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Modeling, Control and Online Optimization of Microalgae-based Biomass Production in Raceway Reactors ⋆

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Abstract: Microalgae production in raceway photobioreactors is a very attractive process for biomass production because of its high sustainability. This paper presents a complete methodology for optimizing production in raceway photobioreactors. A first principles model has been developed that describes the dynamics and steady state of the system and has been used as the core of a real-time optimization to maximize the economic profit of the process, which handles the references of different variables of the system. For that, a steady-state real-time optimization approach complemented with PID controllers is presented in this work. The results obtained demonstrate the potential of steady-state real-time optimization for such systems, as well as the benefits of employing optimization techniques during process operation.

Keywords: Real Time Optimization, Process Control, Microalgae, Biomass Production

1. INTRODUCTION

Microalgae are a highly sustainable source of biomass, which has become increasingly important in recent years (Moreno-Garcia et al. (2017)). Microalgae are photosynthetic microorganisms characterized by a high growth rate and the ability to grow and reproduce in a wide variety of environments without the need for clean water or fertile soil (Deviram et al. (2020)). Like most plant organisms, microalgae use solar energy, water, carbon dioxide, and nutrients in their growth to produce biomass and oxygen (Acién et al. (2017)).

Microalgae production can be carried out in open or closed reactors. This paper considers open or raceway reactors, which are the most used at the industrial level, due to their lower cost and easy scalability (Barceló Villalobos et al. (2019); Handler et al. (2012)). Exposure of the culture to the environment, along with the biological nature of the process, makes modeling, control, and optimization challenging (Guzmán et al. (2021)). The operation depends strongly on solar radiation and ambient temperature, variables that change relatively fast compared to the dynamics of the process (Pawlowski et al. (2015)).

In the literature, many types of models have been developed to describe different aspects of the system. These range from highly complex first-principles models (Banerjee and Ramaswamy (2017)), to data-driven black-box models (del Rio-Chanona et al. (2019); Otálora et al. (2023)). The truth is that the process is so changing that any type of model has to be periodically calibrated and adjusted to adapt to the new dynamics of the culture. Different models describe the growth of microalgae, their dynamics related to pH and dissolved oxygen, or the evolution of temperature in the reactor (Bernard et al. (2016)).

In terms of optimization, most works focus on maximizing the growth of microalgae, although some papers focus on economic or productivity optimization (De Andrade et al. (2016); Dewasme et al. (2017); Ifrim et al. (2016)).

Other studies propose different strategies to control the most influential variables in the productivity of the process, namely pH, dissolved oxygen (DO), and, in some cases, temperature (Carreño-Zagarra et al. (2019); González et al. (2022)). The process has been shown to be highly nonlinear and changing, making its control a non-trivial task and often requiring the use of adaptive control, robust control, or Model Predictive Control techniques.

The aim of this work is to demonstrate by simulations how to control and optimize biomass production in clean-water raceway photobioreactors. To this end, a strategy based on Real-Time Optimization (RTO) using a first-principles model has been proposed to estimate the optimal steady state of the system every hour. This steady state is described in terms of setpoints of water level, biomass concentration, pH, and dissolved oxygen, which will be reached using PID controllers. The work achieves a simple

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Fig. 1. Raceway reactor subject of this work.

and very beneficial optimization for the process, which has never been performed in open photobioreactors.

2. MATERIALS AND METHODS

2.1 Raceway reactor

The raceway photobioreactor studied in this paper is located at the IFAPA research center near the University of Almeria. The reactor, shown in Fig. 1, is composed of two 40 m long, 30 cm high, and 1 m wide channels joined at their ends by 180º bends, through which the medium circulates. A paddle wheel drives the fluid through the channels at a constant speed of approximately 0.2 m/s. The system also has a sump located in front of the paddle wheel in which injection of CO_2 and air, necessary for the control of culture conditions, takes place.

The modeled species is *Scenedesmus Almeriensis*, tolerant to wide temperature ranges and especially suitable for outdoor production (Kay and Barton (1991)). The microalgae are grown in clean water, and the nutrients are added externally during dilution, always guaranteeing that they are in excess.

