An activated-sludge-process application of integrated design and predictive control with instantaneous linearization

I. Guerra, R. Lamanna, S. Revollar, M. Francisco

***Abstract*—In this work the integrated design of the activated sludge process is addressed. The objective is to determine the best plant parameters and working point that minimize the operation costs related to the Effluent Quality and the Aeration Energy, while imposing constraints on the plant condition number (γ) and the perturbation condition number (γp), ensuring open-loop controllability. A linear multivariable predictive control (MPC) is used for the closed loop design, and it is used also a very practical non-linear version of the MPC, based on the instantaneous linearization of non linear models of the plant (the phenomenological model as well as a neural network model obtained by identification). The results are analyzed based on two aspects: the improved performance of the controlled system when using the integrated design instead of a classical economic design, and the convenience of the instantaneous linearization to realize a non-linear MPC.**

I. Introduction

The worldwide movement to protect the environment has increased the demands for efficient control strategies in wastewater treatment plants. The minimization of the investment and operational costs and the achievement of the effluent quality requirements while ensuring good controllability of the plant results into a conflict that is precisely the goal of integrated design. On the other hand, the complexity and variability of the biological processes involved in the activated sludge process in particular introduce non-linear characteristics to the process model, which makes an interesting application to test the integrated design approach. In this work, a model of the activated sludge process focused on the organic matter biodegradation process with a reduced configuration of a bioreactor followed by a secondary clarifier is considered and used as working example. The model is based on the wastewater treatment process of the Manresa plant (Spain). It was developed by Moreno [1] and then modified [2] for its application in the integrated design framework.

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I. Guerra is with Electronic Department, Academia Técnica Militar Núcleo Aviación. Maracay. Venezuela. e-.mail: ismeldacg@gmail.com.

R. Lamanna is with Simón Bolivar University, Venezuela, Processes and Systems Department, Sartenejas, Apdo. 89000, Caracas 1081A, Venezuela. Phone 58212-9062204; e-mail: lamanna@usb.ve

S. Revollar is AECID fellow with the University of Salamanca, Computing and Automation Department; e-mail: srevolla@usal.es.

M. Francisco is with the University of Salamanca, Computing and Automation Department; e-mail: mfs@usal.es

The benefit of considering controllability issues in the early stages of process design has been generally recognized in the literature [3],[4],[5]. Based on this idea, several authors have proposed different methodologies for the integrated design of chemical processes [3], addressing the systematic study of the influence of the process design on the controllability and dynamic behavior of the plant.

Depending on how the controllability issue is addressed, very different procedures of integrated design can be found. A general classification, proposed by [6], distinguishes projecting methods, where controllability indexes are computed during the design to predict the expected dynamic performance [7] [8], from methods of simultaneous design and control [3]. The latter require additionally the optimization of the controller structure and tuning [3], [6], [9], [10].

Predictive controllers have been often used in integrated design applications [3],[11], [12] with performance levels hardly achieved when using PIDs. For non linear processes however special issues must be solved regarding the evaluation of the non linear model in each control iteration. Thus identified non linear models, based on neural networks for instance, have also been used in predictive control [13],[14].

The aim of this work is to perform the integrated design of an activated sludge process by including open loop controllability indexes in the optimization procedure. The activated sludge process of the Manresa's plant was selected to apply this methodology, as was done in [10] and [11]. Basically, the optimization focuses on the minimization of the investment and operation costs and the desired dynamical performance is achieved by imposing a bound over the plant condition number (γ) and the perturbation condition number (γp).

Even if the integrated design performed focuses only in the open loop controllability, the closed loop behaviour of the resulting plant is analyzed with different multivariable model-based predictive controllers (MPC). To avoid the time-consuming dynamical simulations required by the typical realization of the non linear MPC, an instantaneous linearization algorithm [15] is introduced to support the generalized version of the linear predictive controller.

This paper is organized as follows: in section 2 and 3, the process and the formulation of the optimization problem are described; then, in section 4, the alternative MPC are presented, followed by the analysis of the results in section 5. Finally, conclusions and different projections of this work are included.

II. The Activated Sludge Process

The activated sludge process is a typical biological treatment in a waste-water plant. The basic plant layout is represented in Figure 1, and it consists of a simple structure with one aeration tank and one secondary settler.

