

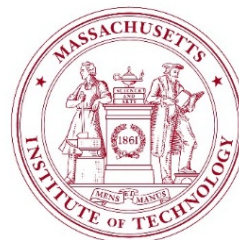
Genetic Circuit Engineering Meets Control Theory



Domitilla Del Vecchio

Mechanical Engineering

MIT



A journey towards modular composition

Engineering biology: Why and how

Modular composition: A grand challenge

Inter-module loads and the *load driver*

Disturbance attenuation via time scale separation

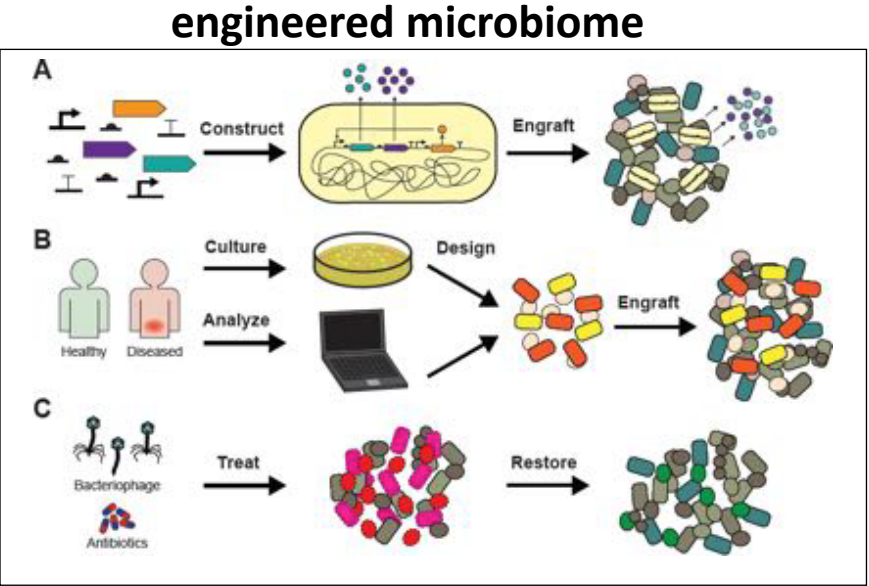
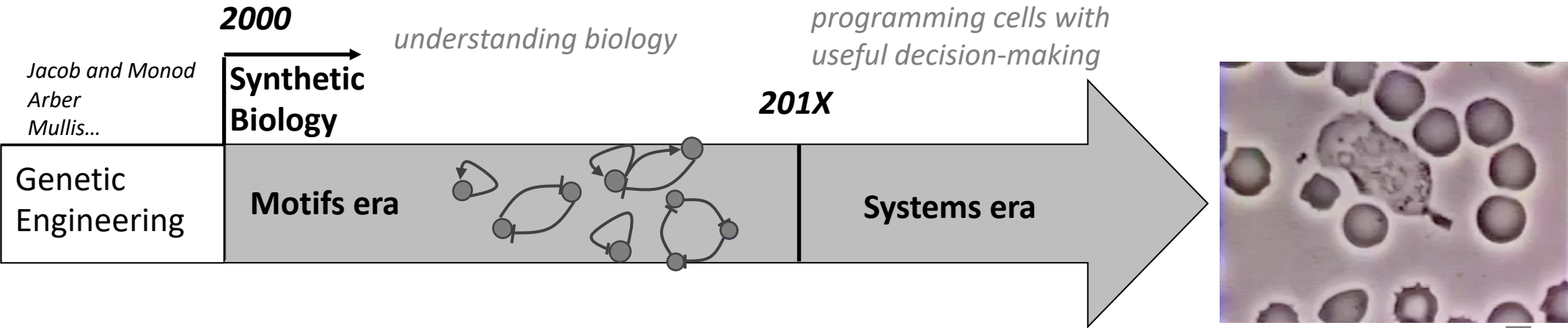
Resource loading and the *resource decoupler*

Disturbance rejection despite leaky integral actions

Decentralized implementation

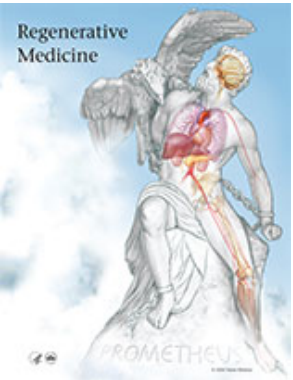
Outlook

Engineering biology: historical view



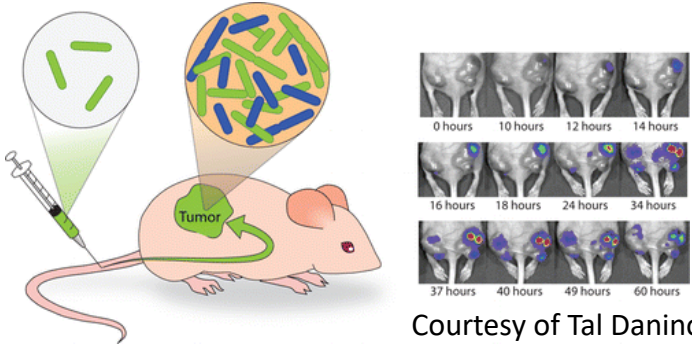
human performance enhancement

regenerative medicine



control of cell fate

curing disease

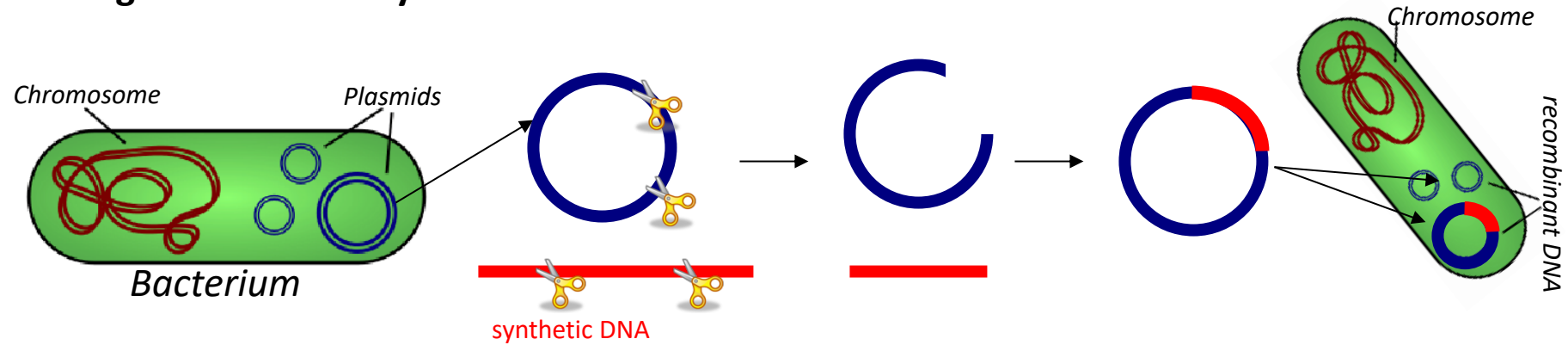


Courtesy of Tal Danino

tracking, recognizing, killing cancer cells

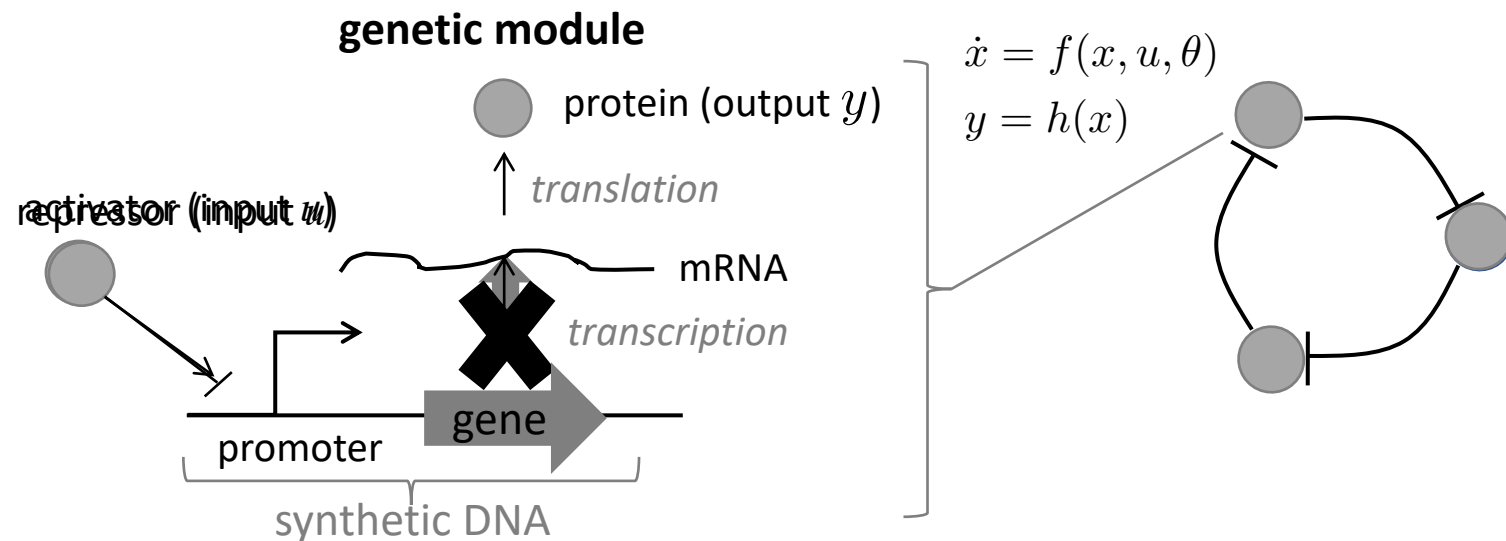
How do we engineer cells with *de novo* decision making

Decision making is encoded in synthetic DNA

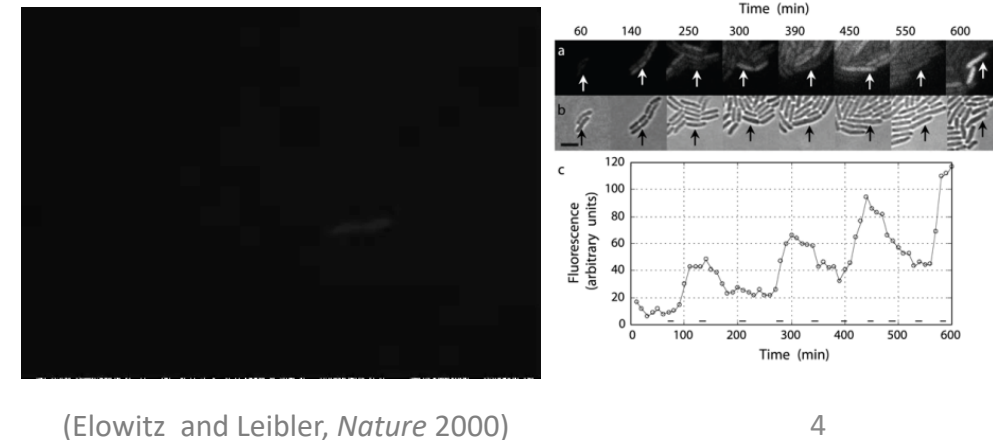


Synthetic DNA encodes genes that express proteins regulating expression of other genes (synthetic/endogenous)

- regulatory interactions create circuits
- interactions can be externally controlled by chemical signals



A biomolecular oscillator



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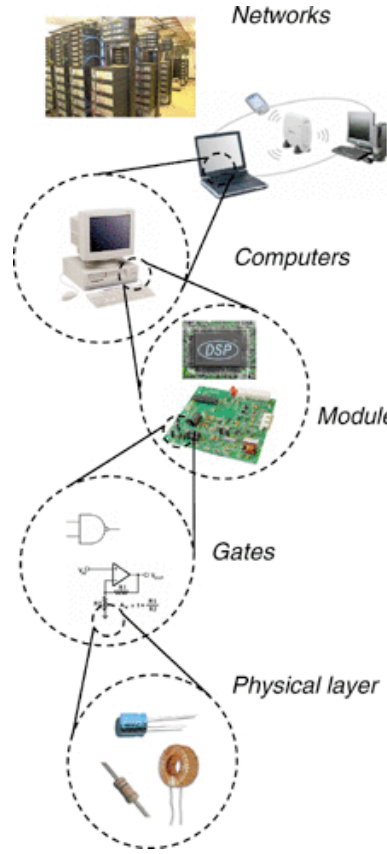
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Modular design in engineering biology



