

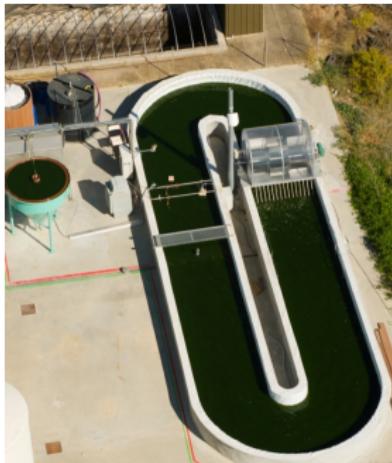
# Some optimization problems in an algal raceway pond

Olivier Bernard, Liu-Di LU, Jacques Sainte-Marie, Julien Salomon

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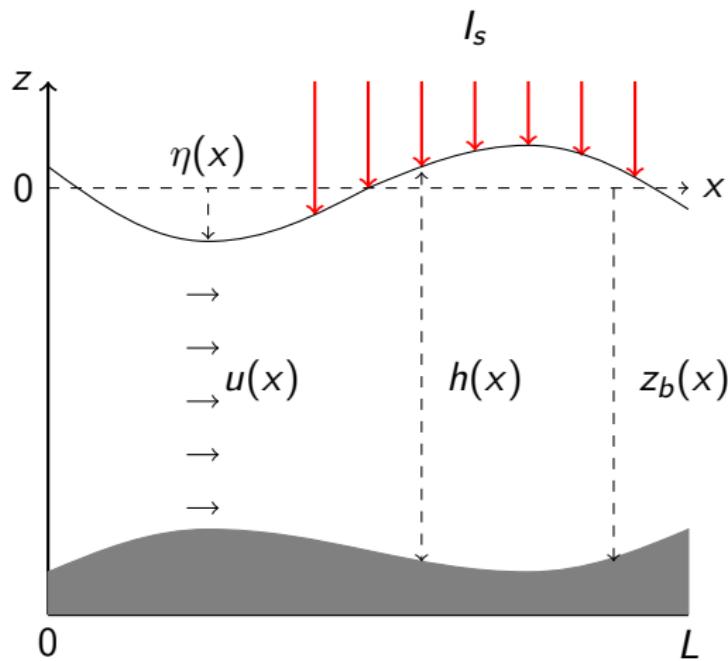
# Introduction

- Motivation: High potential on commercial applications, e.g., cosmetics, pharmaceuticals, food complements, wastewater treatment, green energy, etc.
- Raceway ponds



**Figure:** A typical raceway for cultivating microalgae. Notice the paddle-wheel which mixes the culture suspension. Picture from INRA (ANR Symbiose project) [1].

# 1D Illustration



**Figure:** Representation of the hydrodynamic model.

# Saint-Venant Equations

- 1D steady state Saint-Venant equations

$$\partial_x(hu) = 0, \tag{1}$$

$$\partial_x\left(hu^2 + g\frac{h^2}{2}\right) = -gh\partial_x z_b. \tag{2}$$

# Saint-Venant Equations

- $u, z_b$  as a function of  $h$

$$u = \frac{Q_0}{h}, \tag{1}$$

$$z_b = \frac{M_0}{g} - \frac{Q_0^2}{2gh^2} - h, \tag{2}$$

$Q_0, M_0 \in \mathbb{R}^+$  are two constants.

- Froude number:

$$Fr := \frac{u}{\sqrt{gh}}$$

$Fr < 1$ : subcritical case (i.e. the flow regime is fluvial)

$Fr > 1$ : supercritical case (i.e. the flow regime is torrential)

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- Given a smooth topography  $z_b$ , there exists a unique positive smooth solution of  $h$  which satisfies the subcritical flow condition [4, Lemma 1].

