Event-based selective control strategy for raceway reactor: A simulation study

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Abstract: This work presents a simulation study of an event-based selective control strategy for a raceway reactor. The control system aims to maintain simultaneously a pH and dissolved oxygen within specific limits. In the analyzed control scheme, the pH value is prioritized over the dissolved oxygen, since it has a critical influence on the process performance. Besides, the dissolved oxygen also influences the photosynthesis rate and should be kept within the limits. The control structure is evaluated through simulation, where a nonlinear model for microalgal culture in the raceway photobioreactor is used. Analysis of different configurations allows to determine the most adequate control system setup to achieve the desired goals. The obtained results show that combination of an event-based approach with selective control allows to increase the overall productivity as well as to address effective CO₂ utilization and aeration system energy minimization.

Keywords: raceway reactor, microalgae, pH control, dissolved oxygen control, selective control,

1. INTRODUCTION

Depending on the properties one is looking for, microalgae cultures can be grown in photobioreactors with different architectures. When a high-value algal biomass from particular strains is required, closed photobioreactors are generally used, e.g. tubular photobioreactors. On the contrary, when high production volume is the priority, open photobioreactors are usually employed. The most popular in this group is the raceway photobioreactor. However, independent of the physical configurations, all photobioreactors are designed to assure optimal microalgal growth conditions. As reported in (Costache et al., 2013), the most important variables in microalgal culture are: solar irradiance, medium temperature, pH, and dissolved oxygen (DO). Furthermore, the response of the photosynthesis rate to solar irradiance changes depends on other variables, making the microalgal culture process a complex system. For the raceway photobioreactor, light requirements and operating temperature are determined by the reactor architecture and cannot be manipulated during normal operation. The remaining microalgal bioprocess variables such as pH and DO should be handled using the proper control techniques. The pH and DO values are highly dynamic since they depend on the photosynthesis rate and need to be kept close to their optimal values.

Except for solar irradiance and temperature, pH is the most important variable that influences the photosynthesis rate. It is well known that the application of CO₂ has a direct influence on the pH value since it changes the acidity of the microalgal growth medium. Overabundance of CO₂ can strongly reduce pH thus damaging the culture. Conversely, insufficient CO₂ supply can reduce the inorganic carbon concentration below the minimum resulting in limited growth (Benemann et al., 1987; Berenguel et al., 2004). Although CO₂ limitation can easily be avoided by supplying it in excess, the use of carbon dioxide represents a relevant operational cost for microalgal culture (de Godos et al., 2014). Another important aspect of uncontrolled supply is related to CO₂ losses as unnecessary emission to the atmosphere needs to be minimized by providing efficient control techniques (Benemann et al., 1987; Pawlowski et al., 2014c; Bernard, 2011). Exploiting this interdependence, the control system uses the pH value to determine both the time instant and the amount of carbon dioxide to be injected. Therefore, the trade-off between pH regulation accuracy and minimization of CO₂ losses should be considered in the control approach.

The dissolved oxygen content is another variable that has a significant influence on the microalgal photosynthesis rate and in consequence affects the amount of final product. Dissolved oxygen at high concentrations in the cultures would pose a severe threat to microalgal growth (Peng
et al., 2013; Ugwu et al., 2007). In raceway ponds, it is assumed that no DO control is required since dissolved oxygen excess should be automatically removed to the atmosphere. However, in practice this assumption is incorrect as DO concentration can reach as high as 500 % air saturation (Mendoza et al., 2013; Peng et al., 2013). To minimize DO influence on culture growth, it is necessary to provide an aeration or stirring mechanism. In both cases, the required equipment may add complexity to the photobioreactor and increase the production cost. As reported in (Peng et al., 2013) and (Mendoza et al., 2013), the DO evacuation issue remains a significant challenge despite the considerable technical advances in this field.

