The Enzyme Cost of Metabolic Pathway Fluxes

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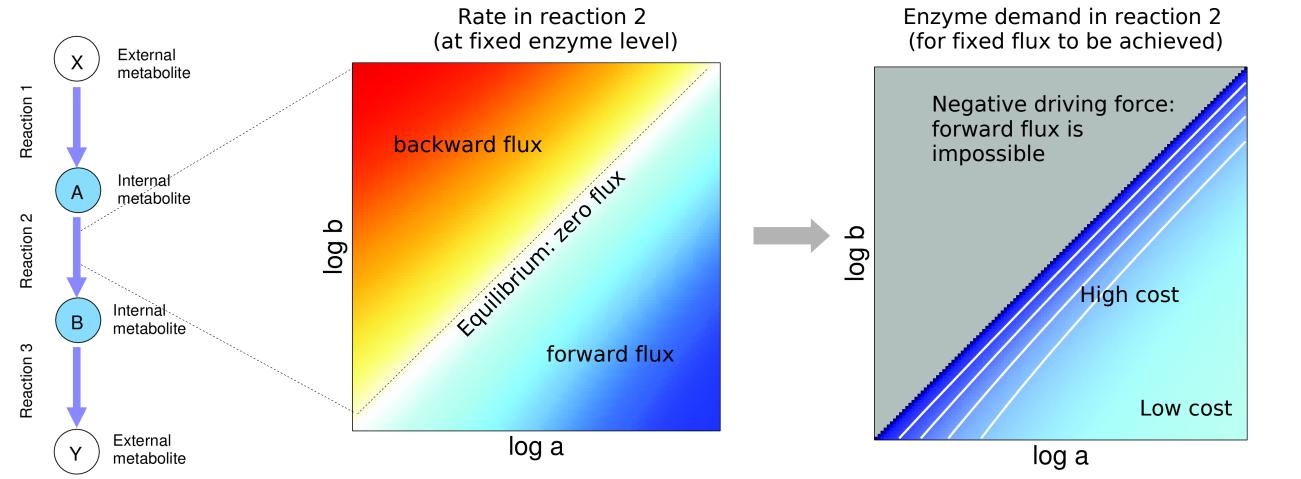
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Enzyme investment plays a major role in choices between alternative metabolic routes in evolution and bioengineering. To study metabolism from an economic perspective, we propose a modelling approach in which metabolic fluxes are predefined and enzyme levels sustaining these fluxes are computed by cost minimization.

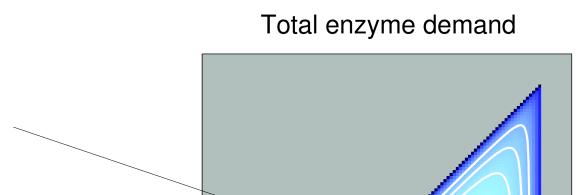
Following previous work [1,2], we define general enzyme cost functions based on known or simplified rate laws. With logarithmic metabolite levels treated as free variables, enzyme optimization becomes a convex problem. Enzyme cost minimization can help construct kinetic models with plausible metabolic and thermodynamic states.

1. Enzyme cost on the metabolite polytope

Enzyme cost in a pathway with reversible Michaeils-Menten rate laws:



Thermodynamically feasible metabolite profiles form a polytope in the space of logarithmic metabolite levels. The total enzyme cost is a convex function on this polytope. Enzyme cost function and resulting optimal metabolite and enzyme levels depend on the choice of fluxes, enzyme cost weights, and rate constants.



cost scores are derived from separable rate laws [3]: Example: Reaction A \leftrightarrow B with Michaelis-Menten law, non-competitive inhibition,

and thermodynamic driving force $\theta = -\Delta G/RT$

2. A hierarchy of enzyme cost functions

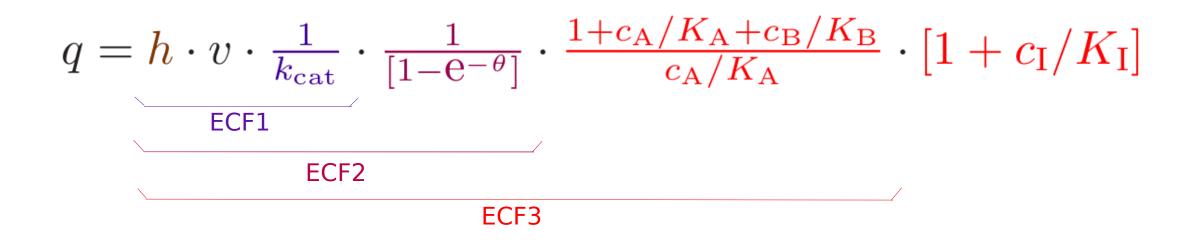
$$v = \mathbf{E} \cdot k_{\text{cat}} \cdot \left[1 - e^{-\theta}\right] \cdot \frac{c_{\text{A}}/K_{\text{A}}}{1 + c_{\text{A}}/K_{\text{A}} + c_{\text{B}}/K_{\text{B}}} \cdot \frac{1}{1 + c_{\text{I}}/K_{\text{I}}}$$