# Lagrangian Trajectories

- Incompressibility of the flow:  $\nabla \cdot \underline{\mathbf{u}} = 0$  with  $\underline{\mathbf{u}} = (u(x), w(x, z))$

$$\partial_x u + \partial_z w = 0. \quad (3)$$

- Integrating (3) from  $z_b$  to  $z$  and using the kinematic condition at bottom ( $w(x, z_b) = u(x)\partial_x z_b$ ) gives:

$$w(x, z) = \left( \frac{M_0}{g} - \frac{3u^2(x)}{2g} - z \right) u'(x).$$

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- The Lagrangian trajectory is characterized by the system

$$\begin{pmatrix} \dot{x}(t) \\ \dot{z}(t) \end{pmatrix} = \begin{pmatrix} u(x(t)) \\ w(x(t), z(t)) \end{pmatrix}.$$

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- A time free formulation of the Lagrangian trajectory:

$$z(x) = \eta(x) + \frac{h(x)}{h(0)}(z(0) - \eta(0)). \quad (4)$$

# Han model and connection

- Reduced Han model:

$$\dot{C} = -(k_d \tau \frac{(\sigma I)^2}{\tau \sigma I + 1} + k_r)C + k_d \tau \frac{(\sigma I)^2}{\tau \sigma I + 1}.$$

- The net growth rate:

$$\mu(C, I) := k\sigma I A - R = k\sigma I \frac{(1 - C)}{\tau \sigma I + 1} - R,$$

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- The Beer-Lambert law describes how light is attenuated with depth

$$I(x, z) = I_s \exp \left( -\varepsilon(\eta(x) - z) \right), \quad (5)$$

where  $\varepsilon$  is the light extinction defined by:

$$\varepsilon = \frac{1}{h} \ln \left( \frac{I_s}{I_b} \right).$$

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- Objective function: Average net growth rate

$$\bar{\mu}_\infty := \frac{1}{V} \int_0^L \int_{z_b(x)}^{\eta(x)} \mu(C(x, z), I(x, z)) dz dx,$$

$$\bar{\mu}_{N_z} := \frac{1}{VN_z} \sum_{i=1}^{N_z} \int_0^L \mu(C_i, I_i) h dx.$$

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- Volume of the system

$$V = \int_0^L h(x) dx. \tag{6}$$

- Parameterize  $h$  by a vector  $a := [a_1, \dots, a_N] \in \mathbb{R}^N$ .

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- Parameterize  $h$  by a vector  $a := [a_1, \dots, a_N] \in \mathbb{R}^N$ .
- The computational chain:

$$a \rightarrow h \rightarrow z_i \rightarrow I_i \rightarrow C_i \rightarrow \bar{\mu}_{N_z}.$$

- Optimization Problem:  $\bar{\mu}_{N_z}(a) = \frac{1}{VN_z} \sum_{i=1}^{N_z} \int_0^L \mu(C_i, I_i(a)) h(a) dx$ , where  $C_i$  satisfy

$$C'_i = (-\alpha(I_i(a)) C_i + \beta(I_i(a))) \frac{h(a)}{Q_0}.$$

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- Lagrangian

$$\begin{aligned} \mathcal{L}(C_i, a, p_i) = & \frac{1}{VN_z} \sum_{i=1}^{N_z} \int_0^L \left( -\gamma(I_i(a)) C_i + \zeta(I_i(a)) \right) h(a) dx \\ & - \sum_{i=1}^{N_z} \int_0^L p_i \left( C'_i + \frac{\alpha(I_i(a)) - \beta(I_i(a))}{Q_0} h(a) \right) dx. \end{aligned}$$

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- The gradient  $\nabla \bar{\mu}_{N_z}(a) = \partial_a \mathcal{L}$  is given by

$$\begin{aligned} \partial_a \mathcal{L} = & \sum_{i=1}^{N_z} \int_0^L \left( \frac{-\gamma'(I_i) C_i + \zeta'(I_i)}{VN_z} + p_i \frac{-\alpha'(I_i) C_i + \beta'(I_i)}{Q_0} \right) h \partial_a I_i dx \\ & + \sum_{i=1}^{N_z} \int_0^L \left( \frac{-\gamma(I_i) C_i + \zeta(I_i)}{VN_z} + p_i \frac{-\alpha(I_i) C_i + \beta(I_i)}{Q_0} \right) \partial_a h dx. \end{aligned}$$