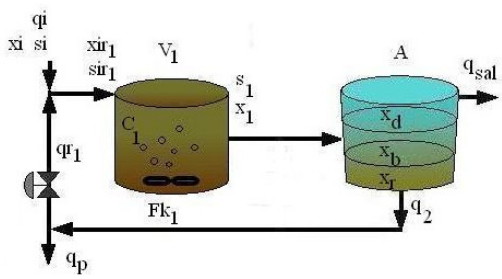

Figure 1. Activated sludge process layout

Several models are available for the activated sludge process; the most commonly used is the ASM1, developed for the International Water Association (IWA). Since the primary goal of this work is to focus on the application of the integrated design methodology, the model presented in [2] is selected, to avoid the excessive complexity of models like the ASM1. It is based on the model developed by [1], founded in the classical Monod and Maynard-Smith model. It is assumed that the reactions take place in only one perfectly-mixed tank.

The process variables are presented in Figure 1. Biomass concentrations are denoted by “x” (mg/l), organic substrate concentrations are denoted by “s” (mg/l), “c” is used for the oxygen concentrations (mg/l), and “q” for flow rates (m3/h).

The control of this process aims to keep the substrate at the output, s1, bellow a certain legal value despite the large variations of the flow rate and the substrate concentration of the incoming water (q_i and s_i). These disturbances are one of the main problems when trying to control the plant properly. The set of dry weather influent disturbances used as system input in dynamic simulations for designing the plant has been taken from the benchmark BSM1 of the European research group COST 624 [16].

III. The Integrated Design Optimization Problem

The integrated design of the activated sludge process pretends to obtain the most economical plant that satisfies the desired control performance. A cost function is defined to measure the economical issues while some indices of open loop controllability are imposed as constraints. Mathematically it is stated as a NLP/DAE optimization of the following cost function, subject to process and controllability constraints.

Cost function:

$$f = \alpha_1 \cdot V_1 + \alpha_2 \cdot A_1 + \alpha_3 \cdot Fk_1 + \alpha_4 \cdot q_2 \tag{1}$$

where V_1 and A_1 are the volume of the reactor and the cross-sectional area of the settler, Fk_1 is the aeration factor in the reactor, q_2 is the total recycling flow and α_i (i = 1,…,4) are the corresponding weights.

Process constraints:

– Residence time and mass load in the aeration tank:

$$2.5 \le \frac{V_1}{q} \le 8 \; ; \qquad 0.001 \le \frac{q_i s_i + q_{ri} s_1}{V_1 . x_1} \le 0.06 \tag{2}$$

– Limits in hydraulic capacity and sludge age in the settler:

$$\frac{q_2}{A} \le 1.5 \quad ; \qquad 3 \le \frac{v \cdot x_1 + Al_r x_r}{q_p x_r 24} \le 10 \tag{3}$$

– Limits in the relationship between the input, recycled and purge flow rates:

$$0.03 \le \frac{q_p}{q_2} \le 0.07 \; ; \qquad 0.5 \le \frac{q_2}{q_i} \le 0.9 \tag{4}$$

– Constraints on the non-linear differential equations of the phenomenological plant model to obtain a solution close to a steady state (ε close to zero):

$$\left|\frac{dx_1}{dt}\right| = \left|\mu_{\max} y \frac{s_1 x_1}{(K_s + s_1)} - K_d \frac{x_1^2}{s_1} - K_c x_1 + \frac{q}{v}(xir - x_1)\right| \le \varepsilon \tag{5}$$

$$\left|\frac{ds_1}{dt}\right| = \left|-\mu_{\max} \frac{s_1 x_1}{(K_s + s_1)} + f_{kd} K_d \frac{x_1^2}{s_1} + f_{kd} K_c x_1 + \frac{q}{v}(sir - s_1)\right| \le \varepsilon \tag{6}$$

$$\left|\frac{dc_1}{dt}\right| = \left|K_{la} fk \;(c_s - c_1) - K_{01} \mu_{\max} \frac{x_1^2}{(K_s + s_1)} - \frac{q}{v} c_1\right| \le \varepsilon \tag{7}$$

