Dissertation Defense

Design of Modular Cell Systems for Biocatalysis with Multi-Objective Optimization

Sergio Garcia

Committee members:

Dr. Steven M. Abel Dr. Brian H. Davison Dr. Tian Hong Dr. Cong T. Trinh (*Advisor*)

Department of Chemical and Biomolecular Engineering University of Tennessee Knoxville

March 25th, 2020

Outline

1. Introduction

- 1.1 Motivation
- 1.2 Cell biocatalysis

2. Modular design

- 2.1 Conventional engineering
- 2.2 Synthetic biology

3. Computational design of modular cells

- 3.1 Genome-scale metabolic models
- 3.2 Multi-objective optimization
- 3.3 What defines a solution?
- 3.4 Solution algorithms

4. Application examples

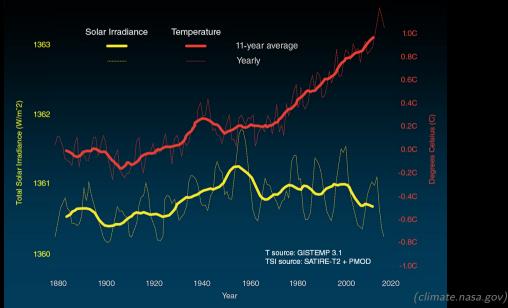
- 4.1 Universal design for 20 products
- 4.2 Designs for 161 product library

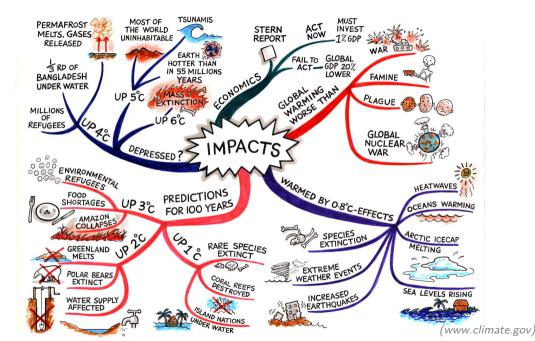
5. Summary



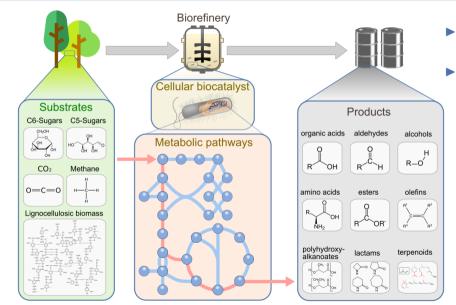
climate.nasa.gov

Temperature vs Solar Activity



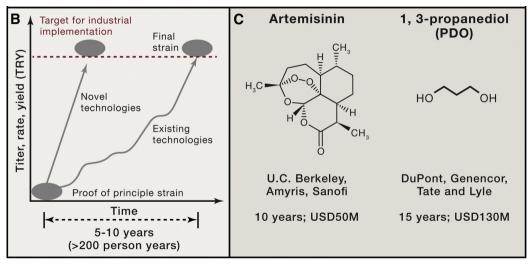


Cell biocatalysis technology: The goal



- Reduce net CO₂ emissions
 - Facilitate decentralized manufacturing

Cell biocatalysis technology: Current state



(Nielsen and Keasling 2016)

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Definition:

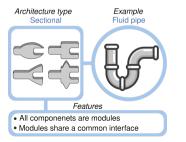
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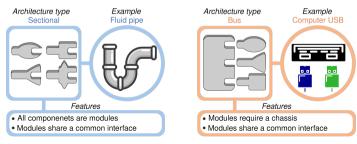
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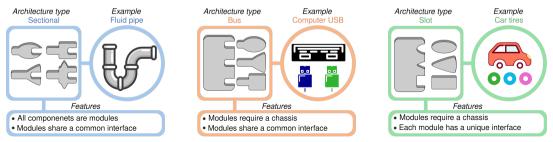
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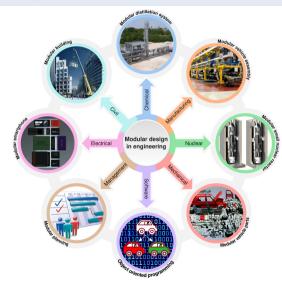


