

# Integral population control of a quadratic dimerization process

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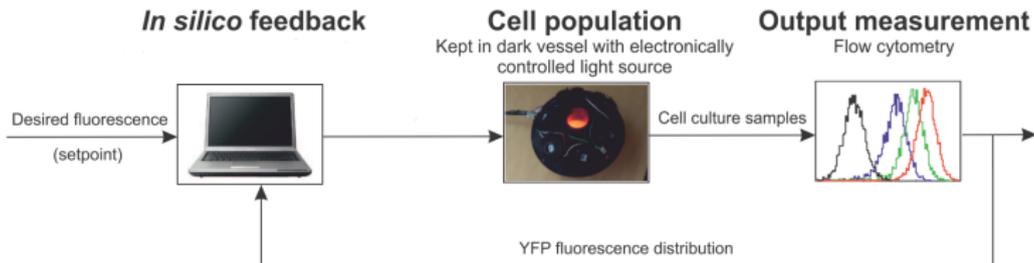
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## Outline

- Setup
- Modeling and analysis of reaction networks
- Mean control of a dimerization process
- Example
- Conclusion



- Considered in the gene expression context
- Mean control<sup>1</sup> and mean+variance control in <sup>2</sup>



1 A. Miliias-Argeitis, et al. *In silico* feedback for in vivo regulation of a gene expression circuit, *Nature Biotechnology*, 2011



2 C. Briat et al. Computer control of gene expression: Robust setpoint tracking of protein mean and variance using integral feedback, *51st IEEE Conference on Decision and Control*, 2012



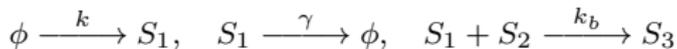
# Modeling and analysis of reaction networks



# Modeling biochemical networks

## Variables

- $N$  molecular species  $S_1, \dots, S_N$
- $M$  reactions  $R_1, \dots, R_M$



## Dynamics

- Deterministic (ODEs)  $\rightarrow$  concentrations  $x(t) \in \mathbb{R}_{\geq 0}^N$
- Stochastic (jump processes)  $\rightarrow$  molecule counts  $X(t) \in \mathbb{N}_0^N$



# Stochastic chemical reaction network

## Randomness in biology<sup>1</sup>

- Intrinsic noise (variability inside a cell)
- Extrinsic noise (cell-to-cell variability)
- External noise (environment)

## Chemical Master Equation

$$\dot{P}(\boldsymbol{x}, t) = \sum_{k=1}^M [\lambda_k(\boldsymbol{x} - \zeta_k)P(\boldsymbol{x} - \zeta_k, t) - \lambda_k(\boldsymbol{x})P(\boldsymbol{x}, t)] \quad (1)$$

- $P(\boldsymbol{x}, t)$ : probability to be in state  $\boldsymbol{x}$  at time  $t$ .
- $\zeta_k$ : stoichiometry vector associated to reaction  $R_k$ .
- $\lambda_k$ : propensity function capturing the rate of the reaction  $R_k$ .



<sup>1</sup> M. B. Elowitz, et al. [Stochastic gene expression in a single cell](#), *Science*, 2002



## Moments expression

### General case

$$\begin{aligned}\frac{dE[X]}{dt} &= SE[\lambda(X)], \\ \frac{dE[XX^\top]}{dt} &= SE[\lambda(X)X^\top] + E[\lambda(X)X^\top]^\top S^\top + S \operatorname{diag}\{E[\lambda(X)]\}S^\top\end{aligned}\quad (2)$$

- $S := [ \zeta_1 \quad \dots \quad \zeta_M ] \in \mathbb{R}^{N \times M}$ : stoichiometry matrix.
- $\lambda(X) := [ \lambda_1^\top \quad \dots \quad \lambda_M^\top ]^\top \in \mathbb{R}^M$ : propensity vector.