# Numerical settings

Parameterization of  $h$ : Truncated Fourier

$$h(x) = a_0 + \sum_{n=1}^N a_n \sin\left(2n\pi \frac{x}{L}\right). \quad (7)$$

Parameter to be optimized: Fourier coefficients  $a := [a_1, \dots, a_N]$ . We use this parameterization based on the following reasons :

- We consider a hydrodynamic regime where the solutions of the shallow water equations are **smooth** and hence the water depth can be approximated by (7).
- One has naturally  $h(0) = h(L)$  under this parameterization, which means that we have accomplished one lap of the raceway pond.
- We assume a **constant volume** of the system  $V$ , which can be achieved by fixing  $a_0$ . Indeed, under this parameterization and using (6), one finds  $V = a_0 L$ .

# Convergence

We fix  $N = 5$  and take 100 random initial guesses of  $a$ . For  $N_z$  varying from 1 to 80, we compute the average value of  $\bar{\mu}_{N_z}$  for each  $N_z$ .

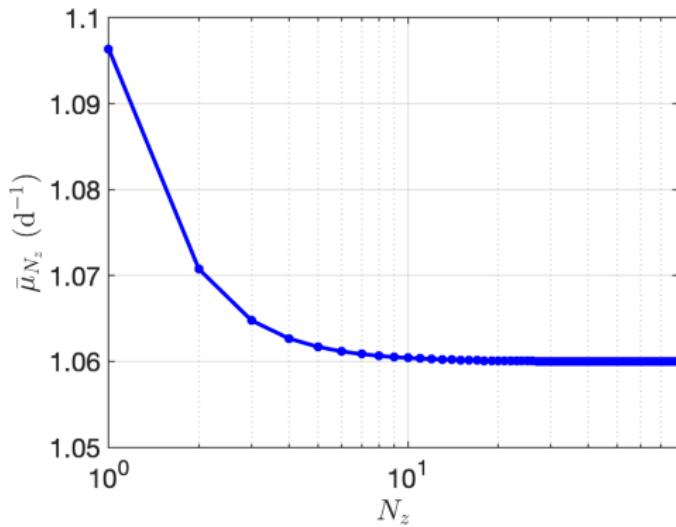


Figure: The value of  $\bar{\mu}_{N_z}$  for  $N_z = [1, 80]$ .

# Optimal Topography

We take  $N_z = 40$ . As an initial guess, we consider the flat topography, meaning that  $a$  is set to 0.

# Periodic case

## Assumption

Photoinhibition state  $C$  is periodic meaning that  $C_i(L) = C_i(0)$

## Consequence

Differentiating  $\mathcal{L}$  with respect to  $C_i(L)$ , we have

$$\partial_{C_i(L)} \mathcal{L} = p_i(L) - p_i(0).$$

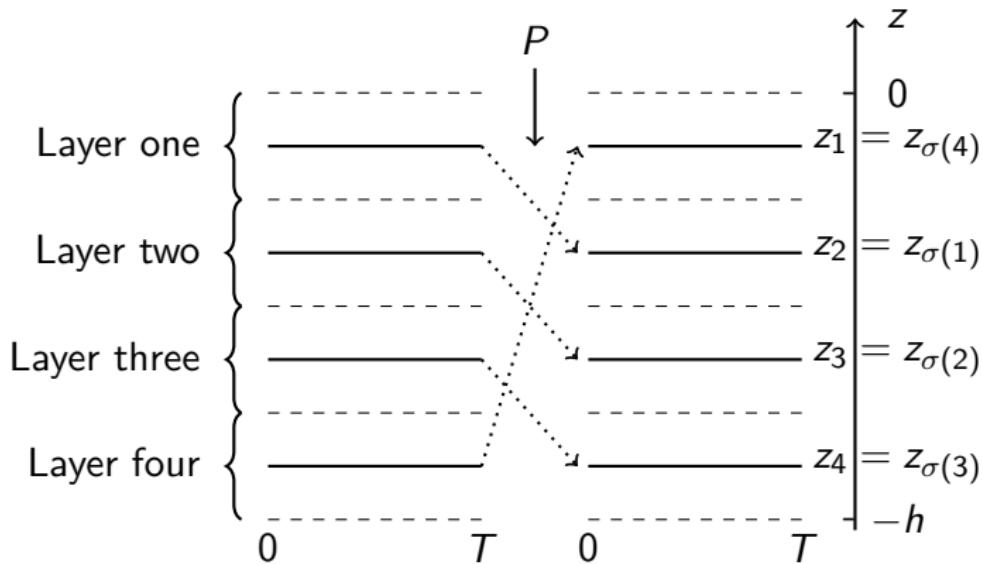
so that equating the above equation to zero gives the periodicity for  $p_i$ .