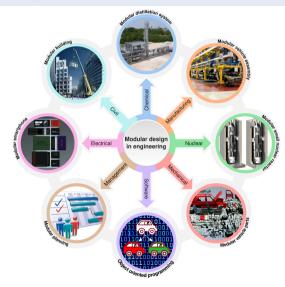






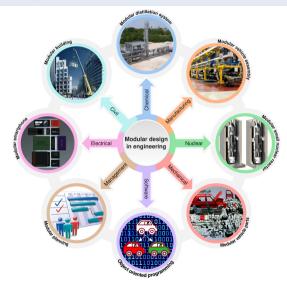




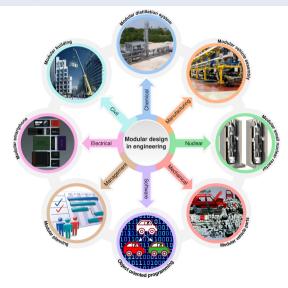


Driving forces for modularization:

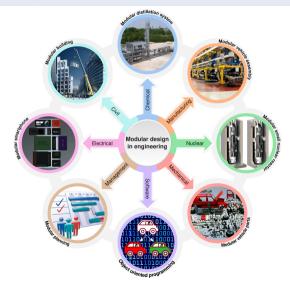
 Innovation: Novel solutions to existing problems



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- Efficiency: Faster and cheaper product construction and maintenance

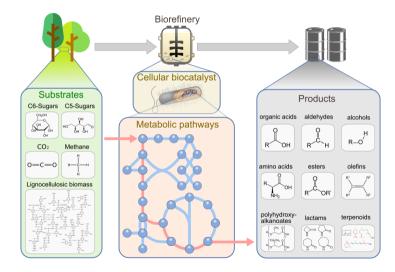


- Innovation: Novel solutions to existing problems
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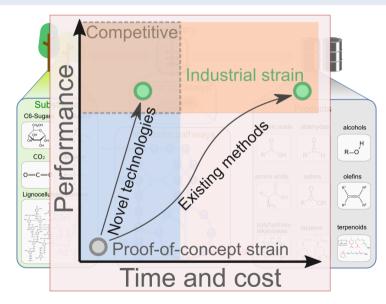
- Innovation: Novel solutions to existing problems
- Efficiency: Faster and cheaper product construction and maintenance
- Customizability: Better tailor a solution to specifics of the problem
- Predictability: Robust system behavior across diverse scenarios

Applications and challenges in microbial catalysis



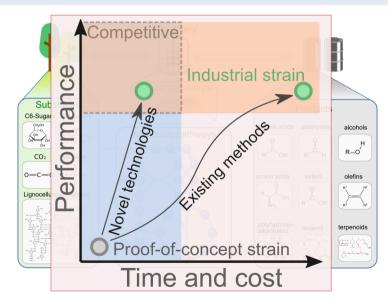
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Applications and challenges in microbial catalysis



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- Challenge: Design-buildtest cycles are too slow to make biocatalysis widely applicable

Applications and challenges in microbial catalysis



- Status: Bioengineering technologies enable microbial biocatalysis
- Challenge: Design-buildtest cycles are too slow to make biocatalysis widely applicable
- Solution: Apply proven modular design principles to biocatalyst engineering

Modular design in synthetic biology

The second wave of synthetic biology: from modules to systems

Priscilla E. M. Purnick & Ron Weiss

Nature Reviews Molecular Cell Biology **10**, 410–422(2009) Cite this article

Modular design in synthetic biology

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The first wave:

- Basic elements (e.g., rbs, promoters, repressors) combined to form small modules (e.g., Switches, oscilators, logic formulas.)
- Modules can be used to regulate gene expression, protein function, metabolism, and cell–cell communication.

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The second wave of synthetic biology: from modules to systems

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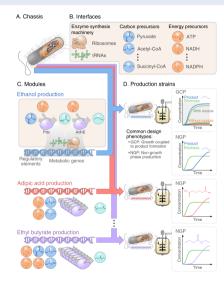
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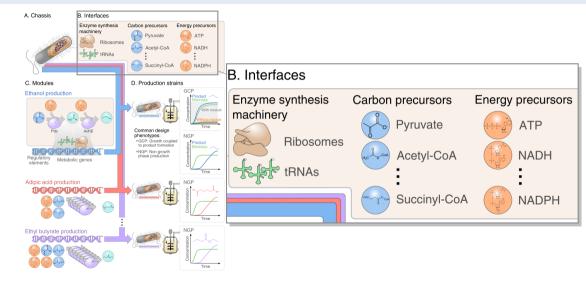
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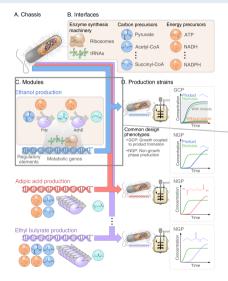
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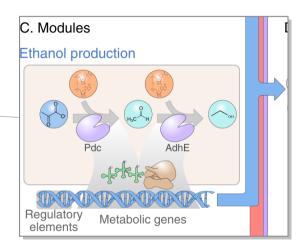
The second wave:

