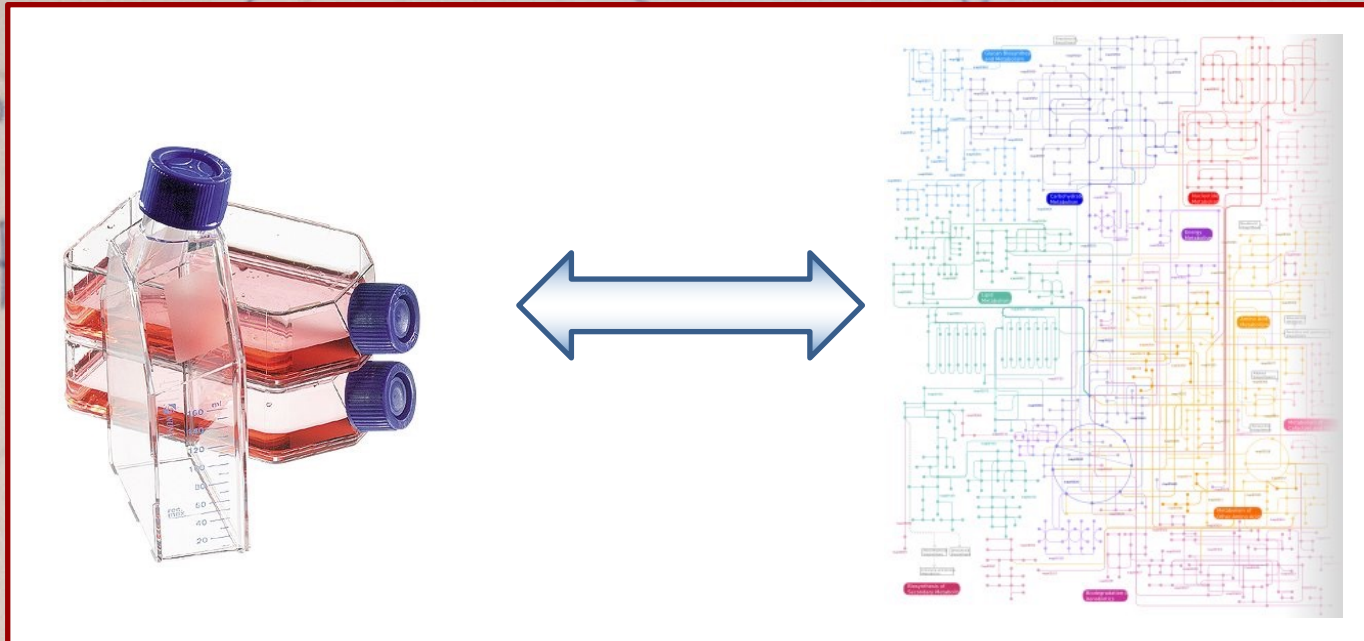


Dynamic modelling of metabolism

Model construction and enzyme kinetics



We are all here to learn and discuss!





The Menu

Principles of dynamic modelling

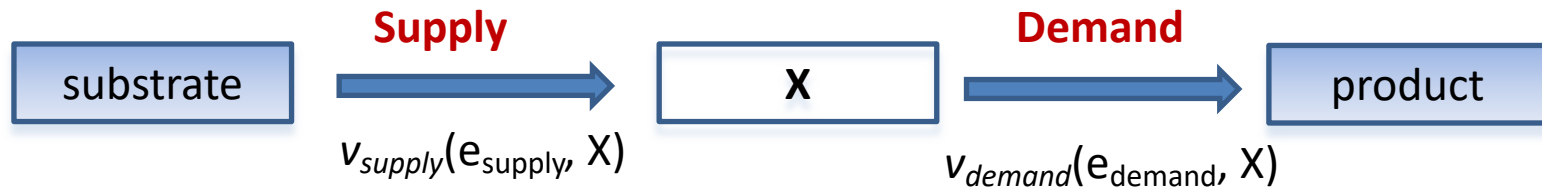
a. Model construction

b. Enzyme kinetics

The Systems Biology cycle



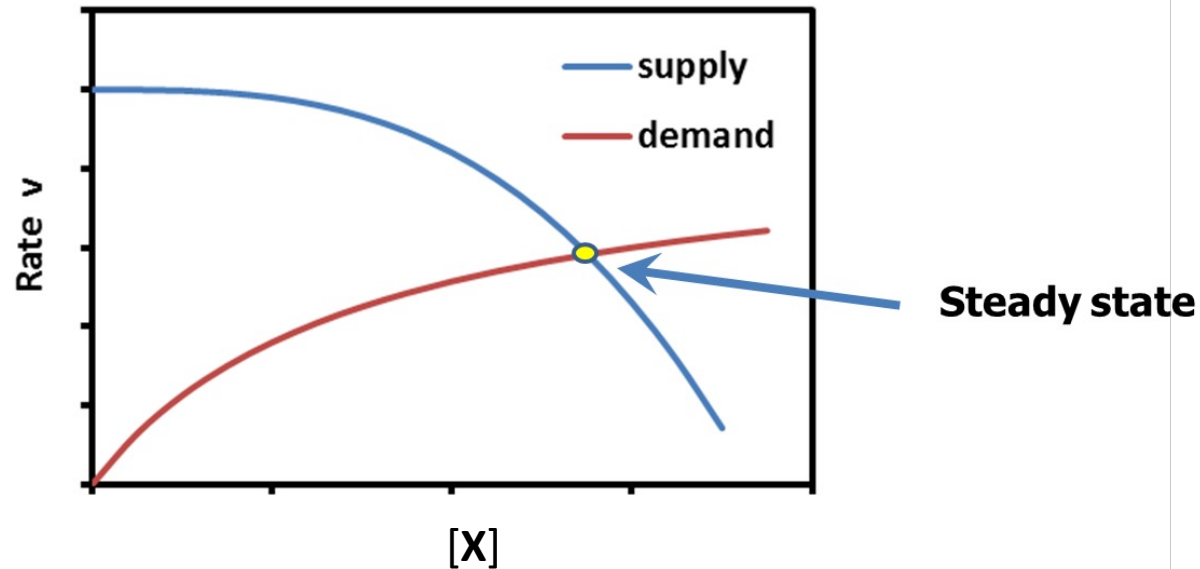
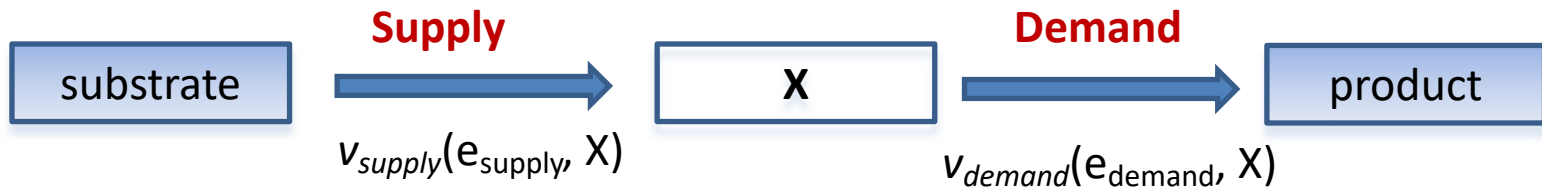
Computational modelling (dynamic)



Simulating concentration of metabolite X in time

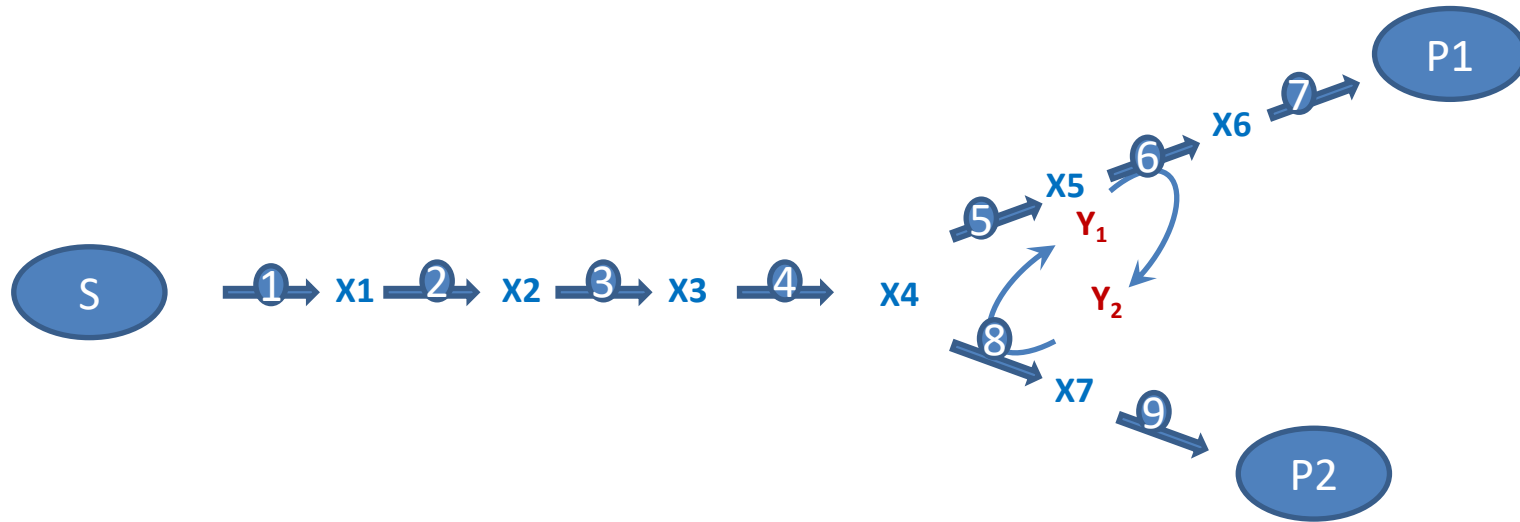
$$d[X]/dt = v_{supply}(e_{supply}, X) - v_{demand}(e_{demand}, X)$$

Computational modelling (steady state)



Kinetic information allows to predict steady-state flux and concentration

Dynamic models: the challenge



$$d[X_1]/dt = v_1 - v_2$$

...

...

$$d[X_4]/dt = v_4 - v_5 - v_8$$

...

$$d[Y_1]/dt = -v_5 + v_8$$

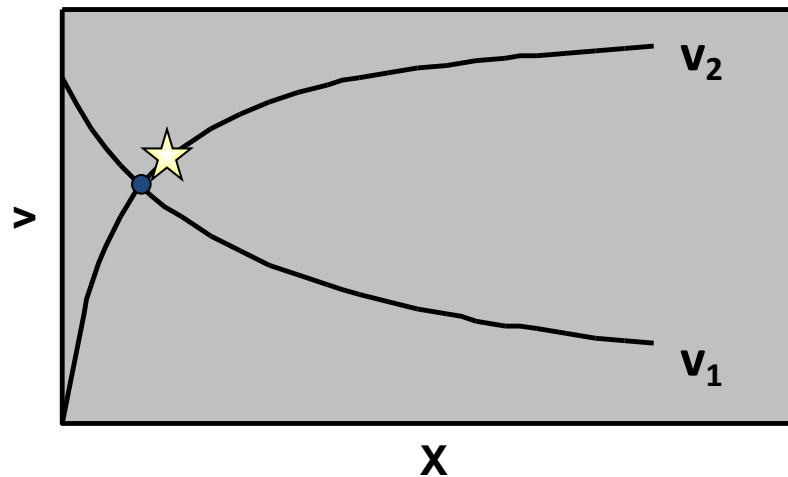
$$d[Y_2]/dt = +v_5 - v_8$$

Velocities (\mathbf{v}) depend on concentrations (\mathbf{X})

Steady state



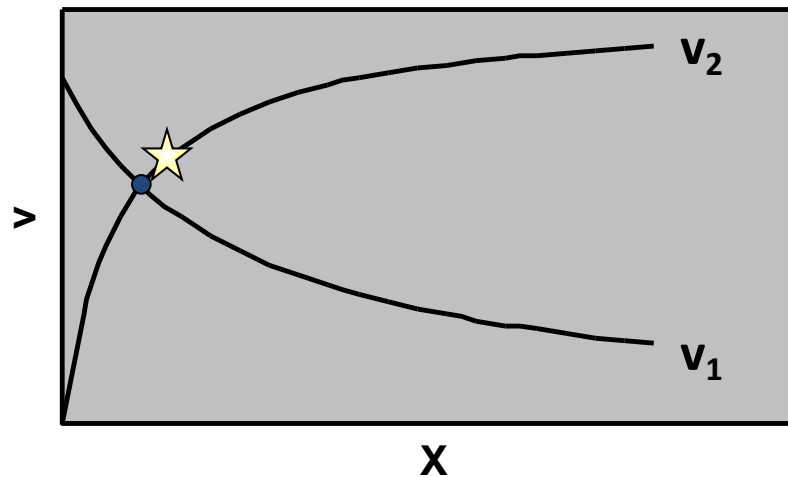
Metabolite X is at steady state if the rate of enzyme 1 (v_1) equals the rate of enzyme 2 (v_2) \rightarrow Production equals consumption.



