Nonlinear Predictive Control for Continuous *Chlorella vulgaris* Culture in a Photobioreactor

R. Filali, S. Tebbani, D. Dumur, S. Diop, D. Pareau and F. Lopes

Abstract— In the framework of environment preservation, microalgae biotechnology appears to be a promising alternative for CO_2 mitigation. Implementation of advanced control strategies can be further considered to improve potential performances of these organisms. In this context, this paper proposes the implementation of predictive control combined with an on-line estimation of the *Chlorella vulgaris* biomass, using Total Inorganic Carbon measurements. The elaboration of interval observers for biomass estimation is first detailed. This estimation is further included in a Nonlinear Model Predictive Control (NMPC) framework considered to regulate the biomass concentration. Finally experimental results are presented which validate the proposed theoretical developments.

I. INTRODUCTION

As a consequence of global warming and greenhouse effect, research on CO_2 mitigation technologies has been investigated in order to reduce carbon dioxide emission into the atmosphere [1]. Biological carbon dioxide sequestration, especially using microalgae biotechnology, has received renewed attention and is believed to be a significant and economically viable CO_2 bio-fixation technology. These microorganisms are able, through photosynthesis process, to convert carbon source into biomass.

Chlorella species are considered very promising candidates for the CO_2 fixation, converting significant levels of carbon dioxide in the airstream of photobioreactors into biomass. In this context, the implication of the green unicellular species *Chlorella vulgaris* for the CO_2 sequestration technology has been highlighted [2], [3].

The optimization of this biological process is related to the implementation of an effective control strategy based on a reliable model that can effectively describe the biochemical dynamics of microalgae. Since the cellular concentration (or biomass) is an important parameter for CO_2 bio-fixation by microalgae, a general objective of the process control is to guarantee that the process will yield the desired amount of biomass along the cultivation period. The regulation of the biomass density can be done by appropriately changing the medium flow rate in the photobioreactor. This study proposes a nonlinear model predictive control (NMPC) strategy for regulation of biomass concentration around a reference value, where the solution of the optimization problem is performed by means of Control Vector Parameterization (CVP) techniques. Moreover, in order to overcome the lack of physical biomass sensors, the control strategy must be coupled to an observer providing reliable biomass estimation. Among several approaches available in the literature, such as the extended Kalman filter [4], asymptotic [5] and interval [6] observers, the latter has been selected here.

The paper is organized as follows: Section II describes the experimental bioprocess on a laboratory-scale bioreactor. Section III introduces the process dynamics and the selected modeling structure for *Chlorella vulgaris*. A robust biomass estimation strategy based on an interval observer is described in Section IV. Then, Section V describes the general structure of the proposed NMPC strategy and the optimization approach via CVP techniques. Experimental validation of this control strategy is presented in section VI for a specific reference biomass profile and including disturbances due to environmental factors. Concluding remarks and perspectives are stated in the last section.

II. PHOTOBIOREACTOR DESCRIPTION

A. Microorganisms and culture medium

The green unicellular microalga *Chlorella vulgaris* AC 149 strain are cultured and maintained in a 1 L Erlenmeyer flasks with the Bristol 3 N medium. Theses flasks are continuously agitated, illuminated under irradiance of 70 µE m^{-2} s^{-1} and aerated with air containing 1% (v/v) CO_2 into an incubator. The sterilization of the medium is achieved by a thermal treatment at 121°C during 20 min. These inoculums are refreshed every two weeks and used to start a culture in the photobioreactor.

B. Description of the photobioreactor equipment and operating mode

Experimental campaigns of the *Chlorella vulgaris* culture are developed in a bubble column photobioreactor with an illuminated area of 0.31 m² and a total culture volume of 9.6 L illustrated in Fig. 1. *Chlorella vulgaris* species is cultivated under an optimal value of surface irradiance of 90 µE m^{-2} s^{-1} and a constant temperature of 25°C, which is maintained by a water circulation system with a transparent jacket connected to a thermostat unit. A filtered gas mixture of air containing 5 % (v/v) CO_2 is continuously supplied with a flow rate of 2.5 V.V.H. (gas volume per liquid culture

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volume per hour) at the bottom of the reactor providing the agitation of the culture by an air-lift system. The regulation of the gas flow rate is achieved by two mass flow meters.