### Affine propensity case $\lambda(X) = WX + \lambda_0$

$$\begin{aligned}\frac{dE[X]}{dt} &= SWE[X] + S\lambda_0, \\ \frac{d\Sigma}{dt} &= SW\Sigma + (SW\Sigma)^\top + S \operatorname{diag}(WE[X] + \lambda_0)S^\top\end{aligned}\quad (3)$$

- $\Sigma$ : covariance matrix
- Linear equations



## Moments expression

### General case

$$\begin{aligned} \frac{dE[X]}{dt} &= SE[\lambda(X)], \\ \frac{dE[XX^T]}{dt} &= SE[\lambda(X)X^T] + E[\lambda(X)X^T]^T S^T + S \text{diag}\{E[\lambda(X)]\}S^T \end{aligned} \quad (2)$$

- $S := [ \zeta_1 \quad \dots \quad \zeta_M ] \in \mathbb{R}^{N \times M}$ : stoichiometry matrix.
- $\lambda(X) := [ \lambda_1^T \quad \dots \quad \lambda_M^T ]^T \in \mathbb{R}^M$ : propensity vector.

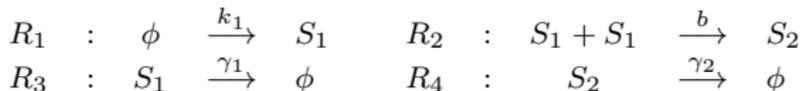
### Polynomial propensity case

- Moment closure problem  $\rightarrow$  first-order moments depend on the second-order ones, and so forth. . .
- Infinite set of linear ODEs (unstructured, non-necessarily Metzler. . .)
- Closure methods



## Dimerization process

### Process



- Stoichiometry matrix:

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

- Propensity function:

$$\lambda(X) = \begin{bmatrix} k_1 & \frac{b}{2}X_1(X_1 - 1) & \gamma_1 X_1 & \gamma_2 X_2 \end{bmatrix}^T.$$

### Motivations

- Goes beyond the affine case (e.g. gene expression<sup>1</sup>) and introduce dimerization
- Check whether the moments equations framework still applicable (closure problem)



<sup>1</sup> C. Briat et al. Computer control of gene expression: Robust setpoint tracking of protein mean and variance using integral feedback, 51st IEEE



## Moments equations

### Dynamical model

$$\begin{aligned}\dot{x}_1(t) &= k_1 + (b - \gamma_1)x_1(t) - bx_1(t)^2 - bv(t) \\ \dot{x}_2(t) &= -\frac{b}{2}x_1(t) - \gamma_2x_2(t) + \frac{b}{2}x_1(t)^2 + \frac{b}{2}v(t)\end{aligned}$$

where

- $x_i(t) := \mathbb{E}[X_i(t)]$ ,  $i = 1, 2$ ,
- $v(t) := V(X_1(t))$  is the variance of the random variable  $X_1(t)$ .

### Difficulties

- Nonlinear system (as opposed to linear for networks with affine propensities)
- Unknown “input” variance  $v(t) := V(X_1(t))$  (closure problem). Is it bounded? Is it converging?
- If  $v \rightarrow v^*$ , we have an infinite number of non-isolated equilibrium points (model artefact since the first-order moments may have a unique stationary value)

$$v^* \rightarrow \begin{bmatrix} x_1^* \\ x_2^* \end{bmatrix} \text{ locally continuous}$$



# Statement of the problem

## Objective

Find  $k_c$  such that the integral control law

$$\begin{aligned} \dot{I}(t) &= \mu - \mathbb{E}[X_2(t)] \\ u(t) &= k_c \cdot \max\{I(t), 0\} \end{aligned} \quad (3)$$

locally steers  $\mathbb{E}[X_2(t)]$  to  $\mu$  (stability and attractivity of the corresponding equilibrium point).

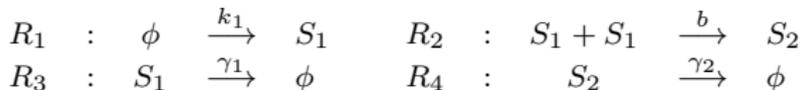
## Subproblems

- Are the moments bounded and converging for some parameter values? (stability)
- Choose a control input that can drive  $E[X_2]$  to  $\mu$  asymptotically
- Find conditions on the controller gain  $k_c$  such that we have local asymptotic stability of the first order moments.