Measurements of pH, DO, and temperature are available at different points of the reactor, although the ones relevant to this work are the most distant from the sump, as these are the hardest spots to control. Water level, biomass concentration, and soil temperature are also measured, as well as other external variables such as wind speed, relative humidity, ambient temperature, and solar radiation. These measurements are recorded with a sample time of one second during the 24 hours of the day.

The system has 4 degrees of freedom for control; these are the dilution (inflow) and harvesting (outflow) flow rates, and the air and CO_2 feedrates, injected at the sump. Flow controllers that manipulate the valves and pumps are assumed to be already implemented and are not relevant in this work.

2.2 Raceway reactor model

A first-principles model has been used to optimize and simulate the system. The model can be decomposed into three parts: the biological model, the dynamic mass balance, and the thermal model. It is a highly nonlinear model based on differential and algebraic equations. The model is dynamic, which is necessary for simulation, but a steady-state simplification is used for optimization. The steady states are computed by setting the derivatives of the dynamic model to zero.

The model has seven states: water level h, biomass concentration C_b, dissolved oxygen DO, pH, carbon dioxide concentration $[CO_2]$, total inorganic carbon concentration $[TIC]$ and water temperature T. The inputs are the four flow rates previously mentioned: air flow rate Q_{air}, CO_2 flow rate Q_{CO2}, dilution flow rate Q_d and harvesting flow rate Q_h. In addition, the model receives as input the value of several disturbances: wind speed, relative humidity, ambient temperature, global irradiance I_0 (i.e., the solar radiation reaching the surface) and soil temperature.

For the biological model (Sánchez-Zurano et al. (2021); Ras et al. (2013)) describe the growth of the microalgae in the reactor. The dynamics of biomass concentration are described by Equation (1), where $\mu(t)$ is the specific growth rate, $g_s(t)$ the evaporation rate, and $V(t)$ the total volume of water.

$$\frac{dC_b(t)}{dt} = C_b(t)\left(\mu(t) - \frac{Q_d(t) - g_s(t)}{V(t)}\right) \tag{1}$$

The specific growth rate is given in Equation (2). In this expression, each of the terms μ_i except for μ_{Iav} can take values from 0 to 1. The term μ_{Iav}, given in (3) is the maximum possible growth, depending on the average radiation within the culture I_{av} (Equation (4)). For pH and temperature, there is an optimum value that maximizes growth, while, for dissolved oxygen, growth decreases significantly at high values. The terms μ_{CO2}, μ_N, and μ_P depend on the availability of CO_2, nitrates, and phosphates. If it is assumed that these are in excess, their value can be set to 1. Finally, m represents the respiration of microalgae and is the only term with a negative effect on the specific growth rate. It results in a negative growth rate in the absence of sunlight.

$$\mu(t) = \mu_{Iav} \cdot \mu_T \cdot \mu_{pH} \cdot \mu_{DO} \cdot \mu_{CO2} \cdot \mu_N \cdot \mu_P - m \tag{2}$$

$$\mu_{Iav}(t) = \mu_{max}\frac{I_{av}(t)^n}{I_{av}(t)^n + I_k^n} \tag{3}$$

$$I_{av}(t) = \frac{I_0(t)}{K_a \cdot C_b(t) \cdot h(t)} \cdot \left(1 - e^{-K_a \cdot C_b(t) \cdot h(t)}\right) \tag{4}$$

Dynamic mass balances are included for oxygen and total inorganic carbon. These equations are described in Fernández et al. (2016). The main phenomena considered are transfer to the atmosphere, microalgae photosynthesis, reactor dilution, and air or CO_2 bubbling. Finally, the thermal model considers all of the heat exchange mechanisms of the reactor with its environment to describe the evolution of the temperature. This model is described in Rodríguez-Miranda et al. (2021). In summary, the inputs, disturbances, and outputs for the system are:

- $u = Q_{air}$, Q_{CO2}, Q_d (feedflow water), Q_h (product flow).
- $d =$ wind speed, relative humidity, T_{air}, I_0, T_{ground}.
- $y = h$, C_b, DO, pH, $[CO_2]$, $[TIC]$, T.
- Constraints: See Table 1.