The photobioreactor is equipped with two sensors: a *pH* sensor connected to a multi-parameter data acquisition Consort D130 and a CO_2 sensor (YSI 8500) connected to a monitor (BIOVISION 8500 type). An arrangement of four OSRAM white fluorescent tubes (L30W/72) and four OSRAM pink ones (L30W/77) around the bubble column is used as an external light source. The carbon dioxide supply is introduced progressively in order to avoid any growth limitation by an important acidification of the medium.

This reactor presents one sampling port at the bottom of the column. In the continuous mode, a sterilized Bristol 3 N medium is supplied thanks to a peristaltic pump through an input situated at the top of the reactor. The supply flow rate is controlled by a NATIONAL INSTRUMENTS board, which manages the rotation speed of the pump through the imposed voltage. The effluent is collected as an overflow at the top of the reactor connected to a bottle, which is placed on a balance in order to check the flow outlet of the culture.

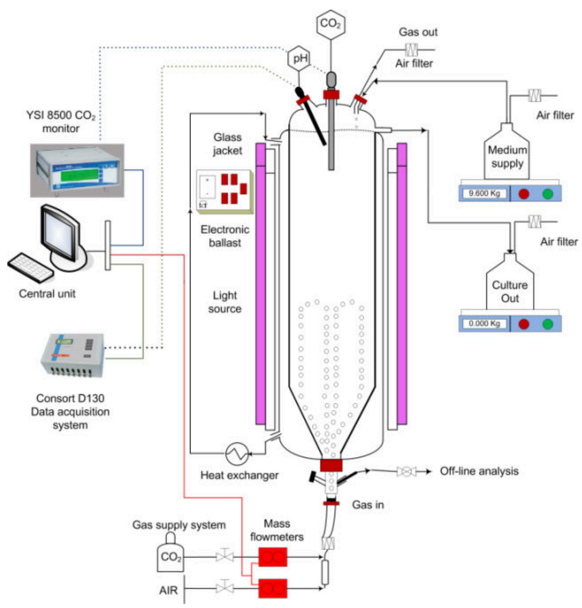

Fig. 1: Schematic representation of the photobioreactor in continuous mode.

C. Available measurements

As mentioned before, several quantities are measured, with samples collected at regular intervals through a sampling port at the bottom of the reactor. In particular, *pH* is measured every 2 minutes whereas dissolved CO_2 concentration is measured every 5 minutes. The incident light intensity over the reactor surface is measured using a flat-surface quantum sensor LI-COR. The average irradiance is obtained from 6 measurements performed distinctly on the total reactor surface. Finally, biomass concentration is measured off-line by a granulometric method based on the principle of analyzing the spot of diffraction of a beam resulting from the interaction of set of microalgae particles with the incident laser beam [7]. An experimental study has quantified the mean error of this measurement methodology, which is equal to 3.44%.

III. Microalgal Bioreactor Model

To accurately describe the growth behavior of *Chlorella vulgaris* in a photobioreactor, a mathematical model is developed in this section, based on the one proposed by Nouals, [8], [9]. Assuming that the photobioreactor is in perfectly-stirred conditions under continuous mode (CSTR), the evolution of the cellular concentration is given by the following standard mass balance equation:

$$\frac{dX}{dt} = \mu X - DX \tag{1}$$

where μ (h^{-1}), X (in billion cells per liter) and D (h^{-1}) are respectively the specific growth rate, the cell number of microalgae or "biomass" and the dilution rate, i.e. the ratio of medium flow rate F to culture volume in the reactor. In continuous mode, the effective volume of the culture remains constant as the inlet and outlet flow rate are equal.