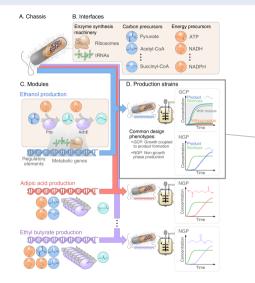
- Basic parts and modules need to be integrated to create systems-level circuitry
- Develop abstract engineering principles and potentially harness biologicallyunique features such as adaptation
- Develop better computational models

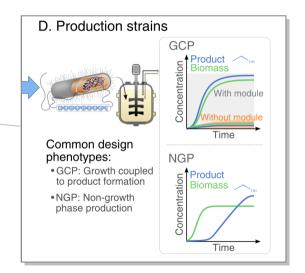


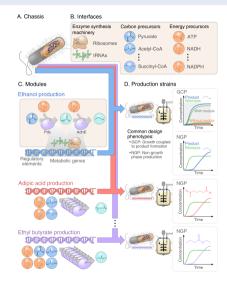






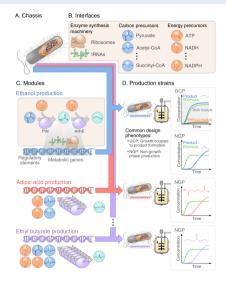






Current approach:

 Integral design of one strain to make a targeted product.

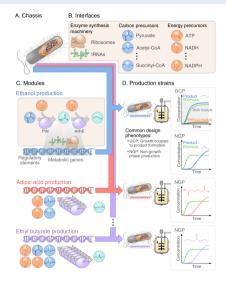


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Advantages of modular cell design:

Efficiency: Combine common elements among the different target phenotypes in the chassis, reducing redundant engineering efforts.



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Integral design of one strain to make a targeted product.

Advantages of modular cell design:

- Efficiency: Combine common elements among the different target phenotypes in the chassis, reducing redundant engineering efforts.
- Predictability: Define and re-uses chassis interfaces to operate with modules, increasing robustness.

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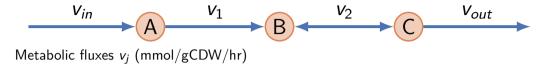
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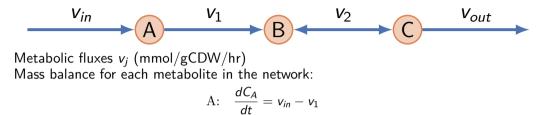
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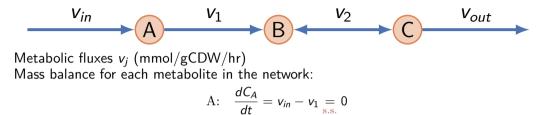
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Vin

Metabolic fluxes *v_j* (mmol/gCDW/hr) Mass balance for each metabolite in the network:

 V_1

A:
$$\frac{dC_A}{dt} = v_{in} - v_1 \underset{\text{s.s.}}{=} 0$$

B:
$$\frac{dC_B}{dt} = v_1 - v_2 = 0$$

C:
$$\frac{dC_C}{dt} = v_2 - v_{out} = 0$$

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Lower and upper bounds for each reaction:

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Lower and upper bounds for each reaction:

 $\begin{array}{rll} 10 \leq v_{in} & \leq 10 & \leftarrow {\rm Specify\ measured\ flux} \\ 0 \leq v_1 & \leq 1000 & \leftarrow {\rm Irreversible\ reaction} \end{array}$

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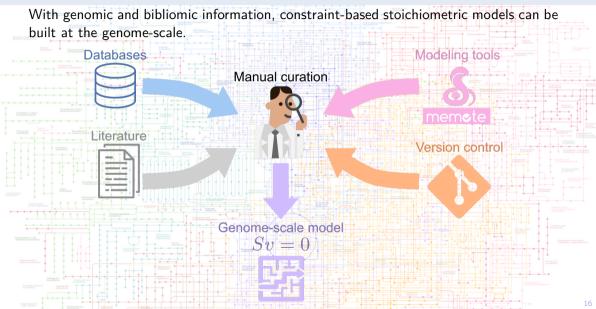
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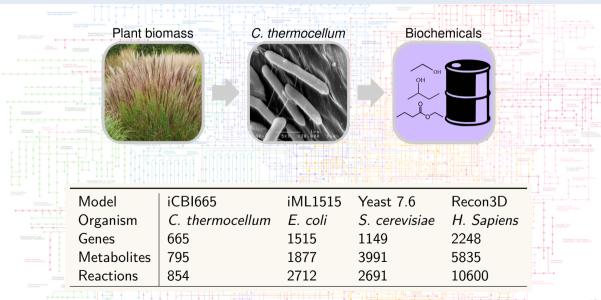
$$\begin{array}{rll} 10 \leq v_{in} & \leq 10 & \leftarrow \mbox{Specify measured flux} \\ 0 \leq v_1 & \leq 1000 & \leftarrow \mbox{Irreversible reaction} \\ -1000 \leq v_2 & \leq 1000 & \leftarrow \mbox{Reversible reaction} \\ 0 \leq v_{out} \leq 1000 \end{array}$$