$$\left|\frac{dx_b}{dt}\right| = \left|\frac{1}{Al_b}\left(q x_1 - q_{sal} x_b - q_2 x_b + Avs(x_d) - Avs(x_b)\right)\right| \le \varepsilon \tag{8}$$

$$\left|\frac{dx_r}{dt}\right| = \left|\frac{1}{Al_r}\left(q_2 x_b - q_2 x_r + Avs(x_b)\right)\right| \le \varepsilon \tag{9}$$

$$\left|\frac{dx_d}{dt}\right| = \left|\frac{1}{Al_d}\left(q_{sal} x_b - q_{sal} x_d - Avs(x_d)\right)\right| \le \varepsilon \tag{10}$$

Controllability constraints:

$$\gamma(G) \; < \; 2 \tag{11}$$

$$\gamma_p(G) \; < \; \gamma(G) \tag{12}$$

The solution of the optimization problem just formulated produces the results shown on the last column of Table 1.

The operating conditions of the nominal plant used for simulations in previous works [17] and those of the optimal economic design (without the controllability constraints) are also included in Table 1. The economic design produces a lower cost function, however without the controllability constraints; it cannot guarantee a well conditioned plant and disturbance rejection capability in the open loop configuration.

Table 1: Dimensions and operation conditions of the designed plants

Process parameters	Nominal Plant	Economic Design	Integrated Design
X_1(mg/l)	2039	1677	1883.1
S_1(mg/l)	49.72	86.2	86.3692
C_1(mg/l)	4.1135	1	3.7124
Q_{r1}(m^3/hr)	1415	724.9	604.7
Q_p(m^3/hr)	48.8	22.8	45.3
F_{k1}	0.52	0.0784	0.496
V_1(m^3)	7924	5369.6	4774.6
A_1(m^2)	2976	1856	3201.6
Cost f	-	0.135092	0.369245
γ(G)	-	-	1.9496
γ_p(G)	-	-	1.7495

IV. Predictive Control for the Activated Sludge Process

The model predictive control (MPC) law is to calculate a control sequence by minimizing a certain cost function. The control sequence *u(t)* is calculated at each time step, based on: set-points, a process prediction model, the measured disturbances and outputs. The closed loop structure of the controlled activated sludge process is shown in Figure 2.

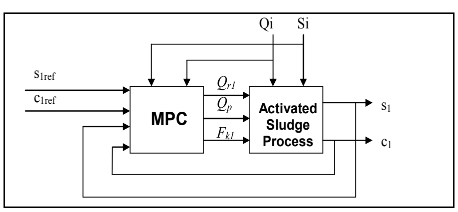

Figure 2. Closed loop system.

Three different strategies of MPC are implemented on the designed activated-sludge process, as explained in the following paragraphs.

1) Linear MPC

A classical linear MPC is used as a first alternative for process control. The prediction model used is a discrete linear model in state space obtained by linearizing the process mathematical model given by equations (5)-(10), about the nominal steady-state conditions:

$$\begin{cases} x(k+1) = A\,x(k) + B_u\,u(k) + B_v\,v(k) \\ y(k) = C\,x(k) + D_v\,v(k) \end{cases} \tag{13}$$

where $x(k) = (X_l, S_l, C_l, X_d, X_b, X_r)^T$ is the state vector, $y(k) = (S_l, C_l)^T$ is the output vector, $u(k) = (Q_{rl}, Q_p, F_{kl})^T$ is the input vector and $v(k) = (Q_i, S_i)^T$ is the vector of measurable disturbances. The matrices A, B_u, B_d are of adequate size. As usual in practice, it is assumed that future measurable disturbances are constant over the last measured value.

The MPC control law allows calculating the manipulated variables online by solving the optimization problem:

$$J = \sum_{j=1}^{Hp} \alpha \left[y_{ref}(k+j) - \tilde{y}(k+j) \right]^2 + \sum_{j=1}^{Hc} \lambda [\Delta u(k+j-1)]^2 \tag{14}$$

where k denotes the sampling instants, $\tilde{y}(k+j)$ is a vector of the predicted output values, $y_{ref}(k+j)$ is a vector of the future set-point values, Δu is a vector of manipulated variables changes. Controller parameters: Hp (prediction horizon), Hc (control horizon), α (vector of weights associated with the manipulated variables) and λ (vector of weights associated with the tracking errors of the reference) are empirically tuned. Constraints are imposed on the input and output variables, as summarized in Table 2.