In this study, the carbon source is illustrated by the Total Inorganic Carbon parameter (denoted *TIC*, in mmol per liter). The dynamics behavior of *TIC* consumption in the aqueous solution is given by the following mass balance:

$$\frac{d[TIC]}{dt} = -\mu \frac{X}{Y_r} - D[TIC] + k_L a([CO_2]^* - [CO_2]) \tag{2}$$

where Y_r and $k_L a$ are the biomass conversion yield (the ratio of the amount of biomass produced to the amount of consumed *TIC*) and the gas-liquid transfer coefficient of carbon dioxide in the reactor, respectively. In this equation, the equilibrium carbon dioxide concentration is defined by the Henry law in the liquid phase, as follows:

$$\left[CO_2\right]^* = \frac{P_{CO_2}}{H} \tag{3}$$

where P_{CO_2} represents the partial pressure of carbon dioxide (0.05 atm under our experimental conditions) and H denotes the Henry constant for Bristol 3 N medium at 25°C.

The carbon dioxide concentration in the culture is derived according to the chemical equilibrium of the carbon dioxide in the aqueous solution, by the following expression:

$$\left[CO_2\right] = \frac{[TIC]}{1 + \frac{K_1}{[H^+]} + \frac{K_1.K_2}{[H^+]^2}} \tag{4}$$

where K_1 (pK_1 = 6.35 at 25°C) and K_2 (pK_2= 10.3 at 25°C) are the dissociation constants of the chemical equilibriums between (CO_2/HCO_3^-) and (HCO_3^-/CO_3^{2-}) respectively. $[H^+]$ represents the concentration of hydrogen ions in the medium, expressed as follows:

$$[H^+] = 10^{-pH} \tag{5}$$

The specific growth rate model for *Chlorella vulgaris* is influenced by the light intensity and the *TIC* limitation effects. During this study, the inhibition effect of *TIC* is neglected, since working around the optimal operating condition does not require modeling this phenomenon. By neglecting this, the specific growth rate is the association of the Monod model for the light effect and the Contois model for the limitation effect of the total inorganic carbon [9]:

$$\mu = \mu_{\max}.(\frac{E}{K_E + E}).(\frac{[TIC]}{K_{CL}.X + [TIC]}) \tag{6}$$

where $\mu_{\max}$, K_E and K_{CL} are respectively the maximal specific growth rate (in h^{-1}), the half saturation constant for light intensity available per cell, denoted by E, (in $\mu E\ s^{-1}\ 10^9\ cell^{-1}$) and the half saturation constant for TIC (in mmol. $10^9\ cell^{-1}$). E is given by the following equation:

$$E = \frac{(I_{in} - I_{out})\ A_r}{V.X} \tag{7}$$

where I_{in}, I_{out} and A_r are respectively the incident and outgoing light intensities, and the reactor illuminated area.

In the context of the control strategy, the outgoing light intensity can be calculated by an analytical expression as a function of biomass and the incident light intensity through the following expression:

$$I_{out} = C_1\ I_{in}\ X^{C_2} \tag{8}$$

with C_1 and C_2 constants depending on the reactor geometry.

These model parameters, identified and validated, through Matlab™ environment, from experimental data of *Chlorella vulgaris* cultures operating in batch and continuous modes [8], are given in Table 1.