Vout

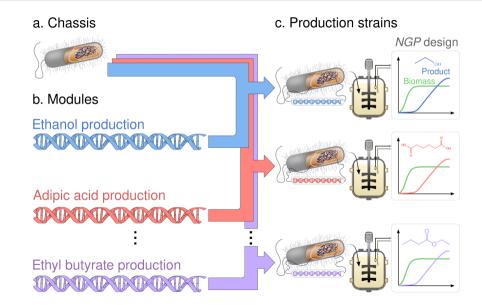
Constraint-based modeling at the genome-scale



Constraint-based modeling at the genome-scale



Modular cell biocatalyst



$$\begin{array}{ll} \displaystyle\max_{y_{j},z_{jk}} & \left(f_{1},f_{2},\ldots,f_{|\mathcal{K}|}\right)^{T} \quad \text{s.t.} \\ f_{k} \in \arg \max \Biggl\{ \frac{1}{f_{k}^{max}} \sum_{j \in \mathcal{J}_{k}} c_{jk} v_{jk} \quad \text{s.t.} \\ & \sum_{j \in \mathcal{J}_{k}} S_{ijk} v_{jk} = 0 & \text{for all } i \in \mathcal{I}_{k} \\ & l_{jk} \leq v_{jk} \leq u_{jk} & \text{for all } j \in \mathcal{J}_{k} \\ & l_{jk} d_{jk} \leq v_{jk} \leq u_{jk} d_{jk} & \text{for all } j \in \mathcal{C} \\ & \text{where } d_{jk} = y_{j} \lor z_{jk} \Biggr\} & \text{for all } k \in \mathcal{K} \\ & \sum_{j \in \mathcal{C}} (1 - y_{j}) \leq \alpha \\ & \sum_{j \in \mathcal{C}} z_{jk} \leq \beta_{k} & \text{for all } k \in \mathcal{K} \\ & z_{jk} \leq (1 - y_{j}) & \text{for all } j \in \mathcal{C}, \ k \in \mathcal{K} \end{array}$$

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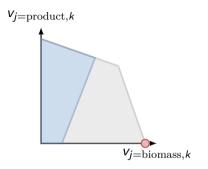
 $z_{jk} \leq (1-y_j)$

 $V_{j=\text{product},k}$ $V_{j=\text{biomass},k}$

for all $j \in C, k \in \mathcal{K}$

 $\in \mathcal{K}$

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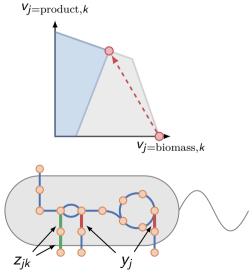
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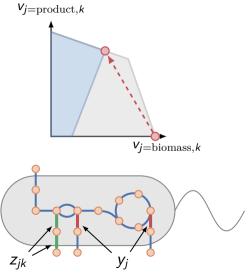
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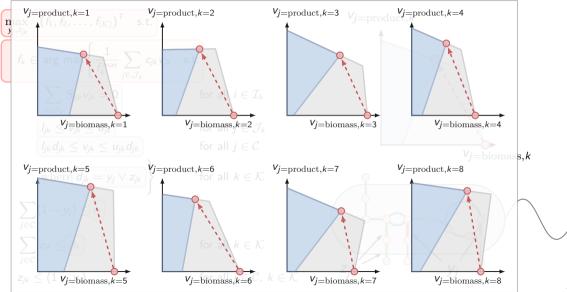
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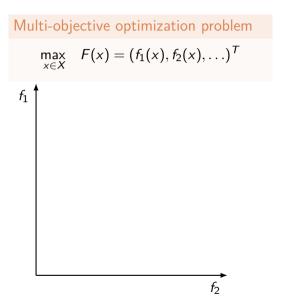
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Multi-objective optimization problem