3. RESULTS

3.1 Cost function

The cost function J [€/s] to be minimized is given by Equation (5). Fixed costs of the process are not considered.

The cost includes the CO_2 flow rate (due to the cost of gas), the dilution flow rate (due to the cost of nutrients added to the dilution water) and the air flow rate (due to the energy consumption of the air blower). There will also be a cost associated with the water level, since the paddle wheel is in charge of driving the medium at a constant speed and thus the power consumed by it will be proportional to the driven water volume.

The yield term (first negative term) represents the profit associated with the biomass produced. The total biomass [kg] is $B(t) = C_b(t) \cdot V(t)$, where from the model $\frac{dB(t)}{dt} = C_b(t) \cdot \mu(t) \cdot V(t)$. Thus, the final cost function J will be defined in Equation (5), where P_b is the price of biomass considering postprocessing costs, C_{CO2} is the cost per liter of CO_2, C_d the cost of nutrients in a liter of dilution water, C_{air} is the cost of blower electricity per liter of bubbled air and C_{pw} the cost associated with the paddle wheel.

$$J = -P_b \cdot C_b \cdot V \cdot \mu + C_{CO2} \cdot Q_{CO2} + C_d \cdot Q_d + C_{air} \cdot Q_{air} + C_{pw} \cdot h^2 \qquad (5)$$

Performing a static optimization on an inherently dynamic system is not a straightforward task. If the optimizer tries to calculate an optimal state without taking into account the dynamics of the system, this will often be unreachable and the operation will not be optimal. However, if the cost function is rewarded by having an optimal evolution, associated with a maximum growth rate, rather than having an optimal state, this could lead to a higher growth and productivity, which will be much more beneficial.

The optimizer will consider the median value of solar irradiance and ambient temperature over the next hour, as well as the current value of floor temperature, relative humidity, and wind speed, to optimize the proposed function. Since this is a static optimization, the optimizer will return the setpoints of biomass concentration, water level, pH, and dissolved oxygen that optimize the proposed cost function, using PID controllers to reach these references.

3.2 Decision variables analysis

Before dealing with the optimization of the system, it is interesting to consider the effect of the different variables that compose the system to facilitate its understanding. The optimizer has to find values of the states and inputs that satisfy a certain steady state and a series of constraints while minimizing the cost function. Possibly, the most straightforward state to analyze is pH, which is a way of representing the concentration of hydrogen ions $[H^+]$. As already mentioned, there is a pH value for which its effect on the specific growth rate is maximized, so it makes sense for the optimizer to bring the pH to that value, which is 8. It may happen that the cost of the CO_2 required for this task is so high that it is more profitable to keep this variable uncontrolled, but this will not normally be the case.

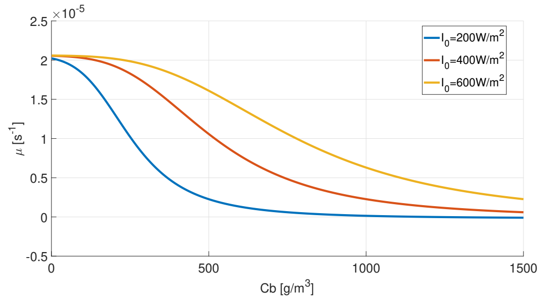

Fig. 2. Relationship between specific growth rate and biomass concentration for different global irradiances.

Dissolved oxygen, also expressed as oxygen concentration $[O_2]$, will reduce the specific growth rate the higher the value. However, this being an exponential relationship, reduced values of dissolved oxygen will not affect the specific growth rate as much; thus, it is expected that the setpoint provided by the optimizer will fluctuate around different values depending on the air flow rate required to maintain the system at a given operating point.

Arguably, the most interesting variables to analyze are biomass concentration and water level. On the one hand, the main yield term of the cost function depends on the product of both variables $(C_b \cdot V)$, since volume is a linear function of level. However, as already described, the average irradiance available to the microalgae decreases as these variables increase, an effect that extends to the specific growth rate. In addition, the water level appears as a cost, influencing the optimization in another way. Therefore, it is not easy to know the value of each of these variables that will optimize the cost function at a given time.

