anoxic zone.

VII. ACKNOWLEDGMENTS

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