What is required to obtain a steady state?



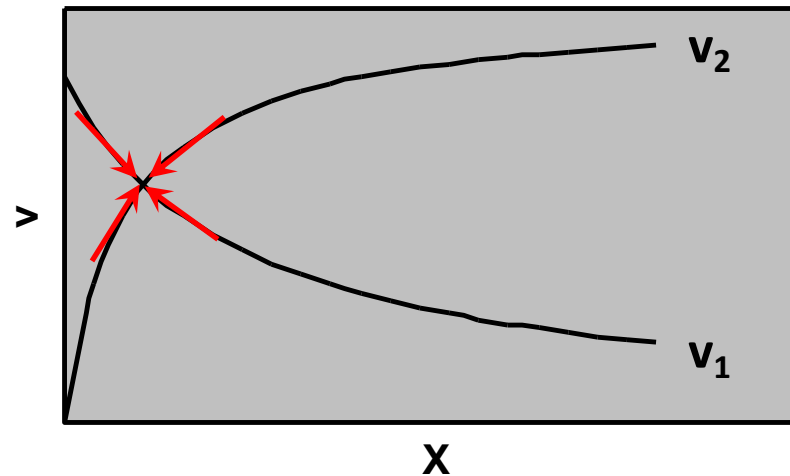
1. Concentrations of S and P are constant or external source / sink
2. Stability of the steady state



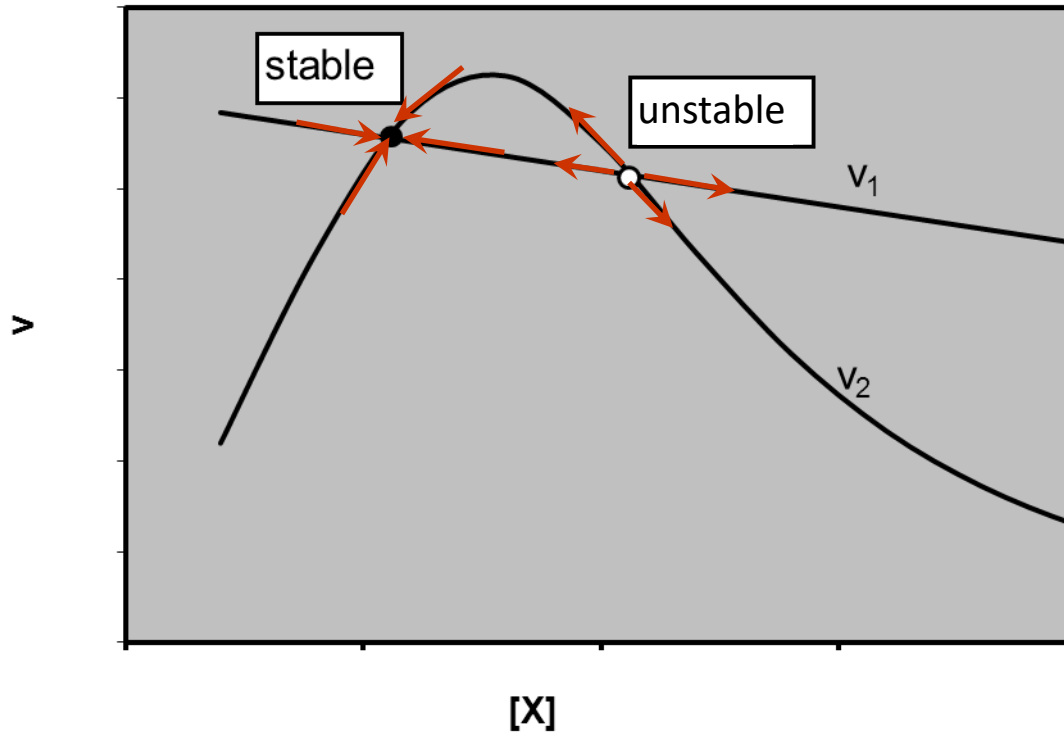
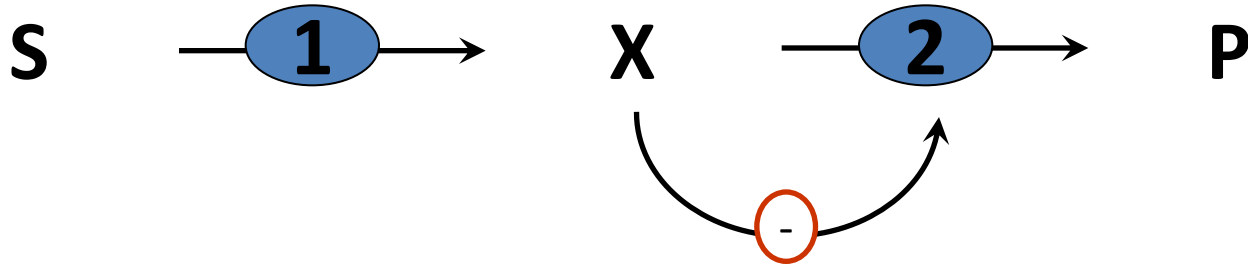
Stability of a steady state



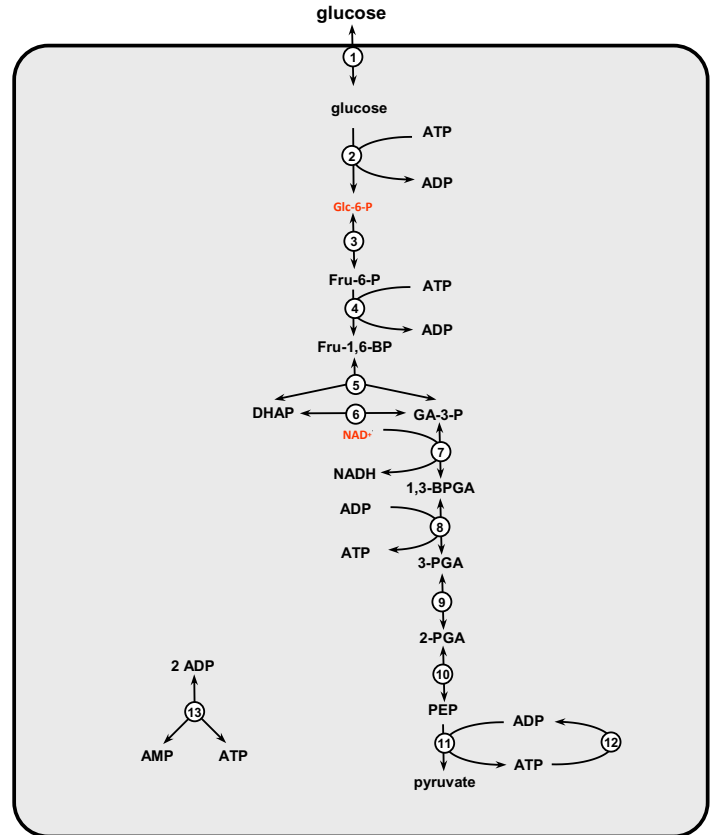
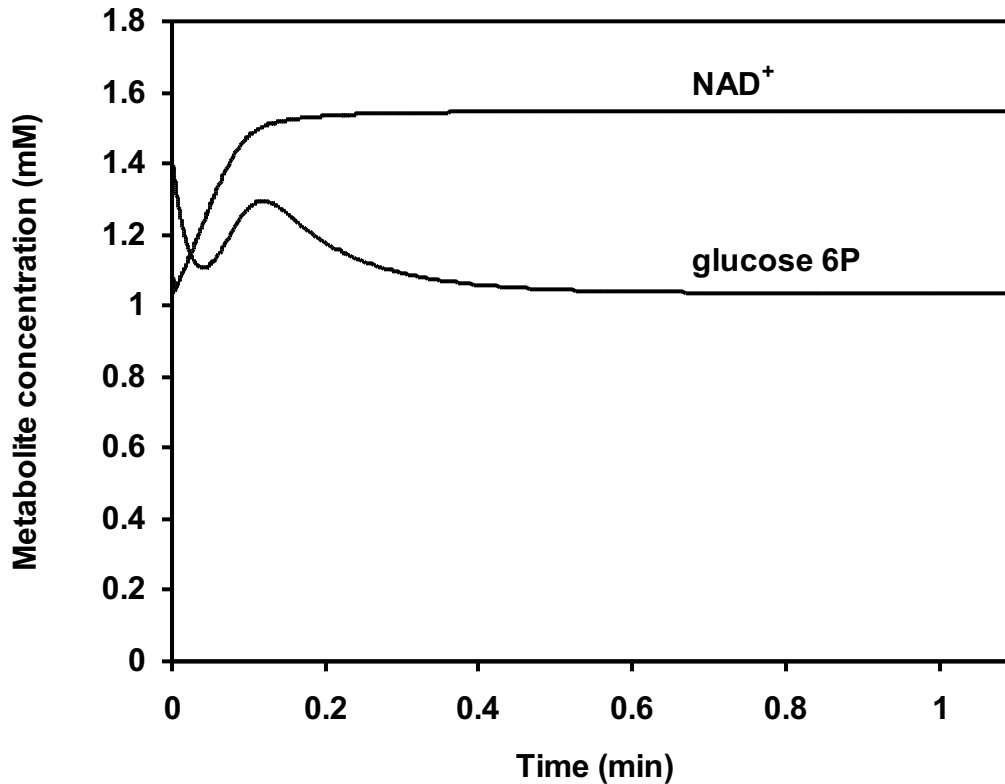
A stable steady state:



(In)stability of a steady state



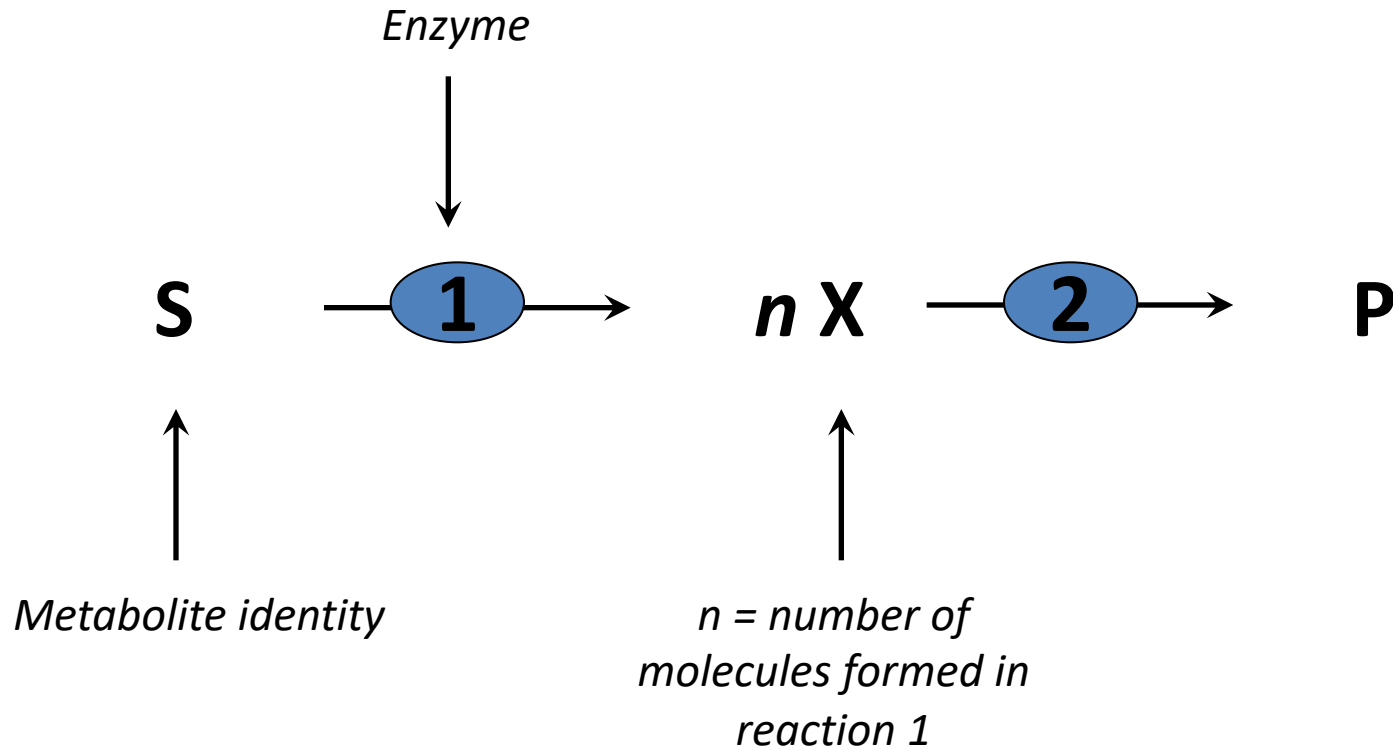
Dynamic model



To simulate (predict) how concentrations and rates in a pathway behave in time; and in which steady state they may settle.