It is interesting to notice how the product $(C_b \cdot h)$ appears in both the cost function and the available irradiance, always appearing in conjunction with each other. This implies that an increase of equal magnitude in either variable must have a similar effect on the yield term. However, the water level is the only one of these two variables that includes a negative effect in the cost function associated with the paddlewheel. Therefore, to achieve an optimal $(C_b \cdot h)$ ratio, it is logical for the optimizer to drive the water level to its lower constraint and calculate the optimal biomass concentration from this value. The only case where the water level should not be at its lower constraint is if the optimum lies in a product $(C_b \cdot h)$ whose value is not achievable for a minimum level with a maximum biomass concentration.

It is convenient to establish a relationship between specific growth rate and biomass concentration, considering the pH, dissolved oxygen, and temperature terms at their maximum, that is, equal to 1. This relationship can be appreciated in Fig. 2, and it becomes evident how growth is maximum for concentrations very close to 0, decreasing with increasing concentration. The higher the overall irradiance, the smaller the decrease with concentration, although in all cases the growth tends to 0 for very high concentrations.

Finally, the effect on the economic yields of the system of the product $(C_b \cdot h)$ can be studied. Fig. 3 shows how the

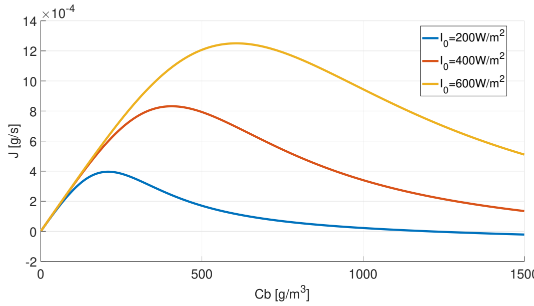

Fig. 3. Relationship between cost function and biomass concentration for different global irradiances.

value of the product ($C_b \cdot h \cdot \mu$) varies with changing biomass concentration, for different global irradiances. This plot illustrates how the optimal value of biomass concentration fluctuates with global irradiance. Consequently, to achieve optimal growth of the culture, it will often be necessary to reduce the concentration and/or level of the culture.

3.3 Optimizer and constraints

The optimizer will be triggered every hour in order to compute the setpoints of water level, biomass concentration, pH, and dissolved oxygen for the next hour. Its objective will be to minimize the cost function already defined according to a set of operational constraints. The imposed constraints are related to the minimum and maximum values of each of the calculated setpoints. These values are listed in the table 1. Limits were also imposed on the flow rates used to achieve the steady state described by the system state variables to avoid unreachable states.

Table 1. Limits of the variables

	C_b[g/m^3]	h[cm]	pH[−]	DO[%]
Min	100	5	7	0
Max	1500	25	9	600

In this way, the optimizer receives as input the value of the disturbances and generates the setpoints of these 4 variables that minimize the cost function. Fig. 4 presents an outline of the hierarchical control structure proposed. Due to its static nature, the optimizer is unable to guarantee that the system will reach its optimum in the future. This can be a problem due to the slow growth of the biomass concentration. In hours with lower global irradiance, the optimal biomass concentration can be very low. Bringing the system to this operating point is feasible and optimal at that time, but since the increase in concentration is limited by the specific growth rate of the microalgae, this may prevent the system from approaching the optimum in later hours when the irradiance is higher, resulting in a generally poor cost function.

To overcome this problem, the set point of biomass concentration generated by the optimizer was enforced so that it could not be lower than the real biomass concentration until 11:00 AM each day. In addition, the optimizer will only be triggered if the global irradiance exceeds 100 W/m^2, since in the absence of growth there is no possibility of optimizing the system.

The solver used for optimization is *Ipopt*, an open source software for non-linear optimization. The optimizer has been developed in *CasADi*, an open source tool that allows the implementation of solvers and numerical methods in an efficient and simple way (Andersson et al. (2019)). Optimization takes less than 0.2 seconds for each hour.