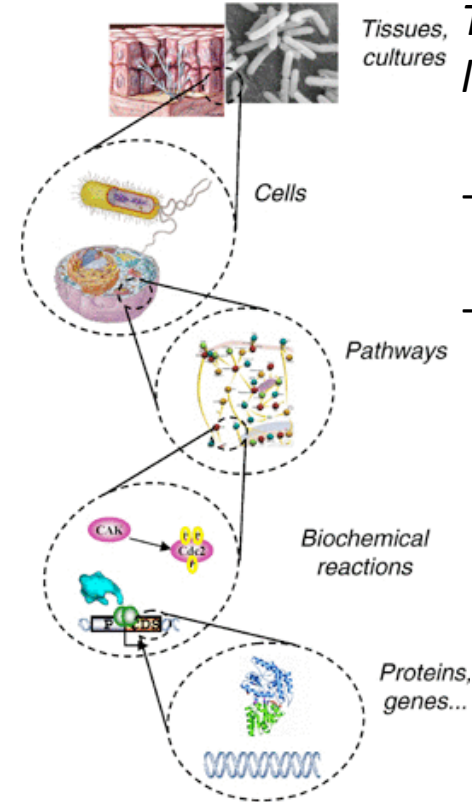
Describing a sophisticated system as the composition of simpler subsystems helps overcoming the complexity of design:

- we “forget” the details within subsystems when we compose them
- feedback can maintain I/O properties providing simplified abstractions for layered design

increased scale is becoming possible

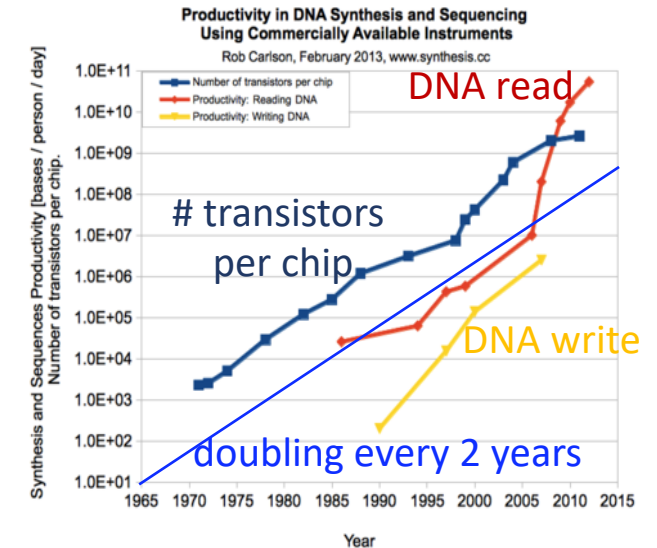
modularity is critical to manage complexity/time

the I/O behavior of a “module” should not change upon composition



Tempting in engineering biology: layered and modular composition

- we have large libraries of genetic parts
- we can synthesize DNA very quickly

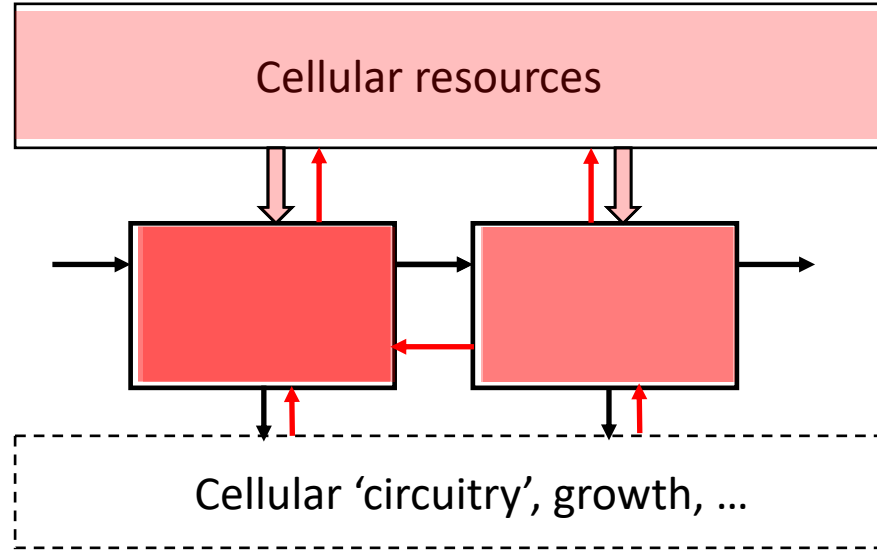


in practice, modularity fails

a system’s I/O properties are affected by surrounding systems
→ need to re-design “modules” after composition

for a circuit with 11 genes it takes
one PhD thesis of 5-6 years

Some reasons why modularity is a challenge



Loads applied by downstream modules change the behavior of upstream systems

(Del Vecchio, Hespanha, Klavins, Papachristodoulou, Sontag, ...)

Modules apply a load the cellular resources: creates subtle couplings

(Bates, Del Vecchio, Murray, Stan, ...)

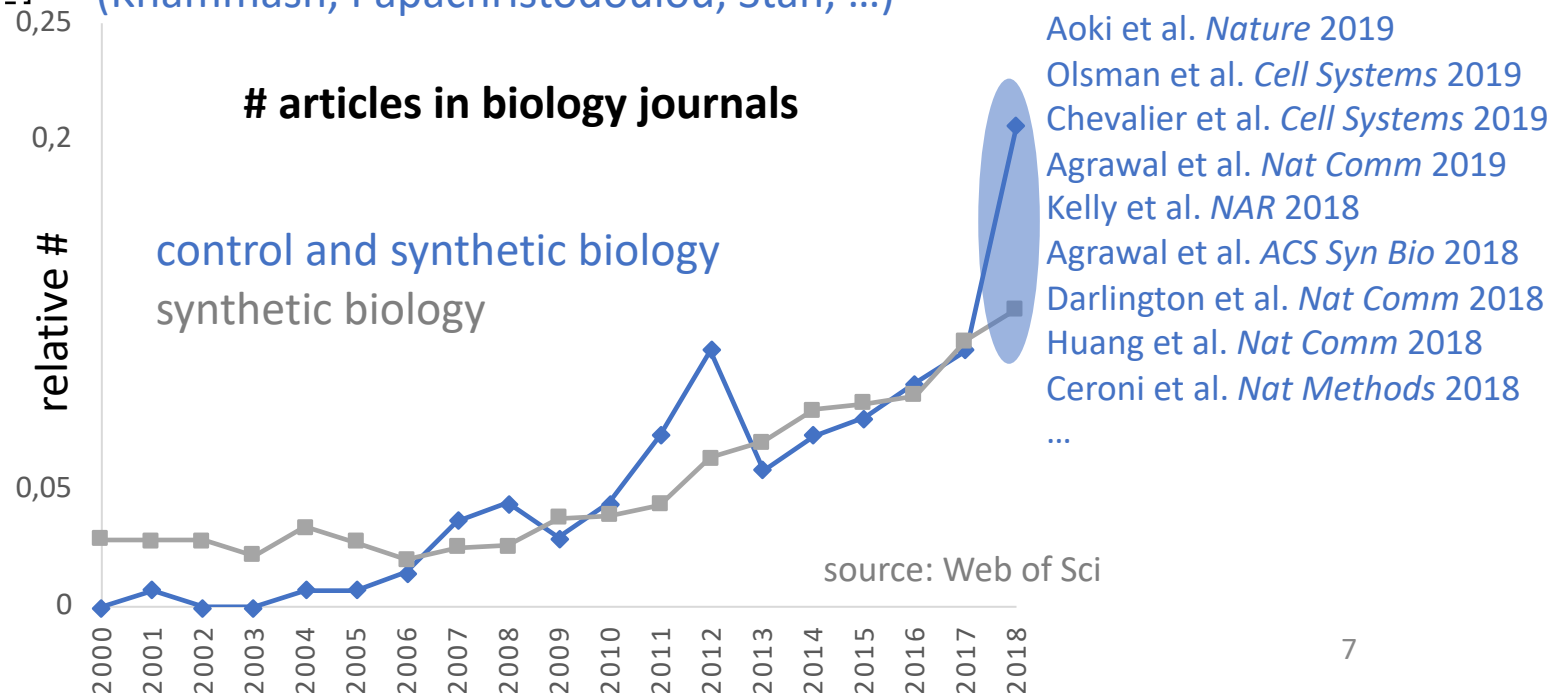
Modules often have “off-target” interactions, affect growth rate, and this, in turn, has global effects on a module’s dynamics

(Khammash, Papachristodoulou, Stan, ...)

these issues can be viewed as *lack of robustness* to perturbations

can we “insulate” desired I/O behaviors from these perturbations?

→ this is a **Control System Design** problem



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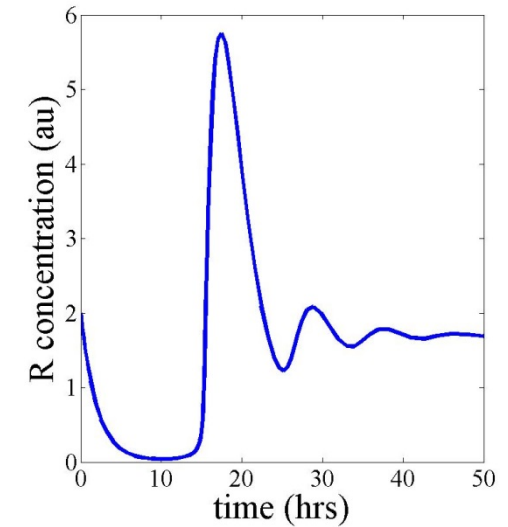
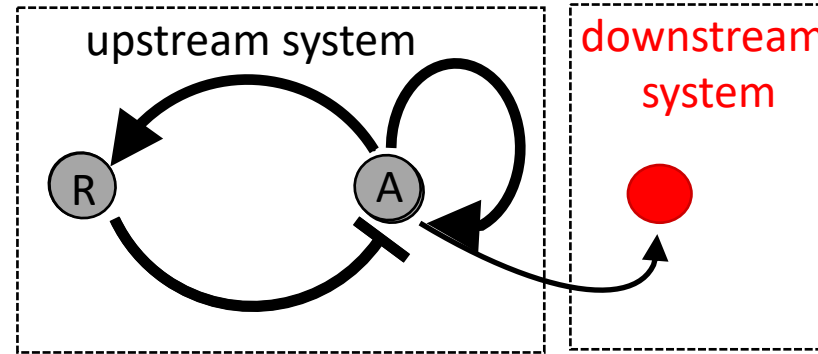
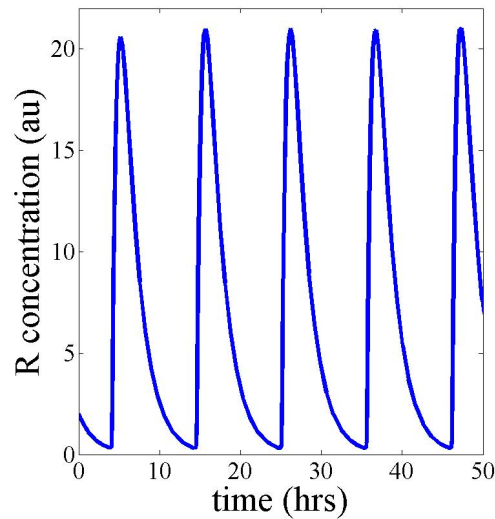
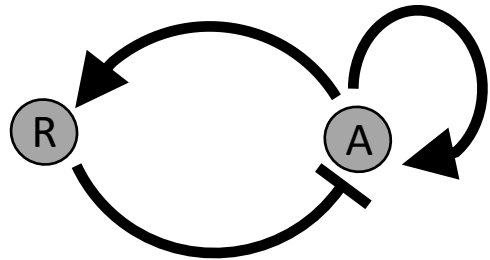
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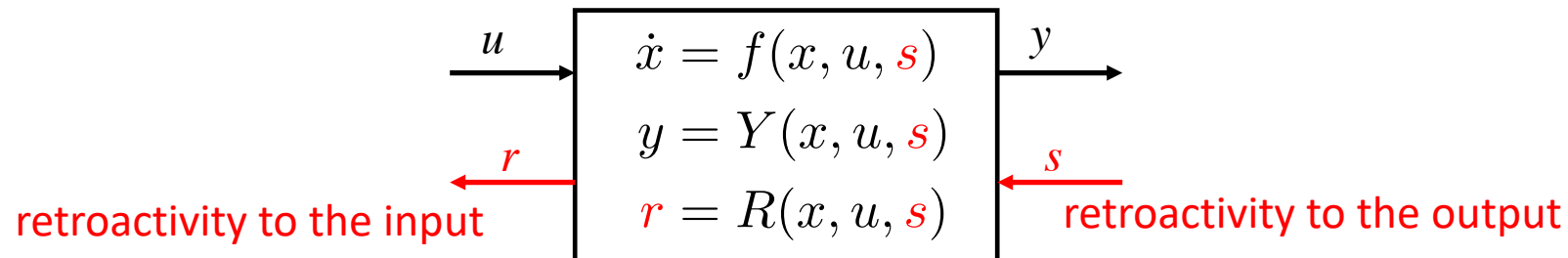
Inter-module loading changes upstream system's dynamics