Construction of a computer model

Pathway stoichiometry

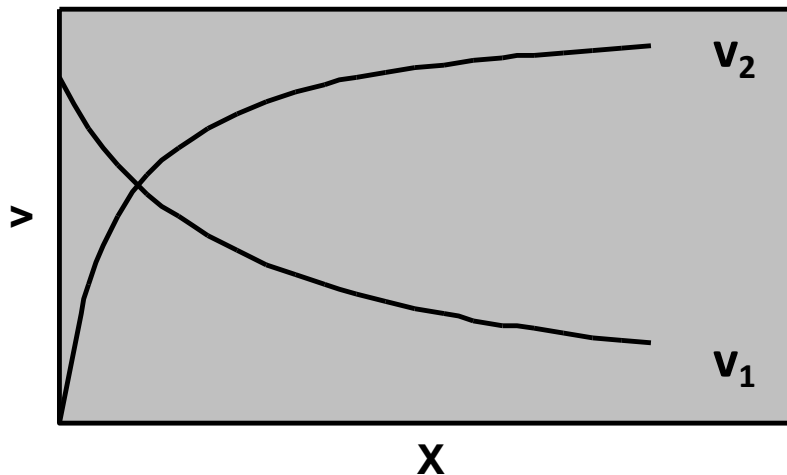


Enzyme kinetics



rate of enzyme 1 = $v_1(e_1, S, X)$

rate of enzyme 2 = $v_2(e_2, X, P)$



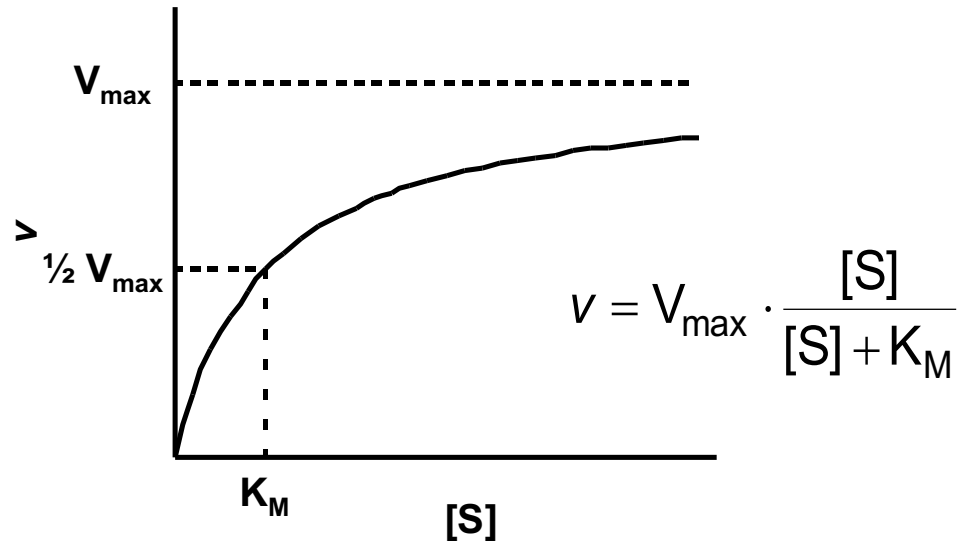
Prediction of dynamics



$$d[X]/dt = v_1(e_1, S, X) - v_2(e_2, X, P)$$

\rightarrow Prediction of $X(t)$ and $v(t)$ at given S, P, e_1 and e_2

Rate equations



Classical Michaelis-Menten kinetics

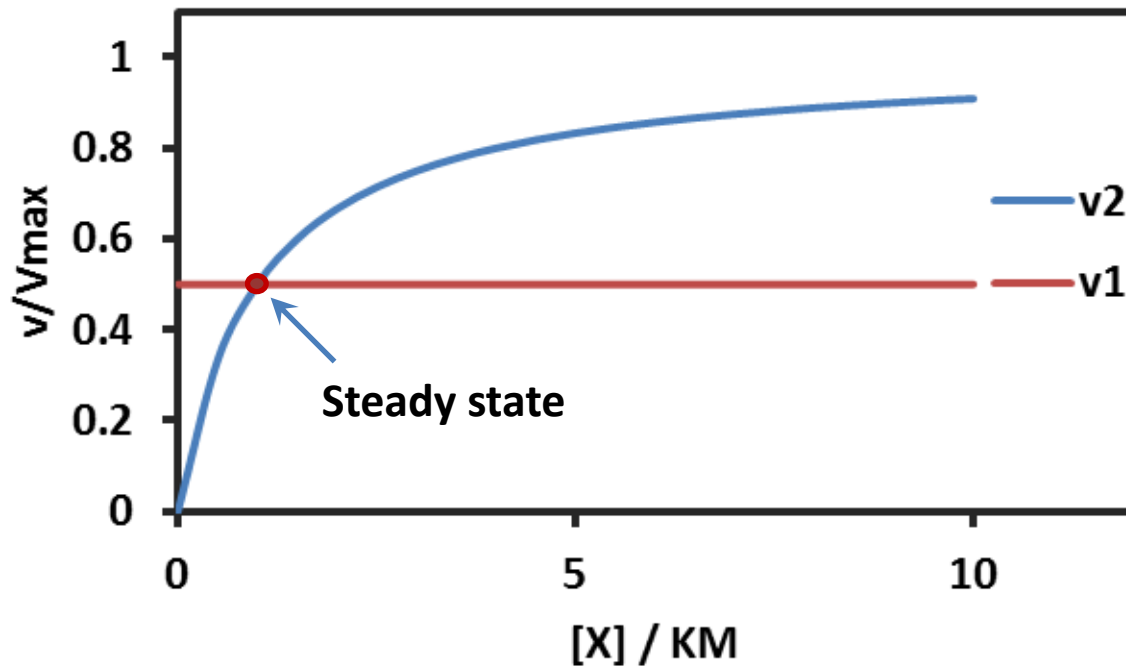
If $[S] \gg K_M$, then $v = V_{\max}$.

If $[S] = K_M$, then $v = \frac{1}{2} V_{\max}$.

Classical MM kinetics in a pathway



Example 1: Steady state

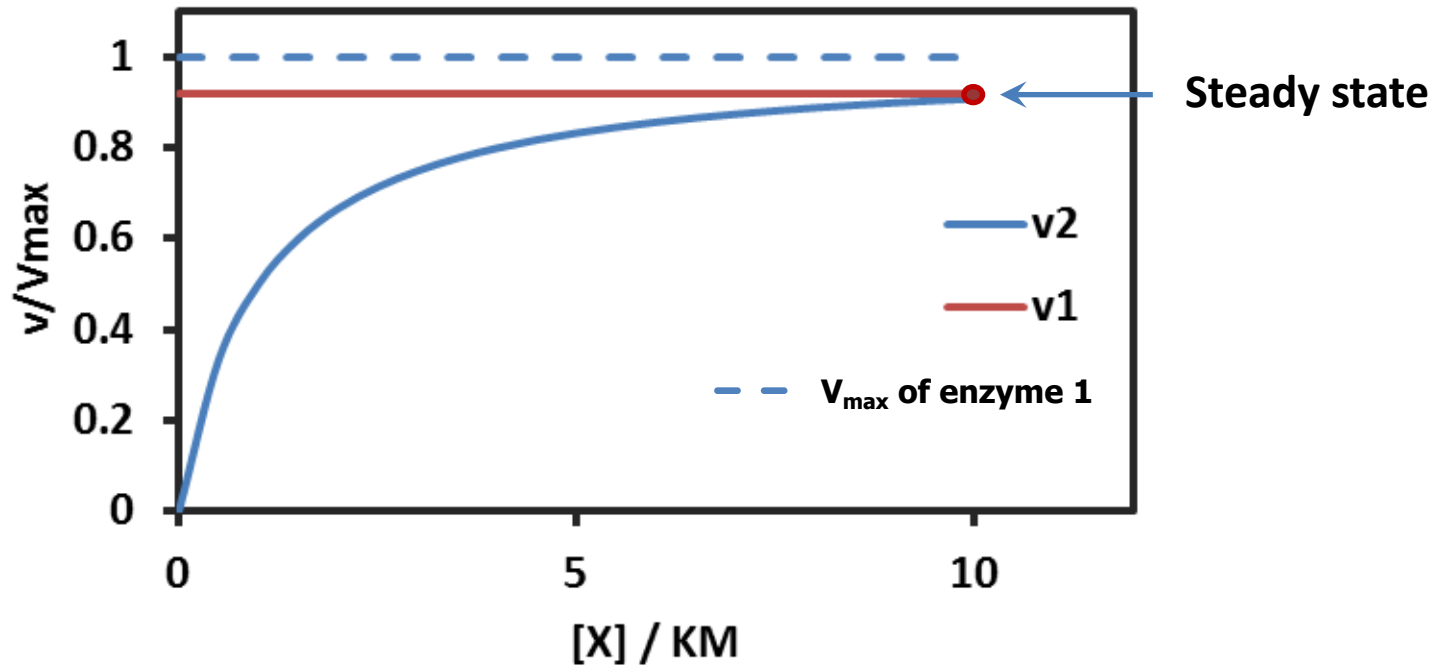


Steady state
 $v_1 = v_2$
 $[X] = \text{constant}$

Classical MM kinetics in a pathway



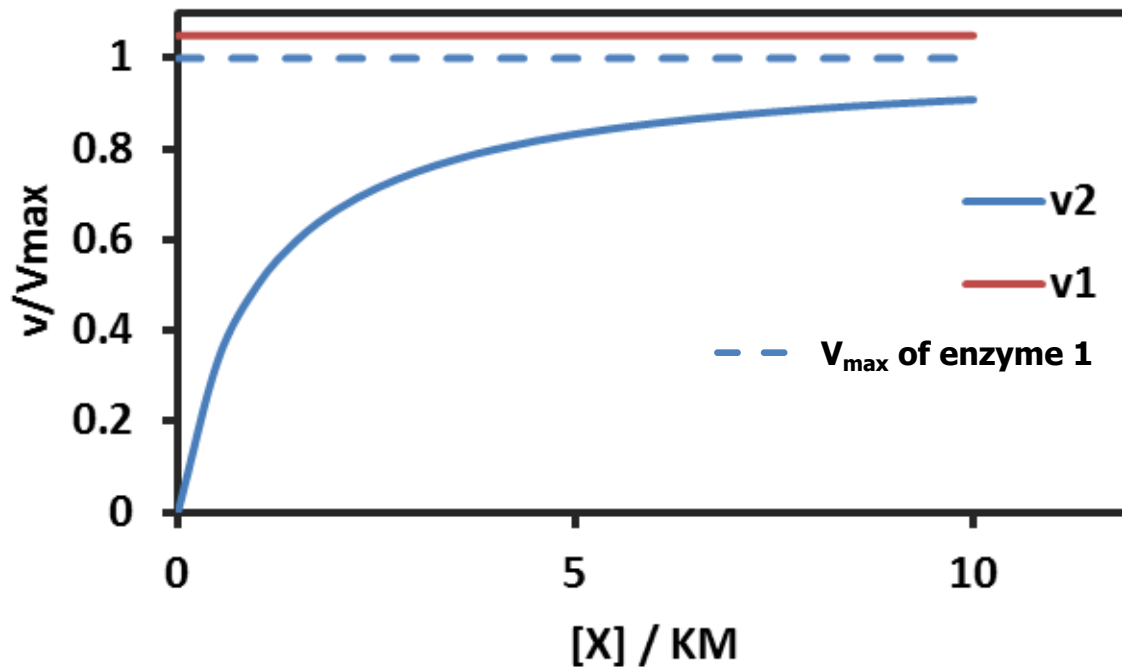
Example 2: Steady state at high [X]



