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Microalgae growth optimization in open ponds with uncertain weather data

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ABSTRACT

Although microalgae-based processes are currently one of the most promising new technologies for the substitution of fossil fuels and chemicals, the theoretical potential of these technologies is currently limited by their low profitability, hence hindering the development of large scale plants in an economically feasible way. One of the process bottlenecks is the cultivation phase, whose operation is complicated by both the involved biological mechanisms complexity and the highly fluctuating weather conditions affecting the system. Available mathematical models describing microalgae growth and pond temperature dynamics through weather data implementation assume perfect knowledge of weather conditions, hence neglecting the inaccuracy of meteorological predictions that is expected even considering short-term forecasts. In this study a sensitivity study is first carried out to evaluate the weather variables that most impact on productivity. Then, two optimization approaches are proposed to prevent potential critical conditions (such as cell death due to too high temperatures) that may arise by using inaccurate weather forecast. The study demonstrates the reliability of the proposed methodologies and compares them in terms of productivity loss and water demand.

1. Introduction

Microalgae are currently being investigated as a promising renewable feedstock for fuel and chemical production (Mata et al., 2010) due to several advantages, such as potential high yields, utilization of non arable land and possible integration with wastewater treatment processes (Foley et al., 2011). Nevertheless, current process alternatives present a number of drawbacks in terms of cost and efficiency (Bennion et al., 2015; Molina Grima et al., 2003). In fact, despite their enormous potential, industrial use of microalgae is still at an early stage of development, and optimization of design, operation and control of such photoproduction processes is yet to be investigated thoroughly, especially in the context of scaling-up the actual production capacity to increase the sustainable portfolio of microalgae-based processes towards commodities and energy applications (Draaisma et al., 2013). In practice, culture conditions at industrial scale differ drastically from the optimal conditions identified in the lab, thereby resulting in significant productivity losses. In this context, model-based approaches and, in particular, model-based optimizaton and control strategies, can be a great help to understand, design (Slegers et al., 2013), optimize (Muñoz-Tamayo et al., 2013), and in turn remedy, the gap between lab-scale observations and the industrial-scale reality (Bernard et al., 2015). In particular, optimizing and controlling open pond systems for algal production is complex because the key state variables of the cultivation system (e.g. biomass concentration, pond temperature, etc.) continuously vary due to fluctuating meteorological conditions (solar irradiance, air temperature, etc.). In order to cope with this problem, De-Luca et al. (2017) recently investigated the benefits derived by implementing a dynamic model to predict microalgae growth from expected weather conditions and adjustable variables (inflows and outflows), with the assumption of perfect knowledge of future weather conditions. This approach allowed one to enhance productivity up to 2.2 times the value obtained in the reference case of constant dilution rate and raceway pond depth (Davis et al., 2011; Rogers et al., 2014), which represents the common way to operate open pond systems. Nevertheless, the resulting operation strategy was dependent on the preliminary assumption that there was no error in the weather forecasts during the first 24 h. Unfortunately, the previous assumption is quite optimistic, since some weather variables can be affected by significant inaccuracy even if predicted only one day ahead. For example, a report by Haiden et al. (2015) showed that relative average error on cloudiness forecasts may exceed 100% even considering shorter than

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daily time intervals. Moreover, the error variability is related to both the geographical region considered and the specific phase of the day at which meteorological data are collected (Lorenz et al., 2009b). In order to cope with this problem, this study proposes a way to operate the plant in such a way to prevent both loss of productivity and occurrence of potential critical conditions (e.g., cell death) as a consequence of inappropriate operation of the process due to inaccurate weather forecast. In particular, the study is based on the evaluation and comparison of: (*i*) a constrained productivity optimization based on the implementation of a dynamic threshold (Kookos and Perkins, 2004) generated by the error on weather data forecasts; (*ii*) a 'worst-case' strategy based on the most critical conditions that may occur in the pond, leading to a fixed operation policy. The objective of this study is therefore to evaluate the effectiveness of the two proposed strategies, to assess how much they depart from an ideal case where perfect knowledge on the weather behavior is assumed, and to compare the two methodologies in terms of performance. The article is structured as follows. In Section 2 the proposed model for microalgae growth representation in open pond systems is described. Then, a preliminary sensitivity analysis on the most significant meteorological variables is reported, together with the methodology used to simulate inaccurate weather data profiles. Finally, the optimization set-up for each case study is described. In Section 3 the results obtained by the different optimization approaches are compared in terms of final productivity and water demand. Section 4 summarizes the main results obtained and proposes some hints for future work.

2. Materials and methods

2.1. The model

The methodology discussed in this study is based on the model presented in De-Luca et al. (2017), predicting algal productivity in outdoor open ponds through meteorological data. Key equations are briefly described in the following subsections. For more details, refer to the original article.

