

Genomics & Computational Biology

Section 10: Metabolic Networks

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Metabolic Networks

- *Why study biological networks?*
 - Genomics and proteomics tell us the ‘parts’ of the cell, but they give limited information about their interactions and co-dependencies. Ideally, we’d like to understand the interactions well enough that we could predict the system’s behavior computationally – “in silico biology”.
- *Applications:*
 - Phenotype prediction
 - Bioengineering
 - Synthetic media design
- *“In Silico Biology”*
 - Uses computational representations of a cell or organism to model the organism’s behavior.
 - Kinetic models (e.g., the red blood cell model discussed in class)
 - **Flux Balance Analysis:** based on the stoichiometry of biochemical reactions associated with different cellular components and mass conservation

Kinetics of Enzymatic Reactions

- **Reaction rate (flux):** the increase/decrease in molar concentration of product/reactant of a reaction per unit time

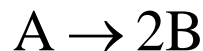
$$v = \frac{1}{S_i} \frac{d[X_i]}{dt}$$

where $[X_i]$: the molar concentration of metabolite X_i

S_i : the stoichiometric coefficient of X_i ,

negative for reactants and positive for products

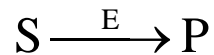
e.g.



$$v = -\frac{d[A]}{dt} = \frac{1}{2} \frac{d[B]}{dt}$$

- Reaction kinetics: generally non-linear functions of
 - Temperature
 - Concentrations of substrates and enzymes

e.g. Michaelis-Menten equation

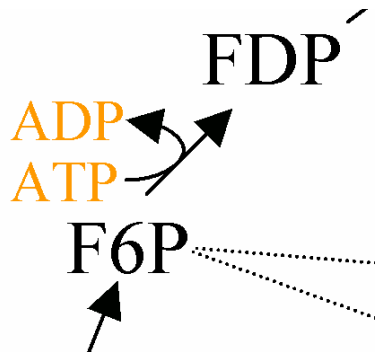


$$v = \frac{V_{\max} [S]}{[S] + K_M}$$

where V_{\max} = Maximum rate

K_M = Michaelis - Menten constant (measures enzyme/substrate affinity)

e.g. Phosphofructokinase



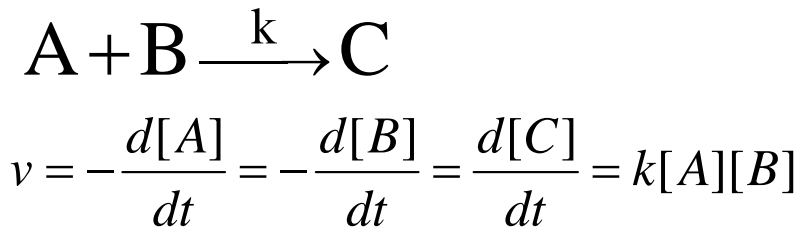
$$v_{PFK} = \frac{v_{mx}^{PFK}}{N_{PFK}} \left(\frac{F6P / K_{F6P}^{PFK}}{1 + F6P / K_{F6P}^{PFK}} \right) \left(\frac{Mg \cdot ATP / K_{Mg \cdot ATP}^{PFK}}{1 + Mg \cdot ATP / K_{Mg \cdot ATP}^{PFK}} \right)$$

$$N_{PFK} = 1 + L_0^{PFK} \frac{\left(1 + \frac{ATP_{free}}{K_{ATP}^{PFK}} \right)^4 \left(1 + \frac{Mg}{K_{Mg}^{PFK}} \right)^4}{\left(1 + \frac{AMP}{K_{AMP}^{PFK}} \right)^4 \left(1 + \frac{F6P}{K_{F6P}^{PFK}} \right)^4}$$

Mass Action Kinetics

- The rate of a reaction is proportional to the product of the concentrations of the reactants

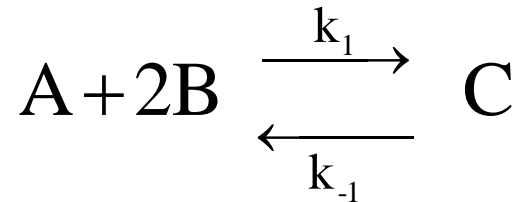
e.g.



$$\frac{d[A]}{dt} = -k[A][B]$$

$$\frac{d[B]}{dt} = -k[A][B]$$

$$\frac{d[C]}{dt} = k[A][B]$$



$$v_1 = k_1[A][B]^2; \quad v_{-1} = k_{-1}[C]$$

$$\frac{d[A]}{dt} = -k_1[A][B]^2 + k_{-1}[C]$$

$$\frac{d[B]}{dt} = -2k_1[A][B]^2 + 2k_{-1}[C]$$

$$\frac{d[C]}{dt} = k_1[A][B]^2 - k_{-1}[C]$$

Michaelis-Menten Kinetics



Assumptions of the mechanism:

- substrate and enzyme form intermediate complex
- the intermediate complex is in steady state with respect to the overall reaction rate
- the reverse reaction of the final step is neglectable

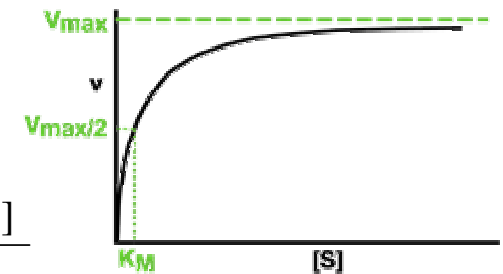
$$\frac{d[ES]}{dt} = k_1[E][S] - (k_{-1} + k_2)[ES] = 0$$

$$E_t = [E] + [ES]$$

$$\Rightarrow [ES] = \frac{k_1[E_t][S]}{k_1[S] + k_{-1} + k_2}$$

$$\Rightarrow v = \frac{d[P]}{dt} = k_2[ES] = \frac{k_1 k_2 [E_t][S]}{k_1[S] + k_{-1} + k_2} = \frac{k_2 [E_t][S]}{[S] + (k_{-1} + k_2)/k_1} \equiv \frac{V_{\max} [S]}{[S] + K_M}$$

where $V_{\max} \equiv k_2[E_t]$; $K_M = (k_{-1} + k_2)/k_1$



Kinetic Models of Metabolic Networks

- Simulation of dynamic processes
- Use of ordinary differential equations (ODEs) correlating the metabolite concentrations and their change rates
 - e.g. Human Red Blood Cell ODE model:
 - 44 rate expressions with ~ 5 constants each $\rightarrow \sim 200$ parameters
- Mass balance equations are linear functions of the reaction rates, BUT are non-linear functions of the actual metabolite concentrations.
- Limitations
 - reaction mechanisms or exact reaction rate expressions are generally unavailable
 - kinetic parameters are hard to measure/obtain
 - *in vitro* values of kinetic parameters may not represent the *in vivo* values
 - difficult to treat mathematically

Flux Balance Analysis (FBA)

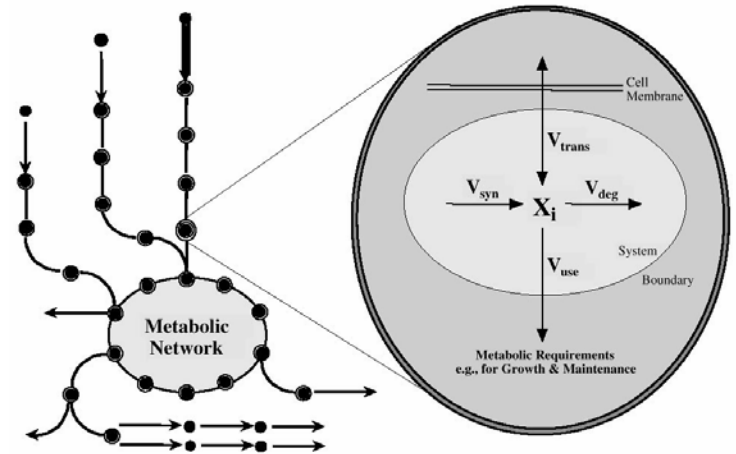
Four basic types of metabolic flux rates affect the concentration of any given metabolite pool:

v_{syn} = synthesis rate

v_{deg} = degradation rate

v_{trans} = transport rate (import and export)

v_{use} = consumption rate (use rate required for growth and maintenance)



The **net flux rate** for a metabolite X_i is:

$$\frac{d[X_i]}{dt} = (V_{syn} - V_{deg} - V_{use}) - V_{trans} = (S_{ij}v_j) - b_i$$

where v_j is the j th reaction rate, b_i is the transport rate, S_{ij} is the “stoichiometric matrix” = moles of metabolite i produced in reaction j

Steady State Analysis

$$\frac{d\mathbf{X}}{dt} = \mathbf{S} \cdot \mathbf{v} - \mathbf{b} = 0$$

- The steady state assumption
 - Time constants for metabolic reactions are very fast (sec - min) compared to cell growth and culture fermentations (hrs)
 - There is not a net accumulation of metabolites in the cell over time.
- Removes \mathbf{X} and t as variables; helps to get around the problem of non-linearity
- Additional constraints
 - specific measurement – typically for uptake rxns
 - the flux level through certain reactions is known
 - maximal internal flux

