Economic Principles in Cell Biology

Vienna, July 23–26, 2025



The enzyme cost of metabolic fluxes

Elad Noor & Wolfram Liebermeister







Outline

- Rate versus Yield
- ► Thermodynamic-focused pathway analysis
- Resource allocation and enzyme cost/demand
- Solutions to the allocation problem
- Example 1: glycolysis in *E. coli*
- Example 2: central metabolism in *E. coli*
- ► From enzyme allocation to growth rate
- Generalizing to whole networks

Why is there diversity in nature?

► Natural ecosystems ⇒ diversity



Credit: Ostrich by Diego Delso, Colibri by The Lilac Breasted Roller

Why is there diversity in nature?

- ► Natural ecosystems ⇒ diversity
- ► Darwin ⇒ survival of the fittest



Credit: Official White House Photo by Amanda Lucidon

Why is there diversity in nature?

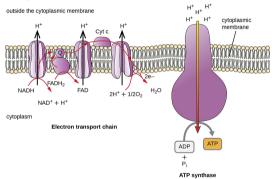
- Natural ecosystems ⇒ diversity
- Darwin \Rightarrow survival of the fittest
- Solving the paradox: tradeoffs!



Credit: Collage by Kiwi Rex

Respiration versus Fermentation

Respiration



Credit: OpenStax College, Microbiology

Fermentation



Lactate dehydrogenase

Credit: Jawahar Swaminathan and MSD staff at the European

Bioinformatics Institute

The ATP yield of respiration is much higher than fermentation

Feature	Respiration	Fermentation
Energy Yield (ATP)	26-32	2
Oxygen required	Yes	No
Membranes required	Yes	No
Involves glycolysis	Yes	Yes
Other pathways	TCA cycle $+$ ETC*	specific fermentation pathway
End products	CO_2+H_2O	$lactate \; / \; ethanol \; + \; CO_2$

^{*}Electron Transport Chain

Glycolysis pathway:

$$S \rightleftharpoons X_1 \rightleftharpoons \ldots \rightleftharpoons P$$
 $(\Delta G_{\sf driv} < 0)$ coupled to:

What should d be?

 $d \text{ ADP} \rightleftharpoons d \text{ ATP} \qquad (\Delta G_{\mathsf{ATP}} > 0)$

^{*}Werner et al. [5]

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Assume* flux is given by:

$$J_{\rm path} = -L \ \underbrace{\left(\Delta G_{\rm driv} + d \ \Delta G_{\rm ATP}\right)}_{\Delta G_{\rm path}} \label{eq:Jpath}$$

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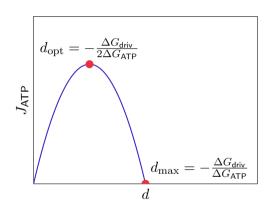
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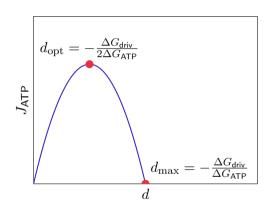
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- Fermentation (glucose to lactate): $d_{\text{opt}} \approx 2$, $d_{\text{max}} = 4$, $d_{\text{human}} = 2$
- Fermentation (glucose to ethanol): $d_{\text{opt}} \approx 3$, $d_{\text{max}} = 5$, $d_{\text{yeast}} = 2$
- respiration (glucose to CO₂): $d_{\text{opt}} \approx 28$, $d_{\text{max}} = 55$, $d_{\text{ecoli}} = 26$



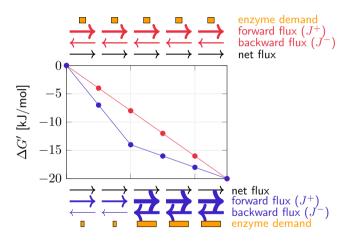
^{*}Werner et al. [5]

Thermodynamic bottlenecks

Is only considering the *overall* thermodynamic force good enough?