(Atkinson et al, *Cell* 2003)



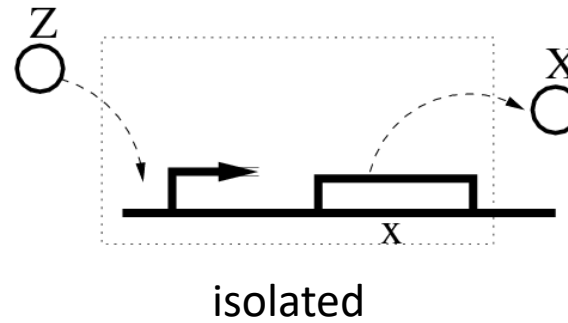
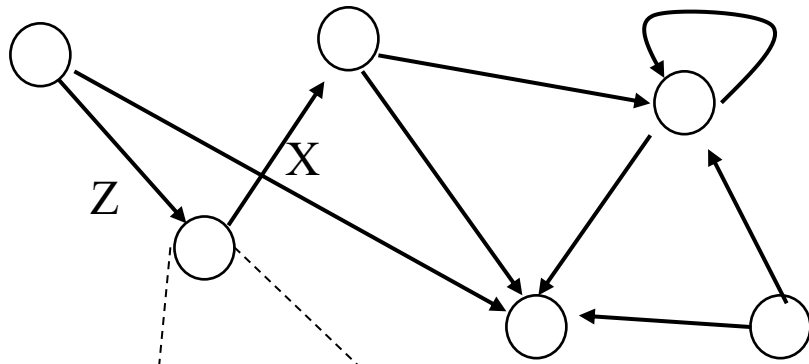
loads change the behavior of the upstream system → we fail to transmit the signal to the downstream system

systems & signals representation of loads: **retroactivity**

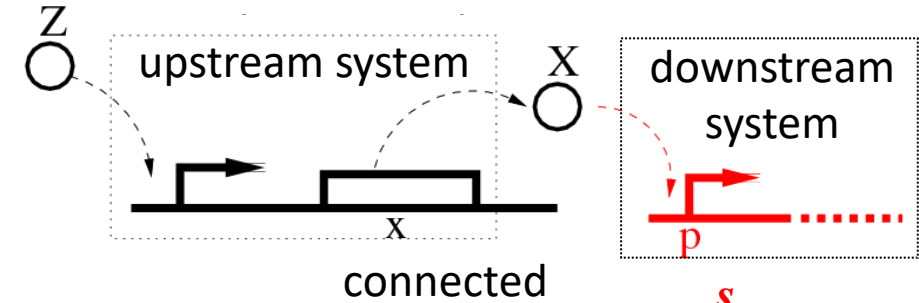


the I/O model of the **isolated system** is obtained when $s=0$

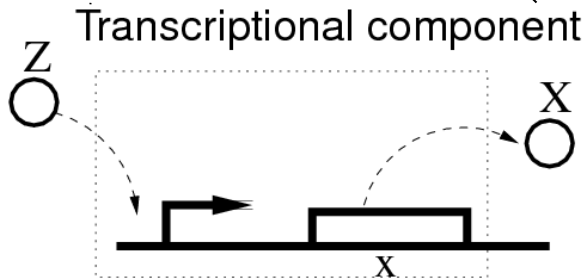
Retroactivity is a reaction flux affecting upstream system's output



$$\frac{dX}{dt} = k(t) - \delta X$$

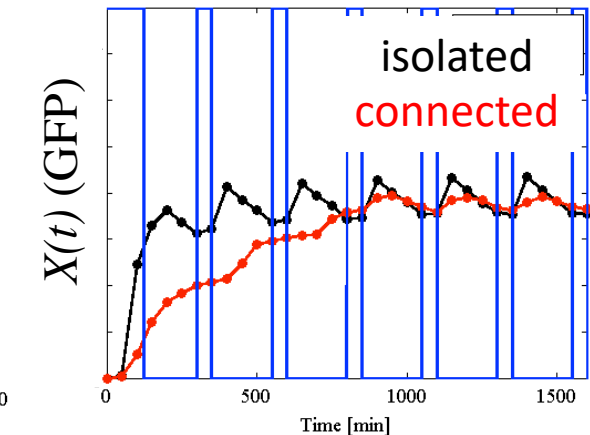
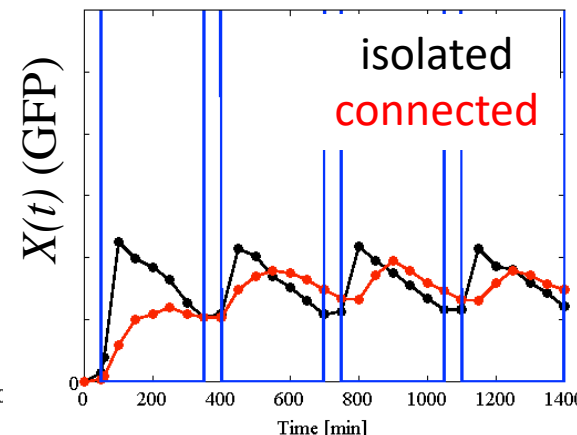
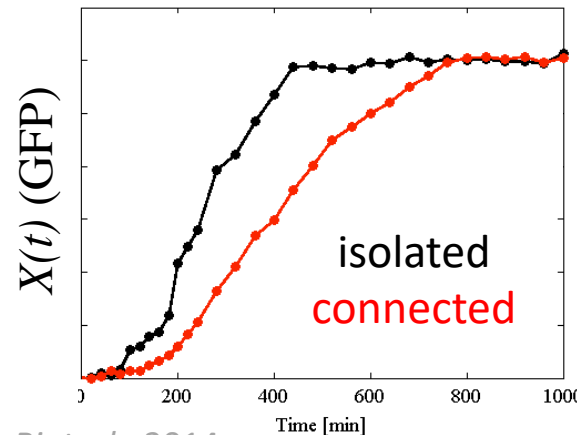


$$\begin{aligned}\frac{dX}{dt} &= k(t) - \delta X + k_{\text{off}}C - k_{\text{on}}pX \\ \frac{dC}{dt} &= -k_{\text{off}}C + k_{\text{on}}pX\end{aligned}$$



experiments in transcriptional components in yeast

retroactivity reduces bandwidth of upstream system



a transcriptional component is an input/output module

how does its input/output response change upon interconnection?

Insulation devices to mitigate retroactivity

consider retroactivity as a state-dependent disturbance



1. $r \approx 0$
2. s is attenuated

Principle 1
high-gain feedback

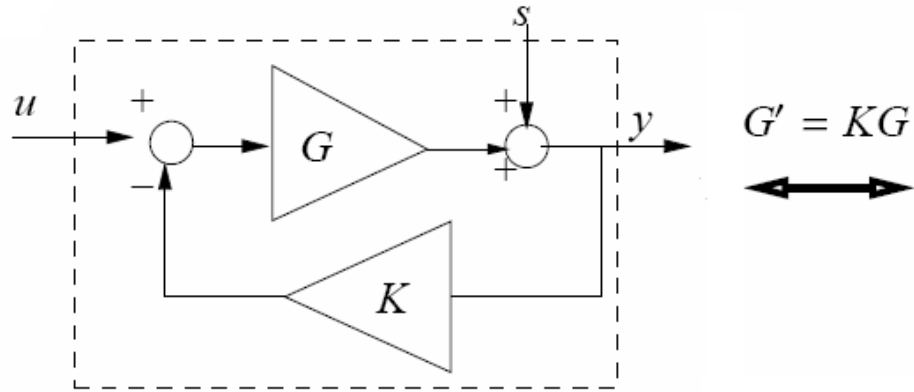
*requires an explicit negative
feedback*



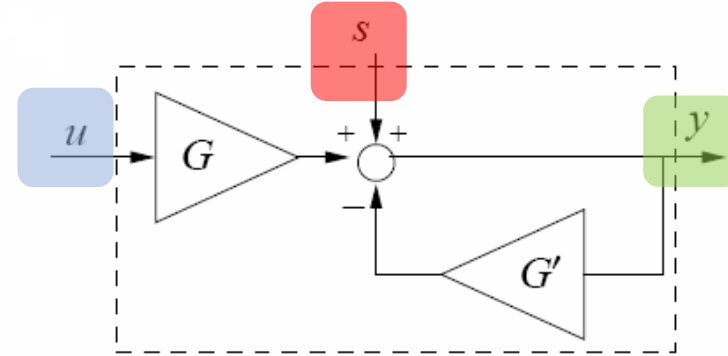
Principle 2
time scale separation

no explicit feedback required

From high-gain feedback to time-scale separation



$$G' = KG$$

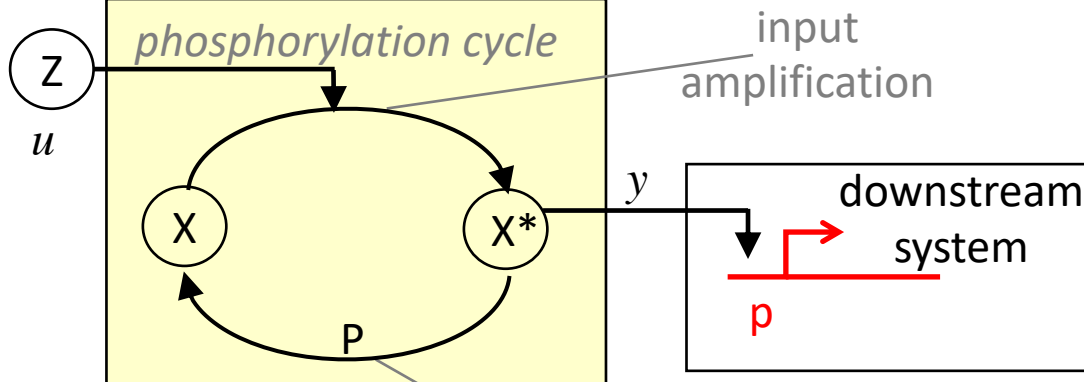


large input amplification
and a large negative feedback

*what biomolecular systems
can realize it?*

$$y = u \frac{G}{1 + KG} + \frac{s}{1 + KG} \xrightarrow{KG \rightarrow \infty} 0$$

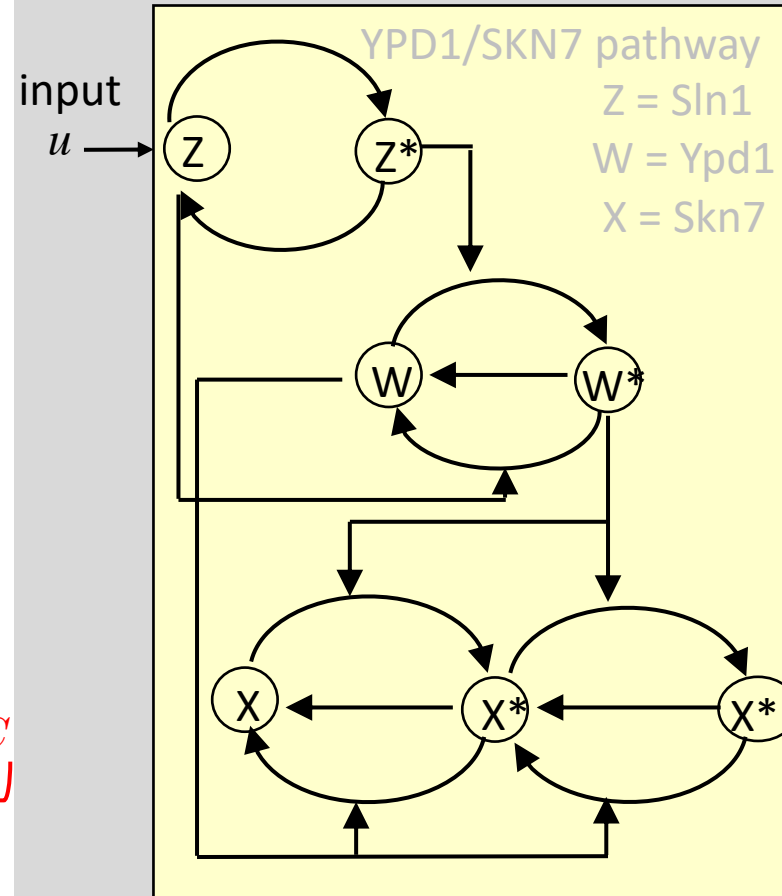
candidate insulation device



input
amplification

negative feedback

$$\frac{dX^*}{dt} = \underbrace{k_1 X_{tot} \left(1 - \frac{X^*}{X_{tot}}\right)}_{G \text{ naturally large}} \underbrace{Z(t)}_{u} - \underbrace{k_2 P X^* - k_{on} X^* p + k_{off} C}_{s}$$



most naturally-occurring
systems are not that
“simple” and involve
multiple modifications

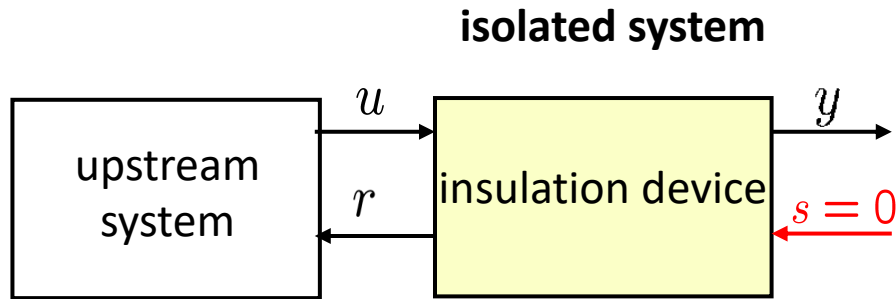
need a different scheme for
retroactivity attenuation:
- no explicit feedback

what is common between
these two systems?