# Ergodicity of the dimerization process

## Reaction network



## Theorem

*For any positive value of the network parameters  $k_1$ ,  $b$ ,  $\gamma_1$  and  $\gamma_2$ , the dimerization process is ergodic and has all its moments bounded and converging.*

$\Rightarrow (x_1(t), x_2(t), v(t)) \rightarrow (x_1^*, x_2^*, v^*)$  globally and exponentially

- Proof relying on an ergodicity result developed in the paper<sup>1</sup>

<sup>1</sup>C. Briat, A. Gupta and M. Khammash, "A scalable computational framework for establishing long-term behavior of stochastic reaction networks", submitted to PLOS computational biology



# Control of the mean population



## Choice of the control input

### Assumption

The function  $S^* := x_1^{*2} - x_1^* + v^*$ , where  $x_1^*$  is the unique equilibrium solution for  $x_1$  and  $v^*$  is the equilibrium variance, verifying the equation

$$k_1 - \gamma x_1^* - bS^* = 0, \quad (4)$$

is a continuous function of  $k_1$ .

### Proposition

For any  $\mu > 0$ , there exists a constant  $k_1 > 0$  such that  $x_2(t) \rightarrow \mu$ .

- The birth rate  $k_1$  can then be chosen as control input
- Good for us, this is also the simplest case!
- Other rates could have been also chosen



## Nominal stabilization

### Theorem

For any finite positive constants  $\gamma_1, \gamma_2, b, \mu$  and any controller gain  $k_c$  satisfying

$$0 < k_c < 2\gamma_2 \left( 2\gamma_1 + \gamma_2 + 2\sqrt{\gamma_1(\gamma_1 + \gamma_2)} \right), \quad (5)$$

the closed-loop system has a unique locally stable equilibrium point  $(x_1^*, x_2^*, I^*)$  in the positive orthant such that  $x_2^* = \mu$ .

The equilibrium variance moreover satisfies

$$v^* \in \left( 0, \frac{2\gamma_2\mu}{b} + \frac{1}{4} \right]. \quad (6)$$



## Proof (sketch)

- We have that

$$\begin{aligned} k_c I^* - \gamma_1 x_1^* - 2\gamma_2 \mu &= 0 \\ x_1^{*2} - x_1^* + v^* - \frac{\gamma_2 \mu}{b} &= 0 \end{aligned} \quad (7)$$

- Study the eigenvalues of the Jacobian system from the characteristic polynomial
- Four different scenarios according to the value  $v^*$ 
  - two positive equilibrium points: one is stable for some  $k_c > 0$ , the other is structurally unstable
  - one positive and one zero equilibrium point: the positive one is stable for some  $k_c > 0$ , the other is structurally unstable
  - one positive and one negative equilibrium point: the positive one is stable for some  $k_c > 0$ .
  - two complex equilibrium points: this case can not occur (existence of unique equilibrium point)
- The existence of an equilibrium point induces a condition on  $v^*$
- Intersection of the conditions on  $k_c$  gives the result



# Robust stabilization

## Uncertainty set

$$\mathcal{P} := [\gamma_1^-, \gamma_1^+] \times [\gamma_2^-, \gamma_2^+] \times [b^-, b^+] \quad (8)$$

defined for some appropriate positive real numbers  $\gamma_1^- < \gamma_1^+$ ,  $\gamma_2^- < \gamma_2^+$  and  $b^- < b^+$ .

We get the following robustification:

### Theorem

Assume the controller gain  $k_c$  verifies

$$0 < k_c < 2\gamma_2^- \left( 2\gamma_1^- + \gamma_2^- + 2\sqrt{\gamma_1^- (\gamma_1^- + \gamma_2^-)} \right). \quad (9)$$

Then, for all  $(\gamma_1, \gamma_2, b) \in \mathcal{P}$ , the closed-loop system has a unique locally stable equilibrium point  $(x_1^*, x_2^*, I^*)$  in the positive orthant such that  $x_2^* = \mu$ . The equilibrium variance  $v^*$ , moreover, satisfies

$$v^* \in \left( 0, \frac{2\gamma_2^+ \mu}{b^-} + \frac{1}{4} \right] \quad (10)$$



# Example



## Example

- Parameters:  $b = 3$ ,  $\gamma_1 = 2$  and  $\gamma_2 = 1$
- Closed-loop stability and tracking ensured if  $0 < k_c < 19.798$
- Choose  $k_c = 1$ ,  $\mu = 5$ ,  $T_s = 10\text{ms}$ ,  $I(0) = 0$ ,  $N = 2000$ ,  $x_0^i$  picked randomly in  $\{0, 1\}^2$ ,  $i = 1, \dots, N$