TABLE I
GROWTH MODEL AND OPERATING CONDITIONS FOR *CHLORELLA VULGARIS* IN A PHOTOBIOREACTOR

parameter	Unit	Value
μ_{max}	h^{-1}	1.068
K_E	$\mu E.s^{-1}.10^9.\ cell^{-1}$	0.0817
K_{CL}	mmol. 10^9. $cell^{-1}$	0.0038
C_1		0.49
C_2		–0.92
V	L	9.6
A_r	m^2	0.31
k_La	h^{-1}	1.36
Y_r	10^9 cell. mol TIC^{-1}	4353
H	atm. L. mol^{-1}	29
I_{in}	$\mu E.s^{-1}.\ m^{-2}$	90
P_{CO2}	atm	0.05

IV. INTERVAL OBSERVER DESIGN

The implementation of the control strategy requires the on-line measurement of biomass concentration. This section presents therefore an observer structure for biomass estimation, using the model structure given in Section III. This approach is based on the interval analysis by reconstructing an upper and lower bounds of the missing state, which is in our case the cellular concentration. The design of this observer considers the properties of the monotone dynamical systems [10], i.e. the missing state must be bounded by a solution of dynamical systems that fulfills the condition of "cooperative systems". This "cooperativity" condition is achieved by imposing positive non-diagonal terms of the Jacobian matrix [10].

Thus, following this cooperativity condition, a state transformation based upon the one in [11] is then used by introducing an auxiliary state Z:

$$Z = X + Y_r\ TIC \tag{9}$$

The new state representation is written as follows:

$$\begin{cases} \dot{Z} = -DZ + Y_r\ k_L a\ ([CO_2]^* - \alpha\ TIC) \\ \dot{X} = \mu X - DX \end{cases} \tag{10}$$

with $\alpha \overset{\Delta}{=} 1 \Big/ (1 + \frac{K_1}{[H^+]} + \frac{K_1.K_2}{[H^+]^2})$

The development of this estimation strategy, fully detailed in previous work of the authors [6], is summarized below. The general structure of the interval observer duplicates the standard observer equation (which includes a correction step between the measurement and the estimation of TIC) leading to an estimation of upper and lower bounds of system states, as follows:

$$\begin{cases} \dot{\hat{Z}}^+ = -D\hat{Z}^+ + Y_r \cdot k_L a \cdot ([CO_2]^* - \alpha \cdot \frac{\hat{Z}^+ - \hat{X}^+}{Y}) \\ \qquad + g_1{}^+ \cdot (y - \frac{\hat{Z}^+ - \hat{X}^+}{Y_r}) \\ \dot{\hat{X}}^+ = \mu^+ \hat{X}^+ - D\hat{X}^+ + g_2{}^+ \cdot (y - \frac{\hat{Z}^+ - \hat{X}^+}{Y_r}) \\ \dot{\hat{Z}}^- = -D\hat{Z}^- + Y_r \cdot k_L a \cdot ([CO_2]^* - \alpha \cdot \frac{\hat{Z}^- - \hat{X}^-}{Y_r}) \\ \qquad + g_1{}^- \cdot (y - \frac{\hat{Z}^- - \hat{X}^-}{Y_r}) \\ \dot{\hat{X}}^- = \mu^- \hat{X}^- - D\hat{X}^- + g_2{}^- \cdot (y - \frac{\hat{Z}^- - \hat{X}^-}{Y_r}) \end{cases} \tag{11}$$

where $g_1{}^{\pm}$ and $g_2{}^{\pm}$ are the gains of the interval observer, y is the measurement of TIC concentration. Initialization of the states of the upper and lower observers is given by:

$$\begin{cases} X^+(0) = X_0^+ \quad Z^+(0) = X_0^+ + Y_r \cdot y(0) \\ X^-(0) = X_0^- \quad Z^-(0) = X_0^- + Y_r \cdot y(0) \end{cases} \tag{12}$$

In (11), only upper and lower bounds on μ are introduced, but this can also be done for k_La and Y_r in a similar way.

