# Layered Synthetic Biomolecular Systems

Dr Thomas P. Prescott
Department of Engineering Science, University of Oxford

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## Decomposition in terms of original variables

#### Decompose the stoichiometry

$$S = S^1 + \dots + S^L$$

System dynamics:

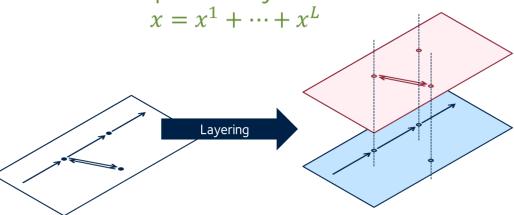
$$\dot{x}(t) = Sv(x)$$

$$\dot{x}^i(t) = S^i v(x^1 + \dots + x^L)$$

$$x(0) = x_0$$

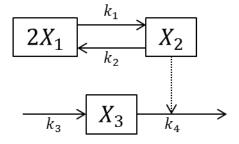
$$x^i(0) = x^i(0)$$

#### Recompose the layered states



Biological Network ODE Model:

$$\dot{x} = Sv(x)$$



Concentration vector:

$$x = [x_1, x_2, x_3]^T$$

Flux vector:

$$v(x) = [k_1(x_1)^2, k_2x_2, k_3, k_4x_2x_3]^T$$

Stoichiometric matrix:

$$S = \begin{bmatrix} -2 & 2 & 0 & 0 \\ 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \end{bmatrix}$$

Key question – how to decompose? Clearly this depends on the application. In the following example, reactions classed as fast or slow. Normally, singular perturbation requires transformation, but we can keep this system in its original variables by layered decomposition.

## Layered Singular Perturbation

$$\dot{x} = \frac{1}{\epsilon} S^f v(x) + S^S v(x)$$
 with  $\epsilon \ll 1$ 



#### **SLOW LAYER**

$$\epsilon \frac{dx^f}{dt} = S^f v(x)$$
 
$$\frac{dx^s}{dt} = S^s v(x)$$

### QSSA

$$0 = S^f v(\tilde{x}) \qquad \qquad \frac{d\tilde{x}^s}{dt} = S^s v(\tilde{x})$$

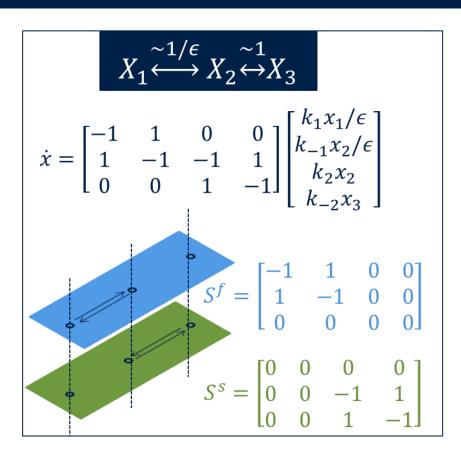
$$\tilde{x} = \tilde{x}^f + \tilde{x}^s$$

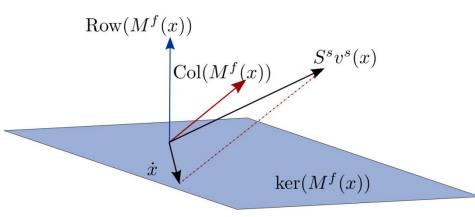
## Original dynamics:

$$\dot{x} = \frac{1}{\epsilon} S^f v(x) + S^s v(x)$$

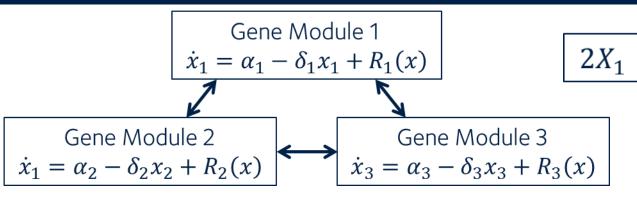
Approximated dynamics:

$$\dot{\tilde{x}} = \left(I + M^f(\tilde{x})\right) S^s v(\tilde{x})$$





## Dynamics under Nonlinear, Tuneable Constraints



The genetic layer is designed by  $R_i(x)$  while the fast PIN (i.e. nonlinear constraint) is tuned separately.

 $X_3$ 