Considering aforementioned features, it can be observed that both objectives for pH and DO processes are advantageous, because applying the aeration mechanism can deteriorate 

\[ \text{CO}_2 \] assimilation. Moreover, for economic reasons it is common practice to provide the same supply structure for both variables. In such a case, the \[ \text{CO}_2 \] and air supply system can be commuted when necessary and only one variable can be controlled (only one quantity can be supplied). To deal with those issues, the selective control system is used with a simultaneous approach. Moreover, due to the simultaneous approach this control system can adapt the structure rate to the process dynamics and process disturbances (Pawlowski et al., 2011). This feature is especially useful in bioprocess application, as confirmed in several recent works (Beschi et al., 2014; Pawlowski et al., 2014a,b,c).

In this study we extend the selective control system configurations presented in (Pawlowski et al., 2015), considering discrete-time Proportional-Integrate (PI) controller for the DO control purposes. Beside, the pH process is controlled with event-based Generalized Predictive Controller (GPC) that was successfully evaluated for this purpose in (Pawlowski et al., 2014c). The evaluation of the modified approach is performed through a simulation study, where the raceway photobioreactor is modelled using a first principle approach. The developed nonlinear model is used as a process simulator as well as a test bed for different control system configurations. In such a case, the effectiveness of prosed control scheme can be validated by verifying the influence of the control system parameters. The modified approach, provides a possibility to reduce the energy required for aeration system and effective use of flue gases (used as \[ \text{CO}_2 \] source). The obtained results are confirmed by several control system performance indexes, including the raceway reactor productivity measures.

2. SYSTEM DYNAMICS AND MODELS

The experimental raceway reactor used for modelling purposes is situated at the Estación Experimental Las Palmerillas owned by the Fundación CAJAMAR (Almería, Spain). The raceway has a total surface area of 100 m² and consists of two 50 m channels, each 1 m wide and connected by U-shaped bends (see (Mendoza et al., 2013) for details). An appropriate model in microalgal production system must consider the relationship between light availability and photosynthesis rate, the mixing and the gas-liquid mass transfer inside the system.

The culture growth can be modelled as a function of the photosynthesis rate. The main parameter that determines the photosynthesis rate is the available light, based on external irradiance, culture characteristics and reactor geometry (Acien et al., 1999, 2013):

\[ I_{as}(t,x) = \frac{I_0(t)}{K_{as}C_b(t,x)}(1 - \exp(-K_{as}C_b(t,x)h)) \] (1)

where \( t \) is the time, \( x \) the space, \( I_0 \) is the solar irradiance on an obstacle-free horizontal surface, \( K_{as} \) is the extinction coefficient, \( C_b \) is the biomass concentration, and \( h \) is the liquid height on the channels.

The available average irradiance is correlated with the photosynthesis rate by a hyperbolical function as proposed in (Molina et al., 1996). This function is completed by adding the rest of factors that limit the microalgal growth (under sufficient conditions of nutrients). So, the influence of the pH culture value and dissolved oxygen of the culture have been modeled as described in (Costache et al., 2013):

\[ P_{O_2}(t,x) = (1 - \alpha_s)P_{O_2,max}^f(x,\bar{x})^n \left( 1 - \frac{[\text{O}_2](t,x)}{K_{O_2}} \right)^n \left( B_1\exp\left(\frac{-C_1}{\text{pH}(t,x)}\right) - B_2\exp\left(\frac{-C_2}{\text{pH}(t,x)}\right) \right) - \alpha_sR_{O_2} \] (2)

where \( P_{O_2} \) is the photosynthesis rate (oxygen production rate per biomass mass unit), \( P_{O_2,max}^f \) is the maximum photosynthesis rate for microorganisms under the culture conditions, \( n \) is the form exponent, and the term in the denominator is the irradiance constant, that increases as an exponential function of average irradiance, \( K_1 \) and \( m \) being form parameters of this relationship, \( K_{O_2} \) is the oxygen inhibition constant and \( z \) is a form parameter. For the pH influence on the photosynthesis rate, \( B_1, B_2 \) are the preexponential factors and \( C_1, C_2 \) the activation energies of the Arrhenius model. Furthermore, a constant respiration rate \( R_{O_2} \) was included in order to represent the respiration phenomenon, and a solar distributed factor \( \alpha_s \) as the shadow projection on the perpendicular axis of the reactor walls.