Classical MM kinetics in a pathway



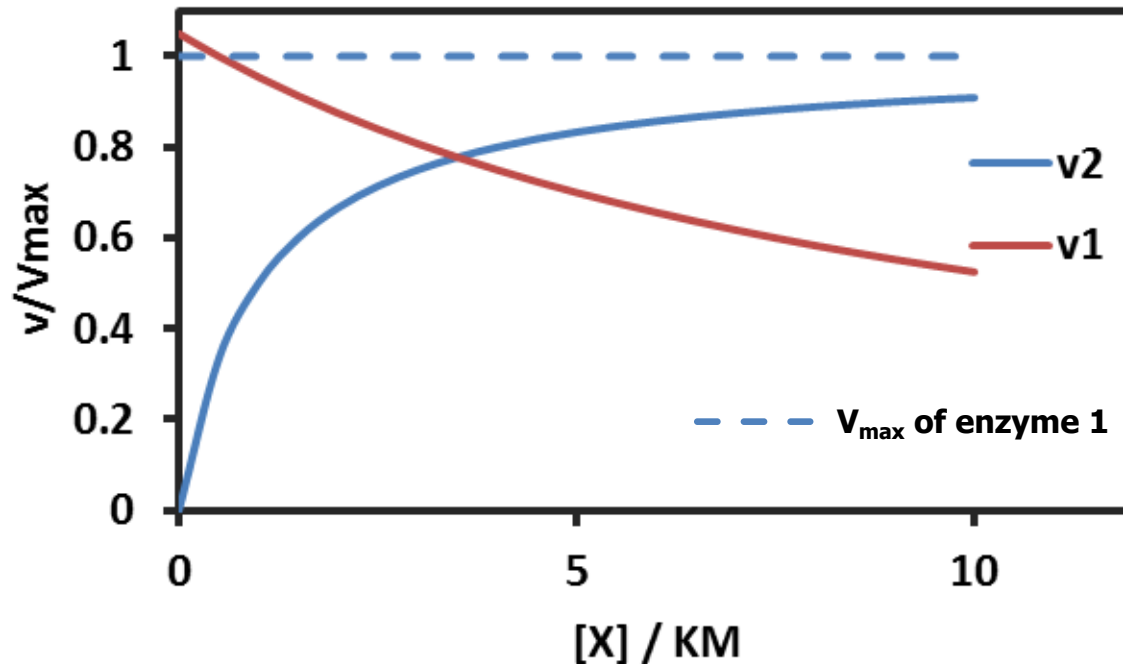
Example 3: No steady state



Product inhibition 'saves' the steady state



Example 4: Product inhibition



Enzymes 'communicate' via metabolite concentrations.

Reversible enzyme reactions (1)



$$v = \frac{V_{+\max} \cdot \frac{[S]}{K_{MS}} - V_{-\max} \cdot \frac{[P]}{K_{MP}}}{1 + \frac{[S]}{K_{MS}} + \frac{[P]}{K_{MP}}}$$

$$V_{+\max} = k_2 \cdot [E_{\text{tot}}]$$

$$K_{MS} = (k_{-1} + k_2) / k_1$$

$$V_{-\max} = k_{-1} \cdot [E_{\text{tot}}]$$

$$K_{MP} = (k_{-1} + k_2) / k_{-2}$$

The equation is symmetrical, like the reaction scheme.

An increase of the enzyme concentration leads to a proportional increase of $V_{+\max}$ and $V_{-\max}$ (\rightarrow effect of gene expression)

Reversible enzyme reactions (2)

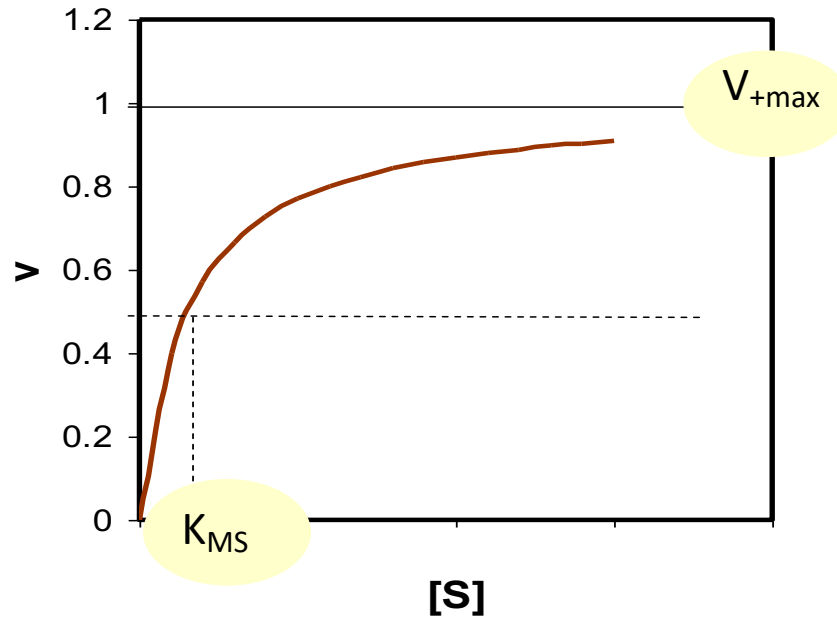


$$v = \frac{V_{+\max} \cdot \frac{[S]}{K_{MS}} - V_{-\max} \cdot \frac{[P]}{K_{MP}}}{1 + \frac{[S]}{K_{MS}} + \frac{[P]}{K_{MP}}}$$

If $[P] = 0$, the equation reduces to the original Michaelis-Menten equation:

$$v = \frac{V_{+\max} \cdot \frac{[S]}{K_{MS}}}{1 + \frac{[S]}{K_{MS}}} = \frac{V_{+\max} \cdot [S]}{K_{MS} + [S]}$$

Reversible enzyme kinetics (2)



If $[P] = 0$, the equation reduces to the original Michaelis-Menten equation:

$$v = \frac{V_{+max} \cdot \frac{[S]}{K_{MS}}}{1 + \frac{[S]}{K_{MS}}} = \frac{V_{+max} \cdot [S]}{K_{MS} + [S]}$$

Reversible enzyme kinetics (3)

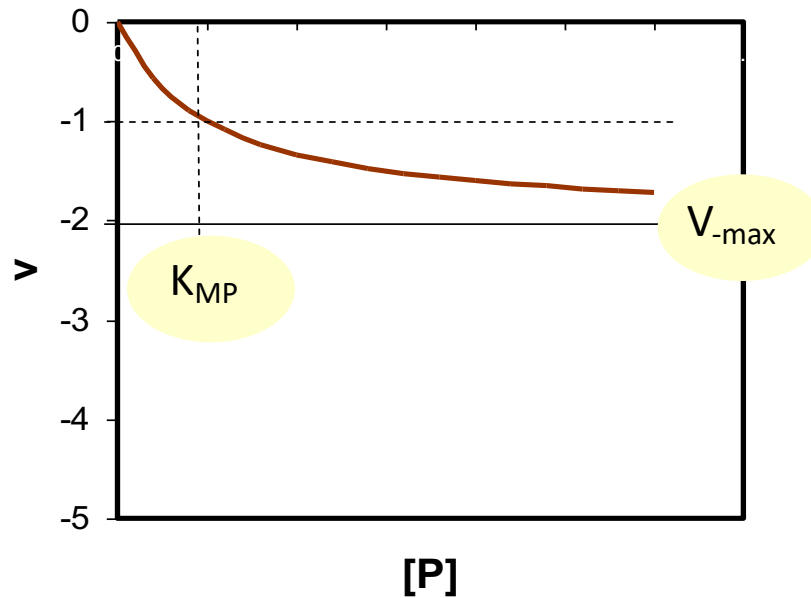


$$v = \frac{V_{+\max} \cdot \frac{[S]}{K_{MS}} - V_{-\max} \cdot \frac{[P]}{K_{MP}}}{1 + \frac{[S]}{K_{MS}} + \frac{[P]}{K_{MP}}}$$

If $[S] = 0$, the equation also reduces to the original Michaelis-Menten equation, but in the reverse direction and as a function of $[P]$:

$$v = -\frac{V_{-\max} \cdot \frac{[P]}{K_{MP}}}{1 + \frac{[P]}{K_{MP}}} = -\frac{V_{-\max} \cdot [P]}{K_{MP} + [P]}$$

Reversible enzyme kinetics (3)



If $[S] = 0$, the equation also reduces to the original Michaelis-Menten equation, but in the reverse direction and as a function of $[P]$:

$$v = -\frac{V_{-max} \cdot \frac{[P]}{K_{MP}}}{1 + \frac{[P]}{K_{MP}}} = -\frac{V_{-max} \cdot [P]}{K_{MP} + [P]}$$

The Haldane relation

$$v = \frac{V_{+max} \cdot \frac{[S]}{K_{MS}} - V_{-max} \cdot \frac{[P]}{K_{MP}}}{1 + \frac{[S]}{K_{MS}} + \frac{[P]}{K_{MP}}} \quad \text{Equation 1}$$

At thermodynamic equilibrium: $[P]/[S] = K_{eq}$ AND $v = 0$

It follows that: $K_{eq} = \frac{V_{+max}}{K_{MS}} \cdot \frac{K_{MP}}{V_{-max}}$ Equation 2 (the Haldane relation)

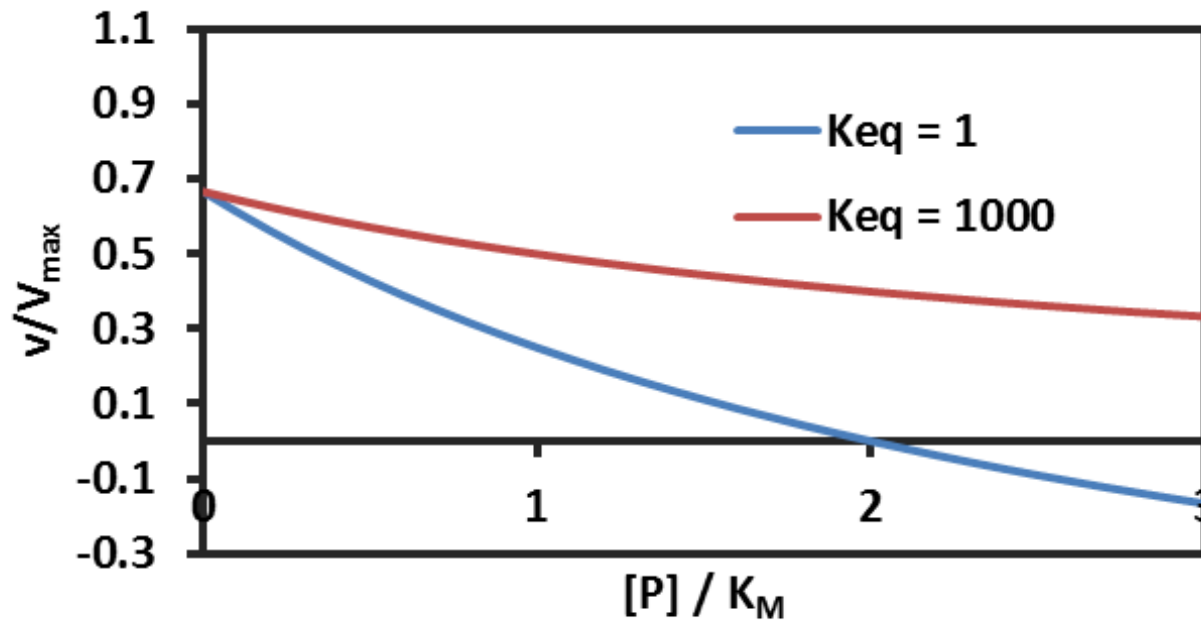
$$v = \frac{V_{+max} \frac{[S]}{K_{MS}} \left(1 - \frac{[P]}{[S]} / K_{eq}^{\star} \right)}{1 + \frac{[S]}{K_{MS}} + \frac{[P]}{K_{MP}}} \quad \text{Equation 3}$$

This is another way of writing the above discussed 'reversible Michaelis-Menten' equation.