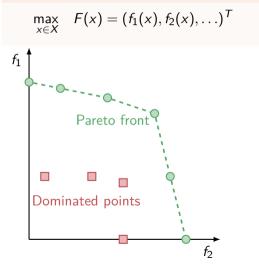
 $\max_{x \in X} F(x) = (f_1(x), f_2(x), ...)^T$

$$f_1 \qquad f_1^a \ge f_1^b, f_2^a \ge f_2^b, \\ and a \ne b, \text{ so } a \prec b \\ \hline f_1^a \qquad a \\ f_1^b \qquad f_2^b \qquad f_2^a \\ f_2^b \qquad f_2^b \qquad f_2^a \\ f_2^b \qquad f_2^b \qquad f_2^c \\ f_2^b \qquad f_2^c \qquad f_2^c \\ f_2^c \qquad f_2^c \qquad f_2^c \qquad f_2^c \\ f_2^c \qquad f_2^c \qquad f_2^c \qquad f_2^c \\ f_2^c \qquad f_2^c \qquad f_2^c \qquad f_2^c \qquad f_2^c \\ f_2^c \qquad f_2^c$$

Definition of domination

A vector *a* dominates another vector *b* (denoted $a \prec b$) iff $a_i \ge b_i \ \forall i \in \{1, 2, \dots, K\}$ and $a_i \ne b_i$ for at least one *i*.

Multi-objective optimization problem



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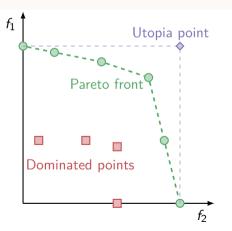
Pareto set