Since parameter values are often missing, we construct simple formulae for

enzyme costs with different demands for parameters to be known. All enzyme

Non-competitive allosteric regulation

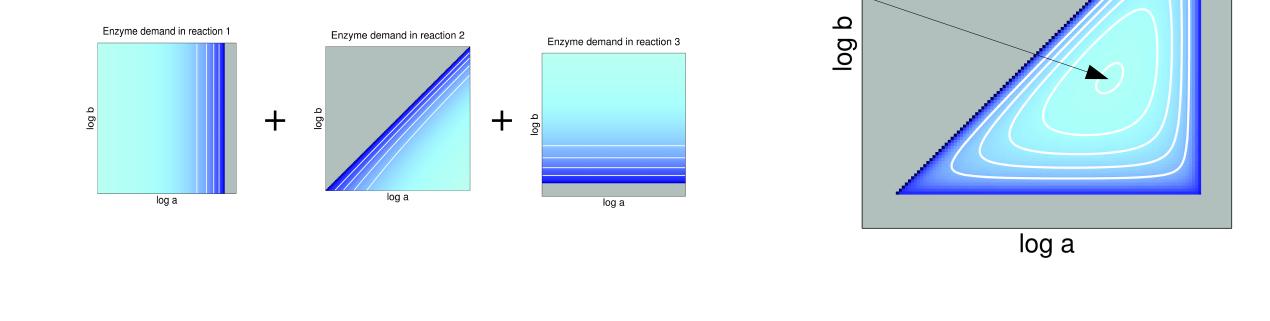
The pathway enzyme cost is a sum $Q = \sum_l q_l = \sum_l h_l \cdot E_l$ of reaction enzyme costs



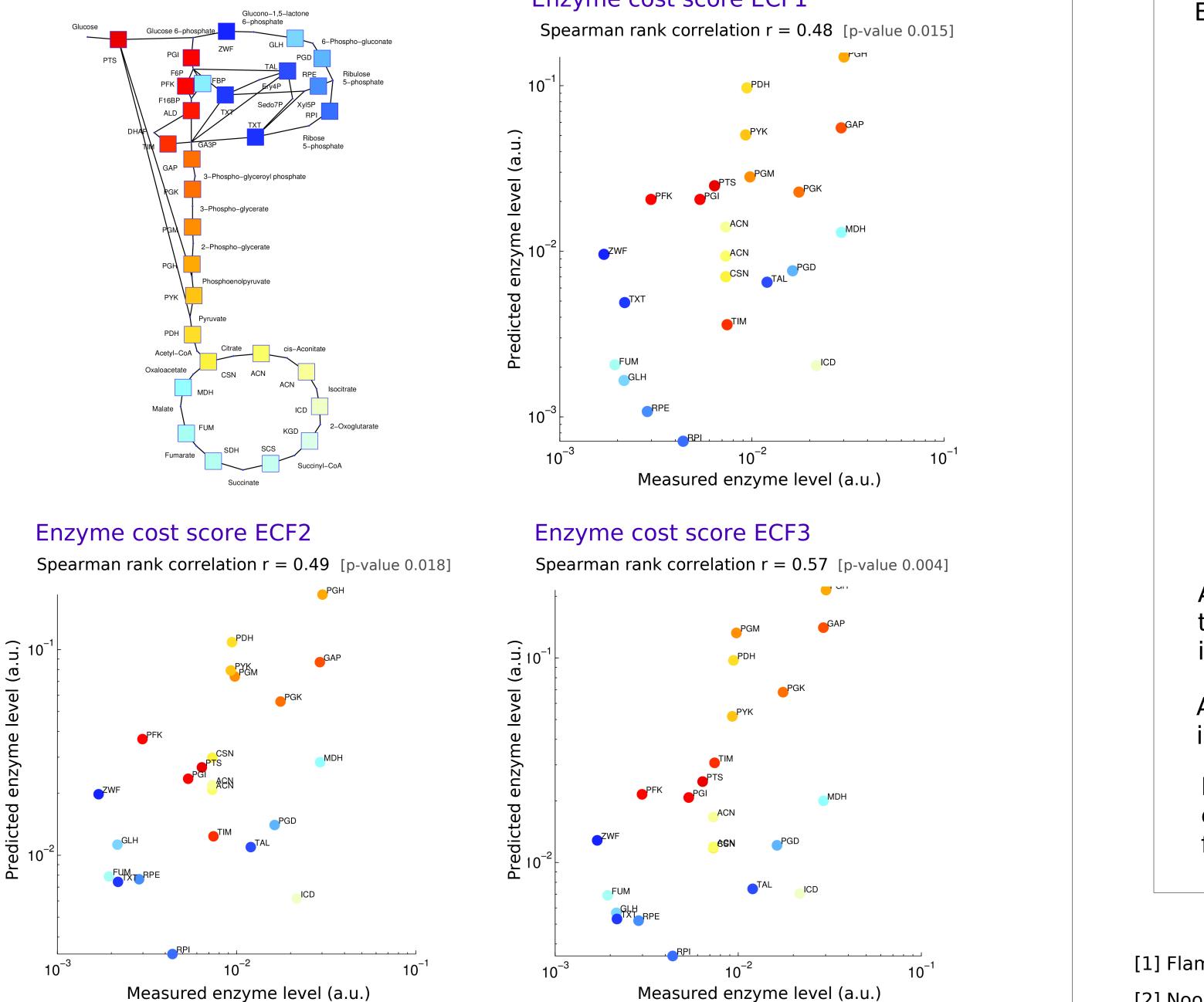
By omitting some terms, simplified enzyme cost functions (ECF) with fewer parameters are obtained. The cost scores hold for any reaction stoichiometries.