- **speed**

output

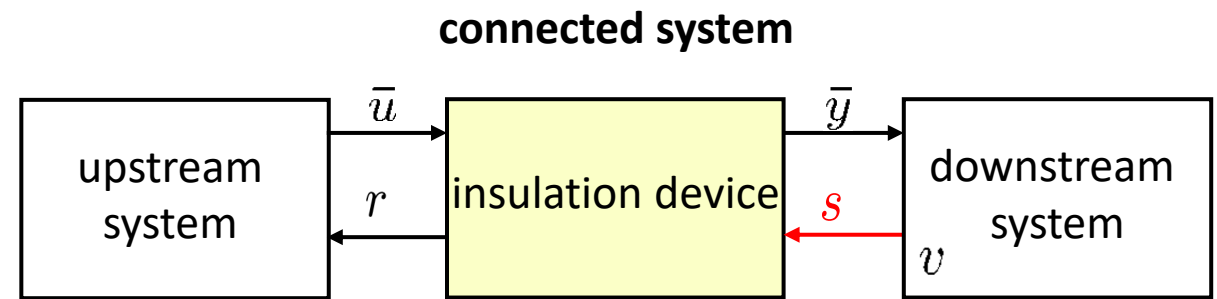
Retroactivity attenuation via time-scale separation



upstream system $\dot{u} = f_0(u, t) + r(u, y)$

insulation device $\dot{y} = G_1 f_1(u, y)$

large $G_1 \gg 1$



upstream system $\dot{\bar{u}} = f_0(\bar{u}, t) + r(\bar{u}, \bar{y})$

insulation device $\dot{\bar{y}} = G_1 f_1(\bar{u}, \bar{y}) + G_2 M s(\bar{y}, v)$

downstream system $\dot{v} = -G_2 N s(\bar{y}, v)$

very large rates
 $G_2 \gg G_1$

Fact: There are a matrix T and a non-singular matrix P such that $P \cdot M - T \cdot N = 0$ (closed system)

Theorem: If $\left. \frac{\partial f_1(u, y)}{\partial y} \right|_{y=h(u)}$ is Hurwitz with $y = h(u) \Rightarrow f_1(u, y) = 0$, then:

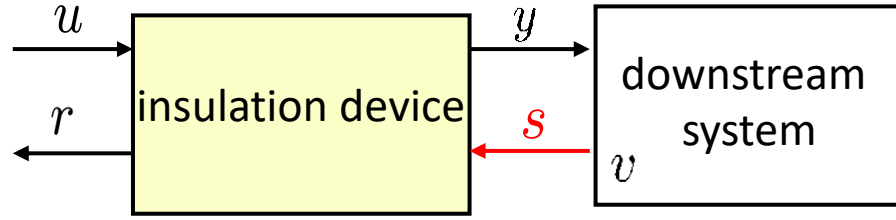
$$\|y(t) - \bar{y}(t)\| = \mathcal{O}(1/G_1), \quad \forall t \in [t_b, t_f] \text{ independent of } G_2 M s$$

Proof: use singular perturbation and nested application of Tikhonov's theorem

change of cords: $x = Py + Tv$

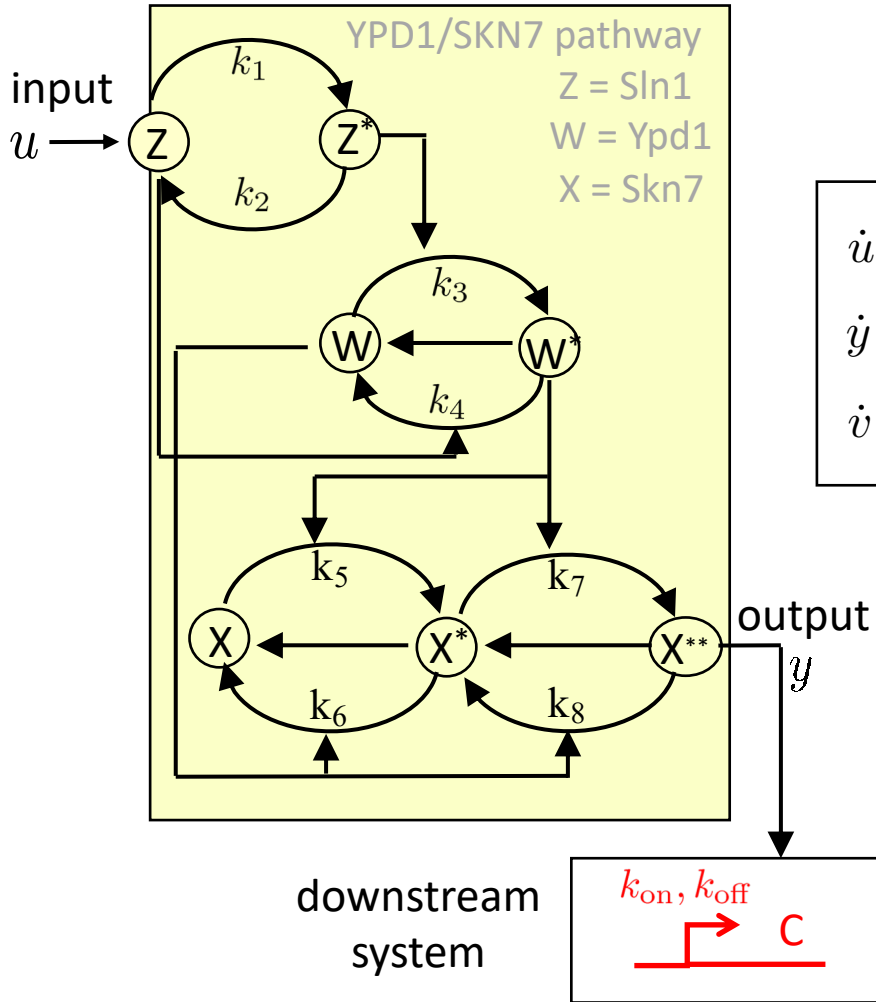
$$\left. \begin{aligned} \epsilon_1 \dot{\bar{x}} &= P f_1(\bar{u}, \bar{y}), \quad \epsilon_1 = 1/G_1 \\ \epsilon_2 \dot{v} &= -s(\bar{y}, v), \quad \epsilon_2 = 1/G_2 \end{aligned} \right\} \epsilon_1 = 0 \Rightarrow \bar{y} = h(\bar{u})$$

Application to signal transduction networks



$$\begin{aligned}\delta &\in [0.001, 0.01] \text{ min}^{-1} \\ k_i W_T &\in [1, 100] \text{ min}^{-1} \\ k_{\text{off}} &\in [0.1, 10^4] \text{ min}^{-1}\end{aligned}$$

$$\left. \begin{array}{l} \text{Z: gene expression time scale} \\ \text{W/X: time scale of signal transduction} \\ \text{C: time scale of reversible binding to DNA} \end{array} \right\} \begin{array}{l} G_1 = (k_i W_T)/\delta \gg 1 \\ G_2 = k_{\text{off}}/\delta \gg 1 \end{array}$$

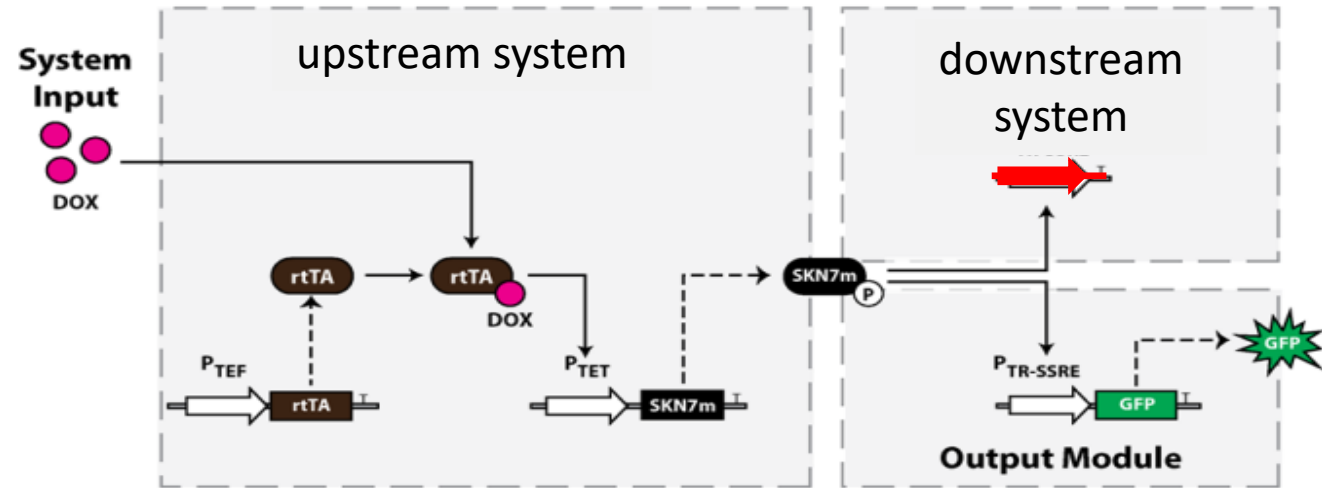
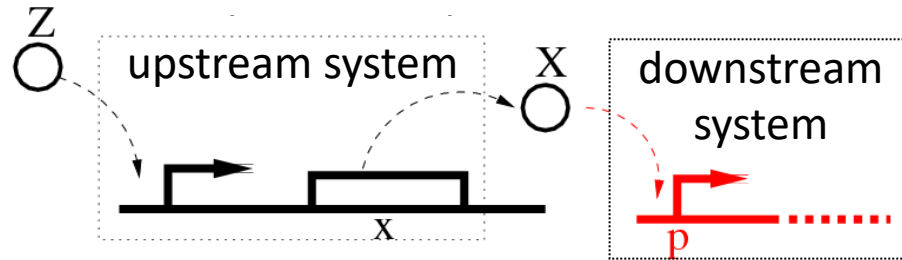


$$\begin{aligned}\dot{u} &= f_0(u, t) + r(u, y) \\ \dot{y} &= G_1 f_1(u, y) + G_2 M s(y, v) \\ \dot{v} &= -G_2 N s(y, v)\end{aligned}$$