 $PS := \{x \in X : \nexists x' \in X, F(x') \prec F(x)\}$

Pareto front $PF := \{F(x) : x \in PS\}$

Multi-objective optimization problem

```
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Utopia point

 $max(f_1(x)) = f_1(x) = f_2(x) = \dots$

Solution algorithms for multi-objective optimization

Solution algorithms for multi-objective optimization

MILP (Mixed integer linear programming)

- Convert to single-objective problem
- Need a priori specification of preference
- Optimality guaranteed

Goal attaintment formulation: define a performance target for each objective g_k

$$\min \quad \sum_{k \in \mathcal{K}} \delta_k \tag{1}$$

s.t.

$$f'_k + \delta_k \ge g_k \ \forall k \in \mathcal{K} \tag{2}$$

$$\delta_k \ge 0 \qquad \forall k \in \mathcal{K}$$
 (3)

$$f' \in \Omega$$
 (4)

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- $\delta_k \geq 0 \qquad \forall k \in \mathcal{K}$ (3)
- $f' \in \Omega$ (4)

MOEA (Multi-objective evolutionary algorithm)

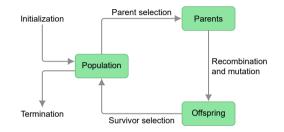
- Directly obtain Pareto front
- Can be easily adapted to different models and design objectives
- Scalable to HPC for problems with many objectives

Basics of genetic algorithms

Population-based heuristic optimization (e.g., Genetic algorithms):

- Individual: Encodes the variables of the problem and hence has an objective value associated with it.
- Operators: Heuristic that modify individuals to enhance their objective values.

The population of individuals is modified with operators to identify potentially optimal solutions to the optimization problem.



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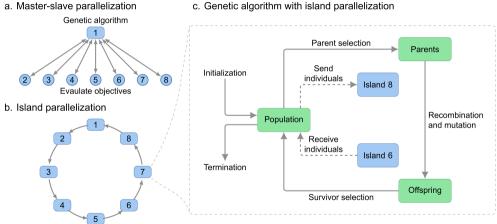
The 2006 NASA ST5 spacecraft antenna. This complicated shape was found by an evolutionary computer design program to create the best radiation pattern.