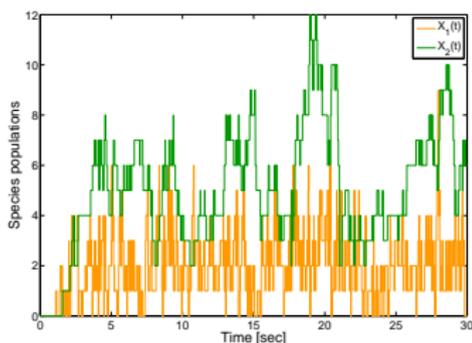


Figure: Evolution of proteins populations in a single cell.

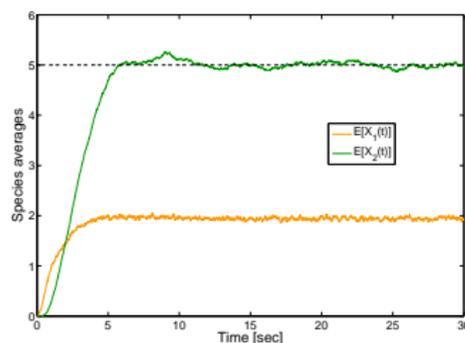


Figure: Evolution of the proteins averages in a population of 2000 cells.



## Example

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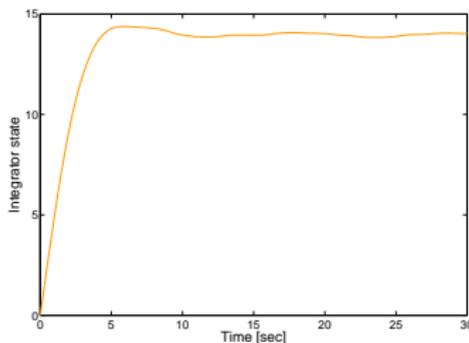


Figure: State of the integrator.

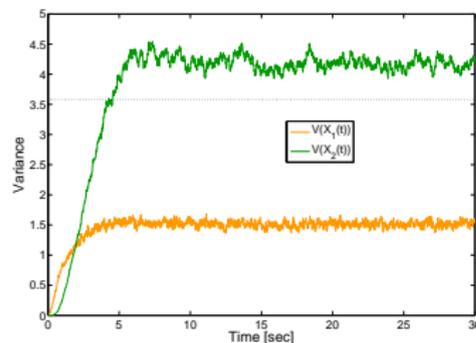


Figure: Evolution of the variances.



## Approximate simulation algorithm

- Require:**  $T_s, \mu, k_c, T > 0$ ,  $N, N_p \in \mathbb{N}$ ,  $\{x_0^1, \dots, x_0^N\} \in (\mathbb{N}_0^2)^N$ ,  $I_0 \in \mathbb{R}$  and  $p \in \mathbb{R}_{>0}^{N_p}$
- 1: Create array  $t$  of time instants from 0 to  $T$  with time-step  $T_s$ .
  - 2:  $N_s = \text{length}(t)$
  - 3: Initialize:  $i \leftarrow 1$ ,  $y \leftarrow \text{mean}(\text{dimer population})$ ,  $I \leftarrow I_0$
  - 4: **for**  $i < N_s$  **do**
  - 5: Update control input:  $u \leftarrow k_c \cdot \max\{0, I\}$
  - 6: Update controller state:  $I \leftarrow I + T_s(\mu - y)$
  - 7: Simulation of  $N$  cells from time  $t[i]$  to  $t[i + 1]$  with control input  $u$  and network parameters  $p$
  - 8: Update output:  $y \leftarrow \text{mean}(\text{dimer population})$
  - 9:  $i \leftarrow i + 1$
  - 10: **end for**



# Conclusion



## Conclusion and Future Works

### Conclusion

- Local integral control of a simple quadratic reaction network
- Moment closure problem can be circumvented
- So the moments framework seems to be still applicable for small systems
- The complexity, however, grows quite fast and shows limits for the moments equations

### Possible follow-ups

- Extensions to more general families of networks
- Good thing: reactions may be considered as worst-case quadratic for mass action kinetics
- Other types of control laws and models can be explored



Thank you for your attention