## Theorem (Flat topography [2])

Assume the volume of the system  $V$  is constant. Then  $\nabla \bar{\mu}_{N_z}(0) = 0$ .

# Mixing devices

- An ideal rearrangement of trajectories: at each new lap, the algae at depth  $z_i(0)$  are entirely transferred into the position  $z_j(0)$  when passing through the mixing device.
- We denote by  $\mathcal{P}$  the set of permutation matrices of size  $N \times N$  and by  $\mathfrak{S}_N$  the associated set of permutations of  $N$  elements.



# General problem

Given a period  $T$ , and initial time  $T_0$  and a sequence  $(T_k)_{k \in \mathbb{N}}$ , with  $T_k = kT + T_0$ , we consider the following resource allocation problem:

## Periodic dynamical resource allocation problem

Consider  **$N$  resources** denoted by  $(I_n)_{n=1}^N \in \mathbb{R}^N$  which can be allocated to  **$N$  activities** denoted by  $(x_n)_{n=1}^N$  where  $x_n$  consists of a real function of time. On a time interval  $[T_k, T_{k+1})$ , each activity uses the assigned resource and evolves according to a linear dynamics

$$\dot{x}_n = -\alpha(I_n)x_n + \beta(I_n), \quad (8)$$

where  $\alpha : \mathbb{R} \rightarrow \mathbb{R}_+$  and  $\beta : \mathbb{R} \rightarrow \mathbb{R}_+$  are given. At time  $T_{k+1}$ , the resources is re-assigned, meaning that  $x(T_{k+1}) = Px(T_k^-)$  for some  $P \in \mathcal{P}$ . In this way,  $k \in \mathbb{N}$  represents the number of re-assignments and  $T_k^-$  represents the moment just before re-assignment.

## Assumption

Resource  $(I_n)_{n=1}^N$  are constant with respect to time.

## Consequence

For a given initial vector of states  $(x_n(T_0))_{n=1}^N$ , we have

$$x(t) = D(t)x(T_k) + v(t), \quad t \in [T_k, T_{k+1}), \quad (9)$$

where  $D(t)$  and  $v(t)$  are time dependent.

Let  $u \in \mathbb{R}^N$  an arbitrary vector. Define

$$f^k := \langle u, \frac{1}{T} \int_{T_k}^{T_{k+1}} x(t) dt \rangle, \quad (10)$$

the benefit attached to the time period  $[T_k, T_{k+1})$  after  $k$  times of re-assignment. Then the average benefit after  $K$  operations is given by

$$\frac{1}{K} \sum_{k=0}^K f^k.$$

According to (9) and by the definition of  $P$ , we have

$$x(T_{k+1}) = P(Dx(T_k) + v). \quad (11)$$

### Lemma

Given  $k \in \mathbb{N}$  and  $P \in \mathcal{P}$ , the matrix  $\mathcal{I}_N - (PD)^k$  is invertible.

### Theorem (One periodic [3])

$(x(T_k))_{k \in \mathbb{N}}$  is a constant sequence and we have for all  $k \in \mathbb{N}$

$$x(T_k) = (\mathcal{I}_N - PD)^{-1} Pv.$$

The result shows that every  $KT$ -periodic evolution will actually be  $T$ -periodic.