FBA

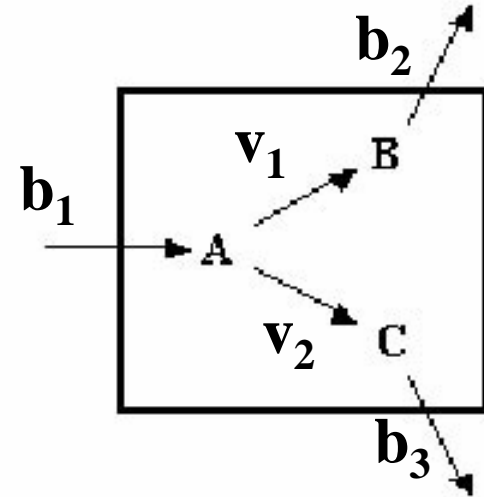
- When enough measurements are available, we can solve the steady state mass balance equations (\mathbf{S} is available from genomic analysis and \mathbf{b} can be determined experimentally)
- Underdetermined system
 - In general, not enough measurements of the metabolic fluxes can be made
 - More fluxes to determine than mass balance constraints on the system
- Identify a specific point within the feasible set under a given condition
 - **Assumption:** The cell has found the optimal solution by adjusting the system specific constraints (enzyme kinetics and gene regulation) through evolution and natural selection
 - Use of linear programming (LP): Determine the optimal utilization of the metabolic network, subject to the physicochemical constraints, to maximize, for example, the growth of the cell

How to Analyze a Network Using FBA

1. Label Fluxes

- External fluxes: b_1, b_2, b_3, \dots
- Internal fluxes: v_1, v_2, v_3, \dots

Note: 1 flux per enzymatic reaction. E.g.: $A \xrightarrow{v_1} B$



2. Derive Equations

- One equation per biological component
- Make sure you include **all** arrows/fluxes
- Keep your signs consistent
 - E.g., arrows towards a component positive, arrows away negative

Here we have three components, so we have three equations.

$$\text{A: } b_1 - v_1 - v_2 = 0$$

$$\text{B: } v_1 - b_2 = 0$$

$$\text{C: } v_2 - b_3 = 0$$

Notice that we have five unknowns (v_1, v_2, b_1, b_2, b_3) and three equations. This is an example of an **underdetermined system**, which means there is no unique solution to it. Instead we get a range of allowable solutions, where any set of values that falls within that range is a solution to the set of equations. This range is called the **null space**. We can find the null space of a set of equations using linear algebra, but to do this we need to convert our equations to matrix form.

How to Analyze a Network Using FBA

3. Convert the system of equations to a matrix equation: $\mathbf{S} \cdot \mathbf{v} = \mathbf{0}$

- \mathbf{S} is a matrix containing the numerical coefficients in the equations
- \mathbf{v} is a vector whose components are the fluxes
- Each row of \mathbf{S} corresponds to one equation, so our matrix has as many rows as the number of metabolites in our system
- Each column of \mathbf{S} corresponds to a flux, so our matrix has as many columns as the number of fluxes in our system
- The equation $\mathbf{S} \cdot \mathbf{v} = \mathbf{0}$ means that the **dot product** of matrix \mathbf{S} and vector \mathbf{v} equals 0
- The matrix equation for our system is:

$$\begin{pmatrix} -1 & -1 & 1 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & -1 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ b_1 \\ b_2 \\ b_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

- Note that you can perform the product to confirm that your matrix is correct.

$$\begin{aligned} - & \text{ A: } (-1)(v_1) + (-1)(v_2) + (1)(b_1) + (0)(b_2) + (0)(b_3) = -v_1 - v_2 + b_1 \\ - & \text{} \end{aligned}$$

How to Analyze a Network Using FBA

4. Solve for the “null space” of S (if interested)

- There are linear algebra techniques that will allow you to do this by hand, but it’s much easier to just do it with Mathematica which has a built-in function for it:

MatrixForm[NullSpace[m]]

- Here ‘ m ’ is the matrix whose null space we want, “NullSpace” is the Mathematica command to do it, and nesting it within “MatrixForm” turns the result into matrix format.
- For our example, the solution is:
$$\begin{pmatrix} 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 \end{pmatrix}$$
- Each row is a linearly- and genetically-independent pathway in our system. Because they are linearly independent, they form a **basis**, meaning any pathway in our system can be constructed from linear combinations (additions and subtractions) of these vectors.
- All linear combinations of the basis vectors are solutions to $S \cdot v = 0$