The pH value of the culture is related to other species such as dissolved carbon dioxide, \([\text{CO}_2]\), carbonate, \([\text{HCO}_3^-]\), or bicarbonate, \([\text{CO}_3^{2-}]\) by several equilibrium equations, as can be seen in (Camacho et al., 1999), being necessary the balance of one of them to obtain predictions of pH along time and space. In this work the total inorganic carbon concentration, \([\text{C}_T]\), is modelled taking into account the photosynthesis process performed by the microalga culture, and the transport phenomena due to the recirculation of the culture along the raceway. Assuming constant velocity, \( v \), and constant cross-sectional area obtained by the multiplication between the liquid height, \( h \), and the channel width, \( w \).

\[ \frac{\partial [\text{CO}_2](t,x)}{\partial t} = -\frac{\partial [\text{CO}_2](t,x)}{\partial x} + \frac{wH_{\text{CO}_2}(t,x)Ch(t,x)}{M_{\text{CO}_2}} + wH_{\text{laCO}_2}([\text{CO}_3^-](t,x) - [\text{CO}_2](t,x)) \] (3)

where \( P_{\text{CO}_2} \) is the carbon consumption rate, \( H_{\text{laCO}_2} \) is the mass transfer coefficient for \( \text{CO}_2, M_{\text{CO}_2} \) is the molecular
weight of carbon dioxide. The total inorganic carbon, \([C_T]\), is related to the carbon dioxide concentration in the liquid phase \([CO_2]\) and the equilibrium concentration in the gas phase \([CO_2]^*\). The equilibrium concentration can be calculated, according to Henry’s law, taking into account the CO₂ properties in the air.

Regarding dissolved oxygen concentration, a homologous balance can be established as follows,

\[
\frac{\partial \theta(t,x)}{\partial t} = -nh\frac{\partial \theta(t,x)}{\partial x} + nwh P_{O_2}(t,x)C_b(t,x)
\]

where \(P_{O_2}\) is the photosynthesis rate (oxygen production rate per biomass mass unit), \(M_{O_2}\) is the molecular weight of oxygen, \(K_{laO_2}\) is the volumetric gas-liquid mass transfer coefficient for oxygen at the channels, and \(([O_2] - [O_2]^*)\) is the driving force. The equilibrium concentration in gas phase \([O_2]^*\) is calculated as a function of the oxygen concentration in the gas phase based on Henry’s law.

Analogous mass balances are applied at the paddle-wheel and sump of the reactor, bearing in mind that these parts can be represented by ODEs expression. In addition to the liquid phase, the sump is designed to incorporate carbon dioxide by means of CO₂ injections in gaseous form, and remove dissolved oxygen accumulated into the channels by air injections. Therefore, mass balances on the gas phases are needed to include these phenomena in the model. Since the nitrogen molar flow can be considered constant because its solubility is approximately zero, the balances presented in this paper are formulated by relations from the rest of gases to nitrogen molar ratio. Owing to oxygen, the next balance (5) can be established.

\[
\frac{dY_{O_2,\text{out}}}(t)}{dt} = -\frac{Q_{\text{gas}}}{V_e(1-\varepsilon_e(t))} (Y_{O_2,\text{out}}(t) - Y_{O_2,\text{in}}(t)) - K_{laO_2} \frac{V_{\text{mol}}}{\varepsilon_e(t)} \frac{([O_2] - [O_2])_{\text{lm}}}{(1-\varepsilon_e(t))}
\]

where \(V_{\text{mol}}\) is the molar volume under reactor conditions (pressure and temperature), \(Y_{O_2}\) is the oxygen to nitrogen molar ratio in the gas phase, which is defined at the inlet and outlet of the sump, and \(Y_{N_2}\) is the nitrogen molar fraction. For the carbon dioxide, an analogous mass balance can be defined (6), where \(Y_{CO_2}\) is the carbon dioxide to nitrogen molar ratio in the gas phase.