The tuning of the observer gains can be achieved considering the fact that these gains must satisfy the conditions of stability and cooperativity [6]:

$$\begin{cases} g_1{}^+ \geq -\alpha \cdot Y_r \cdot k_L a \\ g_2{}^+ < \min \begin{bmatrix} 0 \\ g_1{}^+ + Y_r \cdot \left(2D + \alpha \cdot k_L a - \mu_{\max}{}^+\right) \\ \left(\frac{D \cdot Y_r + g_1{}^+ + \alpha \cdot k_L a \cdot Y_r}{D}\right)\left(D - \mu_{\max}{}^+\right) \end{bmatrix} \end{cases} \tag{13}$$

With these conditions fulfilled, the observer (11) permits to reconstruct a stable and guaranteed interval through the upper and lower bounds of the biomass estimation:

$$\begin{cases} X^-(t) \le X(t) \le X^+(t), \quad \forall t \ge 0 \\ \text{and } X^+(t) - X^-(t) \quad \text{stable} \end{cases} \tag{14}$$

In the sequel, when used in the control law, the estimated biomass concentration at each time is chosen in a simple way to be the mean value of the interval range (denoted X).

V. Nonlinear Model Predictive Control

The purpose of this section is the development of a nonlinear predictive control structure (NMPC) for the regulation of biomass concentration, based on the model described previously in section III, and using the estimated biomass in section IV. The principle of this approach is to create an anticipated effect according to a known trajectory to follow, based on the prediction of the future behavior of the system, and the minimization of this prediction through a cost function under operating constraints [12]. The following control strategy was developed in [13] for *E. coli* culture and was tested in simulation for *Porphiridium purpureum* in [14]. In the sequel, this NMPC control strategy is proposed and experimentally validated for *Chlorella Vulgaris* culture.

A. Optimization problem

The primary objective of the control strategy applied to the biological system is to maintain the cellular concentration close to a reference value while constraining the medium feed rate F to follow a reference one (to smooth the tracking behavior), denoted F_{ref}, and defined by the following relation:

$$F_{ref} = \mu V \tag{15}$$

This feed rate reference value is obtained from (1) assuming that the steady state is reached. At this level, the dilution rate D is therefore equal to the value of the specific growth rate μ of microalgae and the biomass evolution dynamics are cancelled. In the following, $F = DV$ will be used as control variable instead of D.
The principle of this predictive approach is to optimize a performance criterion for each sample period over a finite prediction horizon, whose solution is the best sequence of control. Solving the optimization problem is a fundamental part of the control strategy and is closely related to the complexity of the model.

The optimization problem is formulated as follows:

$$\min_{\chi} \sum_{j=1}^{N} (X_{set_{k+j}} - \hat{X}_{k+j})^2 + \lambda \sum_{j=1}^{N} (F_{k+j-1} - F_{ref_{k+j-1}})^2$$
$$s.t. \begin{cases} \hat{X}_{\mathrm{mod}_{k+1}} = H\, f(X_k, F_k) \\ \vdots \\ \hat{X}_{\mathrm{mod}_{k+N}} = H\, f(\hat{X}_{\mathrm{mod}_{k+N-1}}, F_{k+N-1}) \\ F_k \ge 0, \ \forall k \in IN, \ X_k \ge 0, \ \forall k \in IN \\ \text{with } H = \begin{bmatrix} 1 & 0 \end{bmatrix} \end{cases} \tag{16}$$

where $\chi = \{\hat{X}_{k+1}, \ldots, \hat{X}_{k+N}, F_k, \ldots, F_{k+N-1}\}$ is the optimization vector, N represents the prediction horizon, λ is the control weighting factor and f is the system model; X, X_{set} are respectively the estimated and reference biomass; and $\hat{X}_{\mathrm{mod}}$ represents the prediction of the biomass concentration via the model.
In the case of mismatched parameters between the system and the model, a modified structure, similar to the philosophy developed in [15], takes into account the difference between the system and the model, denoted $\varepsilon_{s/m}$.