Product sensitivity

$$v = \frac{V_{+max} \frac{[S]}{K_{MS}} \left(1 - \frac{[P]}{[S] / K_{eq}} \right)}{1 + \frac{[S]}{K_{MS}} + \frac{[P]}{K_{MP}}}$$

Product sensitivity



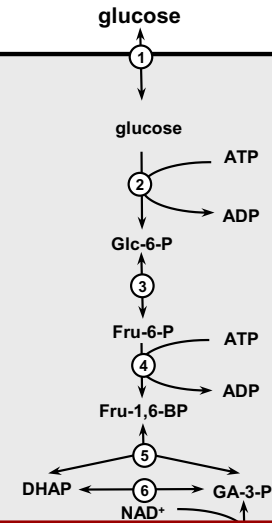
Full-scale kinetic model

$$d[\text{glucose}]/dt = v_1(e_1, \mathbf{X}) - v_2(e_2, \mathbf{X})$$

$$d[\text{Glc6P}]/dt = v_2(e_2, \mathbf{X}) - v_3(e_3, \mathbf{X})$$

$$d[\text{Fru6P}]/dt = v_3(e_3, \mathbf{X}) - v_4(e_4, \mathbf{X})$$

....
 $\mathbf{X} = ([\text{glucose}], [\text{Glc6P}], [\text{Fru6P}], \dots [\text{ATP}])$
 Calculate how \mathbf{X} changes with time



$$d[\text{ATP}]/dt = -v_2(e_2, \mathbf{X}) - v_4(e_4, \mathbf{X}) + v_8(e_8, \mathbf{X}) + v_{11}(e_{11}, \mathbf{X}) - v_{12}(e_{12}, \mathbf{X}) + v_{13}(e_{13}, \mathbf{X})$$

Numerical solution

$$d[\text{glucose}]/dt = v_1(e_1, \mathbf{X}) - v_2(e_2, \mathbf{X})$$

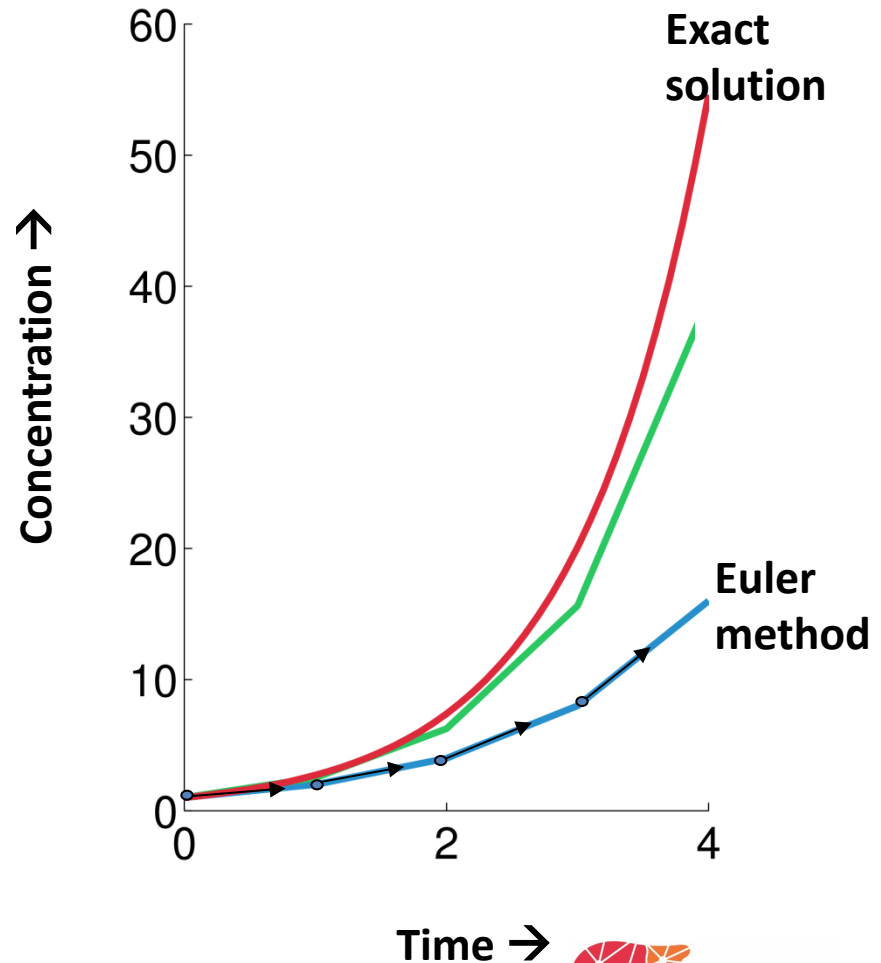
$$d[\text{Glc6P}]/dt = v_2(e_2, \mathbf{X}) - v_3(e_3, \mathbf{X})$$

...

Each rate may depend on multiple concentrations, which in turn depend on multiple rates

Euler approximation

- Calculate rates at time t
- Predict concentrations at next time point
- Recalculate rates
- Iterative procedure → computer power!



Solvers (non-exhaustive)

Euler: *one step method*

Runge-Kutta: *takes intermediate steps*

Adams: *uses information from previous steps*

‘Non-stiff’ problems

BDF (backward differentiation formula) /Gear — ‘Stiff’ problems

LSODA: *switches during the simulation between Adams (non-stiff, fast) and BDF (stiff, more expensive in computer time, more stable)*

Finding the steady state



$$d[X]/dt = v_1(e_1, S, X) - v_2(e_2, X, P)$$

At steady state $d[X]/dt = 0$

→ Find X for which: $v_1(e_1, S, X) - v_2(e_2, X, P) = 0$

Steady state of the full-scale kinetic model

$$d[\text{glucose}]/dt = v_1(e_1, \mathbf{X}) - v_2(e_2, \mathbf{X}) = 0$$

$$d[\text{Glc6P}]/dt = v_2(e_2, \mathbf{X}) - v_3(e_3, \mathbf{X}) = 0$$

$$d[\text{Fru6P}]/dt = v_3(e_3, \mathbf{X}) - v_4(e_4, \mathbf{X}) = 0$$

....

$$\mathbf{X} = ([\text{glucose}], [\text{Glc6P}], [\text{Fru6P}], \dots [\text{ATP}])$$

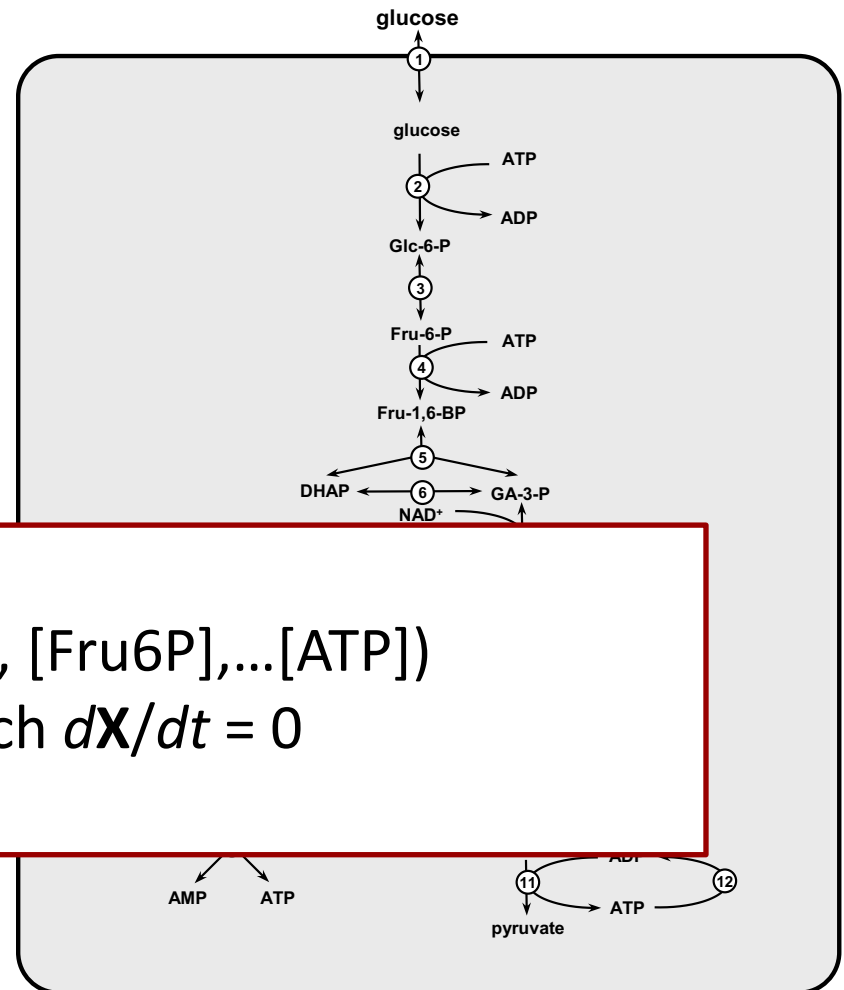
....

$$\rightarrow \text{Find } \mathbf{X} \text{ for which } d\mathbf{X}/dt = 0$$

....

....

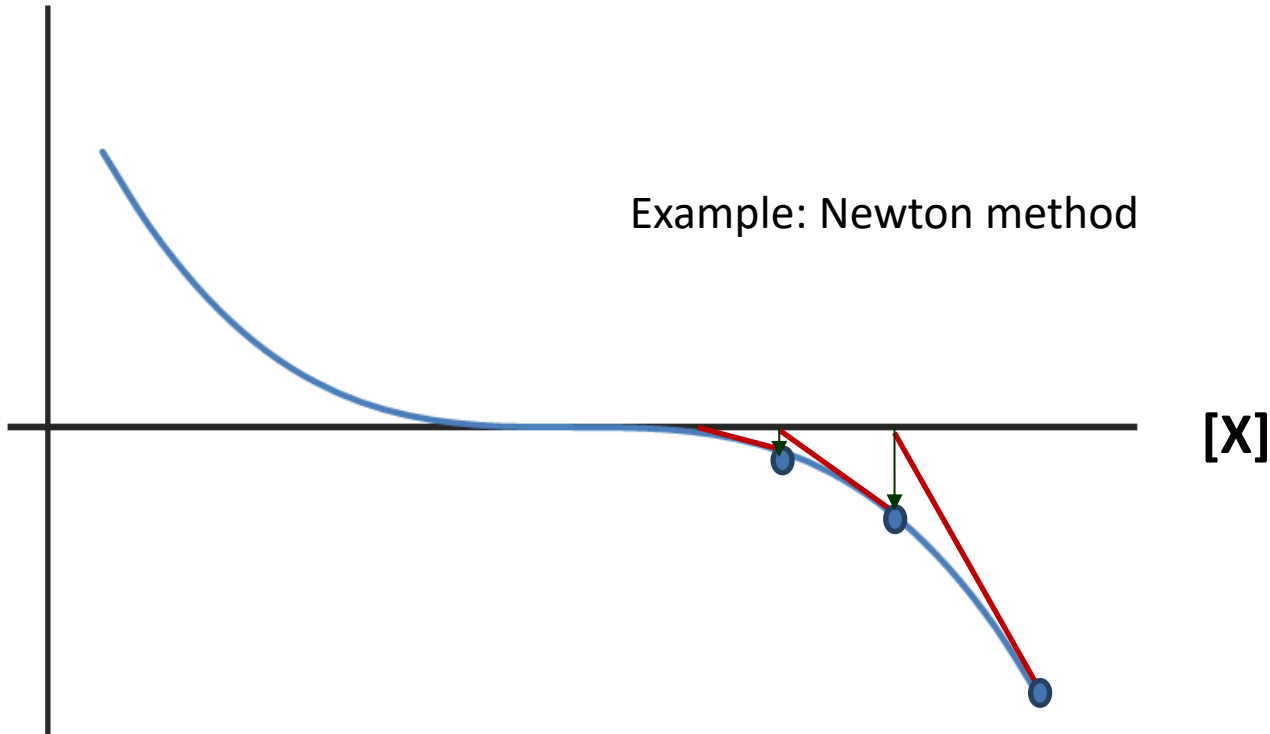
....