The implementation of the controller is based on the MPC Toolbox for Matlab ®.

Table 2: Constraints on the process variables

Output variables	Manipulated variables
$0 < S_1 < 100$	$0 < Qr_1 < 3500$
$0 < C_1 < 10$	$0 < Qp < 100$
	$0 < F_{K1} < 1$

2) Non Linear MPC

Instantaneous linearization of the phenomenological model

A non-linear MPC is structured using the standard MPC formulation described in the previous section. However, the linear state-space model changes in every iteration and is produced by the iterative linearization of the non-linear phenomenological model of the process, given by equations (5)-(10), in the region of the current operating point.

Instantaneous linearization of a neural model

A scheme similar is implemented using as the non-linear model a neural network trained off line to emulate the dynamic behavior of the activated-sludge plant (Figure 3).

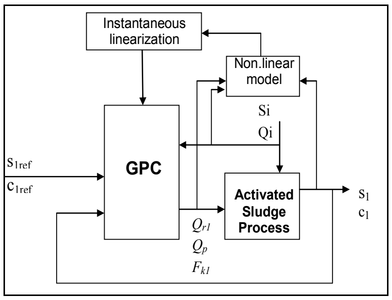

Figure 3. MPC scheme with instantaneous linearization.

The neural model contains two feedforward neural networks (FNN), each one to estimate one of the process outputs (see Figure 4). The manipulated variables and perturbations are introduced as inputs to the FNN along with the one and two-step delayed corresponding outputs.

Each FNN contains one hidden layer with six neurons using sigmoid functions and a linear output layer. The usual training and validation protocol is used to adjust the networks coefficients, by means of the well known *Levenberg-Marquardt* algorithm, found in the Neural Networks Toolbox for Matlab ®.

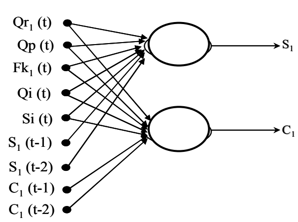

Figure 4: Neural Network structure.

Given the input-output character of the neural models, the implementation of the MPC scheme is now based on an ARMA model of the type:

$$A(z^{-1})\,y(t) = B(z^{-1})\,u(t) + D(z^{-1})\,v(t) + \frac{1}{\Delta}C(z^{-1})\,e(t) \tag{15}$$

where

e(t) is a white noise vector, $\Delta = 1 - z^{-1}$,

$C = I_{nxn}$, and

$$A(z^{-1}) = I_{n\times n} + A_1 z^{-1} + A_2 z^{-2} \tag{16}$$

$$B(z^{-1}) = bo + B_1 z^{-1} + B_2 z^{-2} + B_3 z^{-3} \tag{17}$$

$$D(z^{-1}) = D_1 z^{-1} + D_2 z^{-2} \tag{18}$$

In fact, the model described by the two identified FNNs is of the form :

$$y(t) = \sum_j W_j * \log sig\left(\sum_k W_{jk}\,\varphi_k(t) + b_{j0}\right) + b_0 \tag{19}$$

where:

$$\varphi_1(t) = [S_1(t-1),\ S_1(t-2),\ Qr_1(t),\ Q_p(t),\ F_{k1}(t),\ Q_i(t),\ S_i(t)] \tag{20}$$

$$\varphi_2(t) = [C_1(t-1),\ C_1(t-2),\ Qr_1(t),\ Q_p(t),\ F_{k1}(t),\ Q_i(t),\ S_i(t)] \tag{21}$$

Linearization of each output variable, from equation (19) about the actual value of the associated regressive vector *φ(t)*, yields:

$$\widetilde{S}_1(t) = -a_1 S_1(t-1) - a_2 S_1(t-2) + b_1 Qr_1(t) + b_2 Q_p(t) + b_3 F_{k1}(t) + d_1 Q_i(t) + d_2 S_i(t) \tag{22}$$

$$\widetilde{C}_1(t) = -a_3 C_1(t-1) - a_4 C_1(t-2) + b_4 Qr_1(t) + b_5 Q_p(t) + b_6 F_{k1}(t) + d_3 Q_i(t) + d_4 S_i(t) \tag{23}$$

Coefficients a_i, b_i and d_i are then grouped within the matrices *A*, *B* and *D* already mentioned.