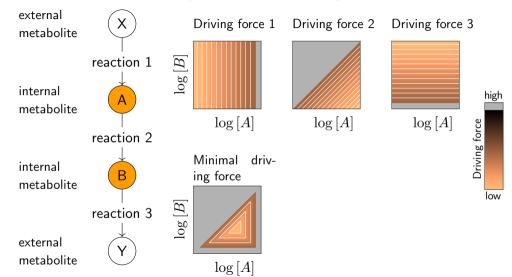
Thermodynamic force affects enzyme efficiency

Based on the flux-force relationship*: $\frac{J^+}{J^-}=e^{-\Delta G'/RT}$



^{*}Noor et al. [3]

Example with 3-step pathway: Max-min Driving Force



Mechanistic models

Stoichiometric models usually ignore thermodynamics, while Max-min Driving Force is heuristic.

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Is there a mechanistic model that can capture the rate/yield trade-off?

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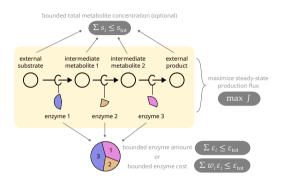
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- 3. bounded by the enzyme maximal rate: $v_i \leq e_i \cdot k_{\rm app}$

In reality $k_{\rm app}$ is a function of the metabolic state: $v = e \cdot f(\mathbf{c}; \mathbf{k})$:

- ▶ k kinetics constants (turnover number, affinity, etc.)
- c concentrations of all substrates and products
- $ightharpoonup f(\cdot)$ depends also on other factors (e.g. pH, temperature, crowding), but we assume the changes are small

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Reversible enzyme kinetics based on Haldane

For a reversible enzyme catalyzed reaction*: $S \stackrel{\mathrm{E}}{\Longleftrightarrow} P$

$$v = e \cdot \underbrace{\frac{k_{\text{cat}}^+ s/K_{\text{S}} - k_{\text{cat}}^- p/K_{\text{P}}}{1 + s/K_{\text{S}} + p/K_{\text{P}}}}_{k_{\text{app}}}$$

^{*}where s, p, and e are the concentrations of S, P, and E

[†]where $\Delta_r G' \equiv \Delta_r G'^{\circ} + R T \ln(p/s)$ and $\Delta_r G'^{\circ} = -R T \ln(K^{\text{eq}})$

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Haldane further showed that the equilibrium constant satisfies the following relationship:

$$K^{\text{eq}} = \frac{k_{\text{cat}}^{+}}{k_{\text{cat}}^{-}} \frac{K_{\text{P}}}{K_{\text{S}}}$$

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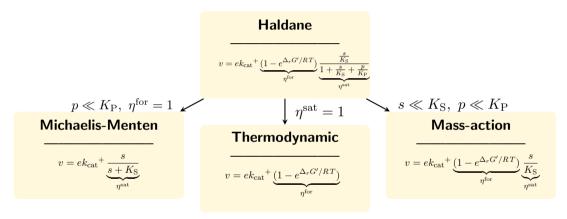
The Haldane rate law can be rewritten (Noor and Liebermeister [2]) as[†]:

$$v = \underbrace{e \cdot k_{\text{cat}}^{+}}_{V_{\text{max}}} \cdot \underbrace{\left(1 - e^{\frac{\Delta_{r}G'}{RT}}\right)}_{\eta^{\text{for}}} \cdot \underbrace{\frac{\frac{s}{K_{\text{S}}}}{1 + \frac{p}{K_{\text{P}}} + \frac{s}{K_{\text{S}}}}}_{\eta^{\text{sat}}}$$

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The factorized Haldane rate law and some simplification



Noor and Liebermeister [2]

Unbranched pathway with "thermodynamic" kinetics

$$\mathsf{S}_0 \stackrel{\mathsf{v}_1}{\longleftarrow} \mathsf{S}_1 \stackrel{\mathsf{v}_2}{\longleftarrow} \dots \stackrel{\mathsf{v}_n}{\longleftarrow} \mathsf{S}_n$$

$$J = e_i \ k_{\mathsf{cat,i}} \left(1 - e^{\Delta_r G_i'/RT} \right)$$

(equivalent to assuming $\eta^{\rm sat} = 1$)

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Optimized flux (approximated) solution*

$$J^* pprox e_{
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where:
$$\bar{k}_{\rm cat} \equiv \underbrace{\left(\sum_j \frac{1}{k_{\rm cat,j}}\right)^{-1}}_{\rm pathway \, specific \, activity}$$
, $\alpha \equiv \left(\sum_j \frac{1}{k_{\rm cat,j}}\right) \cdot \left(\sum_j \frac{1}{\sqrt{k_{\rm cat,j}}}\right)^{-2}$, $\Delta G'_{\rm tot} = \left(\sum_j \Delta_r G'_j\right)$



