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Exploiting meteorological forecasts for the optimal operation of algal ponds

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ABSTRACT

Biofuel production from microalgae requires optimizing the operation of cultivation systems (i.e. outdoor raceway ponds) for this process to be economically sustainable. Controlling algal ponds is complex as the cultivation systems are exposed to fluctuating conditions. The strategy investigated in this study uses weather forecasts coupled to a predictive model of algal productivity to optimize pond operation. Productivity was optimized by dynamically controlling rates of fresh medium injection and culture removal into and from the pond. This optimization strategy when applied to a cultivation plant in Nice, South of France, increases the productivity by 2.13 compared to the reference case where the pond depth and dilution rate were kept constant over time. The underlying Model Predictive Control consists of playing with raceway pond thermal inertia and supply of fresh water to reach rapidly optimal temperature, and then keep a balance between photosynthesis and respiration in the darkest layers of the raceway pond. The meteorological inaccuracy for forecasts beyond 24 h was compensated by frequent updates of the optimal control problem. Finally, this scheme turned out to be robust to inaccurate weather forecasts, and the net productivity value reached was close to the productivity obtained for perfectly known meteorology.

1. Introduction

Microalgae have emerged during the last decade as one of the most promising new technologies for providing innovative molecules for the cosmetic and pharmaceutical industries, and as a source of proteins for animal and human nutrition [1,2]. At larger time horizon, microalgae are expected to contribute to fossil carbon replacement with renewable carbon, especially for supplying green chemistry and liquid biofuel in the transport sector [3]. The great interest in this technology is not only the substantial higher productivity compared to terrestrial plants, but also the possibility of coupling the microalgal production process to industrial CO_2 mitigation and wastewater treatment to finally recycle carbon, nitrogen and phosphorus.

Nevertheless, further developments and optimization steps are required to reduce both the cost and the environmental footprint of these processes. One way to increase the profitability of the system is to develop control strategies to maximize productivity while better managing the nutrient and water use. Controlling an outdoor algal production system is complex because the state variables of the cultivation system (e.g. biomass concentration, pond temperature, etc.) are continuously driven by the meteorological conditions (solar irradiance, air temperature, etc.). A first approach was derived by [4] who used the Pontryagin's maximum to identify the set of necessary conditions to be satisfied in order to guarantee optimal control in a periodically varying environment. Nevertheless, the simplifications required by this approach, which assumed a known and periodic meteorology, reduced the applicability of the proposed optimal strategy in the case of algal outdoor cultivation.

Model Predictive Control (MPC) [5] has proven to be very efficient to manage situations with complex modelling, where classical model based control cannot be easily derived. MPC seems especially relevant when meteorology plays a key role, such as energy efficient building climate control [6] or management of distributed power system with wind turbines [7]. MPC was already applied to microalgae [8–10], but never to manage weather forecasts in the control strategy.

Alternatively, we propose a MPC strategy accounting for the knowledge of future weather conditions. This technique is based on mathematical models able to predict algal productivity from

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the knowledge of weather conditions [11,12]. In practice, this optimization task consists of determining the optimal rates at which fresh medium has to be injected into or extracted from a mixed algal pond (also named "raceway") based on weather forecasts. The first objective of this study was to propose an improvement to the standard management approach, and assess the productivity gain of this optimized approach. The secondary objective was to understand and analyze the rational behind the predictive controller.

We first detail the model consisting in a coupled biology-physical model. Then we define the model predictive controller and we detail the numerical approach developed for solving the problem. We first consider the case where weather forecasts are perfect, and we analyse the logic behind the control action. Finally, we consider the more realistic case where meteorology becomes uncertain after 24 h.

2. The microalgal raceway pond productivity model

The model couples two submodels: a physical submodel predicting the temperature in the raceway pond and a biological submodel computing microalgal production. Both submodels are driven by meteorological conditions determining the fluxes of heat and photons through the system. The model has a triangular structure since the biological submodel does not influence the thermal dynamics of the physical submodel. The model is a simplified version of the model in [13]. However in [13], the pond depth is maintained at a constant level, while here we exploit the idea of changing the depth to modify the thermal inertia of the system.

The scheme of the model structure (coupling biological and thermal equations) and the objective function is shown in Fig. 1. The model equations are detailed in the following paragraphs.