\[
\frac{dY_{CO_2,\text{out}}}(t)}{dt} = -\frac{Q_{\text{gas}}}{V_e(1-\varepsilon_e(t))} (Y_{CO_2,\text{out}}(t) - Y_{CO_2,\text{in}}(t)) - K_{laCO_2} \frac{V_{\text{mol}}}{Y_{N_2}} \frac{([CO_2] - [CO_2])_{\text{lm}}}{(1-\varepsilon_e(t))}
\]

2.1 Simplified linear models for control purposes

Regarding the controllers design, linear models for both controlled variable are used to determine the process dynamics. Considering that the main process output is the culture pH, the aperture of the flue gases injection valve is the manipulated variable and the solar irradiance is the main system disturbance. The second controlled variable, DO, is manipulated by the aperture of air injection valve. The linear reduced-order model must identified taking into account the layout of the raceway reactor, the local distribution of the sensors and actuators, and the dynamics observed in the data. In this work a First-Order-Plus-Dead-Time (FOPDT) process model is identified around the operation point of the process, which is characterized by: gain \(k\), time constant \(\tau\) and input-output time delay \(t_r\). Once the pH and DO process dynamics are captured by the FOPDT models, it is possible to develop the GPC architecture and tune the PI controller.

3. EVENT-BASED SELECTIVE CONTROL

The selective control scheme is frequently used for process synchronization, especially in cases where several control objectives exist and only one control variable can be used (Liptak, 2004). In a selective control scheme, it is possible to combine several controllers that are commuted with each other for process optimization. Using these properties, selective control algorithms allow one to switch between pH and DO controllers simultaneously, satisfying the control requirements. The proposed selective control scheme is depicted in Figure 1. In this work, selective logic was implemented within the event-based approach, which allows control scheme adaption to the dynamical process evolution. The selective logic uses a deadband sampling approach, that is frequently used in event-based systems. The control signal selection is performed using the following expression:

\[
u_{SC} = \begin{cases} \ u_{pH} : |SCSP_{pH} - pH| > \beta \\ u_{DO} : |SCSP_{pH} - pH| < \beta \& DO > SCSP_{DO} \end{cases}
\]

where, \(SCSP_{pH}\) and \(SCSP_{DO}\) are selective control scheme setpoints for pH and DO, respectively; \(\beta\) is the deadband value (control tolerance) for pH control, and \(pH\) and \(DO\) are the pH and DO measurements, respectively. Following this control signal selection criteria, the pH controller will be prioritized when the pH value is outside the established limits. Otherwise, when pH is within the limits, the DO controller will be selected.

3.1 Event-based GPC for pH control

The Generalized Predictive Control (GPC) consists of applying a control sequence that minimizes a multistage cost function in the form:

\[
J = \sum_{j=N_1}^{N_2} [\tilde{y}(t+j\mid t) - w(t+j)]^2 + \sum_{j=1}^{N_2} \lambda(j) [\Delta u(t+j-1)]^2
\]

where \(\tilde{y}(t+j\mid t)\) is an optimum \(j\) step-ahead prediction of the system output on data up to time \(t\), \(\Delta u(t+j)\) is the future control signal increments, \(N_1\) and \(N_2\) are the
minimum and maximum costing horizons, \( N_u \) is the control horizon, \( \lambda(j) \) is the control effort weighting sequence (considered constant in this work) and \( w(t+j) \) is the future reference trajectory (Camacho and Bordons, 2007). The J minimum, assuming there are no constraints on the control signals, can be found by making the J gradient equal to zero. Nevertheless, most physical processes are subjected to constraints and the optimal solution can be obtained by minimizing a quadratic function. The obtained quadratic function is minimized subject to system constraints; they can be expressed in a shorted form as \( R\Delta u \leq r \) (Camacho and Bordons, 2007).

The classical GPC was extended with the actuator deadband approach, previously developed in (Pawlowski et al., 2014a). The main idea of this approach is to develop a control structure where the control signal is updated in an asynchronous manner. The main goal is to reduce the number of control signal updates, saving system resources while retaining acceptable control performance. The actuator deadband can be understood as a constraint on control signal increments \( \Delta u(t), |\Delta u(t)| \geq \beta_u \), where \( \beta_u \) is the proposed deadband. Introducing two logical variables, \( \varphi_1 \) and \( \varphi_2 \), to determine a condition on the control signal increments, \( \Delta u(t) \); these logical variables are used to describe the different stages of the control signal with respect to the deadband, as follows:

\[
x(t) = \begin{cases} 
\Delta u(t) : \Delta u(t) \geq \beta_u & \varphi_1 = 1 \\
0 : \Delta u(t) \leq \beta_u & \varphi_2 = 0 \\
0 : \Delta u(t) \geq -\beta_u & \varphi_1 = 0 \\
\Delta u(t) : \Delta u(t) \leq -\beta_u & \varphi_1 = 1 
\end{cases} \tag{8}
\]

To make this solution more general, minimal \( m \) and maximal \( M \) values for control signal increments are included in the control system design procedure, resulting in \( M = \max\{\Delta u(t)\} \) and \( m = \min\{\Delta u(t)\} \). In this way, it is possible to determine the solution region based on binary variables. Thus, the proposed logic determined by equation (8) can be translated into a set of mixed-integer linear inequalities involving both continuous variables, \( \Delta u \in \mathbb{R} \), and logical variables \( \varphi_1 \in \{0, 1\} \) (Bemporad and Morari, 1999). Finally, a set of mixed-integer linear inequality constraints for the actuator deadband are established as:

\[
\begin{bmatrix}
1D & 0D & -(M - \beta_u)D \\
1D & (M + \beta_u)D & 0D \\
1D & 0D & -M D \\
-1D & (m + \beta_u)D & 0D \\
-1D & 0D & -(m - \beta_u)D \\
\end{bmatrix} \times \begin{bmatrix}
\Delta u_d \\
\varphi_1 \\
\varphi_2 \\
\end{bmatrix} \leq \begin{bmatrix}
\beta_u d \\
M d \\
0D \\
-\beta_u d \\
0d \\
0d \\
\end{bmatrix}
\]

where \( D \) is a matrix \((N_u \times N_u)\) of ones and \( d \) is a vector of ones with size \((N_u \times 1)\). The previous matrices that contain linear inequality constraints can be expressed in a general form as \( Cx \leq \rho \), with \( x = [x_c, x_d]^T \), where \( x_c \) represents the continuous variables \( \Delta u \), and \( x_d \) are those of the logical variables \( \varphi_i \). Introducing the matrix \( Q(3N_u \times 3N_u) \) and \( I(3N_u \times 1) \) defined as:

\[
Q = \begin{bmatrix} H \ 0 \ 0 \\ 0 \ 0 \ 0 \\ 0 \ 0 \ 0 \end{bmatrix} : = \begin{bmatrix} b \\ 0 \\ 0 \end{bmatrix}
\]

where \( 0 = N_u \times N_u \), \( 0 = N_u \times 1 \) both of zeros, \( H \) and \( b \) are matrices used in classical QP optimization; the GPC optimization problem is expressed as:

\[
\min_{x} x^T Qx + 1^T x \tag{10}
\]

subject to \( Cx \leq \rho \), which is a Mixed Integer Quadratic Programming (MIQP) optimization problem (Bemporad and Morari, 1999). The optimization problem involves a quadratic objective function and a set of mixed linear inequalities. Moreover, the classical set of constraints, \( R\Delta u \leq r \) can also be included into the optimization procedure, introducing an auxiliary matrix \( \tilde{R} \) of the form \([R \ 0 \ 0] \), where \( 0 \) is a matrix of zeros with the same dimensions as \( R \).

### 3.2 PI controller for dissolved oxygen

In the analyzed approach, the DO process is controlled with a discrete time PI (Proportional and Integrative) controller. In particular, the controller is discretized by using the backward Euler method obtaining the following discrete-time representation (with sampling period \( h \)):

\[
C(z^{-1}) = (K_p h + K_i) - K_p z^{-1} \tag{11}
\]

where \( K_p \) is the proportional gain and \( K_i \) is the integral gain (Aström and Hägglund, 2006). Moreover, a classical on/off controller with deadzone is used for the DO control. This controller is used for comparison purposes, since it is the most common control technique for DO control in raceway reactors.