$$d[\text{ATP}]/dt = -v_2(e_2, \mathbf{X}) - v_4(e_4, \mathbf{X}) + v_8(e_8, \mathbf{X}) + v_{11}(e_{11}, \mathbf{X}) - v_{12}(e_{12}, \mathbf{X}) + v_{13}(e_{13}, \mathbf{X}) = 0$$

Numerical root finding algorithm

$d[X]/dt$



- $\mathbf{X} = (X_1, X_2, \dots, X_n) \rightarrow$ many dimensions
- Iterative procedure \rightarrow computer power

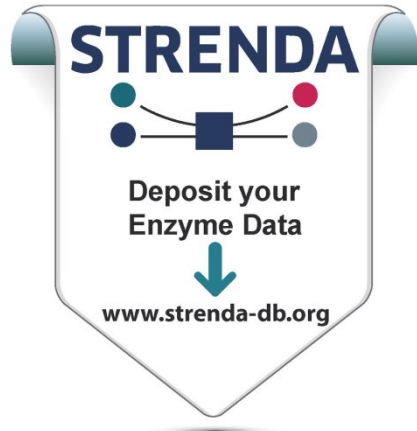
Enzyme kinetics

Model parameters

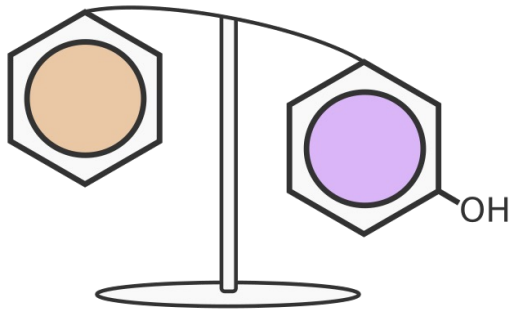
For a metabolic model typically:

- Kinetic parameters: V_{max} , K_m , ...
- Equilibrium constants
- Enzyme concentrations
- Compartment volumes
- Conserved moieties (*e.g.* $[ATP] + [ADP] + [AMP] = \text{constant}$)

Enzyme kinetic databases



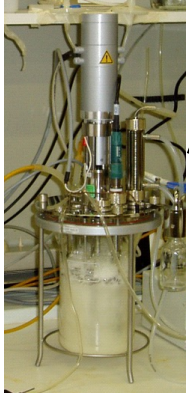
Equilibrium constants



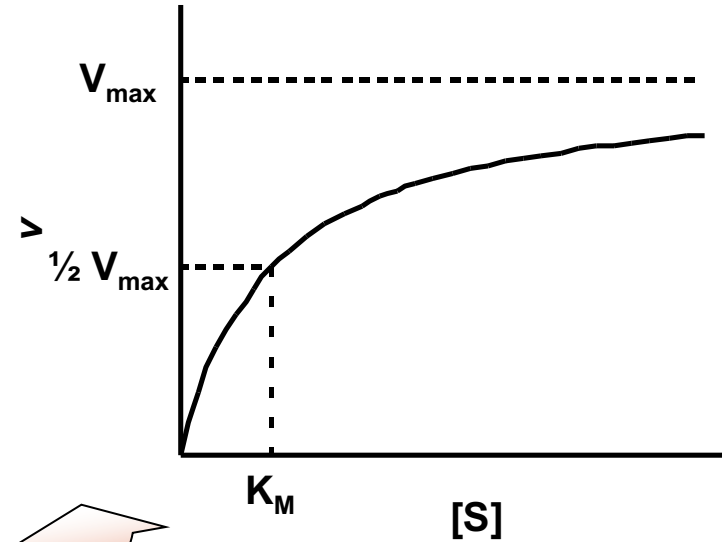
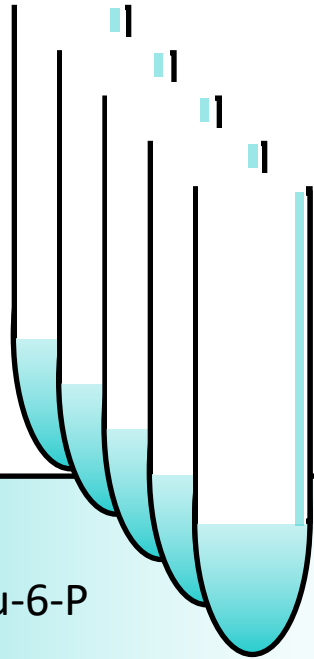
eQuilibrator

<http://equilibrator.weizmann.ac.il/>

1. Independent biochemical analysis



Enzyme purification



Variation of substrate concentration

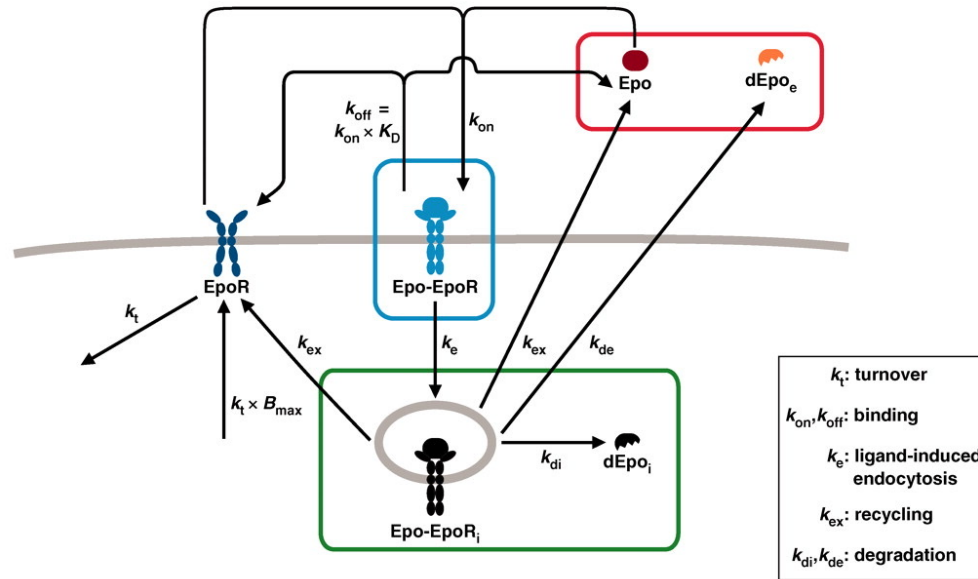


$$v = \frac{V_{\max} \cdot [\text{Glc6P}] / K_{\text{Glc6P}} \cdot (1 - \Gamma / K_{\text{eq}})}{1 + [\text{Glc6P}] / K_{\text{glc6P}} + [\text{Fru6P}] / K_{\text{fru6P}}}$$

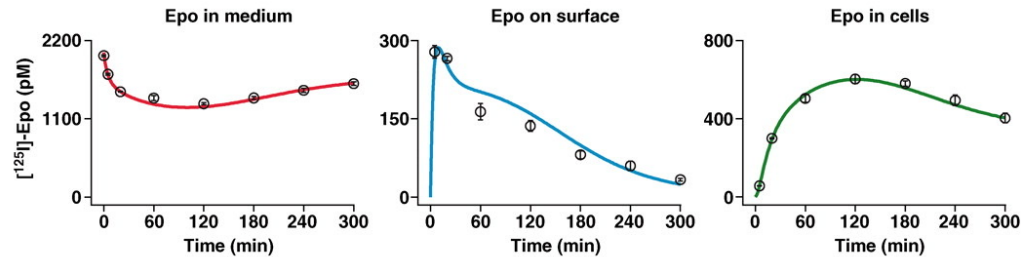
2. Parameter fitting

Dynamic modeling of the EpoR system.

A Mathematical core model



B Model calibration



Modelling 'schools'

1. Independent biochemical measurement of parameters

Biochemical school, accessible parameters (e.g. enzyme kinetics),

Number of parameters too large for fitting, aim of the model

2. Parameter fitting

Engineering school, parameters not directly accessible (e.g. protein-

protein interactions in signalling, number of parameters small)

Model validation

Classical example: glycolysis in bakers' yeast

- Compare new data to independent model prediction
- Independent biochemical analysis of parameters
- Special feature: the assay medium mimicked the cytosolic environment of the cells

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PLoS COMPUTATIONAL BIOLOGY

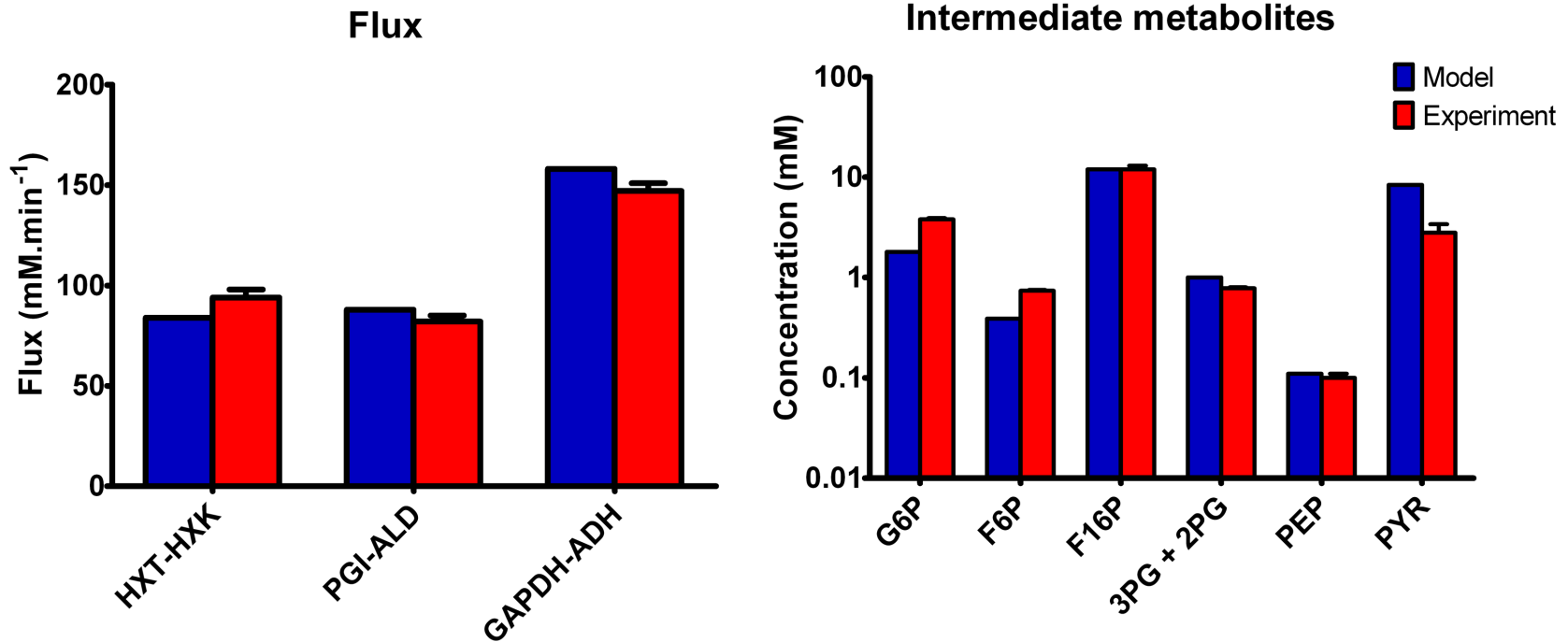
*Testing Biochemistry Revisited: How *In Vivo* Metabolism Can Be Understood from *In Vitro* Enzyme Kinetics*