The relation between the predicted system output $\hat{X}$ and the predicted model output $\hat{X}_{\mathrm{mod}}$ after j prediction intervals is defined by the following equation:

$$\hat{X}_{k+j} = \hat{X}_{\mathrm{mod}_{k+j}} + j\underbrace{(X_k - \hat{X}_{\mathrm{mod}_k})}_{\varepsilon_{s/m}(k)}, \quad j = \overline{1, N} \tag{17}$$

In the case of the implementation of the NMPC strategy coupled with an observer for the estimation of biomass concentration, the general control structure is represented in Fig. 2.

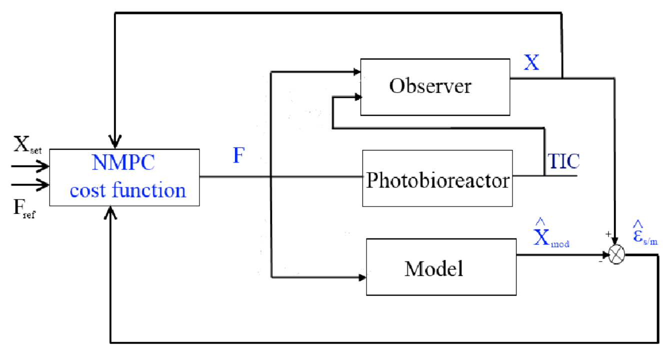

Fig. 2: General structure of NMPC coupled with biomass estimation.

Through the optimization problem under nonlinear constraints (16), the algorithm calculates, at the present sampling instant, the optimal control sequence to be applied over a prediction horizon. At the next sampling period, only the first element of the sequence is applied and the solution of the optimization problem is solved again by considering the new initial state value, following the receding horizon principle.

B. Control Vector Parameterization (CVP)

The solution of the optimization problem presents several difficulties according to the discretization of the system and the presence of nonlinear constraints, which induces the increase of the on-line computation time during the solution of the optimization problem. To avoid these difficulties, (16) is replaced by a nonlinear programming problem (NLP), which is solved using a Control Vector Parameterization (CVP) approach [16], applied to chemical and biochemical processes [17]. This nonlinear program is based on the time-discretization of the control actions $F(t)$ over the prediction horizon. This implies fewer constraints. The control actions are approximated by a piecewise constant function. Another advantage is the possibility of choosing a sufficiently important sampling time for the predictive criterion. Thus, from the CVP approach and with the following change of variable $F = \exp(v)$, the formulation of the optimization problem becomes unconstrained and is rewritten as:

$$\min_{\chi'} \sum_{j=1}^{N} (X_{set_{k+j}} - \hat{X}_{k+j})^2 + \lambda \sum_{j=1}^{N} (\exp(v_{k+j-1}) - F_{ref_{k+j-1}})^2 \quad (18)$$

where $\chi' = \{v_k \; v_{k+1}, \ldots, v_{k+N-1}\}$ is the optimization vector.

VI. Experimental Results

The presented NMPC strategy is implemented in real time for the regulation of the *Chlorella vulgaris* biomass in the photobioreactor of 9.6 L under optimal conditions of growth, with parameters and operating conditions given in Table 1.

The implementation of the interval observer is carried out assuming uncertainties of the growth model parameters and of k_La. Indeed, a variation of 20% of the identified values of the model parameters (μ_{max}^+, μ_{max}^-, K_E^+, K_E^-, K_{CL}^+ and K_{CL}^-) and 30% of the identified value of k_La (k_La^+ and k_La^-) is applied. In addition, an initialization error of 2 billion cells per liter is introduced. The major purpose of this experimental validation is to analyze the performance of the proposed control strategy according to a step profile of the reference value of biomass concentration and under disturbance of environmental factors. The sample time of the NMPC algorithm is chosen equal to 5 min. This duration is much more important than the computational time needed to solve one optimal control problem (30 times higher). The tuning parameters of the NMPC law are $N = 5$, $\lambda = 0.1$.

Figs. 3 and 4 show the efficiency of the NMPC strategy for the regulation of the biomass to the reference value.