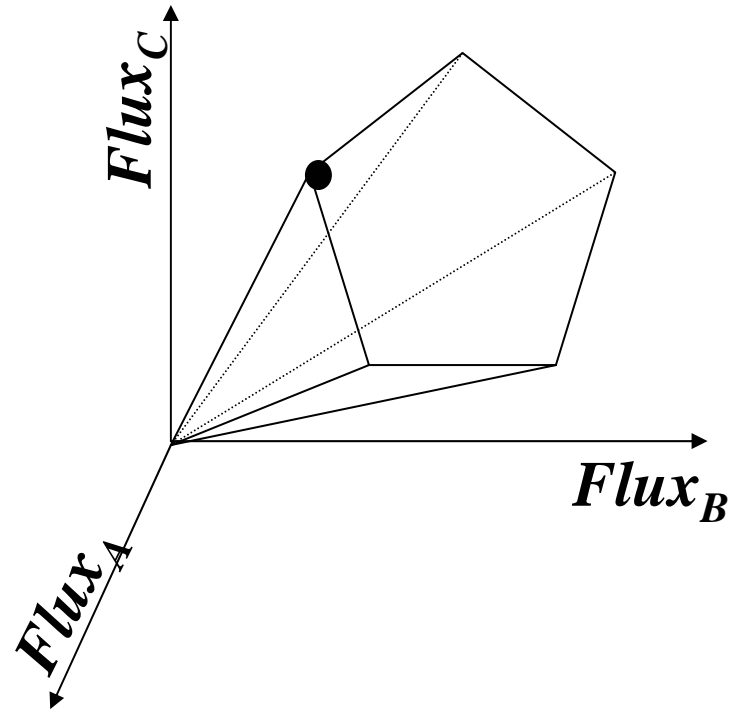
How to Analyze a Network Using FBA

5. Predict system-level behavior based on optimality assumptions

- We can predict the behavior of the system under a variety of different conditions/constraints. We do this by using **linear programming (LP)**, which is a type of algorithm that optimizes with respect to a set of **decision variables** for a given **objective function** and under a set of **constraints**.
- The **objective function** is the function or component that you would like to optimize. For example, if we want to minimize the export of C, the cost function is b_3 .

$$\begin{array}{ll} \underset{v}{Max} & Z = f(v) \\ \text{subject to} & \mathbf{S} \cdot \mathbf{v} = \mathbf{b} \\ & \alpha_i \leq v_i \leq \beta_i \end{array}$$

- The feasible space for the flux distribution (the null space of S) is a **convex polyhedral cone** and represents the **metabolic capabilities** of the network.
- The actual flux distribution is determined by the cell's regulatory mechanisms.
- In absence of kinetic information, we can estimate the metabolic flux distribution by postulating **objective functions**(Z) that underlie the cell's behavior.



A schematic representation of the feasible space in a hypothetical 3-flux system

- The **constraints** are:
 - Steady state: $S \cdot v = 0$
 - Biochemically feasible: non-negativeness
 - The range of values each flux can take
- We can use **Excel** to solve linear programs
- Here we are telling Excel the following:
 - Minimize the export flux b_3
 - The fluxes must satisfy matrix $S \cdot v = 0$
 - Internal fluxes v_1 and v_2 can take any positive value
 - Export fluxes b_1 , b_2 , and b_3 can be between 0 and 100, 5 and 10, and 0 and 10, respectively
- This gives the following result: **{5,0,5,5,0}**
- This means that b_3 reaches its lowest value given the above constraints when the fluxes are: $v_1 = 5$, $v_2 = 0$, $b_1 = 5$, $b_2 = 5$, $b_3 = 0$.

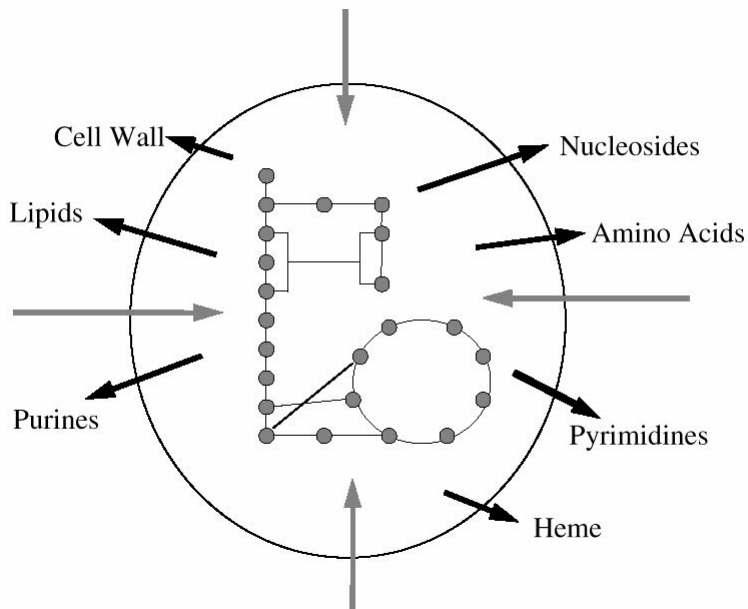
Excel

Flux Balance Example		
Objective		
Z	0	
Decision variables		
v1	5	
v2	0	
b1	5	
b2	4.999999	
b3	0	
Constraints		
Export limit 1: b1 <= 100	5	100
Export limit 2: b2 >= 5	4.999999	5
Export limit 3: b2 <= 10	4.999999	10
Export limit 4: b3 <= 10	0	10
Non-negativity 1: v1 >= 0	5	0
Non-negativity 2: v2 >= 0	0	0
Non-negativity 3: b1 >= 0	5	0
Non-negativity 4: b2 >= 0	4.999999	0
Non-negativity 5: b3 >= 0	0	0
Steady state A: b1-v1-v2 = 0	0	0
Steady state B: v1-b2 = 0	1E-06	0
Steady state C: v2-b3 = 0	0	0

- One widely used biologically meaningful objective function, at least for prokaryotic metabolic networks such as *E. coli*, is the biomass growth function.

$$\sum_{all M} d_M \cdot M \xrightarrow{v_{growth}} biomass$$

where d_M represents the stoichiometric ratio in which metabolite M is required for growth.