Scaling MOEA for many-objective problems



- ▶ We wish to solve modular cell design problems with 100s of products
- Many-objective problems are notoriusly difficult to solve and HPC approaches are not well explored in the field
- Develop and benchmark an HPC MOEA

MOEA parallelization



c. Genetic algorithm with island parallelization

Outline

1. Introduction

- 1.1 Motivation
- 1.2 Cell biocatalysis

2. Modular design

- 2.1 Conventional engineering
- 2.2 Synthetic biology

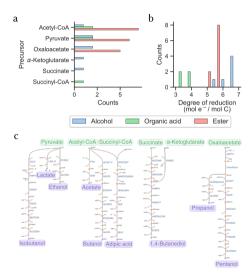
3. Computational design of modular cells

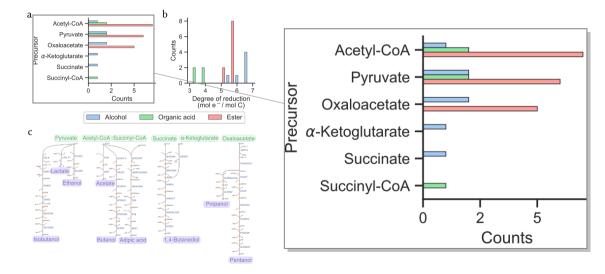
- 3.1 Genome-scale metabolic models
- 3.2 Multi-objective optimization
- 3.3 What defines a solution?
- 3.4 Solution algorithms

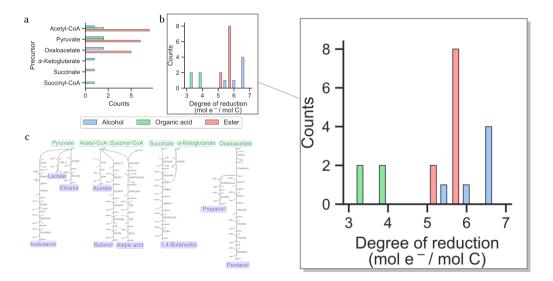
4. Application examples

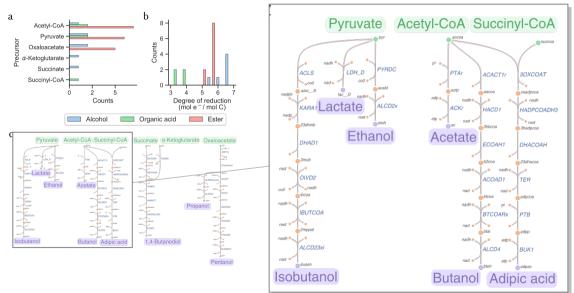
- 4.1 Universal design for 20 products
- 4.2 Designs for 161 product library

5. Summary

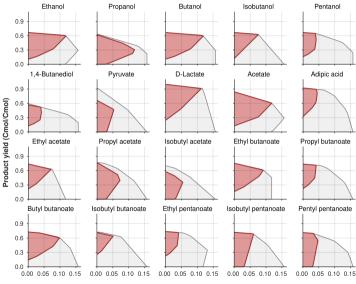








Universal design for 20 products

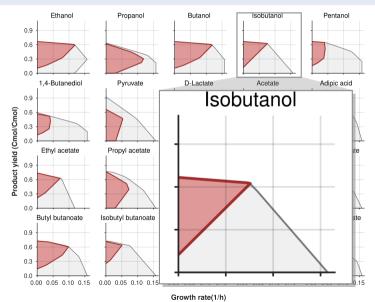


Phenotypic spaces:

 Represent feasible metabolic states according to stoichiometric constraints

- Gray region: Wild type + production module
 - Red region: Designed chassis + production module

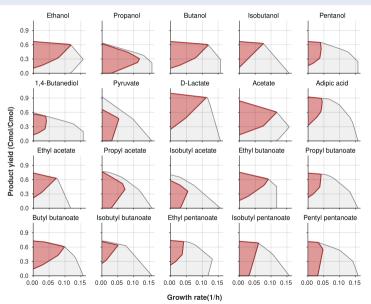
Universal design for 20 products



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Universal design for 20 products



Phenotypic spaces:

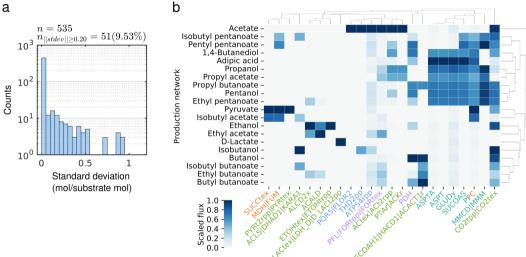
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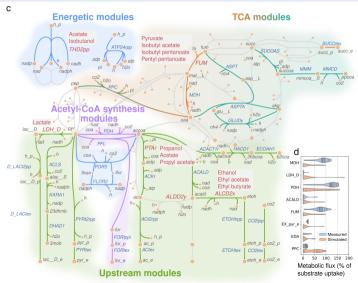
The universal design leads to high product yields at the maximum growth rate for all combinations of chassis and production modules.

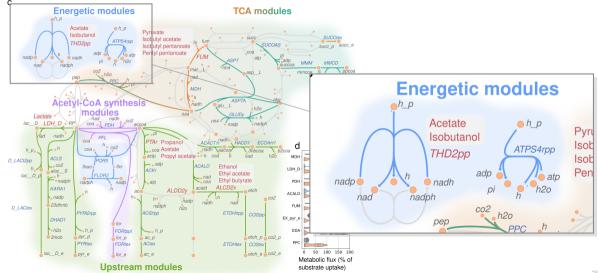
Identification of chassis metabolic interfaces

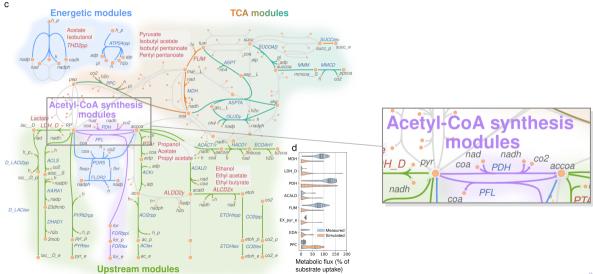


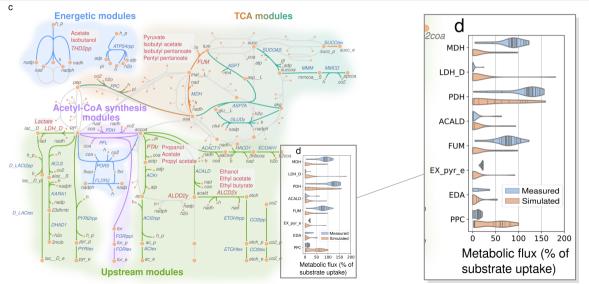


Reaction





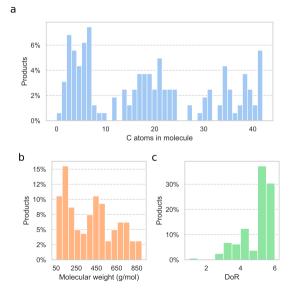


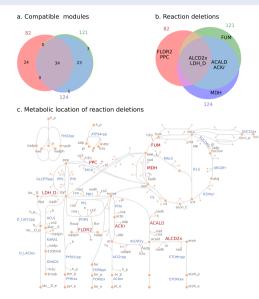


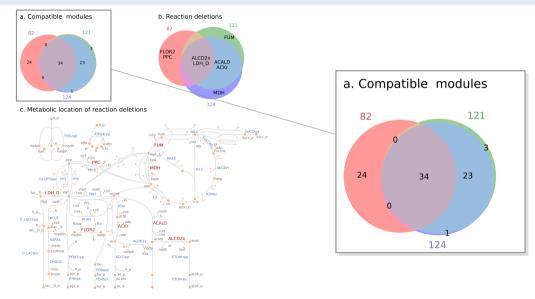
Input: 161 endogenous products

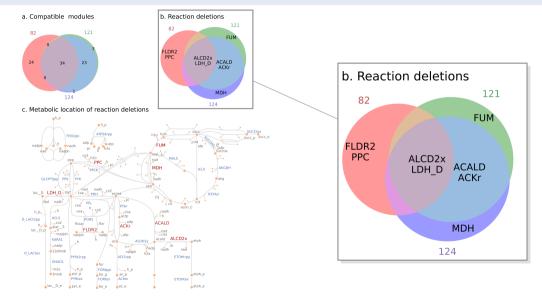
Endogenous metabolites in *E. coli* that are organic and can be coupled to growth under anaerobic conditions.

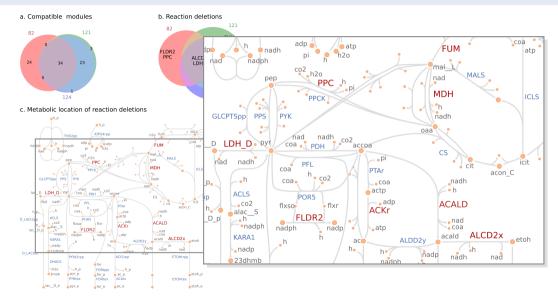
- Diverse molecule size
- Highly reduced due to anaerobic conditions.

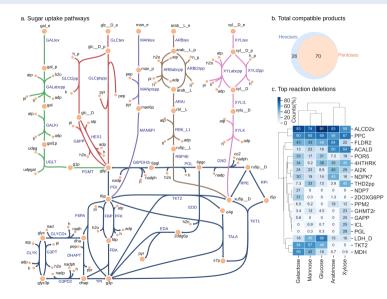


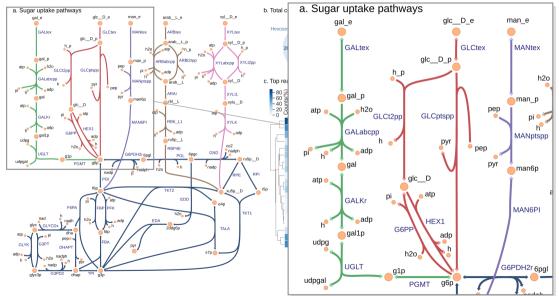


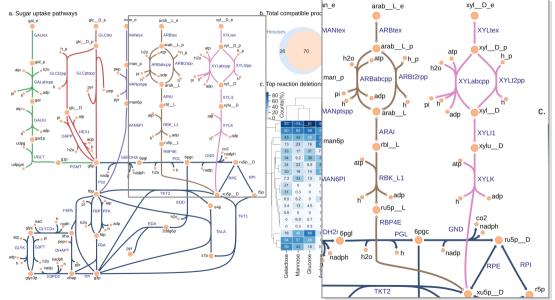




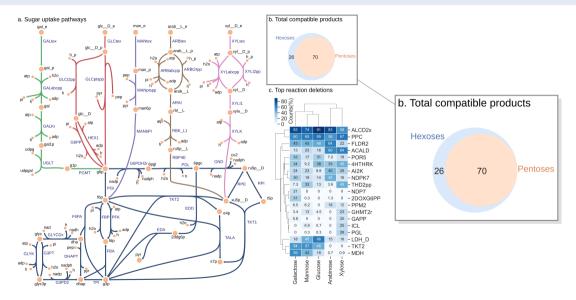


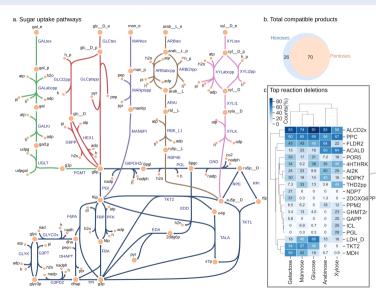


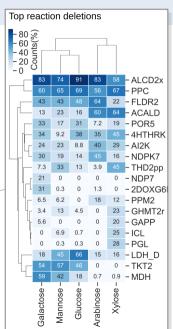




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ModCell tools

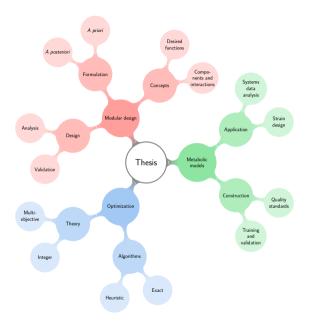
Primer: Metabolic engineering strategies repeat across target molecules **ModCell2**: Multiobjective optimization formulation to design Pareto optimal chassis and modules **Modcell2-HPC**: Design chassis for hundredths of endogenous products providing general principles for synthetic and natural modular design

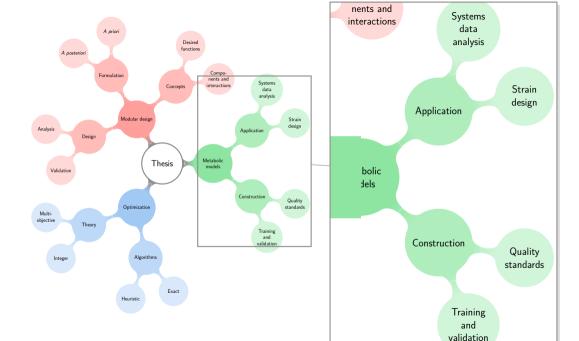
> Modular design principles in metabolic engineering for efficient and robust systems

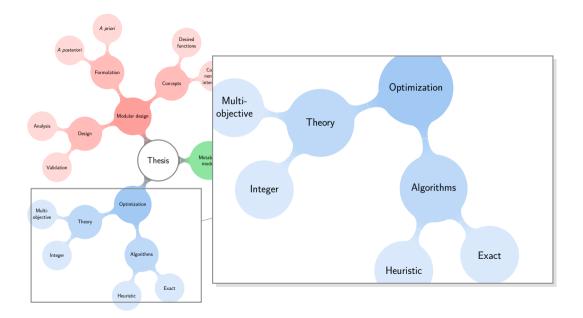
MODCELL: Design strains for individual products and find common manipulations

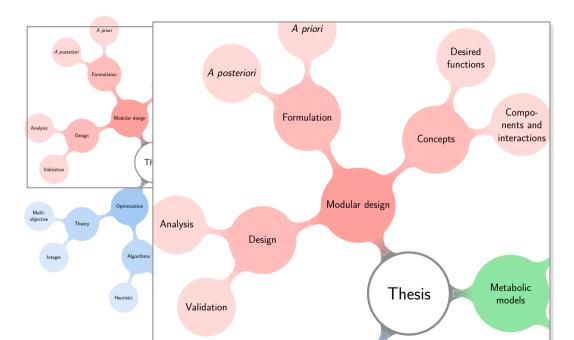
ModCell2-MILP:

Identify optimal solutions to design universal chassis and define key metabolic interfaces









Acknowledgements

Funding Sources

Trinh Lab