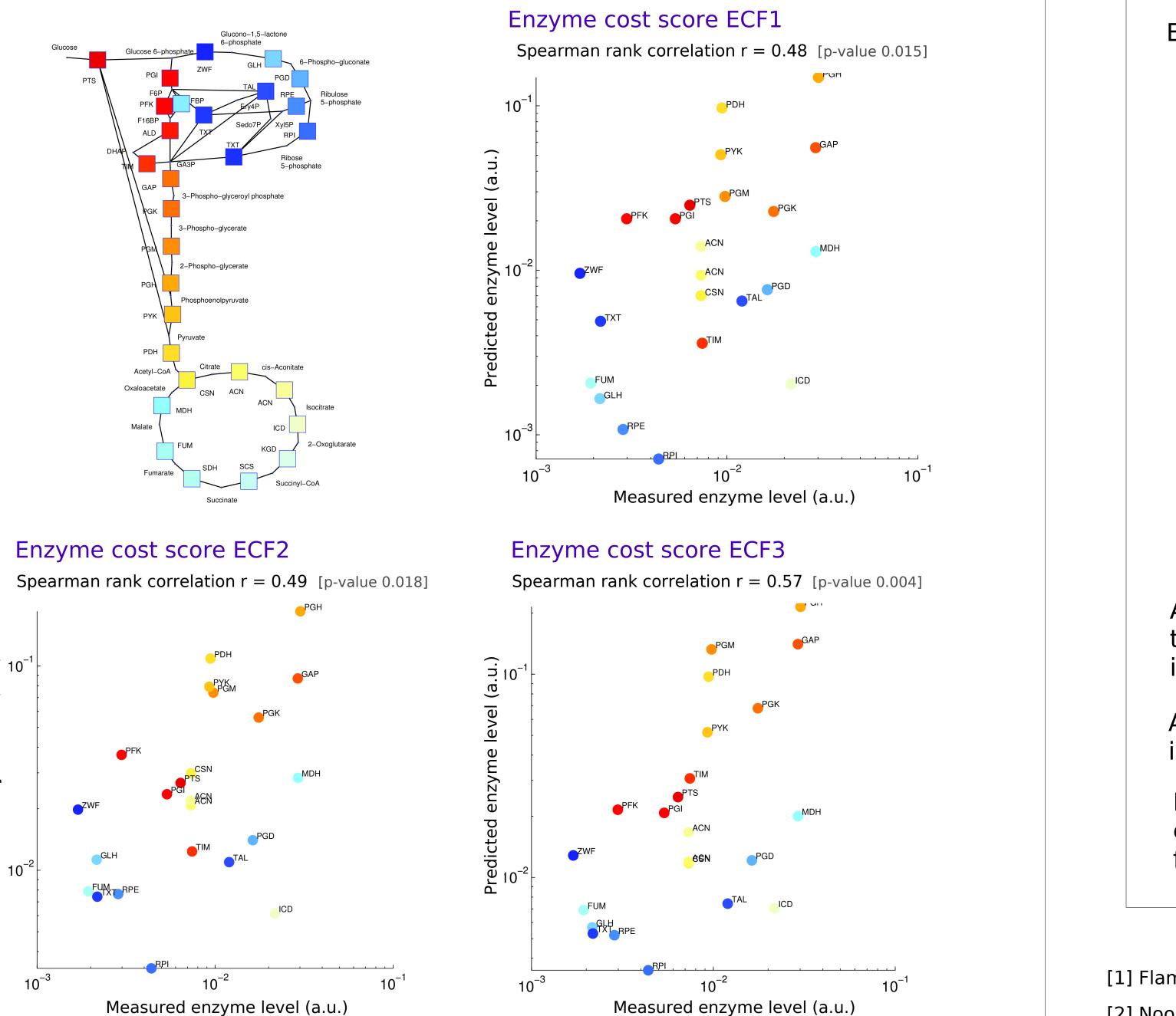
Short	Enzyme	Catalytic	Thermodyn.	Enzyme	Depends on / can predict
name	cost	constant		saturation	
	h	$k_{\rm cat}^+$	$\eta^{\mathrm{th}}(\Theta)$	$\eta^{ m kin}({f c},K_{ m M})$	
ECF0	-/ \/	-	-	-	Enzyme
ECF1	-/__		– ,	-	Enzyme
ECF2	-/ \/			- ,	Enzyme + Thermodynamic force
ECF3	-/ \/				Enzyme + Metabolite levels
ECF4	-/ \/			\bigvee_{-}	Enzyme + Metabolite levels