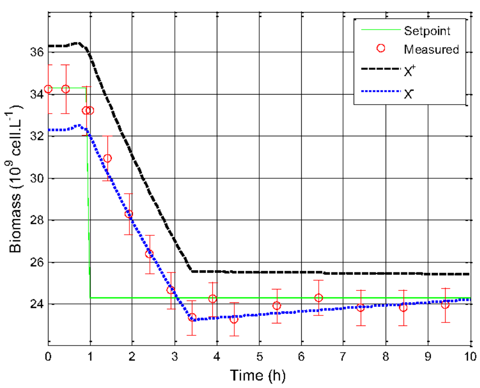

Fig. 3: Biomass evolution with NMPC coupled with interval observer.

Indeed, the measurements of the biomass concentration track accurately the reference profile with a slight overshoot. Fig. 4 shows that the control strategy anticipates the variation of the reference value of the biomass concentration by diluting the culture in order to reduce the cell concentration to its final reference value. In steady state, the feed rate tends to its reference value in order to maintain the cell concentration to its reference value. Also, it can be noticed the efficiency and the robustness of the estimation strategy against uncertainties of growth model and k_La. Indeed, the developed interval observer reconstructs an upper and lower bound that form a stable interval for biomass concentration.

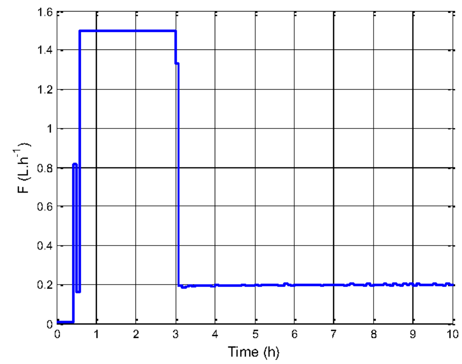

Fig. 4: Medium feed rate for NMPC coupled with interval observer in the case of biomass reference trajectory tracking.

In a second time, the robustness of the proposed NMPC strategy is tested under disturbances of environmental parameters, i.e. light intensity, *pH* and inlet CO_2 pressure variations. Figs. 5 and 6 illustrate the robustness of this control strategy with a disturbance occurring on the light intensity at t = 45 min (decrease of the incident light intensity from 90 to 50 µE m^{-2} s^{-1}). The NMPC controller acts on the medium feed rate to maintain the biomass constant around the reference value. In addition, the efficiency and the robustness of the biomass estimation are validated under this light intensity variation.

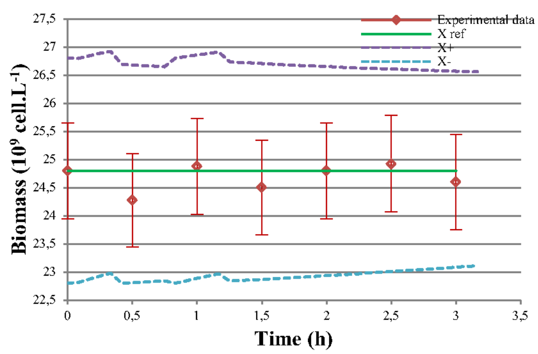

Fig. 5: Biomass evolution with NMPC coupled with interval observer under disturbance of light intensity.

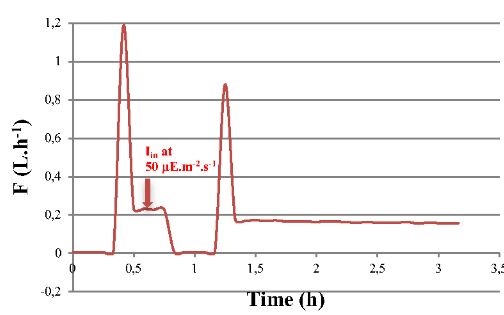

Fig. 6: Medium feed rate for NMPC coupled with interval observer under disturbance of light intensity.