2.1.1. Growth model

The open pond is considered as an ideal open system, with fresh medium inflow rate defined as q^{in} (m^3 s^{-1}) and culture extraction rate defined as q^{out} (m^3 s^{-1}). The biomass dynamics is therefore expressed through the following mass balance:

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

where t is the time variable (s), x_b is the algal biomass concentration (kg m^{-3}), $G(\cdot)$ and $R(\cdot)$ are, respectively, the specific growth and respiration rates (kg m^{-3} s^{-1}), and V is the pond volume (m^3). The pond volume (V) is therefore treated as a time dependent variable, according to the following equation:

$$\frac{dV}{dt} = q^{in} - q^{out} + v_r S - m_e S/\rho_w, \tag{2}$$

where S is the pond surface area (m^2), ρ_w is the pond density (kg m^{-3}; assumed equal to water density), v_r is the rainwater flow (m s^{-1}), and m_e is the evaporation mass flux (kg m^{-2} s^{-1}). The specific growth rate $G(\cdot)$ in Eq. (1) depends on the biomass concentration x_b, the pond temperature T_p, and the solar irradiance H_s (W m^{-2}). In particular, the growth function $G(x_b, H_s, T_p)$ was expressed as (Béchet et al., 2015):

$$G(x_b, H_s, T_p) = \frac{1}{l_p}\int_0^{l_p} \mu_m(T_p) x_b \frac{\sigma_b \eta_H H_s e^{-\sigma_b x_b z}}{K_I(T_p) + \sigma_b \eta_H H_s e^{-\sigma_b x_b z}} dz, \tag{3}$$

where μ_m is the maximum specific growth rate (s^{-1}), σ_b is the extinction coefficient (set equal to 120 m^2 kg^{-1}), η_H is the fraction of photosynthetically active fraction (PAR) in solar light (set equal to 0.47), z is the local depth (m) and K_I is the half-saturation parameter (W kg^{-1}). The specific respiration rate $R(\cdot)$ in Eq. (3) depends on biomass concentration and pond temperature through the following law (Béchet et al., 2015):

$$R(x_b, T_p) = \lambda_r(T_p) x_b, \tag{4}$$

where λ_r is the respiration coefficient (s^{-1}). The detailed description of parameters $\mu_m(T_p)$, $K_I(T_p)$ and $\lambda_r(T_p)$ is reported in the supplementary material (S1.1).

Table 1
Heat fluxes direct dependence on weather data. Checkmarks are used to point out the direct relation of each thermal flux to weather variables, whereas crosses indicate the absence of direct dependence on meteorological data.

Heat Flux	RH	CC	v_r	T_a	v_w
$Q_{ra,p}$	×	×	×	×	×
$Q_{ra,s}$	×	✓	×	×	×
$Q_{ra,a}$	×	×	×	✓	×
Q_{ev}	✓	×	×	✓	✓
Q_{conv}	×	×	×	✓	✓
Q_{cond}	×	×	×	×	×
Q_i	×	×	×	×	×
Q_r	×	×	✓	✓	×

2.1.2. Temperature model

The validated universal model for temperature prediction in shallow algal pond developed by Béchet et al. (2011) is coupled to the above growth model. This model assumes that the pond temperature T_p depends on eight main heat fluxes that are quantifiable through the available meteorological data and the design parameters of the system, as described in the following equation:

$$\rho_w V c_{p_w} \frac{dT_p}{dt} = Q_{ra,p} + Q_{ra,s} + Q_{ra,a} + Q_{ev} + Q_{conv} + Q_{cond} + Q_i + Q_r, \tag{5}$$

where c_{p_w} is the specific heat capacity of water (J $kg^{-1}K^{-1}$), $Q_{ra,p}$ is the radiation flow from the pond surface (W), $Q_{ra,s}$ is the total (direct+diffuse) solar irradiance (W), $Q_{ra,a}$ is the radiation flow from the air to the pond system (W), Q_{ev} is the evaporation flow (W), Q_{conv} is the convective flow at the pond surface (W), Q_{cond} is the conductive flow with the ground at the pond bottom (W), Q_i is the heat flow due to the water inflow (W), and Q_r is the heat flow associated with rain (W). A detailed description of equations and the list of parameters used to describe each heat flux are reported in the supplementary material (S1.2).

2.2. Weather data impact on system variables

According to the model discussed in the previous sections, the system response is directly related to the meteorological conditions under which the system operates. Namely, the air temperature T_a, the sky cloudiness CC, the relative humidity RH, the wind velocity v_w and the rain volumetric flux v_r are the (five) weather data affecting the system response. From a qualitative point of view we can say that:

- the pond volume V dynamics is directly related to the rain volumetric flux v_r and to the evaporation rate m_e. In order to describe the latter term in a proper way information is required on air temperature T_a, relative humidity RH and wind velocity v_w;
- the pond temperature T_p dynamics depends on the heat fluxes described in Eq. (5), where five heat fluxes directly depend upon meteorological data (see Table 1 and the supplementary material (S1.2));