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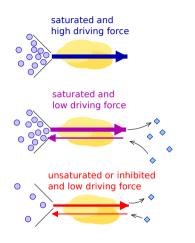
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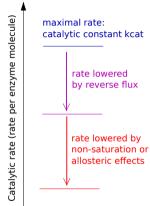
Compare to: $J_{\text{path}} = -L \cdot \Delta G'_{\text{tot}}$

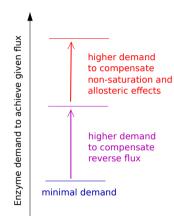
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Enzyme efficiency is also affected by saturation







Minimal demand can be expressed as the inverse of the rate law

Reversible Haldane rate law decomposition:

$$v = e \cdot k_{\text{cat}}^+ \cdot \underbrace{\left(1 - e^{\Delta G'/RT}\right)}_{\eta^{\text{for}}} \cdot \underbrace{\frac{s/K_S}{1 + p/K_P + s/K_S}}_{\eta^{\text{sat}}}$$

And the demand q is defined as the minimum required e for achieving a certain rate v:

$$e = v \cdot \frac{1}{k_{\mathsf{cat}}^+} \cdot \underbrace{\frac{1}{1 - e^{\Delta G'/RT}}}_{1/\eta^{\mathsf{for}}} \cdot \underbrace{\frac{1 + p/K_P + s/K_S}{s/K_S}}_{1/\eta^{\mathsf{sat}}}$$

The minimal enzyme cost of a pathway

Given a pathway:

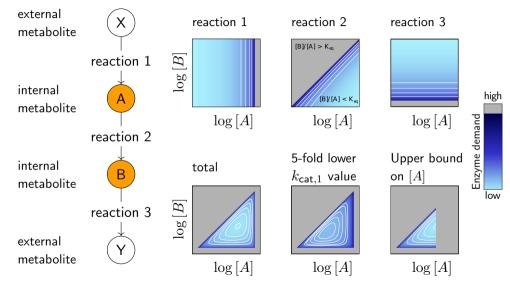
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The enzyme cost is defined as:

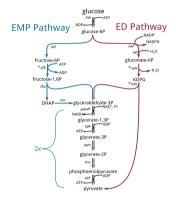
$$\begin{split} e_{\mathsf{tot}} &= \sum_{i} e_{i} \\ e_{i} &= v_{i} \cdot \frac{1}{k_{\mathsf{cat,i}}^{+}} \cdot \frac{1}{\eta_{i}^{\mathsf{for}}(\mathbf{c})} \cdot \frac{1}{\eta_{i}^{\mathsf{sat}}(\mathbf{c})} \end{split}$$

where minimizing e_{tot} over all possible metabolite concentrations (c) gives us the ECM score. This is a convex optimization problem.

Example with 3-step pathway: Enzyme Cost Minimization



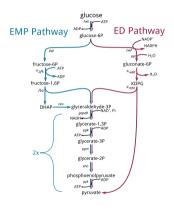
How do bacteria choose between two glycolyses?



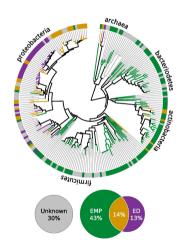
EMP: Embden-Meverhof-Parnas, ED: Entner-Doudoroff*

^{*}Flamholz et al. [1]

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Overall thermodynamics

Stoichiometry of both glycolytic pathways:

 $Glucose + 2 NAD(P)^{+} + n ADP + n Phosphate \longrightarrow 2 Pyruvate + 2 NAD(P)H + n ATP + n H_2O$

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The EMP pathway generates twice as much ATP:

- ► EMP: d = 2 (reminder: $d^{\text{opt}} = 2$, according to Werner et al. [5])
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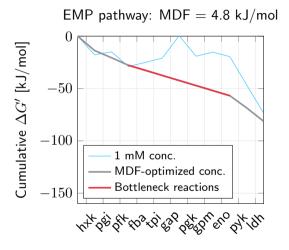
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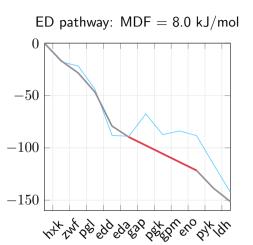
- ► EMP: d = 2 (reminder: $d^{\text{opt}} = 2$, according to Werner et al. [5])
- ▶ ED: d = 1