Figs. 7 and 8 also confirm the robustness of the NMPC law in the presence of disturbance occurring on the *pH* at t = 1 h (variation of the *pH* value from 6.4 to 6) and on the inlet CO_2 pressure at t = 3 h (P_{CO2} varies from 0.05 to 0.03 atm). This control strategy, coupled with a robust interval observer, allows tracking the desired reference value under variation of operating conditions of *Chlorella vulgaris* culture.

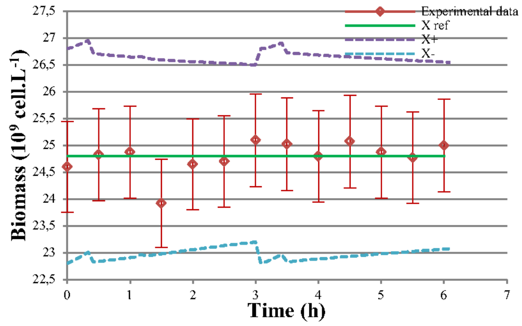

Fig. 7: Biomass evolution with NMPC coupled with interval observer under disturbance of *pH* and inlet CO_2 pressure.

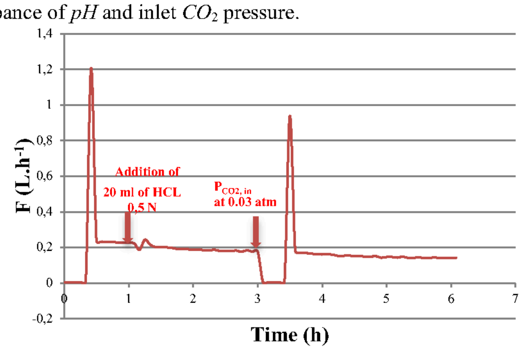

Fig. 8: Medium feed rate for NMPC coupled with interval observer under disturbance of *pH* and inlet CO_2 pressure.

Finally, Fig. 9 shows the results obtained when tracking a similar reference as previously, with the GMC (Generic Model Control) controller [18], which is classically used in such kind of processes. The basic idea of GMC consists in minimizing the difference between the desired derivative of the process output and the actual one leading to a nonlinear control law. The obtained experimental results when using the GMC show worse performances compared to NMPC ones, especially in terms of overshoot and accuracy. In particular, the sum of squared errors between experimental data and the reference value is 3 for NMPC compared to 4 for GMC (summation starting at the end of feed rate saturation).

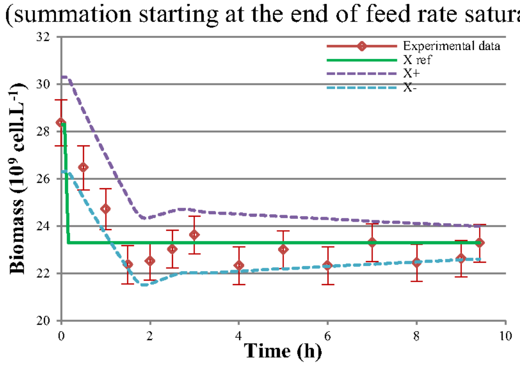

Fig. 9: Biomass evolution with GMC coupled with interval observer.

VII. Conclusion

This paper presents the implementation of a nonlinear model predictive control strategy for the regulation of the biomass concentration of *Chlorella v.* cultures in a continuous mode photobioreactor. The approach is based on the minimization of a quadratic cost function and the solution of the optimization problem by a nonlinear algorithm through the CVP method. The biomass concentration is estimated thanks to an interval observer, based on *TIC* and *pH* measurements. The efficiency and the robustness of the proposed control strategy are validated experimentally on a lab-scale photobioreactor. The biomass concentration reference trajectory is tracked accurately, with a slight overshoot and even in the presence of disturbance of environmental factors. The NMPC also proves to provide better results in terms of overshoot compared to more classical control strategies. This control strategy is a potential first step in the direction of optimization of the CO_2 mitigation by microalgae.

Acknowledgment

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