These metabolic demands for growth are based on composition analysis of cell mass which for *E. coli* are:

Cofactor	d_M (mmol)	Precursor	d_M (mmol)	Precursor	d_M (mmol)
ATP	41.2570	G6P	0.2050	3PG	1.4960
NADH	-3.5470	F6P	0.0709	PEP	0.5191
NADPH	18.2250	R5P	0.8977	Pyr	2.8328
		E4P	0.3610	AcCoA	3.7478
		T3P	0.1290	OA	1.7867
				α KG	1.0789

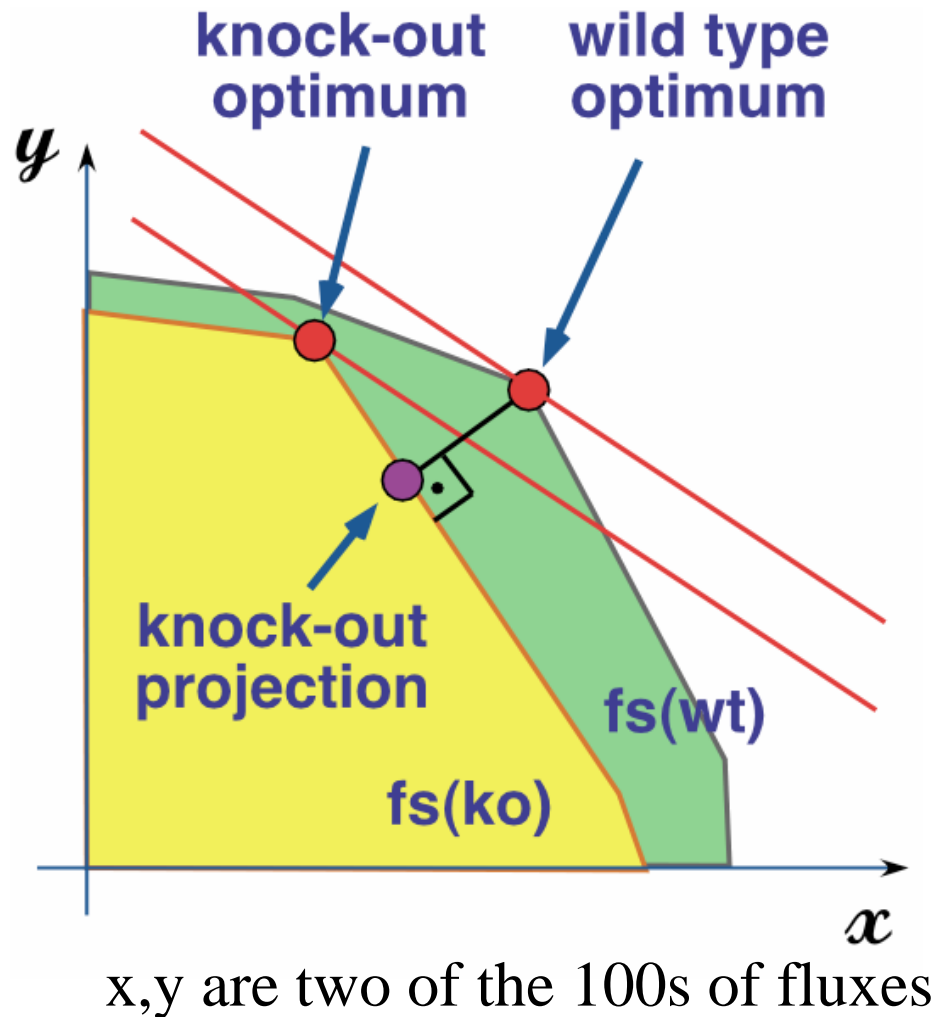
- **Comparison between model predicted fluxes and experimentally measured ones.**

Example E. coli:

Experimental/<i>in silico</i>									
Gene	Glucose	Glycerol	Succinate	Acetate	Gene	Glucose	Glycerol	Succinate	Acetate
<i>aceEF</i>	-/+				<i>pgl</i>	+/+			
<i>aceA</i>				-/-	<i>pntAB</i>	+/+	+/+	+/+	+/+
<i>aceB</i>				-/-	<i>glk</i>	+/+			
<i>ackA</i>				+/+	<i>ppc</i>	+/+	-/+	+/+	+/+
<i>acs</i>				+/+	<i>pta</i>				+/+
<i>acn</i>	-/-	-/-	-/-	-/-	<i>pts</i>	+/+			
<i>cyd</i>	+/+				<i>pyk</i>	+/+			
<i>cyo</i>	+/+				<i>rpi</i>	-/-	-/-	-/-	-/-
<i>eno</i>	-/+	-/+	-/-	-/-	<i>sdhABCD</i>	+/+			
<i>fba</i>	-/+				<i>tpi</i>	-/+	-/-	-/-	-/-
<i>fbp</i>	+/+	-/-	-/-	-/-	<i>unc</i>	+/+		+/+	-/-
<i>gap</i>	-/-	-/-	-/-	-/-	<i>zwf</i>	+/+			
<i>gltA</i>	-/-	-/-	-/-	-/-	<i>sucAD</i>	+/+			
<i>gnd</i>	+/+				<i>zwf, pnt</i>	+/+			
<i>idh</i>	-/-	-/-	-/-	-/-	<i>pck, mez</i>			-/-	-/-
<i>ndh</i>	+/+	+/+			<i>pck, pps</i>			-/-	-/-
<i>nuo</i>	+/+	+/+			<i>pgi, zwf</i>	-/-			
<i>pfk</i>	-/+				<i>pgi, gnd</i>	-/-			
<i>pgi</i>	+/+	+/+			<i>pta, acs</i>				-/-
<i>pgk</i>	-/-	-/-	-/-	-/-	<i>tktA, tktB</i>	-/-			

Minimization of Metabolic Adjustment (MOMA)

- **Perturbed metabolic networks** (mutants, growth under conditions that seldom exist naturally)
- An **alternative optimality assumption**: the cell adjusts its flux distribution through regulations such that its metabolic state is as close to its wild type state as possible
- The cell has not been optimized towards growth through evolution and instead, its flux distribution is close to the wild type counterpart.



MOMA- Quadratic Programming (QP)

$$\begin{array}{ll} \underset{\mathbf{v}}{\text{Min}} & Z = \sum_{\mathbf{v}} (v - v_{wt})^2 \\ \text{subject to} & \mathbf{S} \cdot \mathbf{v} = \mathbf{b} \\ & \alpha_i \leq v_i \leq \beta_i \\ & v_m = 0 \end{array}$$

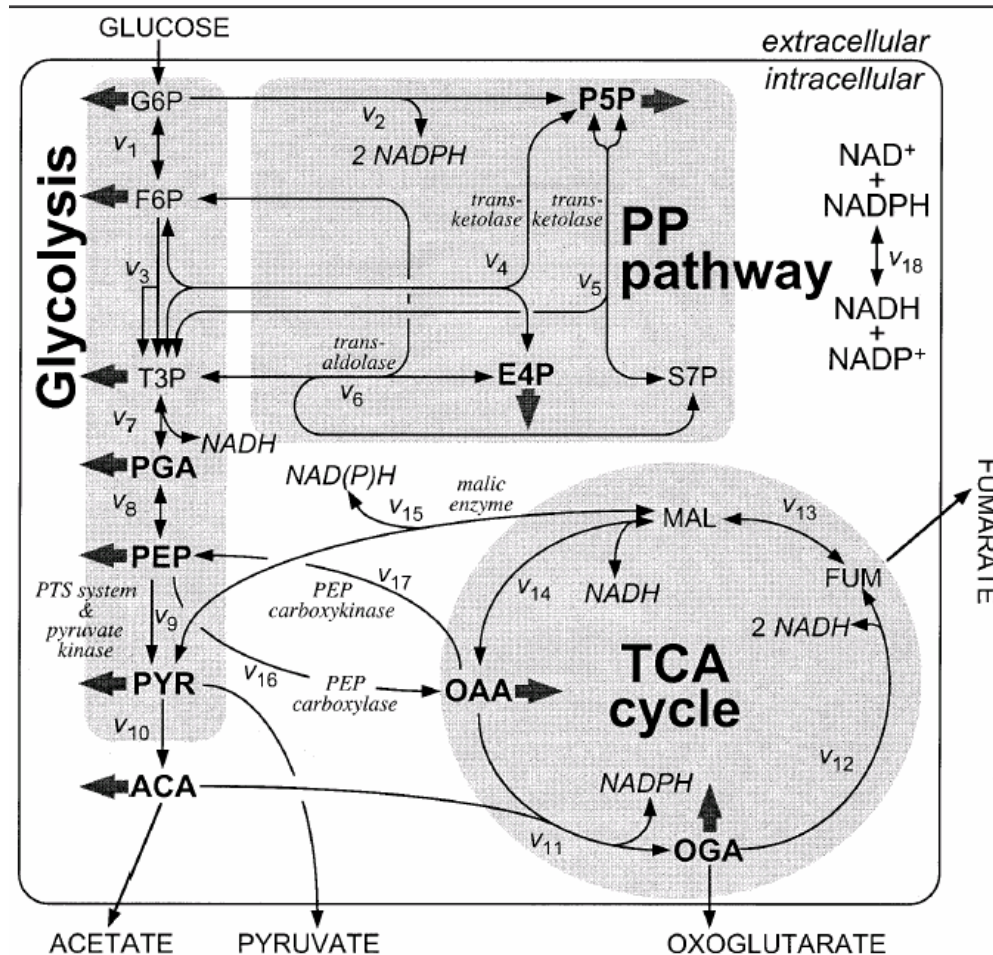
where v_{wt} is the optimal flux distribution of the wild type cell; v_m are the fluxes that get eliminated due to gene knockouts.