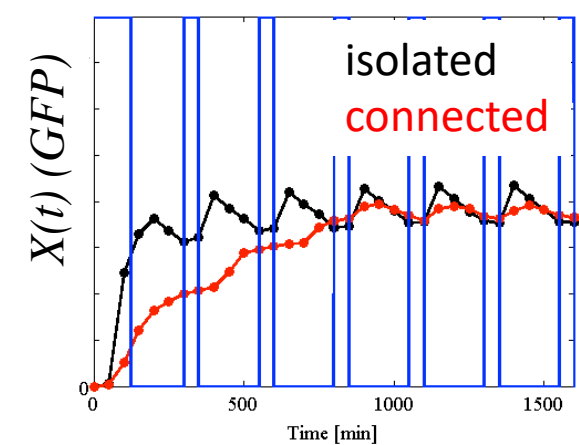
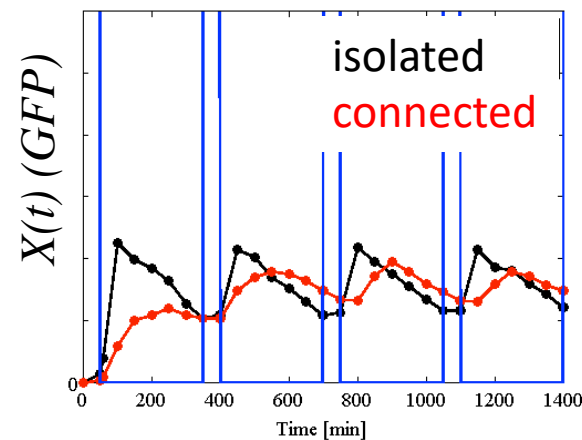
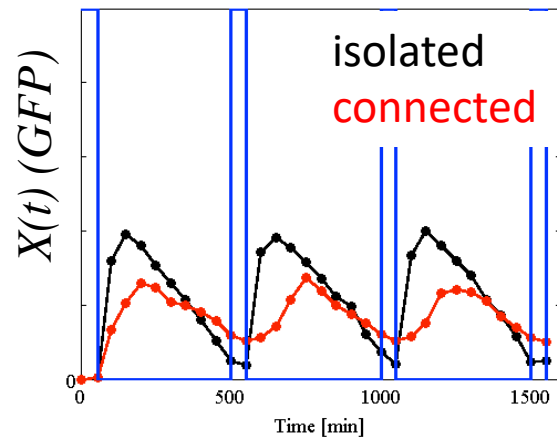
$$\begin{aligned}\dot{z}_T &= k(t) - \delta(z_T - Z^*) \\ \dot{Z}^* &= G_1 \delta \left(-c_1 Z^* \left(1 - \frac{W^*}{W_T} \right) + c_2 \frac{W^*}{W_T} (z_T - Z^*) \right. \\ &\quad \left. + c_p (z_T - Z^*) - c'_p Z^* - \frac{\delta}{G_1} Z^* \right) \\ \dot{W}^* &= G_1 \delta \left(c_1 Z^* \left(1 - \frac{W^*}{W_T} \right) - c_2 \frac{W^*}{W_T} (z_T - Z^*) + c_4 X^* \left(1 - \frac{W^*}{W_T} \right) \right. \\ &\quad \left. - c_3 (X_T - X^* - X^{**} - C) \frac{W^*}{W_T} - c_3 X^* \frac{W^*}{W_T} \right. \\ &\quad \left. + c_4 X^{**} \left(1 - \frac{W^*}{W_T} \right) - c_7 \frac{W^*}{W_T} \right) \\ \dot{X}^* &= G_1 \delta \left(c_3 (X_T - X^* - X^{**} - C) \frac{W^*}{W_T} - c_4 X^* \left(1 - \frac{W^*}{W_T} \right) \right. \\ &\quad \left. - c_3 X^* \frac{W^*}{W_T} + c_4 X^{**} \left(1 - \frac{W^*}{W_T} \right) - c_5 X^* + c_6 X^{**} \right) \\ \dot{X}^{**} &= G_1 \delta \left(c_3 X^* \frac{W^*}{W_T} - c_4 X^{**} \left(1 - \frac{W^*}{W_T} \right) - c_6 X^{**} \right) \\ &\quad + G_2 \left(\delta C - \frac{\delta}{K_d} X^{**} (p_T - C) \right) \\ \dot{C} &= -G_2 \left(\delta C - \frac{\delta}{K_d} X^{**} (p_T - C) \right)\end{aligned}$$

The *Load Driver*: Insulation by time scale separation

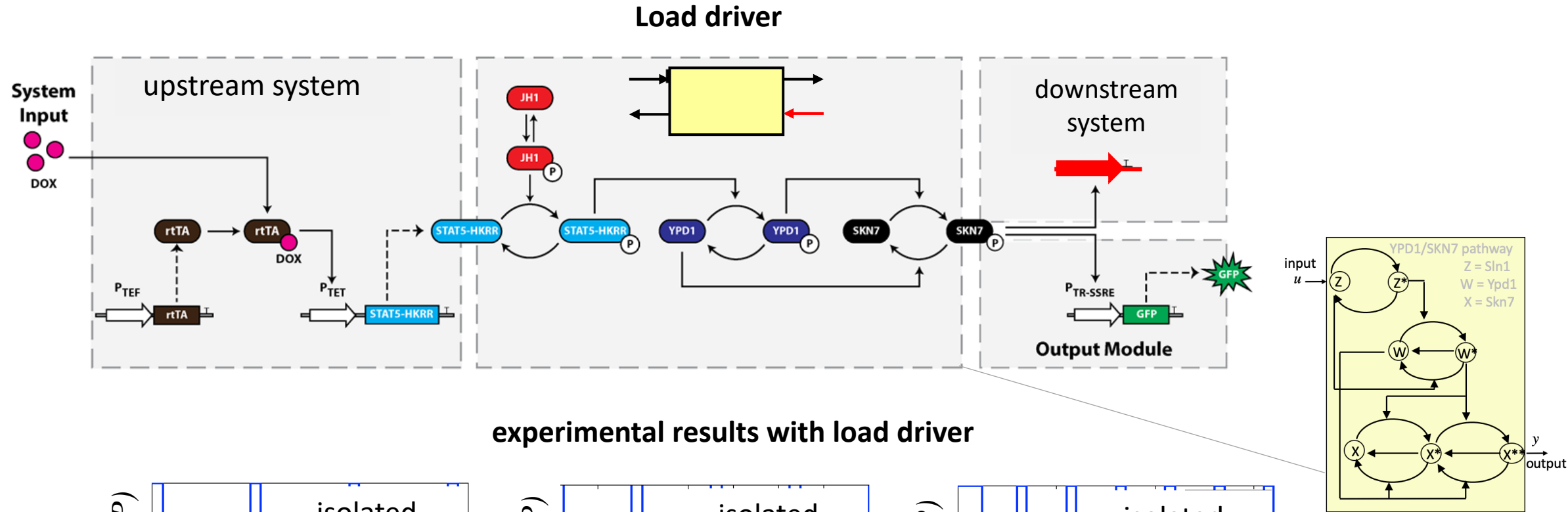
recall



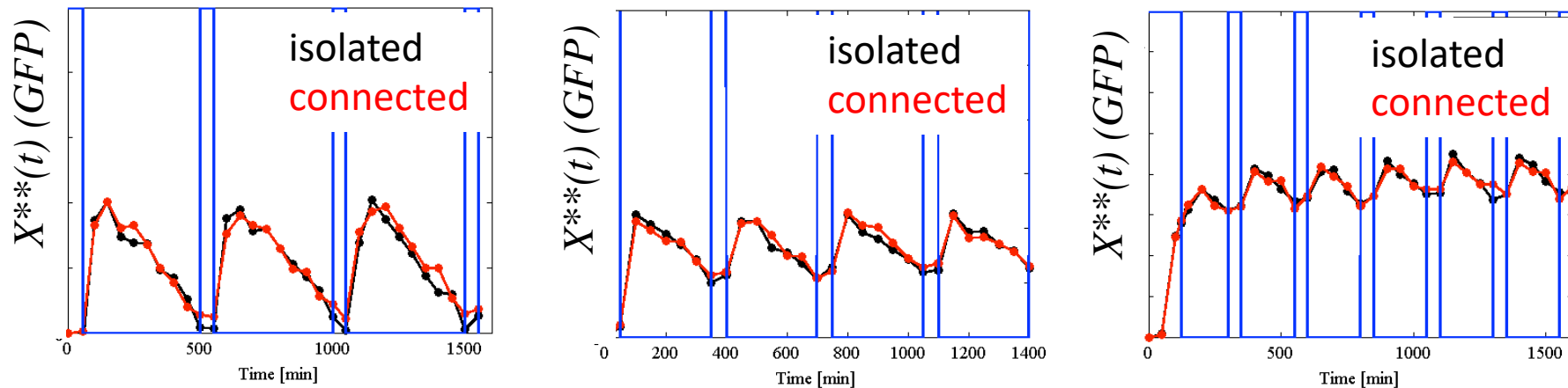
directly connecting the downstream system to the upstream system



The *Load Driver*: Insulation by time scale separation



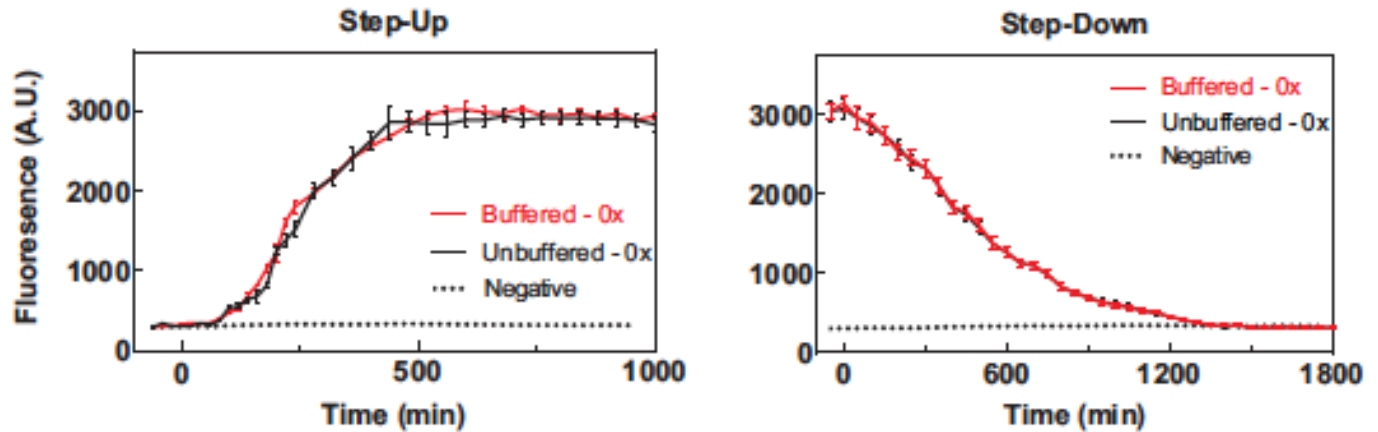
experimental results with load driver



The *Load Driver*: Insulation by time scale separation

Experiments with fast time scales

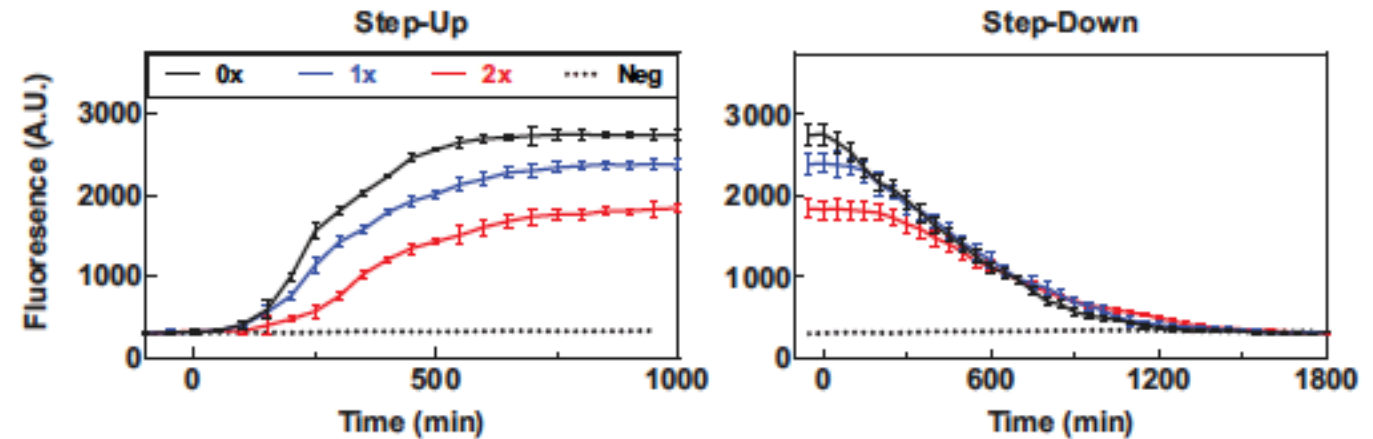
(endogenous amounts of YPD1 and SKN7)



Experiments with slow time scales

(reduced amounts of YPD1 and SKN7 obtained through weaker constitutive promoters)

insulation property is lost



Slow/fast/slow pattern allow to reliably transmit signals to large loads: the synergy between slow transcription and fast signal transduction is likely to be used by natural systems to insulate signals from downstream loads