## Optimization problem

$$\max_{P \in \mathcal{P}} J(P) := \max_{P \in \mathcal{P}} \langle u, (\mathcal{I}_{N_z} - PD)^{-1} Pv \rangle, \quad (12)$$

### Remark

Since  $\#\mathfrak{S} = N!$ , this problem cannot be tackled in realistic cases where large values of  $N$  must be considered, e.g., to keep a good numerical accuracy.

Expand the functional (12) as follows

$$\langle u, (\mathcal{I}_{N_z} - PD)^{-1} Pv \rangle = \sum_{l=0}^{+\infty} \langle u, (PD)^l Pv \rangle = \langle u, Pv \rangle + \sum_{l=1}^{+\infty} \langle u, (PD)^l Pv \rangle,$$

## Approximation problem

$$\max_{P \in \mathcal{P}} J^{\text{approx}}(P) := \max_{P \in \mathcal{P}} \langle u, Pv \rangle. \quad (13)$$

## Lemma

Let  $\sigma_+, \sigma_- \in \mathfrak{S}$  such that  $v_{\sigma_+(1)} \leq v_{\sigma_+(2)} \cdots \leq v_{\sigma_+(N)}$  and  $v_{\sigma_-(N)} \leq v_{\sigma_-(N-1)} \leq \cdots \leq v_{\sigma_-(1)}$  and  $P_+, P_- \in \mathcal{P}$ , the corresponding permutation matrices. Then

$$P_+ = \operatorname{argmax}_{P \in \mathcal{P}} J^{\text{approx}}(P), \quad P_- = \operatorname{argmin}_{P \in \mathcal{P}} J^{\text{approx}}(P).$$

## Remark (Optimal matrix)

- $P_+$ : associates the *largest coefficient of  $u$*  with the *largest coefficient of  $v$* , the second largest coefficient with the second largest, and so on.
- $P_-$ : associates the *largest coefficient of  $u$*  with the *smallest coefficient of  $v$* , the second largest coefficient with the second smallest, and so on.

## Theorem (Criterion [3])

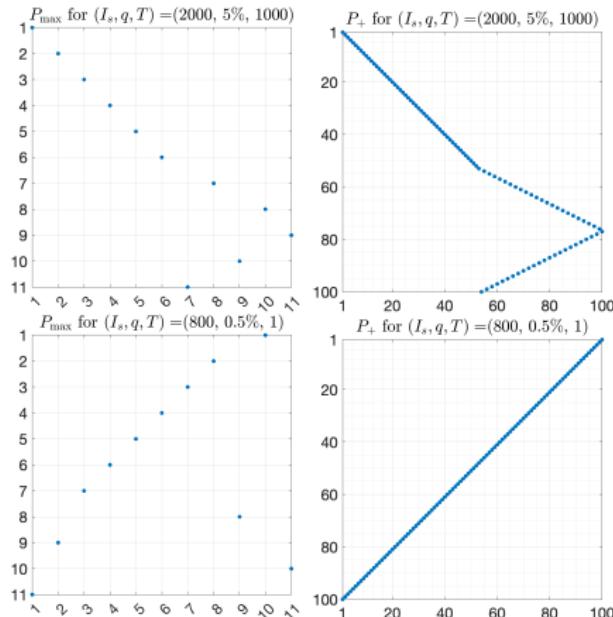
Assume that  $u$  and  $v$  have positive entries and define

$$\phi(m_1) := \frac{1}{s_{\lceil \frac{m_1}{2} \rceil}} \left( \sum_{l=1}^{+\infty} d_{\max}^l F_{(l+1)m_1}^+ - d_{\min}^l F_{(l+1)m_1}^- \right), \quad (14)$$