On the other hand, the total driving force of the ED pathway is larger:

- ightharpoonup EMP: $\Delta G'_{\rm tot} \approx -100 \text{ kJ/mol}$
- ► ED: $\Delta G'_{\rm tot} \approx -160 \text{ kJ/mol}$

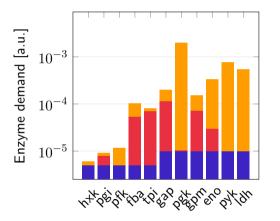
ED has a better thermodynamic profile than EMP



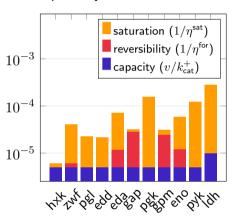


ED has a 5-times lower minimal enzyme cost than EMP

EMP pathway: total demand = 168.5



ED pathway: total demand = 33.9



More than a single pathway

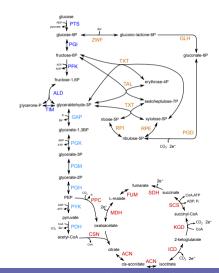
Can we use ECM more generally to predict enzyme/metabolite concentrations in vivo?

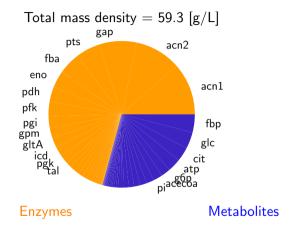
Given any flux (e.g. measured using ¹³C flux analysis) we can find the minimal enzyme cost based on the kinetic model*

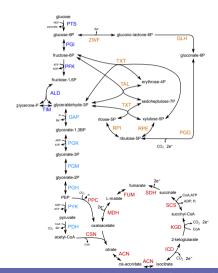
^{*}Noor et al. [4]

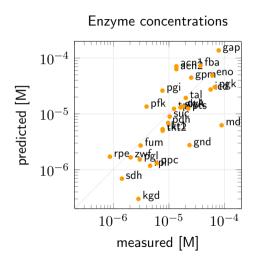
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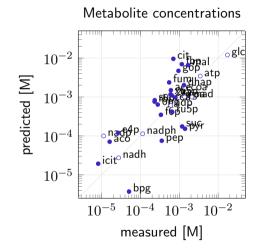
A small model of E. coli's central metabolism – upper glycolysis, lower glycolysis, pentose phosphate pathway. TCA cycle











We considered 4 models with increasing complexity, where pathway flux depends on:

1. the total $\Delta_r G'$ (analytical)

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- 2. the reaction with the lowest driving force (linear programming)

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- 4. the enzyme cost, allowing $\eta^{\rm sat} \leq 1$ (convex optimization)

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- $ightharpoonup e_{tot}$ the enzyme cost [gr]
- $ightharpoonup r_{BM}$ normalized biomass rate [1 / h]
- $\sim \alpha_{\rm ccm}$ fraction of enzyme in proteome [unitless]
- $ightharpoonup \alpha_{prot}$ fraction of protein in dry mass [unitless]

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$$\alpha_{\mathsf{ccm}} = a - \mu b$$

$$\mu = \frac{\alpha_{\mathrm{prot}} \cdot a \cdot r_{\mathrm{BM}}}{1 + b \cdot \alpha_{\mathrm{prot}} \cdot r_{\mathrm{BM}}}$$

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- ▶ Wortel et al. [6] showed that optimal flux strategies must be Elementary Flux Modes (EFMs)

Further extensions of FCM

- ► ECM can be solved efficiently using convex optimization
- But what if we don't know the flux in advance?
- ▶ Wortel et al. [6] showed that optimal flux strategies must be Elementary Flux Modes (EFMs)
- Since there is a finite number of EFMs, we can enumerate them and find the one with the lower ECM score

Bibliography

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Lecture #5: "The enzyme cost of metabolic fluxes"