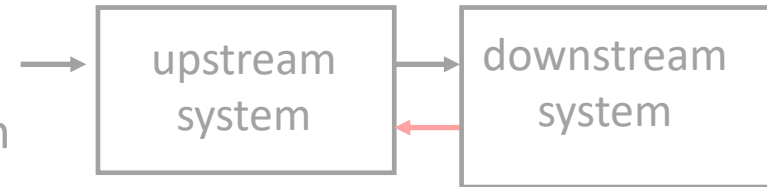
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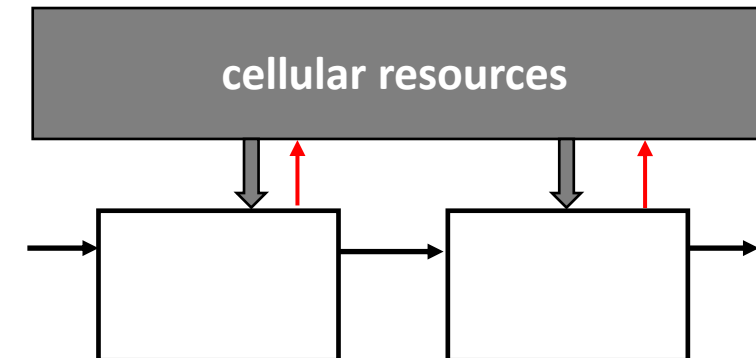
Disturbance attenuation via time scale separation



Resource loading and the *resource decoupler*

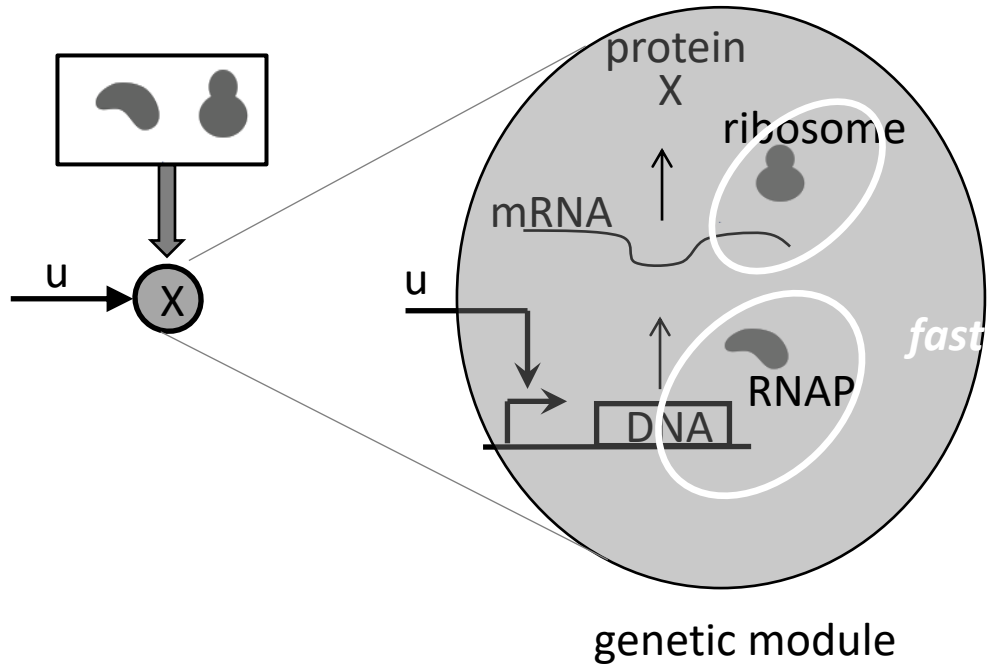
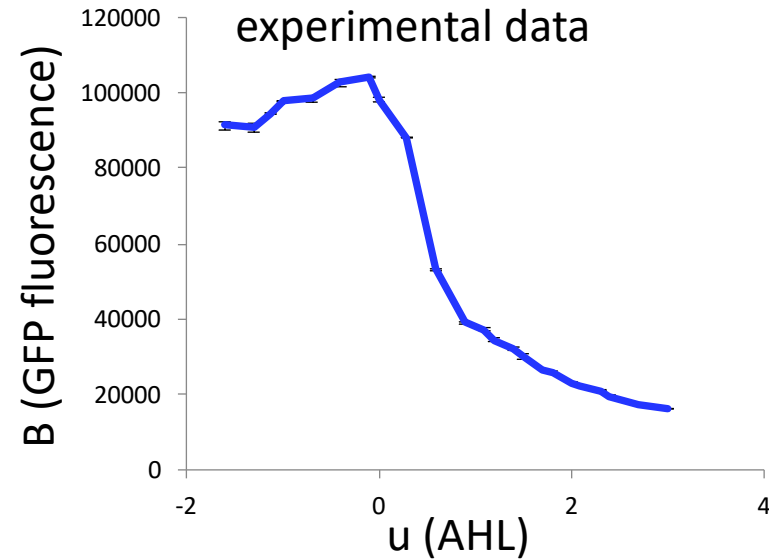
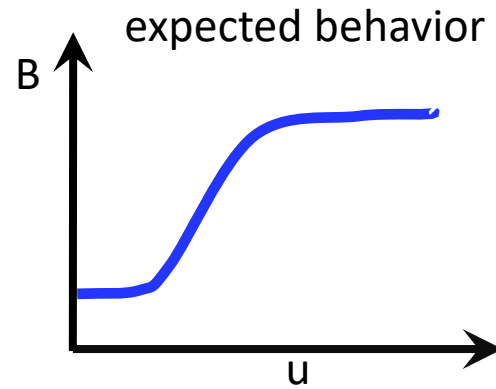
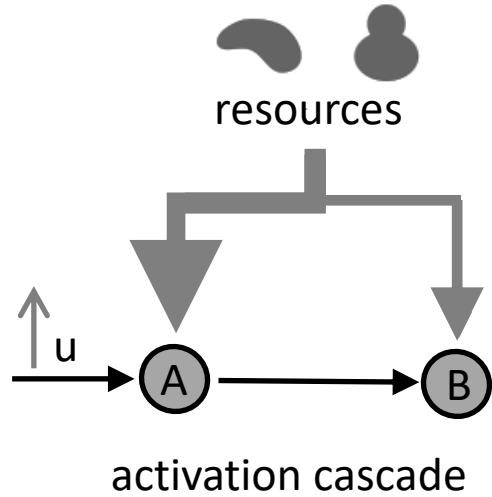
Disturbance rejection despite leaky integral actions

Decentralized implementation

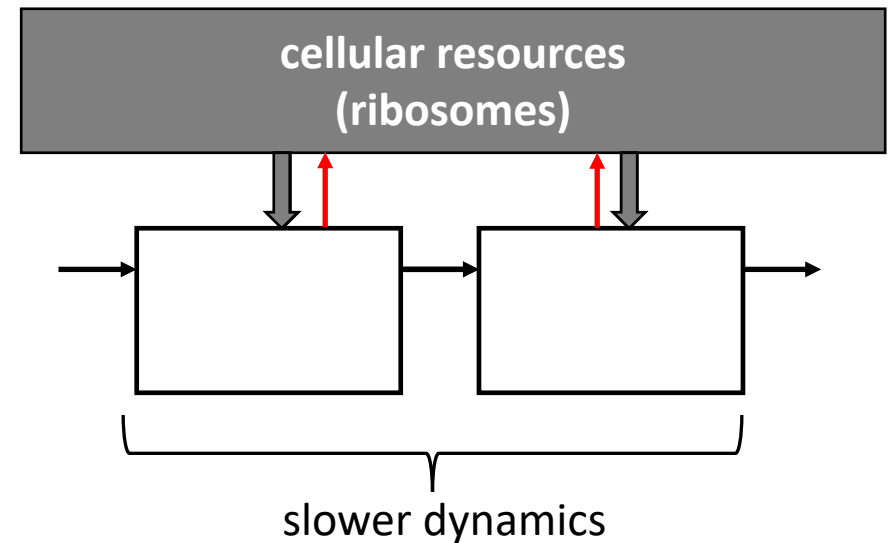


Outlook

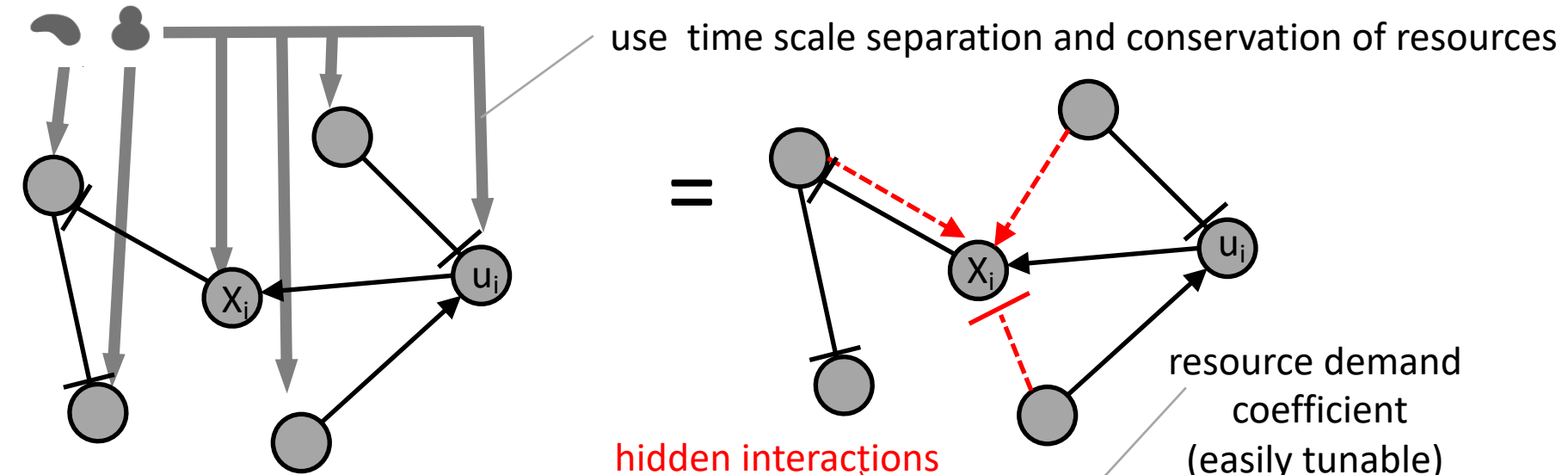
Modules become coupled by loading cellular resources



fast dynamics
 \rightarrow QSS



Coupling can be mathematically captured by “hidden” graphs



$$\dot{X}_i = F_i(u_i) - \delta X_i$$

intended regulatory function

$$\dot{X}_i = \frac{F_i(u_i)}{1 + \sum_k J_k F_k(u_k)} - \delta X_i$$

$H_i(u)$ effective regulatory function

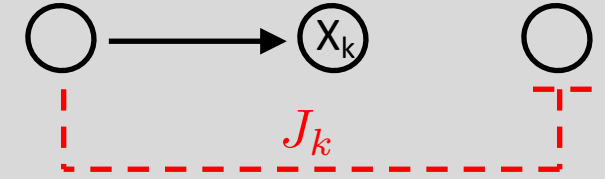
effective
interaction
graph

$$\frac{\partial H_i(u)}{\partial u} = \underbrace{\frac{\partial F_i / \partial u}{(1 + \sum_j J_j F_j)^2}}_{\text{re-scaling of intended regulatory links}} - \underbrace{\frac{F_i \sum_j J_j \partial F_j / \partial u}{(1 + \sum_j J_j F_j)^2}}_{\text{“hidden” interaction graph}}$$