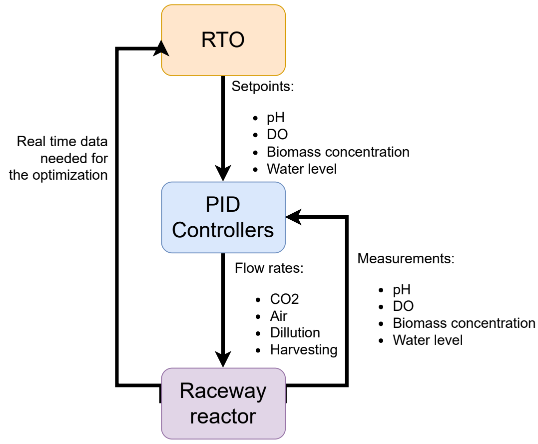

Fig. 4. Hierarchical control structure proposed in this work.

3.4 PID Control

Finally, the operating points calculated by the optimizer are sent as references to the PID controllers for each of these variables. Since there are 4 flow rates available for the control of the system, it is important to perform a proper variable pairing. This has been achieved by considering the inputs with the most direct effect on each output, using CO_2 injection for pH control, air injection for dissolved oxygen control, dilution flow rate for concentration control and harvesting flow rate for level control. It is important to note that these two last variables can only be controlled during their descents, since their rises depend on the specific growth rate (for biomass concentration) and the dilution flow rate (for level).

The controllers have been tuned using the SIMC rule based on integrator-type models for each of the controlled variables (Skogestad (2003)). These controllers have been enhanced with antiwindup in anticipation of the very likely saturation of the manipulated variables. Similarly to the optimizer, these controllers will only be active during daylight hours.

3.5 Optimization results

The described strategy was tested using data corresponding to October 25-29, 2023. The full simulation took less than 20 seconds. Fig. 5 presents the setpoints calculated by the optimizer along with the actual values of each of the four controlled variables. Fig. 6 presents the manipulated variables for each of these. It should be noted that the variables are not under control during the night, as there is no growth, and therefore their control has no impact on the productivity of the system. This period lasts around 14 hours for the month of October.

It can be seen how the optimizer behaves as expected. First, the pH is driven to its optimum value throughout the simulation, which is 8. The controller with a flow rate of CO_2 takes care of keeping this variable at its reference

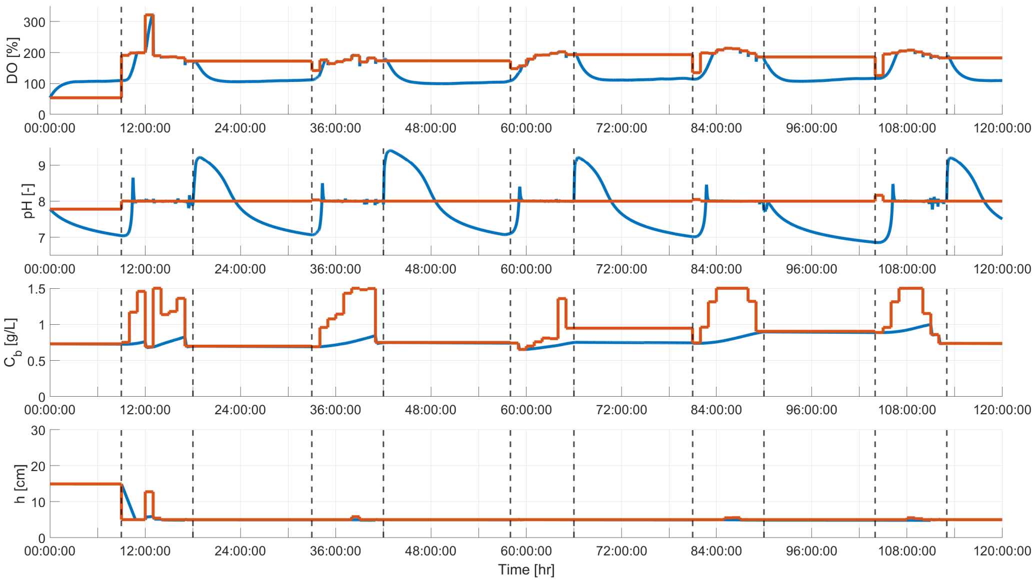

Fig. 5. Real time simulation results for the four controlled variables. In red, the optimal setpoints and in blue the simulated value. Dashed vertical lines mark the beginning and end of the optimization each day.