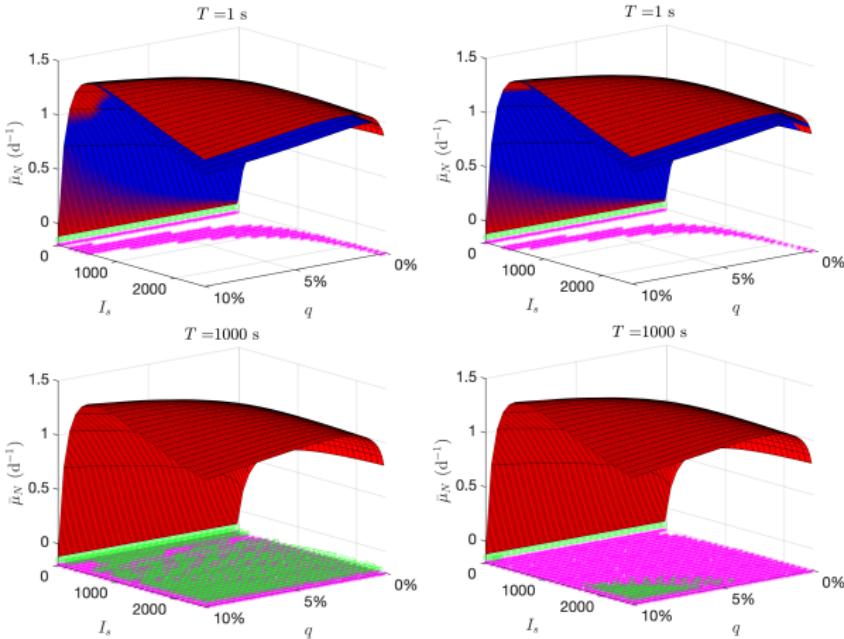
where  $m_1 := \# \{n = 1, \dots, N \mid \sigma(n) \neq \sigma_+(n)\}$ ,  $d_{\max} := \max_{n=1,\dots,N}(d_n)$  and  $d_{\min} := \min_{n=1,\dots,N}(d_n)$ . Assume that:

$$\max_{m_1 \geq 2} \phi(m_1) \leq 1. \quad (15)$$

Then the problem  $\max_{P \in \mathcal{P}} \langle u, (\mathcal{I}_{N_z} - PD)^{-1} Pv \rangle$  (resp.  $\min_{P \in \mathcal{P}} \langle u, (\mathcal{I}_{N_z} - PD)^{-1} Pv \rangle$ ) and the problem  $\max_{P \in \mathcal{P}} \langle u, Pv \rangle$  (resp.  $\min_{P \in \mathcal{P}} \langle u, Pv \rangle$ ) have the same solution.



**Figure:** Optimal matrix  $P_{\max}$  for Problem (12) and  $N = 11$  (Left) and  $P_+$  for Problem (13) and  $N = 100$  (Right) for the two parameters triplets. The blue points represent non-zero entries, i.e., entries equal to 1.



**Figure:** Average net specific growth rate  $\bar{\mu}_N$  for  $T = 1\text{s}$  (Top) and for  $T = 1000\text{s}$  (Bottom). Left:  $N = 5$ . Right:  $N = 9$ . The red surface is obtained with  $P_{\max}$  and the blue surface is obtained with  $P_+$ . The purple stars represent the cases where  $P_{\max} = P_+$  or, in case of multiple solution,  $\bar{\mu}_N(P_{\max}) = \bar{\mu}_N(P_+)$ . The green circle represent the cases where the criterion (15) is satisfied.



Olivier Bernard, Anne-Céline Boulanger, Marie-Odile Bristeau, and Jacques Sainte-Marie.

A 2d model for hydrodynamics and biology coupling applied to algae growth simulations.

*ESAIM: Mathematical Modelling and Numerical Analysis*,  
47(5):1387–1412, September 2013.



Olivier Bernard, Liu-Di Lu, Jacques Sainte-Marie, and Julien Salomon.  
Shape optimization of a microalgal raceway to enhance productivity.  
Submitted paper, November 2020.



Olivier Bernard, Liu-Di Lu, and Julien Salomon.  
Optimization of mixing strategy in microalgal raceway ponds.  
Submitted paper, March 2021.



Victor Michel-Dansac, Christophe Berthon, Stéphane Clain, and Françoise Foucher.  
A well-balanced scheme for the shallow-water equations with topography.