A generalized predictive controller (GPC) can be derived using model (15) to obtain the output predictions (see [18]). Finally, the control signals are obtained minimizing the cost function (14) solving the optimization problem as stated in the linear case.

V. RESULTS OF MPC FOR THE DESIGNED PLANT

The three alternatives of MPC just presented are implemented on the activated sludge plant. The following measures of performance are used to analyze the behavior of the controlled process over a T time period:

- the integral square of errors ISE:

$$ISE = \int_{t=0}^{T\max} (s_{1r} - s_1)^2 \cdot dt$$

- the pumping energy PE (kWh/d):

$$PE = \int_{t=0}^{T\max} (Q_{r1} + Q_p)\,dt$$

- an effluent quality EQ estimator, (Kg pollution/d):

$$EQ = \frac{1}{T.1000}\int_{t=0}^{T\max} [x_d + s_1 + 0.25(s_1 + 0.92x_d)]\,Q_{sal}\,dt$$

Several simulation experiments are carried out to test the performance of the different plants shown in Table 1. The nominal plant closed loop performance is compared with the plants obtained by economical design and by integrated design. The controller parameters are tuned manually.

Nominal plant

The two process outputs responses of the nominal plant with the different control schemes are presented in Figure 5. The performance indexes are summarized in Table 3.

Table 3: Results for the controlled nominal plant

Performance indexes	Lineal MPC	IL- MPC	N- GPC
ISE	25182	14689	33732
PE	985.7543	926.39	997.93
EQ	6545.9	7364.6	7461.2

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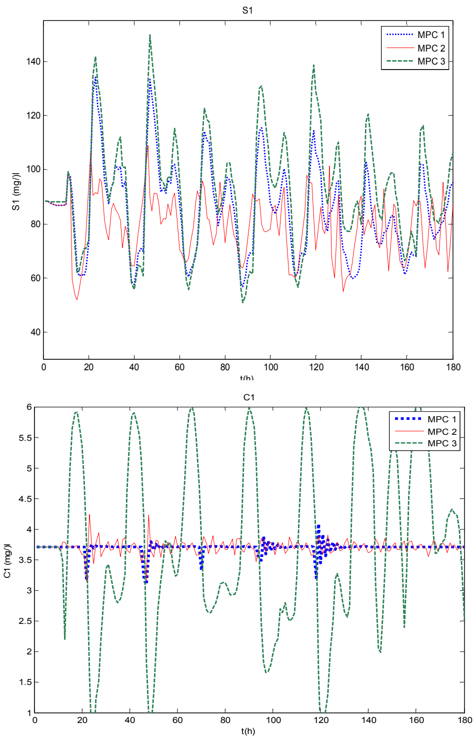

Figure 5. Outputs for the controlled nominal process

Economical optimization plant

Likewise results of the controlled process outputs for the plant obtained by economical optimization, using also the three different control schemes are presented in Figure 6, and the performance indexes are summarized in Table 4.

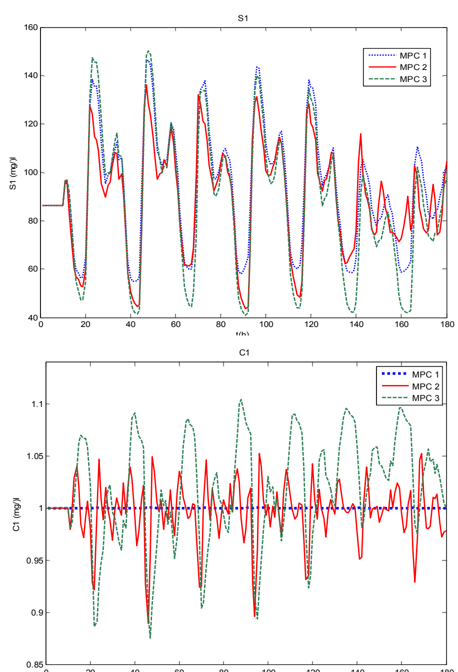

Figure 6: Outputs S1 and C1 of the economic plant

Table 4: Results for the controlled economic plant

Performance indexes	Lineal MPC	IL- MPC	N-GPC
ISE	114040	70441	135070
PE	857.05	922.9	696.09
EQ	10537	11979	11063

Integrated design plant

Finally, the results of the controlled process outputs for the plant obtained by integrated design, using also the three different control schemes are presented in Figure 7, and the performance indexes are summarized in Table 5.