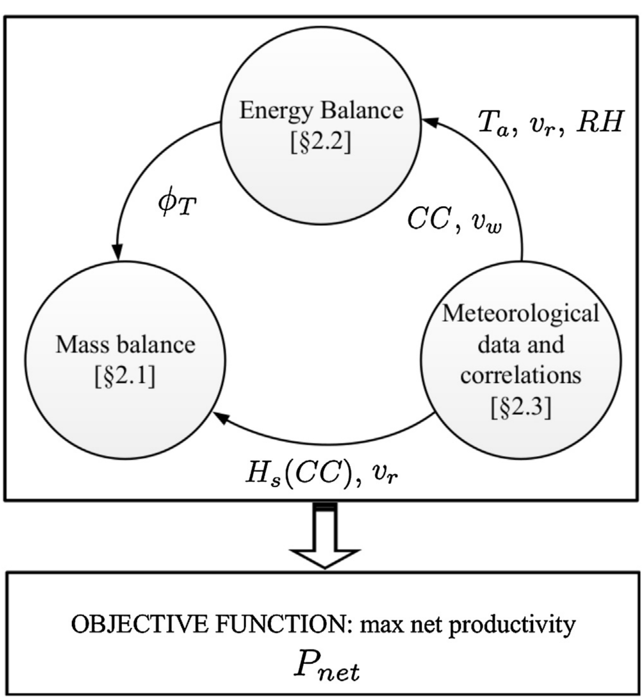

Fig. 1. Schematic representation of the models implemented in this work. The arrows show the interconnection between the various models.

2.1. Deriving the biological model from mass balance

The biological model describes the dynamics of a microalgal biomass (which concentration is $x(t)$ in kg m^{-3}). Microalgae are photosynthetic microorganisms which capture CO_2 in the presence of light and incorporate this carbon into their biomass, while they continuously loose a fraction of their carbon by respiration. Both activities are temperature dependent. The open algal raceway pond of volume V (m^3) and depth $l_p(t)$ (m) is supposed to be perfectly mixed [14,15]. The total biomass $x(t)V(t)$ in the open raceway pond varies over time according to the following equation:

$$\frac{d(x(t)V(t))}{dt} = -x(t)q^{out}(t) + G(\cdot)V(t) - R(\cdot)V(t), \quad (1)$$

where t is the time variable (s), $G(\cdot)$ is the depth-averaged specific growth rate (kg m^{-3} s^{-1}) and $R(\cdot)$ is the specific respiration rate (respiration causes carbon loss) (kg m^{-3} s^{-1}). The fresh medium is injected at the rate $q^{in}(t)$ (m^3 s^{-1}) whereas the culture is extracted from the raceway pond at the rate $q^{out}(t)$ (m^3 s^{-1}).

The raceway pond volume varies over time according to the following equation:

$$\frac{dV(t)}{dt} = \frac{q^{in}(t) - q^{out}(t) + v_r(t)S - m_e(t)S}{\rho_w}, \quad (2)$$

where S is the raceway pond surface area (m^2), ρ_w is the water density (kg m^{-3}), $v_r(t)$ is the rainwater flow (m s^{-1}), and $m_e(t)$ is the evaporation mass flux (kg m^{-2} s^{-1}). The average specific growth rate $G(\cdot)$ in Eq.(1) depends on the biomass concentration $x(t)$, the raceway pond temperature $T_p(t)$, and the solar irradiance $H_s(t)$ (W m^{-2}). The resulting function $G(t, x(t), H_s(t), T_p(t))$ was expressed as [16,17]:

$$G(t, x(t), H_s(t), T_p(t)) = \frac{1}{l_p(t)} \int_0^{l_p(t)} \mu_m x(t) \frac{\sigma \eta_H H_s(t) e^{-\sigma x(t) z}}{K_I + \sigma \eta_H H_s(t) e^{-\sigma x(t) z}} dz \quad (3)$$

where μ_m is the maximum specific growth rate (s^{-1}), σ is the extinction coefficient (set at 120 m^2 kg^{-1}), due to light absorption and scattering, η_H is the photosynthetically active radiation (PAR) fraction of solar light (set at 0.47 [17]), z is the local depth (m) and K_I is the half-saturation parameter (W kg^{-1}).

The impact of photoinhibition on microalgal growth was not explicitly included in this study. Indeed, as suggested by [11], a Monod kinetics can efficiently represent algal growth at high biomass density. This is explained by the fact that only a small fraction of cells are photo-inhibited in the dense cultures, leading to an average behaviour of Monod type.

The specific respiration rate $R(\cdot)$ in Eq.(1) depends on raceway pond temperature $T_p(t)$ and biomass concentration $x(t)$ through the following equation:

$$R(t, x(t), T_p(t)) = \lambda_r(T_p)x(t), \quad (4)$$

where λ_r is the respiration coefficient (s^{-1}). The temperature dependence of the two functions $G(\cdot)$ and $R(\cdot)$ is justified by experimental evidences demonstrating that μ_m, K_I and λ_r values change with temperature (see [17]). Function $\mu_m(T_p)$ could be experimentally described by the following equation [18]:

$$\mu_m(T_p) = \mu_{m,\max}\phi_T(T_p), \quad (5)$$

where $\mu_{m,max}$ is the maximum value of $\mu_m(T_p)$ (s^{-1}) and $\phi_T(T_p)$ is the temperature-dependent function reported in the following equation [18]: