



Engineering *Pseudomonas putida* for production of muconic acid

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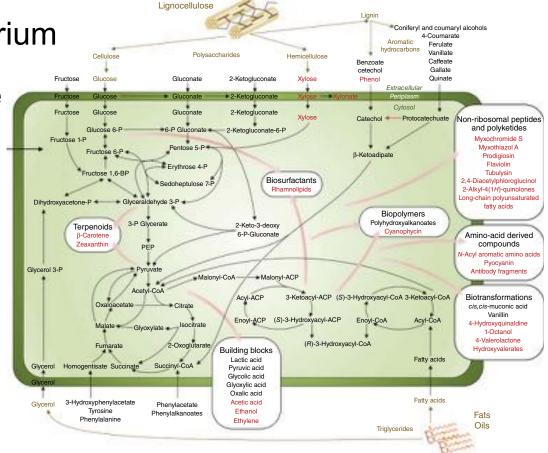


Host: Pseudomonas putida KT2440

Saprophytic soil bacterium

Gram-negative aerobe

- GRAS
- Fast growing
- Stress tolerant
- Metabolically versatile
- Genetically tractable

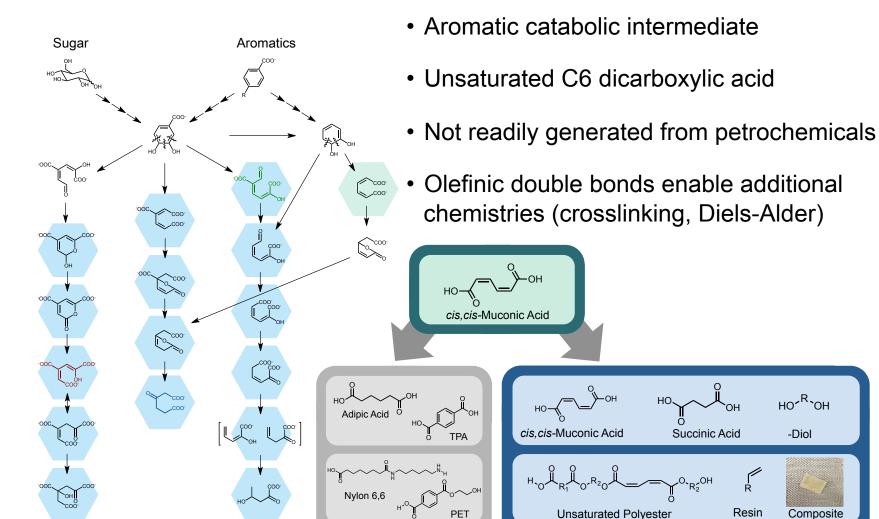


Poblete-Castro I, Borrero-de Acuña JM, Nikel PI, Kohlstedt M, Wittmann C. Host Organism: Pseudomonas putida. In: Wittmann C, Liao JC, editors. Industrial Biotechnology: Microorganisms. 2017. p. 337.





Target: Muconic acid



Direct Replacements

Functional Replacements

Resin

Succinic Acid



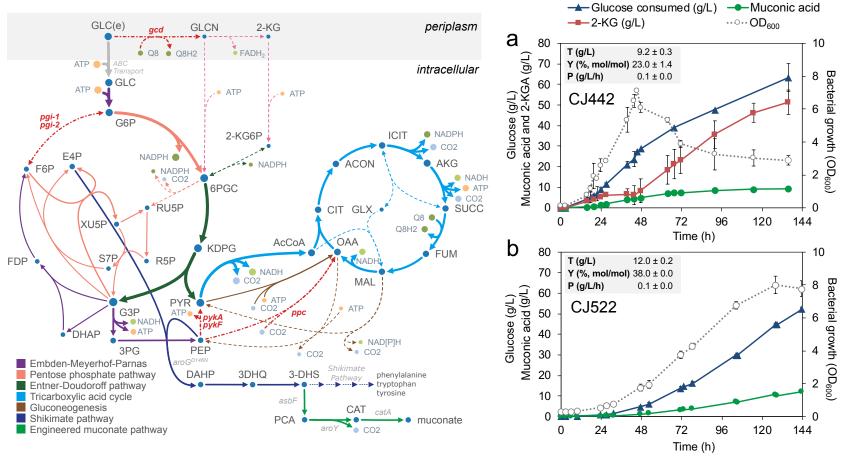


HO'R OH

-Diol

Composite

Production of muconic acid from sugar



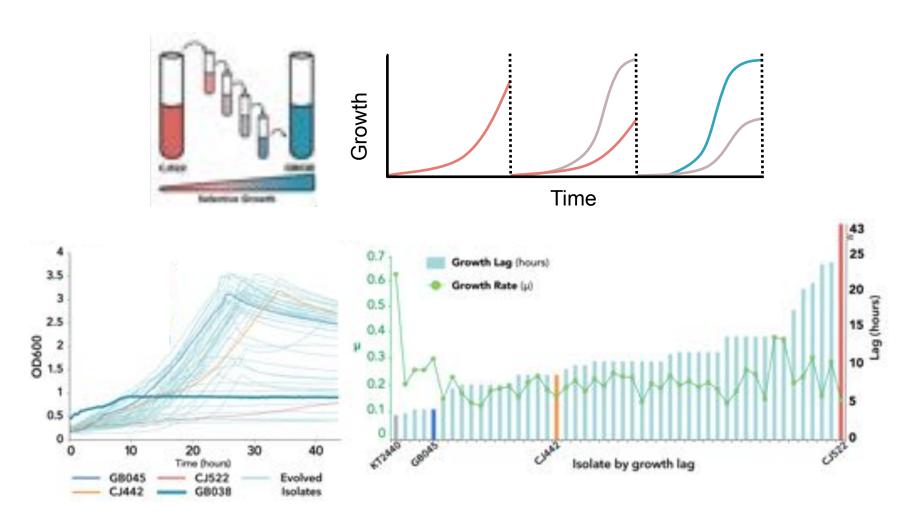
Johnson, C.W., et al., 2019. Innovative Chemicals and Materials from Bacterial Aromatic Catabolic Pathways. Joule 3, 1523–1537.

- Engineering achieved ~35% yield of muconic acid from glucose
- Elimination of 2-ketogluconate byproduct slowed growth and productivity





Laboratory evolution to improve growth

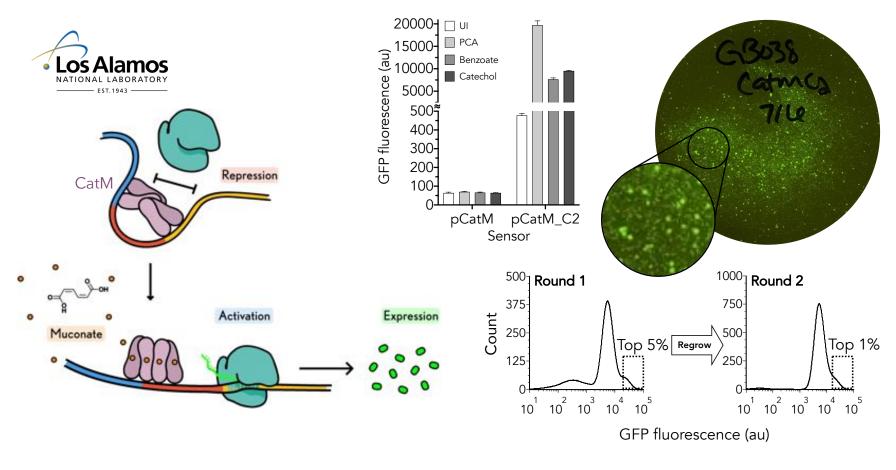


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Biosensor development and selection



Adaptive evolution





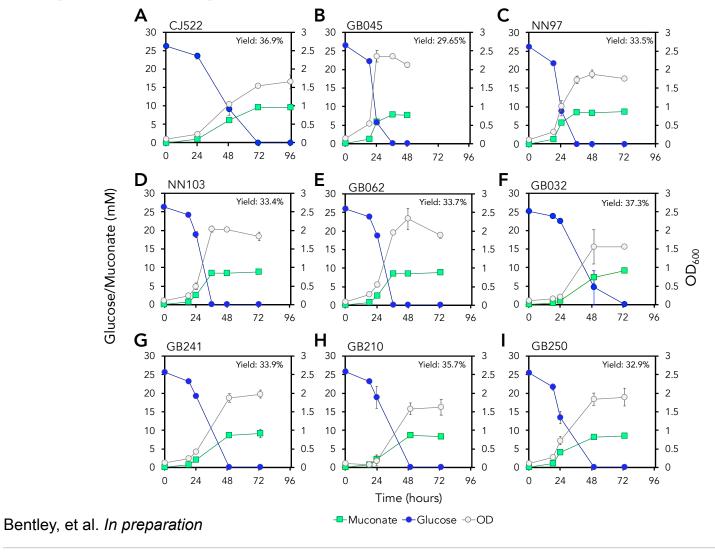
Improved production

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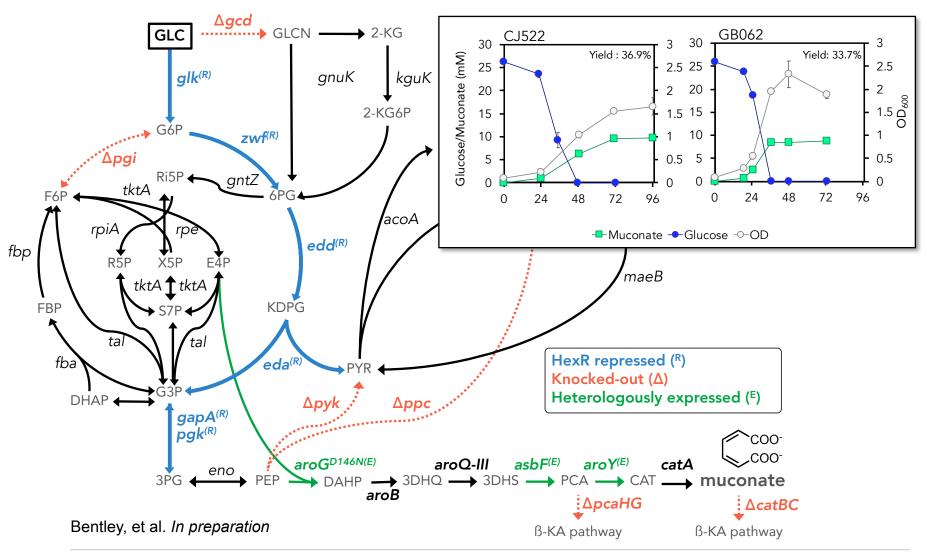
Evolution, screening, and rational engineering improved muconate production







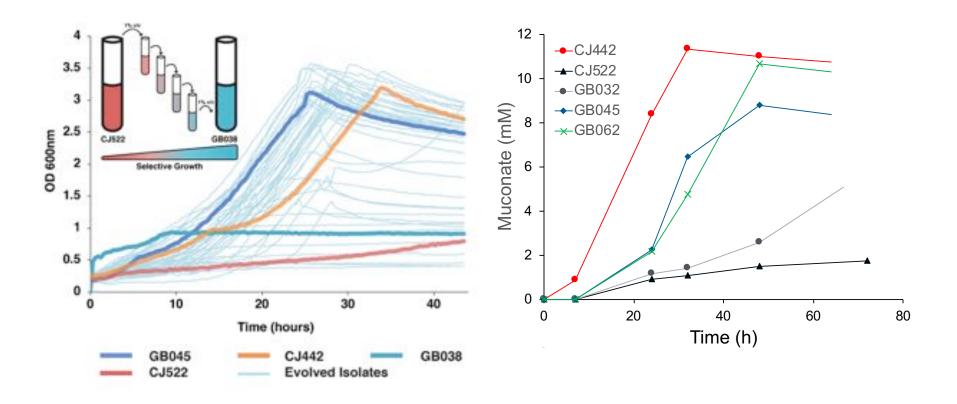
Deletion of hexR improves production







Diverse phenotypes to feed machine learning interface



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Diverse phenotypes to feed machine learning interface Fructose Glucose Gluconate

GLC(e)

GLC

G₆P

F6P

NADPH

NADPH

• RU5P

2-KG

2-KG6P

6PGC

. • ATP

ACON

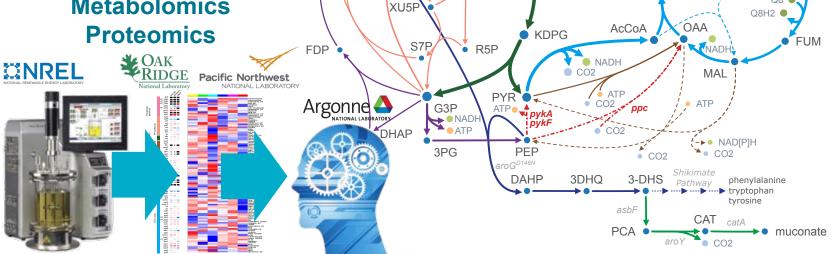
CIT GLX.

Input:

 5 strains with varying muconate and growth phenotypes

6 carbon source combinations to query different metabolic nodes

> **Transcriptomics Metabolomics**





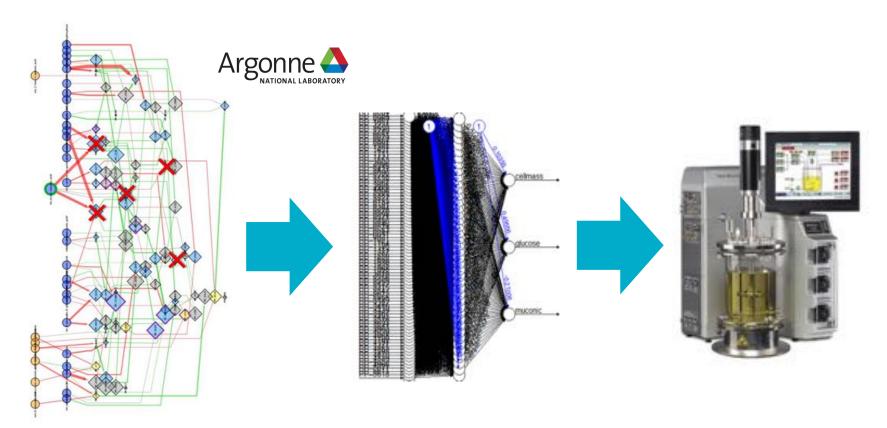
periplasm

intracellular

NADPH

SUCC

Going beyond rational engineering with machine learning



Predict TF expression pattern as functions of (observed) metabolome and (modeled) TF KO

Use predicted TF expression pattern as input to ANN

Predict fermentation phenotype, relative to strain without TF knockout

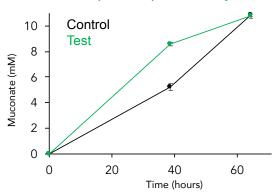




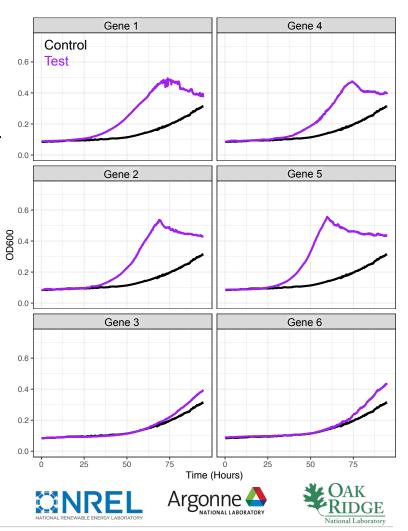
Evaluating non-intuitive Learn targets

- Machine learning targets were provided on August 1, 2019
- Constructs to either delete or overexpress genes were constructed
- Resulting strains were generated, all with chromosomal modifications
- By September 30, 2019, 111 strains had been generated AND characterized for performance, in biological triplicate

Improved productivity



Improved growth







Enabling Hydrolysate Utilization in P. putida

Corn Stover DMR-EH

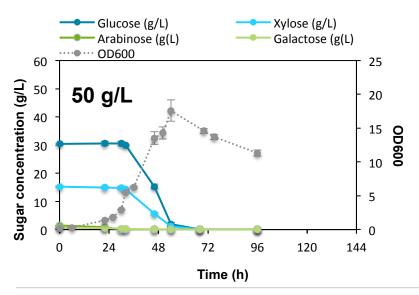
(deacetylation and mechanical refining, enzymatic hydrolysis)

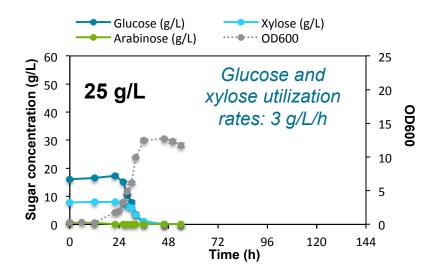
Glucose	85 g/L	(472 mM)
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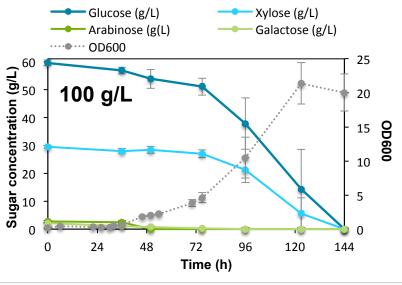
Xylose 37 g/L (245 mM)

L-arabinose 5.5 g/L (37 mM)

Galactose 1.2 g/L (7 mM)











OAK

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