Karen van Eunen^{1,2,3}, José A. L. Kiewiet^{1,2}, Hans V. Westerhoff^{1,2,4,5}, Barbara M. Bakker^{1,2,3*}

1 Department of Molecular Cell Physiology, VU University Amsterdam, Amsterdam, The Netherlands, **2** Kluyver Centre for Genomics of Industrial Fermentation, Delft, The Netherlands, **3** Department of Pediatrics, Center for Liver, Digestive and Metabolic Diseases, University Medical Center Groningen, University of Groningen, Groningen, The Netherlands, **4** Manchester Centre for Integrative Systems Biology, Manchester Interdisciplinary BioCentre, The University of Manchester, Manchester, United Kingdom, **5** Synthetic Systems Biology, Netherlands Institute for Systems Biology, University of Amsterdam, Amsterdam, The Netherlands

Model validation

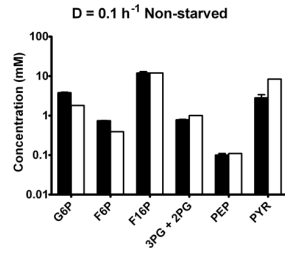
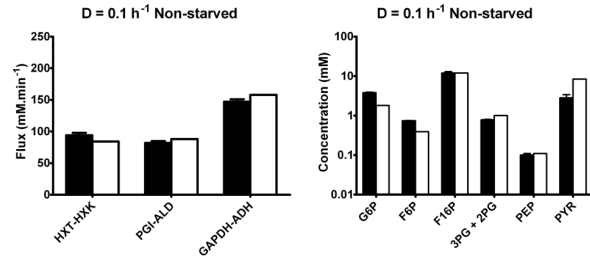
Classical example: glycolysis in bakers' yeast



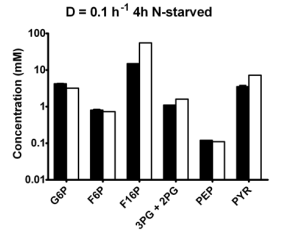
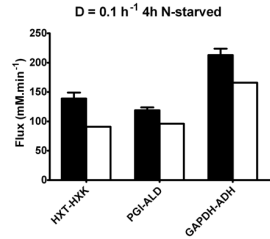
- V_{max} values measured in samples from yeast chemostat culture $D=0.1 \text{ h}^{-1}$
- \rightarrow inserted in model \rightarrow prediction of metabolite concentrations and fluxes
- Independent measurement of metabolite concentrations and fluxes

Model validation

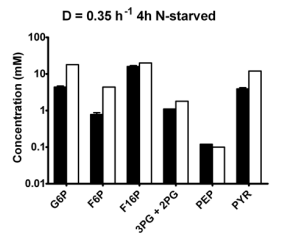
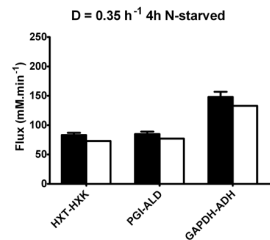
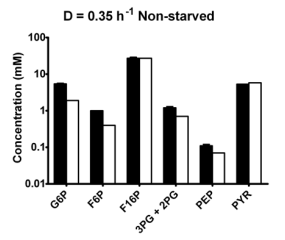
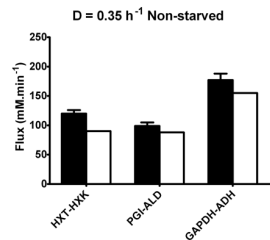
Classical example: glycolysis in bakers' yeast



■ Experiment
□ Model



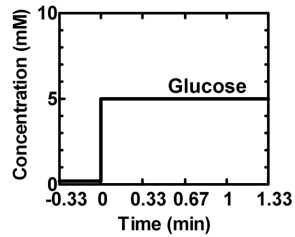
The model gives reasonable predictions for 4 independent culture conditions



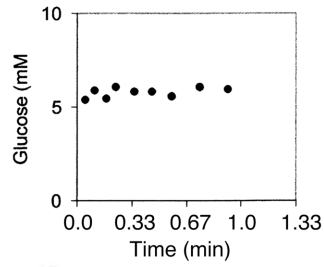
Model validation

Classical example: glycolysis in bakers' yeast

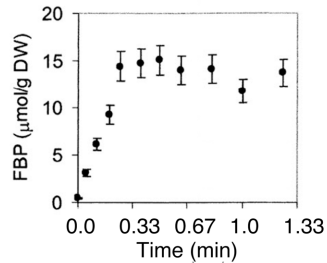
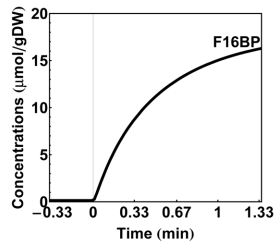
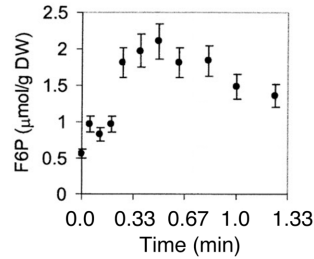
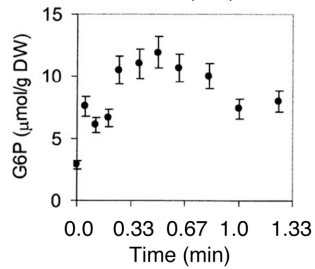
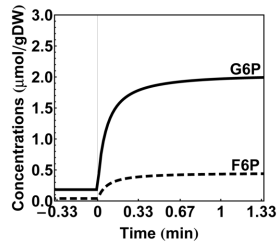
Simulation



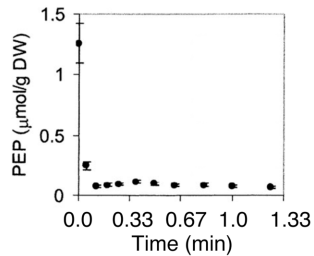
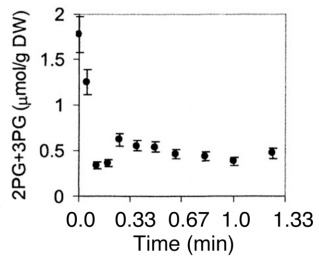
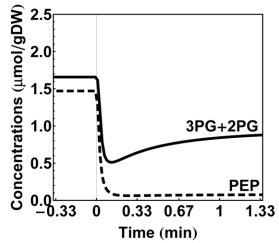
Experiment



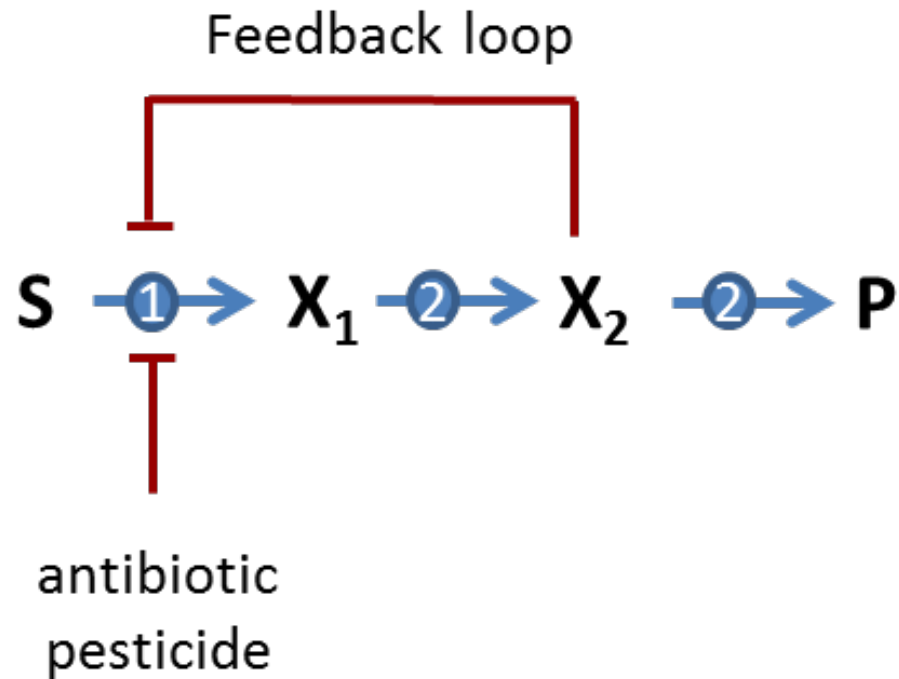
Experimental data were taken from
Visser *et al.* 2004, Biotechnol. Bioeng.