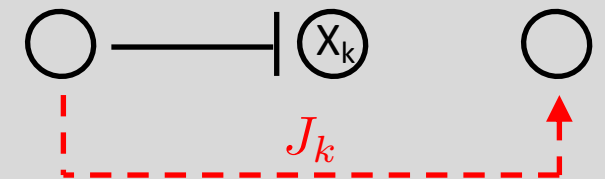
re-scaling of intended
regulatory links

“hidden” interaction
graph

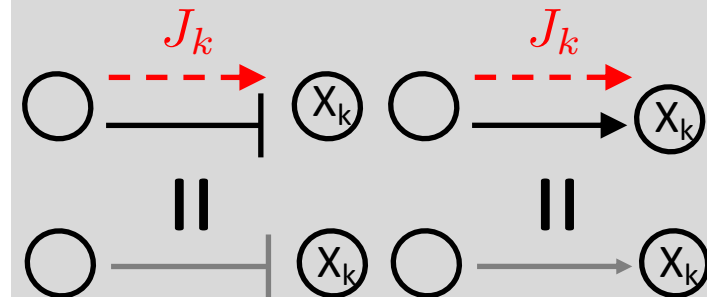
rules to draw hidden interactions



activators become “effective
repressors” for non-target nodes

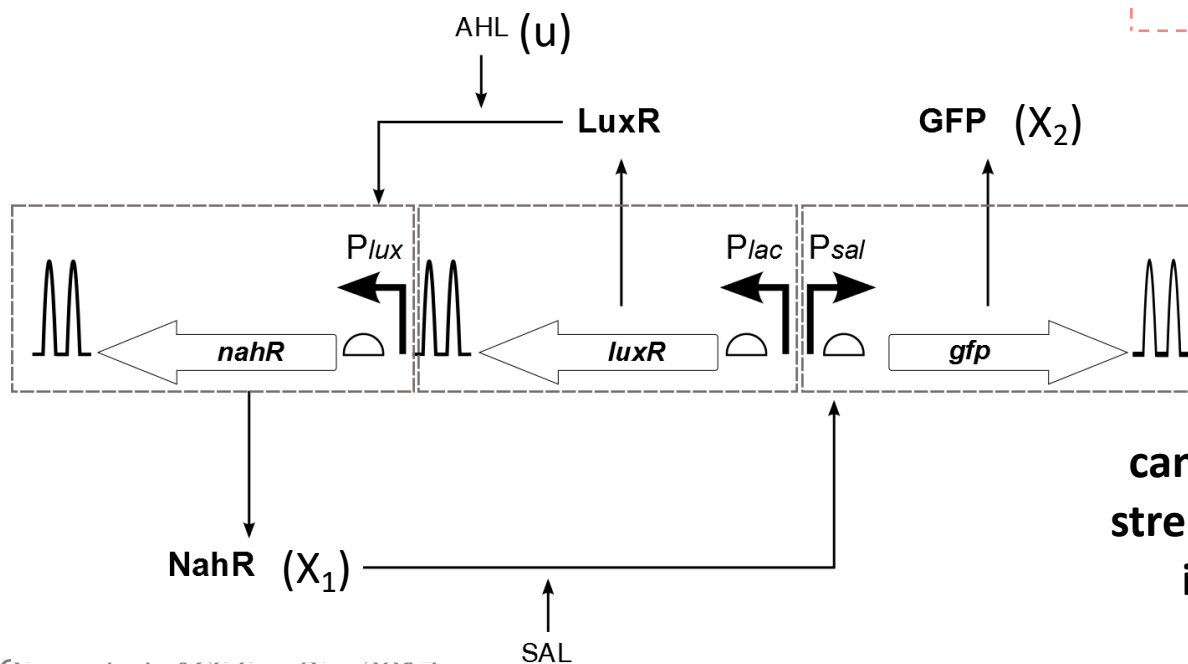
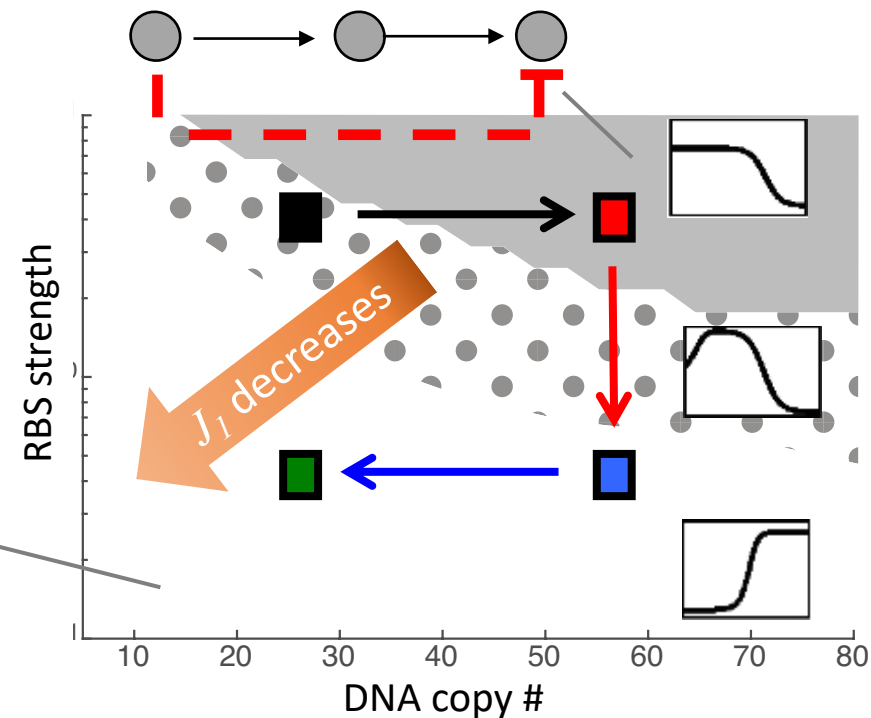
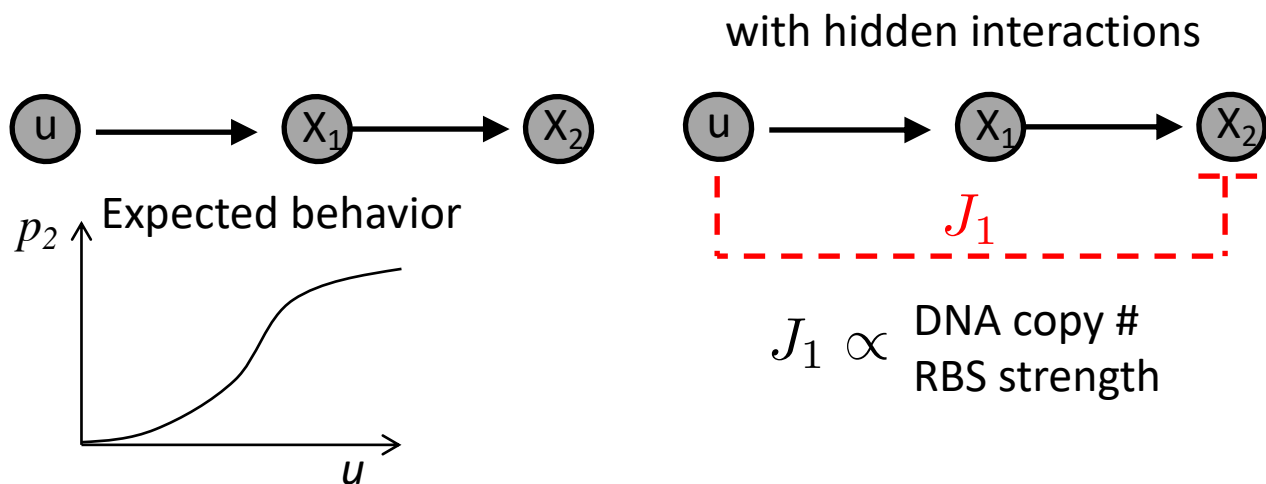


repressors become “effective
activators” for non-target nodes

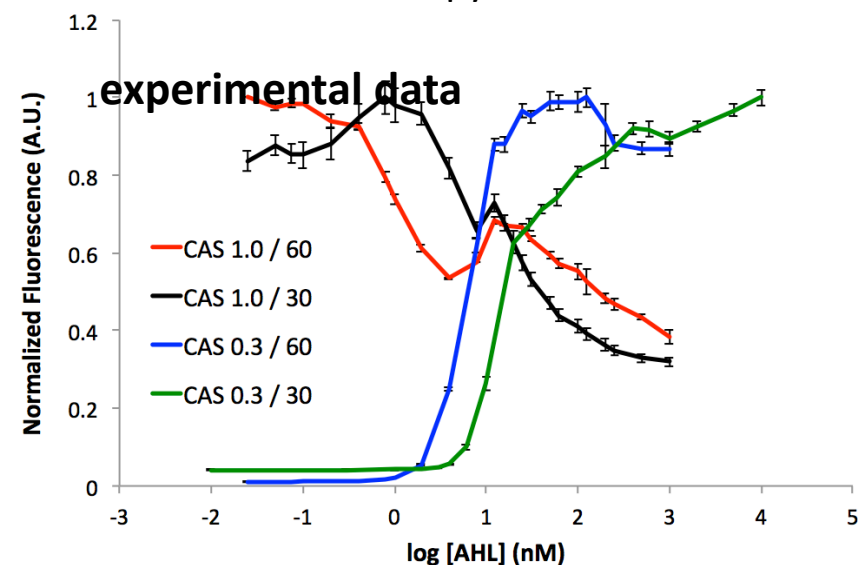


the effect on target nodes
is weaker

The effective interaction graph of an activation cascade is an iFFL

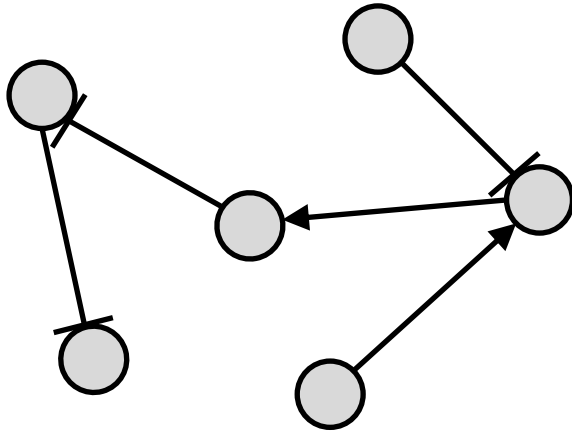


can use J to tune strength of hidden interactions

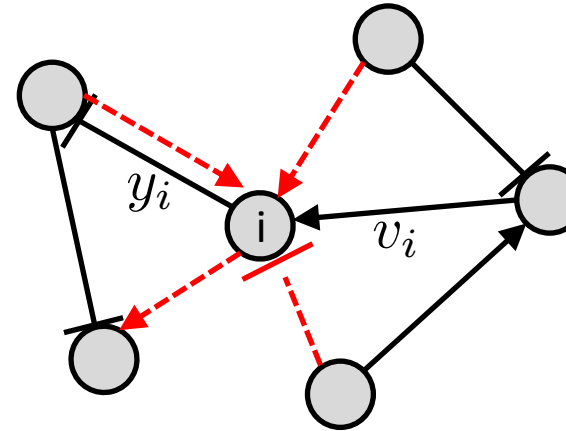


Network disturbance attenuation

system without hidden interactions

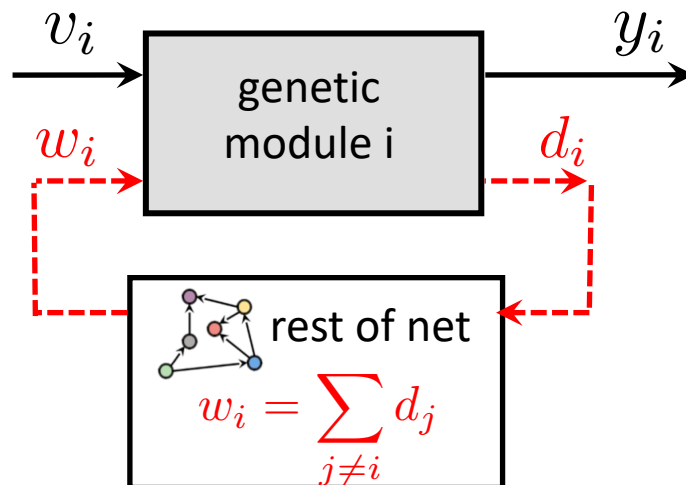


system with hidden interactions



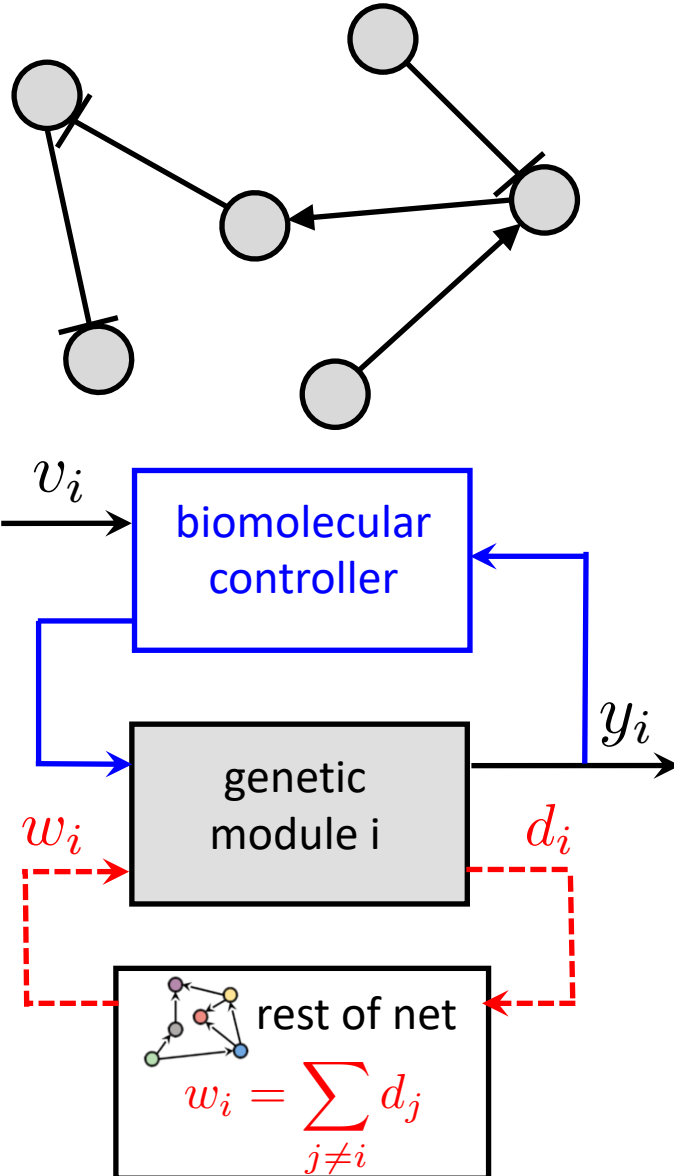
$d_i \propto J_i$
resource demand
at node i