### 4. RESULTS

The simulation study presented in this section uses the raceway setup described above and meteorological data from the spring 2015 season. All tested control system configurations were simulated for a seven-days period in order to provide reliable data. In the implemented scheme, both inlet valves are driven with the PWM (Pulse Width Modulation) technique. In this way, the continuous signals from the controllers are translated into pulse trains with a variable width. The width of the pulse is determined by the control signal and it is constrained between 0 and 100\%. The PWM modulation frequencies were set to 0.1 Hz for the pH and 0.2 Hz for the DO process.

The first step in control system development consists in capturing the dynamics of both processes using the FOPDT linear model. For this end, several step changes were made in manipulated variables around the desired operating point (pH=8, and DO=200 [%Sat]) in order to obtain dynamical responses for each variable. The pH process was characterized with following parameters: \( k = -0.012 \ \text{pH}^{-1} \), \( \tau = 11.5 \ \text{min} \), and \( t_r = 7 \ \text{min} \). The DO process the system dynamics was given by: \( k = -0.4 \ \text{[%Sat]}^{-1} \), \( \tau = 20.8 \ \text{min} \), and \( t_r = 6.6 \). For this simulation study, the event-based GPC parameters for pH process control were set to the following values: the control horizon was set to \( N_u = 5 \), the prediction horizon was \( N_p = 15 \) in order to capture main pH process dynamics, and the control signal weighing factor \( \lambda \) was evaluated experimentally and set to 0.08 to obtain desired control system performance. The GPC controller was implemented using 1 minute sampling time. Additionally, the actuator deadband was set to \( \beta_u = 1.5 \) following the recommendation presented in (Pawlowski et al., 2014c).
Moreover, the event-based GPC includes physical limitations of the control signal constrains (\( u_{\text{pH}} \in 0-100\% \)) into the optimization procedure. The setpoint for event-based GPC with actuator deadband was set to \( \text{pH} = 8 \). The PI controller parameters for the DO were calculated using the AMIGO tuning method (Åström and Hägglund, 2006), obtaining the following controller gains: \( K_p = -1.59 \%/[\%\text{Sat}] \) and \( K_i = 0.09 \%/[s]/[\%\text{Sat}] \). Additionally, due to control signal saturation limits, the PI controller was extended with anti-windup mechanism. Furthermore, the on/off controller for DO was implemented with a sampling time of 1 minute, and it can manage the on/off solenoid valve that supply the compressed air to the sparger. Finally, the selective control switching condition uses the following parameters: \( \text{pH} \) setpoint was set to \( \text{SCSP}_{\text{pH}} = 8 \), the deadband tolerance for \( \text{pH} \) value \( \beta = 0.3 \) and the DO setpoint was established to \( \text{SCSP}_{\text{DO}} = 200 \) [%Sat] (significantly lower than the level established as dangerous DO > 250 [%Sat]).

The selective control scheme was tested in four different configurations, namely: \( \text{pHEBGPC} \), \( \text{pHEBGPC} + \text{DO}^{\text{On/Off}} \), \( \text{pHEBGPC} + \text{DO}^{\text{SP}=200} \), and \( \text{pHEBGPC} + \text{DO}^{\text{SP}=210} \). In all those configurations the \( \text{pH} \) process is controlled with the event-based GPC and three different strategies are used for the DO variable. The first configuration considers only the event-based GPC for \( \text{pH} \) process, and the DO variable is left uncontrolled. The second configuration applies the simple on/off controller for the DO, and the last two use a PI controller to regulate the DO. Additionally, the setpoints for the PI controllers were established to 200 and 210 [%Sat] in order to evaluate their influence on the control system performance. All those configurations were simulated considering a seven-days period. Since a graphical result with seven days does not allow the results to be seen properly, only one representative day has been selected, which is shown in Figure 2. The possibility of simultaneous control for the \( \text{pH} \) and the DO is provided at the expense of \( \text{pH} \) control accuracy. In consequence, the control performance of the \( \text{pH} \) value oscillates around the setpoint, due to the selective control working principles. However, despite of the commutation in the selective control system the \( \text{pH} \) value is kept close to its optimal value with selected tolerance \( \pm \beta = 0.3 \). Moreover, in contrast to the \( \text{pH}^{\text{EBGPC}} \), the event-based selective control configurations handled the DO control task, keeping its value under dangerous value. The DO controllers are triggered when \( \text{pH} \) is inside the established limits and the DO value is over selected setpoint. In the first case, the on/off controller, the DO value is driven even below the setpoint, due to high volume of the injected air. The second selective control configuration, that uses PI controller, reaches the setpoint applying significantly less air volume, what can be observed comparing the sixth and the seventh plots. Therefore, it can be deduced that the event-based selective control that uses PI controller for the DO control reduces the control effort, reaching the same objective. This reduction is directly related with the energy required to compress the air and in consequence with the reactor maintenance costs. This phenomena can be better explained through a performance indexes analysis.