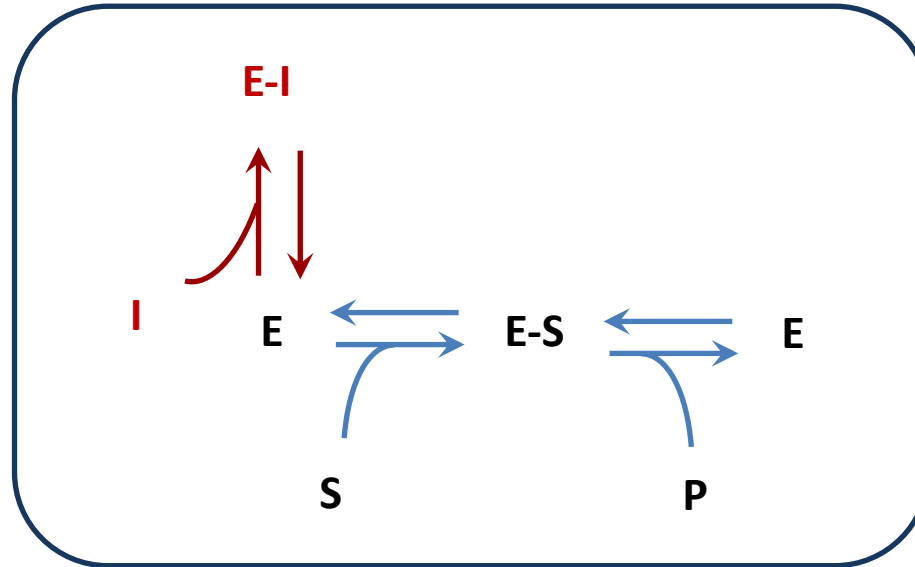
... and under dynamic conditions



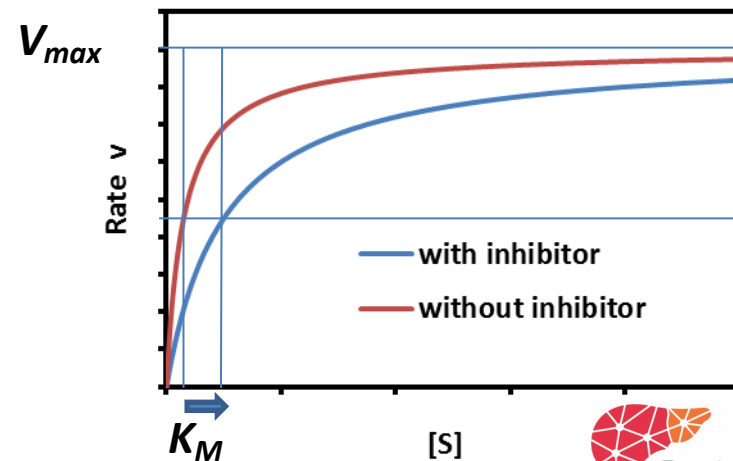
Enzyme inhibition



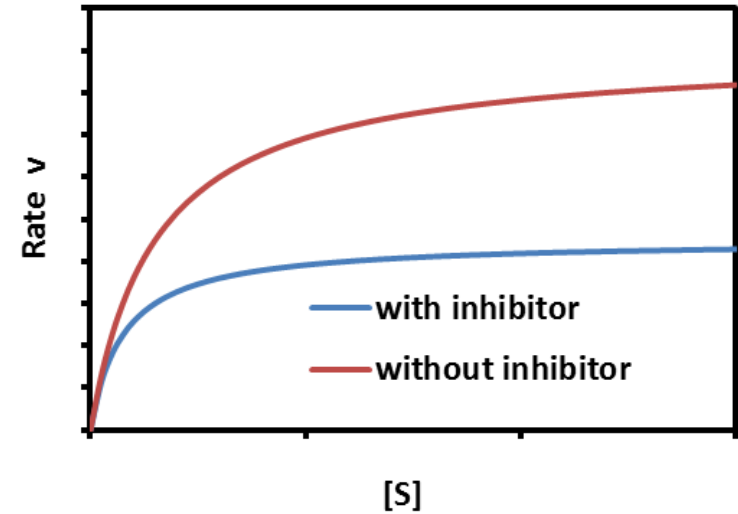
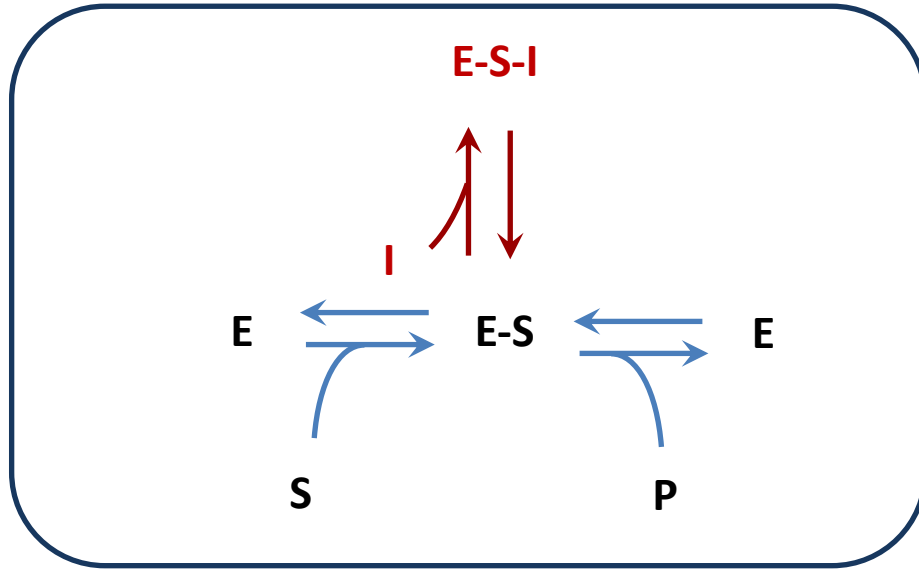
Competitive enzyme inhibition



$$v = \frac{V_{+max} \frac{[S]}{K_{MS}} \left(1 - \frac{[P]}{[S]} / K_{eq} \right)}{1 + \frac{[S]}{K_{MS}} + \frac{[P]}{K_{MP}} + \frac{[I]}{K_I}}$$



Uncompetitive enzyme inhibition



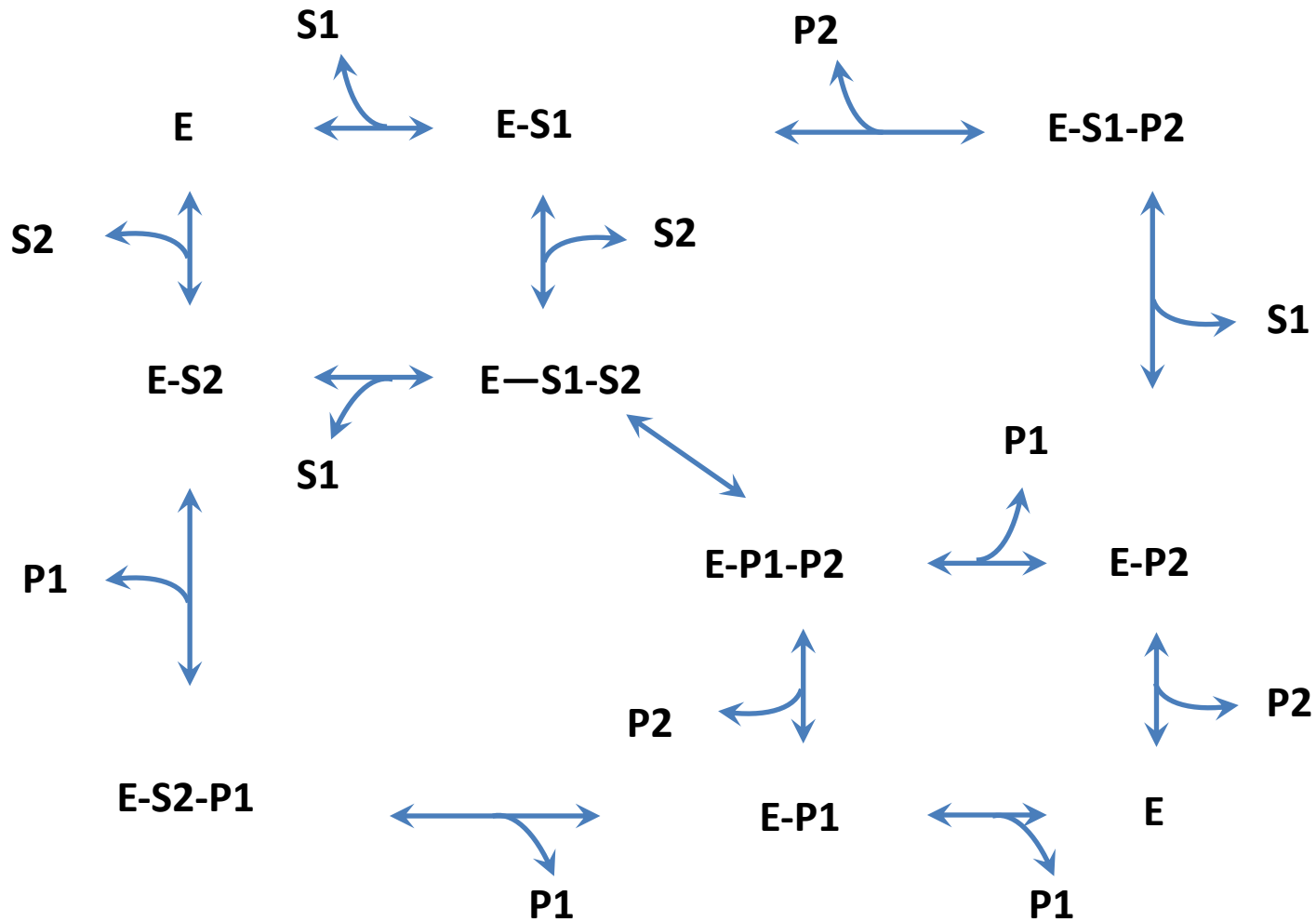
$$v = \frac{V_{\max,app} \frac{[S]}{K_{MS,app}} \left(1 - \frac{[P]}{[S]K_{eq}} \right)}{1 + \frac{[S]}{K_{MS,app}} + \frac{[P]}{K_{MP,app}}}$$

$$V_{\max,app} = V_{\max} / (1 + [I]/K_i)$$

$$K_{MS,app} = K_{MS} / (1 + [I]/K_i)$$

$$K_{MP,app} = K_{MP} / (1 + [I]/K_i)$$

2-substrate 2-product reaction



2-substrate 2-product reaction



$$v = \frac{V_{+max} \frac{[S_1]}{K_{MS1}} \cdot \frac{[S_2]}{K_{MS2}} \left(1 - \frac{[P_1] \cdot [P_2]}{[S_1] \cdot [S_2]} / K_{eq} \right)}{\left(1 + \frac{[S_1]}{K_{MS1}} + \frac{[P_1]}{K_{MP1}} \right) \cdot \left(1 + \frac{[S_2]}{K_{MS2}} + \frac{[P_2]}{K_{MP2}} \right)}$$

2-substrate 2-product reaction with competitive inhibitor



competitive inhibitor

$$v = \frac{V_{+max} \frac{[S_1]}{K_{MS1}} \cdot \frac{[S_2]}{K_{MS2}} \left(1 - \frac{[P_1] \cdot [P_2]}{[S_1] \cdot [S_2]} / K_{eq} \right)}{\left(1 + \frac{[S_1]}{K_{MS1}} + \frac{[P_1]}{K_{MP1}} + \frac{[I]}{K_I} \right) \cdot \left(1 + \frac{[S_2]}{K_{MS2}} + \frac{[P_2]}{K_{MP2}} \right)}$$

Model databases



Biomodels

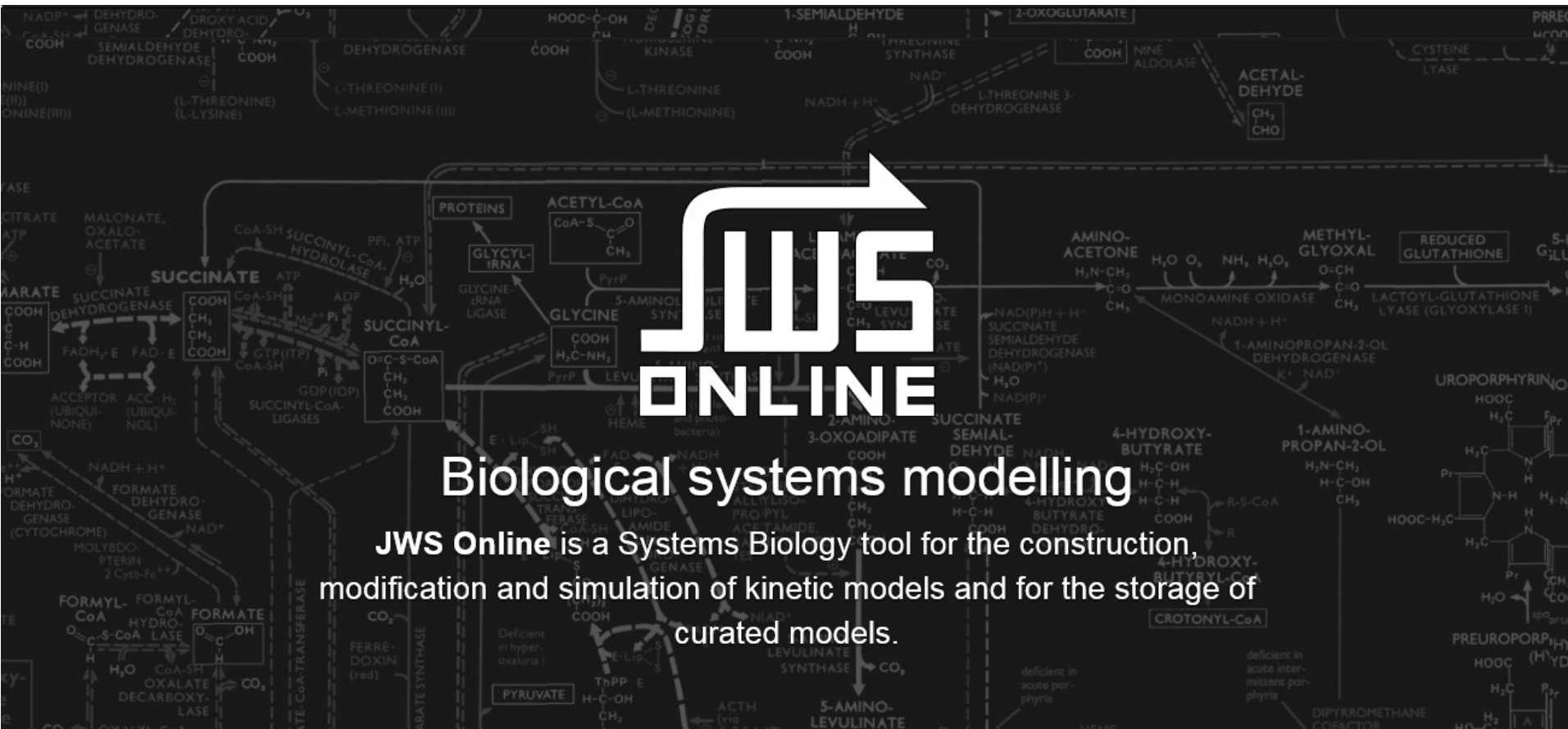


JWS online

Both deliver models in the SBML format (systems biology markup language)

Implementation in JWS Online

Interactive modelling database at:
<http://jws.biochem.sun.ac.za/>



Tutorial!