- Distance function
 - Normalization
 - 1-norm, **2-norm (Euclidean)**, and infinity-norm distances
 - inclusion of growth flux
- Quadratic programming
 - quadratic objective function; linear constraints
 - many solvers available (e.g. Excel)

Metabolic Flux Responses to Pyruvate Kinase Knockout in *Escherichia coli*

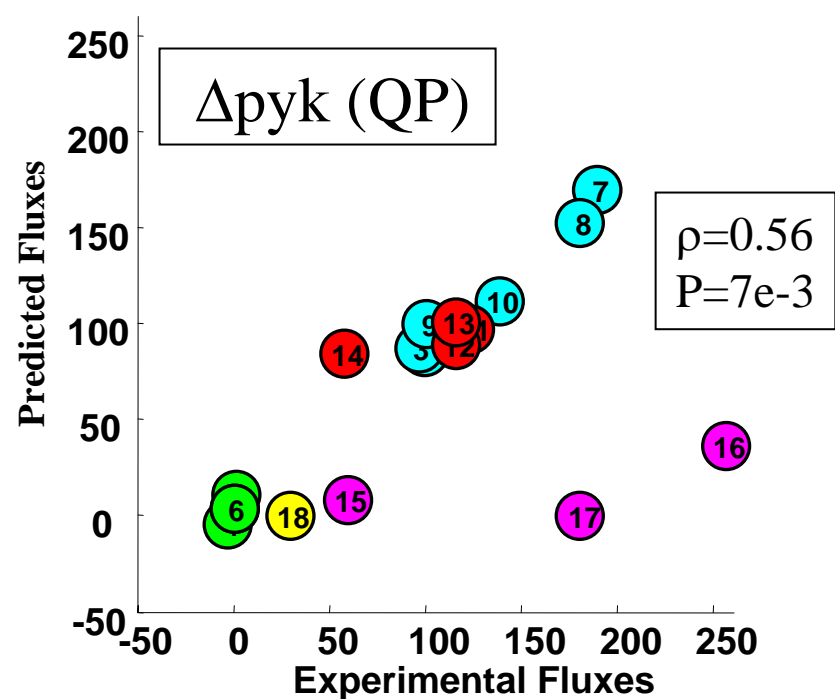
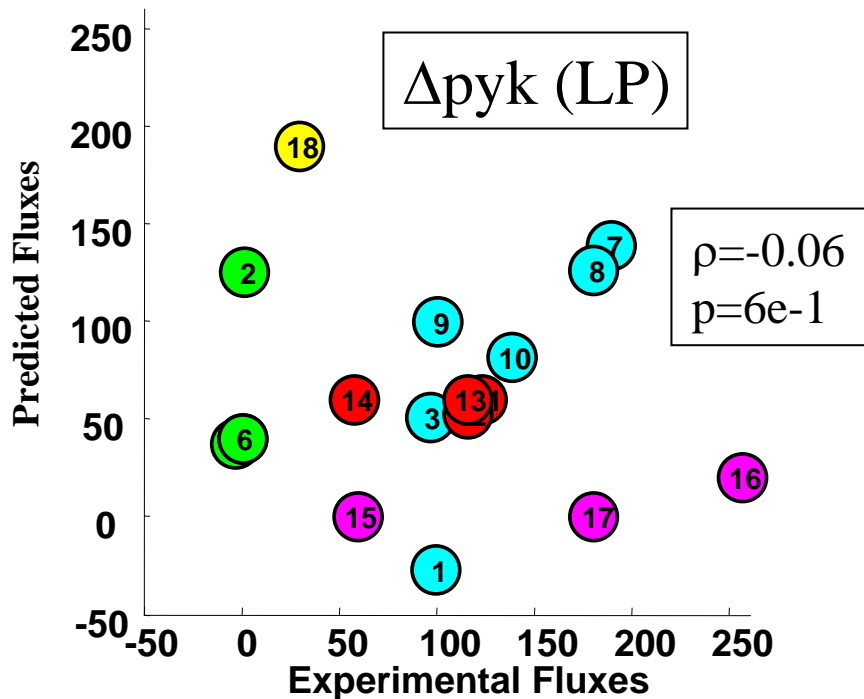
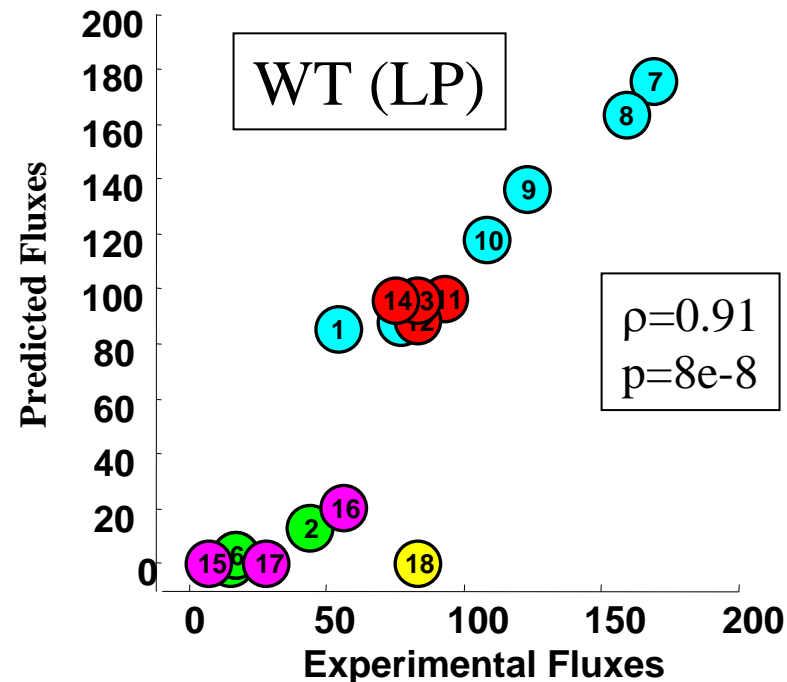
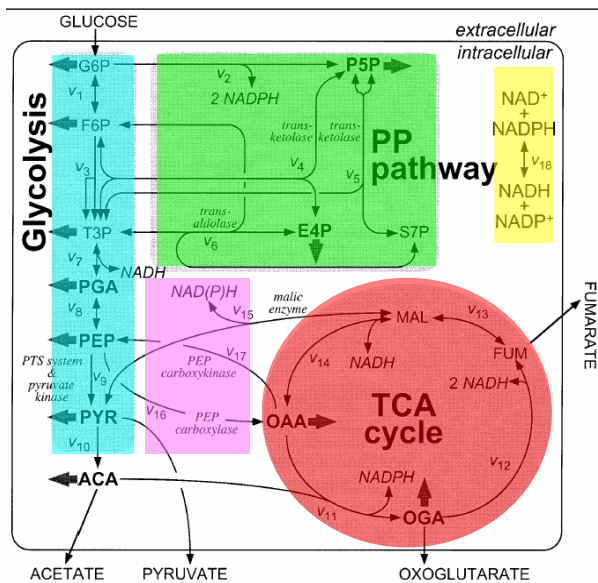
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Flux
Data