Thus, Table 1 collects performance indexes for the analyzed selective control configurations. This table shows the Integrated Absolute Error (\( \text{IAE}_{\text{pH}} \) and \( \text{IAE}_{\text{DO}} \), for \( \text{pH} \) and DO respectively), the flue gases injection time (\( \text{GIT} \)), the air injection time (\( \text{AIT} \)), the total amount of flue gases (\( \text{Gas} \)), and total amount of air (\( \text{Air} \)) supplied to the raceway reactor. Moreover, two complementary indexes are included for average biomass concentration \( \bar{C}_b \), and average photosynthesis rate \( \bar{P}_{O_2} \), respectively. From Fig. 2. Event-based selective control performance for one representative day.
obtained results it can be verified that the event-based selective control schemes obtain lower accuracy in the pH and good performance in the DO control, when compared to the pHEBGPC (the IAEpH indexes). Moreover, it can be observed that the control effort required for pH control purposes is similar in all selective control configurations (GIT and Gas measures). The second controlled variable, DO, obtains the best control performance with PI controllers. On the other hand, this reduction does not influence the photobioreactor productivity, that is represented by the Cb and PO2 measures. From these indexes, it can be observed that similar productivity is achieved for all selective control configurations, improving the pHEBGPC algorithm about 8% and 10% for Cb and PO2, respectively. The application of PI controller in selective control scheme allows to reduce the control effort and in consequence the raceway reactor maintenance costs. Additionally, the raceway reactor productivity was of the same level as in the previously proposed scheme with an on/off controller.

5. CONCLUSIONS

This work presented a simulation study for a modified selective control with an event-based approach and its application to raceway photobioreactor for pH and DO control. In the analyzed scheme, the raceway reactor was modelled using a nonlinear first principle model. The analysis of different configurations allows to determine the most adequate control system setup to achieve the desired goals. From all analyzed control systems, the event-based selective structure with PI controller for the DO process provides both improved productivity and reduced energy for aeration system. In consequence, the application of PI controller in the selective control scheme allows to reduce the control effort for the DO process in raceway photobioreactor operation about 25%. This fact is important for the reactor maintenance costs, since the improved productivity can be obtained without physical modification of the reactor setup and keeping the required energy within the limits.

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Table 1. Performance indexes for analyzed selective control schemes and seven days period.

| Selective Control Configuration | IAEpH | GIT | Gas | IAEPO2 | AIT | Air | Cb | PO2 |
|-------------------------------|-------|-----|-----|--------|-----|-----|----|-----|
| pHEBGPC                       | 480   | 49.8| 39.1| 18.7   | 0   | 4   | 0.562| 0.00509 |
| pHEBGPC + DOEBGPC             | 301   | 41.1| 44.1| 31.5   | 8.8 | 74.5| 0.563| 0.00529 |
| pHEBGPC + DOEBGPC/On/OFF       | 290   | 41.3| 42  | 23.8   | 9   | 44.3| 0.562| 0.00524 |
| pHEBGPC + DOEBGPC/On/OFF      | 291   | 41.7| 42  | 23.8   | 9   | 44.3| 0.562| 0.00524 |