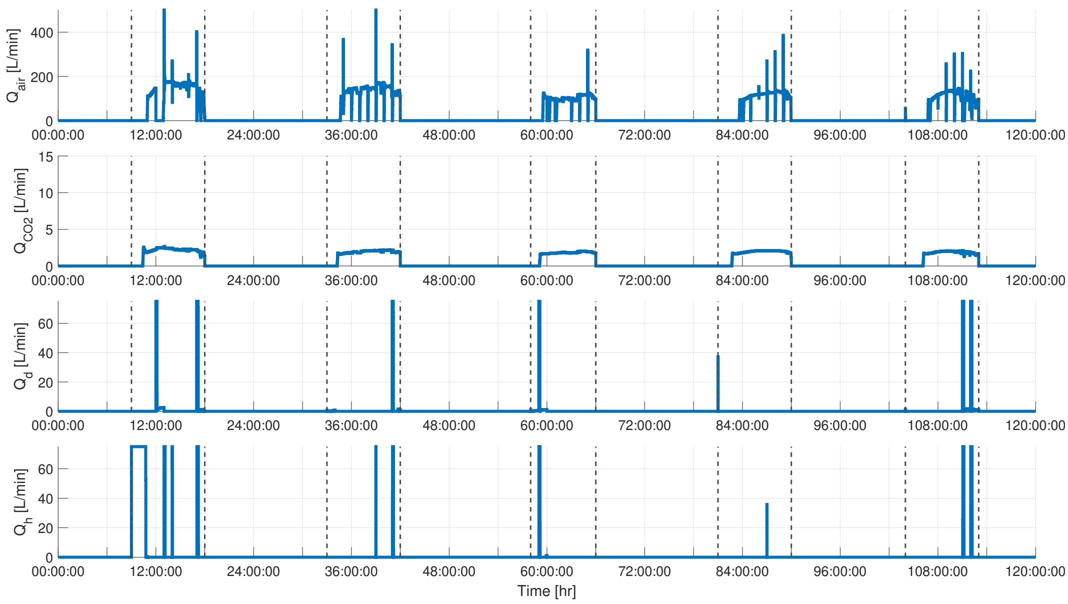

Fig. 6. Manipulated variables corresponding to Figure 5.

despite changes in radiation. For dissolved oxygen, the optimal value is not excessively high but does not lead to very large air injections, thus preserving a high specific growth rate without too much cost.

The most interesting variables are the water level and the biomass concentration. The level is kept to a minimum (5 cm) during most of the test, due to the costs associated with the paddle wheel, as mentioned above. On the other hand, biomass concentration has a very variable setpoint, since, as previously discussed, its optimum value varies with the global irradiance. This is why, at the central hours of the day, its setpoint is generally higher. Likewise, the third day, which presents much lower setpoints, also has significantly lower irradiance. Dilution and harvesting typically take place at the end of the day, corresponding to the lowest radiation hours, as expected.

It should be noted that for a significant period, the system is unable to reach the biomass concentration setpoint. The reason for this is that the increase of this variable is associated exclusively with the specific growth rate and, therefore, the manipulated variable cannot influence it in any way. This also explains the on/off behavior of the dilution (inflow) and corresponding harvesting (outflow), as most of the time the setpoint on biomass (C_b) is far from being reached and therefore the controllers sets the dilution (Q_d) to zero. Although the setpoint is not reached, this does not compromise the optimization, as the system is doing the best it can.

4. CONCLUSIONS

This work presents a solution to optimize biomass production in raceway photobioreactors. The proposed methodology allows for the optimization of microalgae growth during daylight hours despite the dynamic nature of the process, with a simple and fast solution. The hierarchical division between setpoint tracking and optimization makes it possible to reach the references generated by the optimizer as well as possible, while rejecting any potential disturbances or modeling errors. The application of this methodology is simple, only requiring a static model of the process and knowledge of the process when imposing constraints.

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