C009-limited



Flux data (MOMA & FBA)

Condition	Method	ρ_1	p-val (a)	p-val (b)	ρ_2	p-val (c)	p-val (d)
C-0.09	wt	0.91	8.2E-08				
	ko (FBA)	-0.064	6.0E-01	3.3E-03	-0.36	9.0E-01	2.4E-04
	ko MoMA	0.56	7.4E-03		0.48	2.3E-02	
C-0.4	wt	0.97	8.1E-12				
	ko (FBA)	0.77	8.1E-05	2.5E-03	0.36	7.0E-02	1.4E-02
	ko MoMA	0.94	2.6E-09		0.74	2.3E-04	
N-0.09	wt	0.78	7.1E-05				
	ko (FBA)	0.86	3.0E-06	9.0E-02	0.096	3.5E-01	4.6E-02
	ko MoMA	0.73	2.8E-04		0.49	2.0E-02	

Segre, et al, 2002 Analysis of optimality in natural and perturbed metabolic networks. PNAS 99: 15112-7.

References for FBA

Review:

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Application to E. Coli:

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MOMA

- Segre, et al, 2002 Analysis of optimality in natural and perturbed metabolic networks. **PNAS** 99: 15112-7. (Minimization Of Metabolic Adjustment)
<http://arep.med.harvard.edu/moma/>

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- Reference for enzymatic kinetics:

Biochemical Systems Analysis: A Study of Function and Design in Molecular Biology. Michael A. Savageau, Addison-Wesley Publishing Company, 1976.