Minimum point yields optimal metabolite and enzyme profiles



3. Enzyme levels predicted for *E. coli* central metabolism



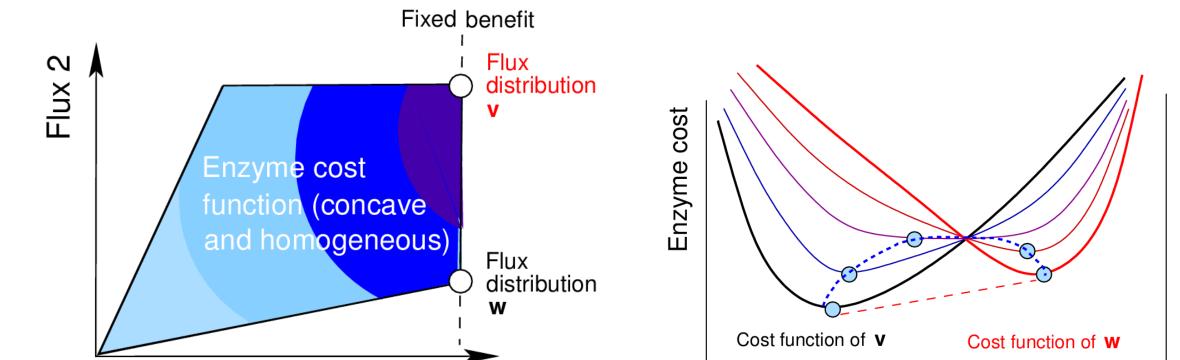


4. Mathematical results relevant to flux analysis

Enzyme cost functions as defined here show two general properties:

(i) The enzyme cost function is convex on the metabolite polytope.

(ii) The optimized enzyme cost is a concave function on the segments of the flux polytope (i.e. flux polytopes with defined flux directions)



Date sources: Equilibrium constants computed using component contributions [4]; Rate constants from Brenda, processed by parameter balancing [5]; Flux data: [6]; Protein data: [7] Flux 1

Space of logarithmic metabolite levels

A convex combination of two flux modes v and w has typically a higher cost than the costs of **v** and **w** together. Moreover, separating the pathway fluxes in cell compartments or distinct temporal phases can provide an advantage.

Among the stationary flux distributions with predefined benefit, the enzyme cost is minimized by an elementary mode, as previously shown in [8,9].

FBA methods based on flux minimization ignore the exact relationship between enzyme levels and stationary fluxes. Our enzyme costs could replace the linear flux costs typically used in FBA.

[1] Flamholz et al. (2013), PNAS 110(24), 10039–10044 [2] Noor et al. (2014), PLoS Comp. Biol. 10:e100348 [3] Noor et al. (2013), FEBS Letters 587 (17), 2772-2777 [4] Noor et al. (2013), PLOS Comp. Biol. 9:e1003098 [5] Lubitz et al. (2010) J. Phys. Chem. B 114 (49), 16298-16303

[6] Chen et al. (2010), Metabolic Engineering 13 (1), 38-48 [7] Valgepea *et al.* (2013), Mol. Biosyst. 9 (9), 2344-23458 [8] Wortel et al. (2014), FEBS Journal 281 (6), 1547-1555 [9] Müller et al. (2014). J. Theor. Biol. 190, 347-182