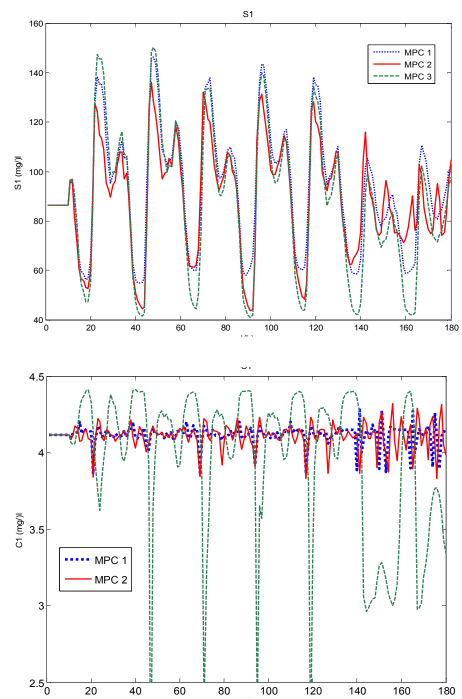

Figure 7: Outputs S1 and C1 for the plant obtained by the integrated design

Table 5: Results for the controlled integrated plant

Performance indexes	Lineal MPC	IL- MPC	N-GPC
ISE	51939	31132	143090
PE	677.91	289.3	1320
EQ	6462.2	7914.3	9148,1

As can be observed in the previous results the non linear MPC schemes produce logically a better closed-loop behavior of the controlled variables than the linear MPC. Also to be expected is the fact that the predictive controller does not perform as well when using the neural model for predictions, instead of the phenomenological model, since the latter is the base of the plant simulations. However, the neural network approach is more practical and easily available in real applications.

Some measures to compare the performance of the plant obtained by integrated design with the plant designed only considering economic objectives are summarized in Table 6. They show the superiority of the integrated design on both aspects, economical and of process control.

Table 6: Comparison of the performance of the different designs controlled with IL-MPC .

	Economic Plant	Plant by Integrated Design
ISE	70441	31132
PE	1068.8	289.3
γ	6.504	1.949
γ_d	6.503	1.749

Additionally, the cost indexes ISE and PE obtained in open loop operation, namely:

- Economic Plant: ISE: 141480 PE: 1068.8
- Integrated Plant: ISE: 148106 PE: 289.30

When compared to the values in Table 6, show the good performance of the proposed controllers achieving a significant improvement in the closed loop operation.

VI. CONCLUSIONS

In this work, the integrated design of an activated sludge process was addressed. Open loop controllability constraints were imposed on the design procedure so as the plant designed is optimal in costs and is well conditioned in plant and disturbance rejection capabilities. Note also that the plant non-linear dynamics are considered in the integrated design because the formulation ensures that non-linear model of the plant is satisfied, as well as the operation, process and controllability constraints.

Afterwards, a type of advanced controller (MPC) was implemented. The performance of the typical linear MPC was not satisfactory as expected for a plant with many non-linearities. Non-linear MPC schemes were also developed by means of instantaneous linearization, with good results even after just a manual tuning of the controller parameters. Obviously the integrated control errors are higher when the prediction model is the neural network obtained by identification, when compared to those of the MPC based on the exact phenomenological model used in the simulations. However, off-line training of FNN with real plant data can be easily achieved in practice and the linearization procedure of such simple equations is straightforward.

Comparison between the closed loop performance of the plant obtained by integrated design and that of the classical-design-plant surely indicates the convenience of the integrated design approach in spite of its somewhat higher costs.

On the other hand, the undemanding execution of the iterative linearization makes a very practical extension of MPC to non linear processes.

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