$$w_i = \sum_{j \neq i} d_j$$

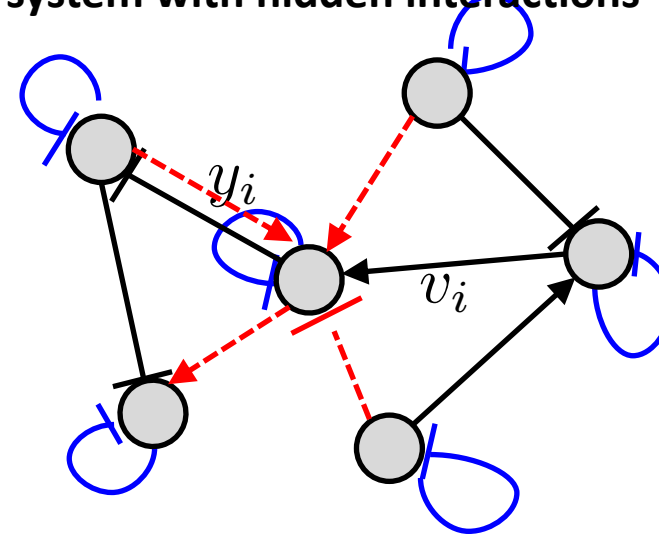


Network disturbance attenuation

system without hidden interactions



system with hidden interactions

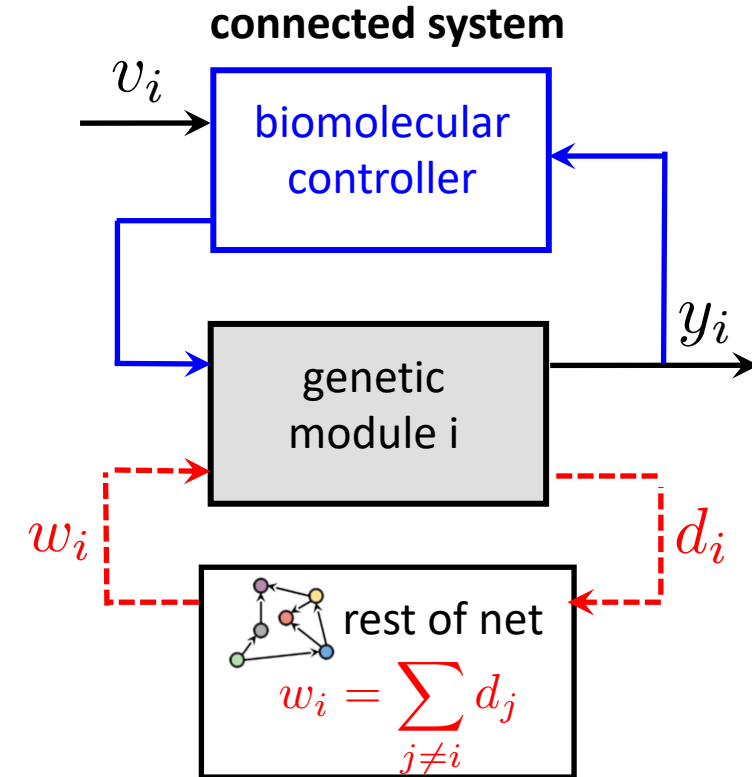
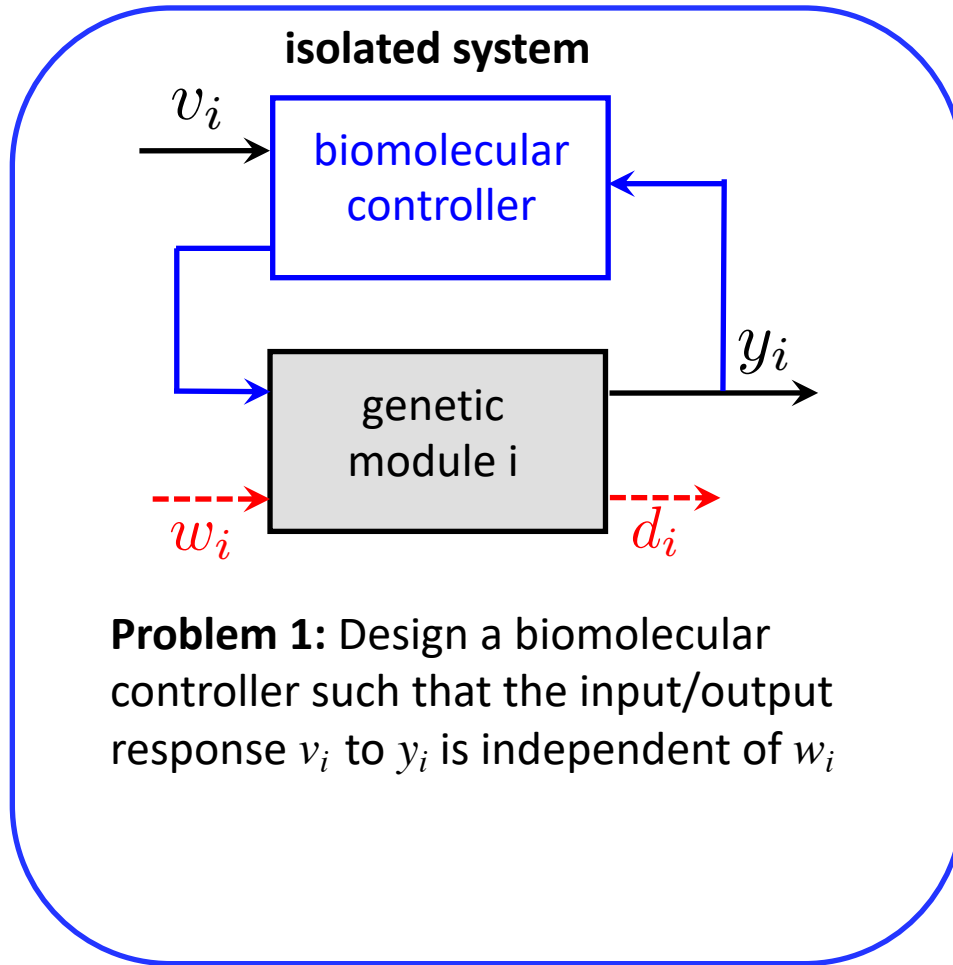


$d_i \propto J_i$
resource demand
at node i

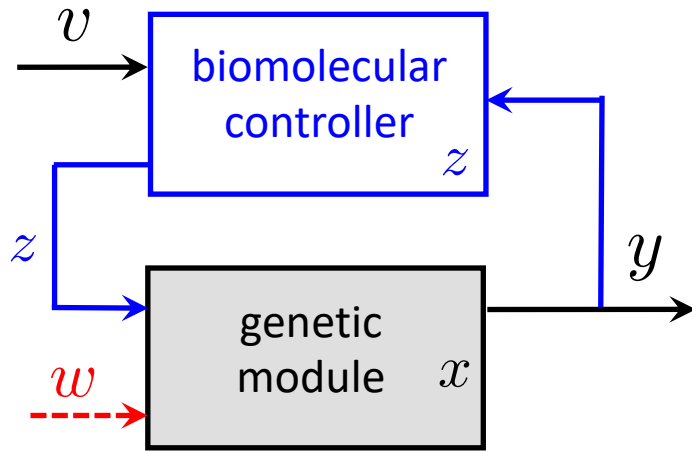
$$w_i = \sum_{j \neq i} d_j$$

Problem: Design a local feedback controller such that y_i depends only on v_i and it is independent of w_i

Network disturbance attenuation



Disturbance rejection despite leaky integrators



Approach: For v and w constants, use integral control, e.g.

$$\dot{x} = f(x, v, z, w), \quad y = g(x)$$

$$\dot{z} = k(v - y)$$

under stability conditions, y is independent of w at steady state

Challenge: molecular decay is unavoidable *in vivo* due to cell growth \rightarrow integrator leakiness

$$\dot{x} = f(x, z, w), \quad y = g(x)$$

$$\dot{z} = k(v - y) - \gamma z$$

cannot send growth to zero
 \rightarrow increase speed of
all controller's reactions

$$\dot{x} = f(x, z, w), \quad y = g(x) \quad \text{quasi-integral control (QIC) structure}$$

$$\dot{z} = \frac{1}{\epsilon}(v - y) - \gamma z$$

Theorem: $\dot{x} = f(x, z, w)$

$$\dot{z}_1 = \frac{1}{\epsilon} h(v, z, y) - \gamma z_1$$

$$\dot{z}_2 = \frac{k}{\epsilon}(v - y) - \gamma z_2$$

$$y = g(x)$$

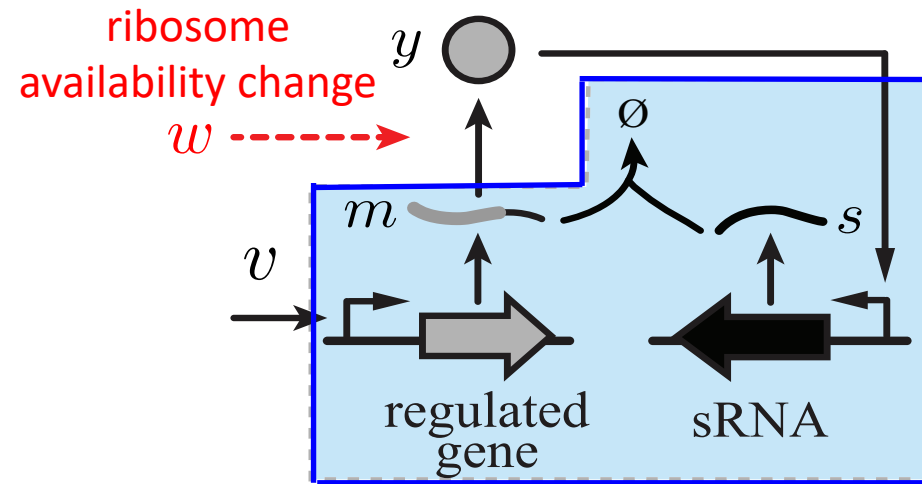
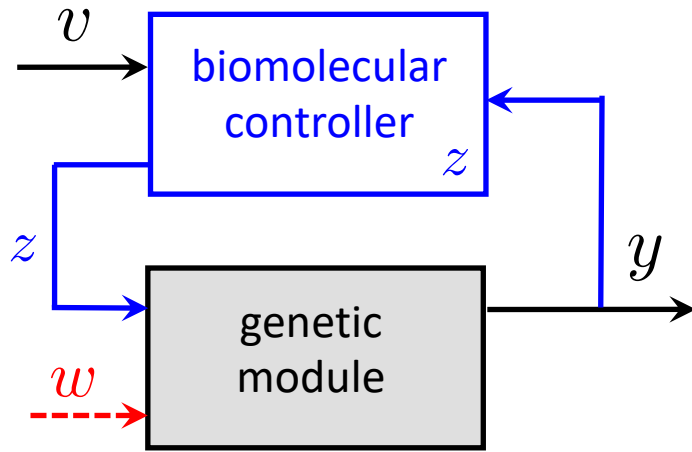
If this closed loop system with $\gamma = 0$
is LES for small $\epsilon > 0$

Then: $y(\epsilon) \rightarrow v$ as $\epsilon \rightarrow 0$ independent of w

biomolecular implementation:

all fast controller reactions
compute the difference and
integrate

Quasi-integral control implementation via sRNA silencing



Briat et al. (2016)
sequestration-based
feedback

$$\dot{y} = R(w)m - \delta y$$

$$\begin{aligned} \dot{m} &= \frac{v}{\epsilon} - \frac{\theta}{\epsilon}ms - \gamma m \\ \dot{s} &= \frac{y}{\epsilon} - \frac{\theta}{\epsilon}ms - \gamma s \end{aligned}$$

fast RNA interactions
(for "free")

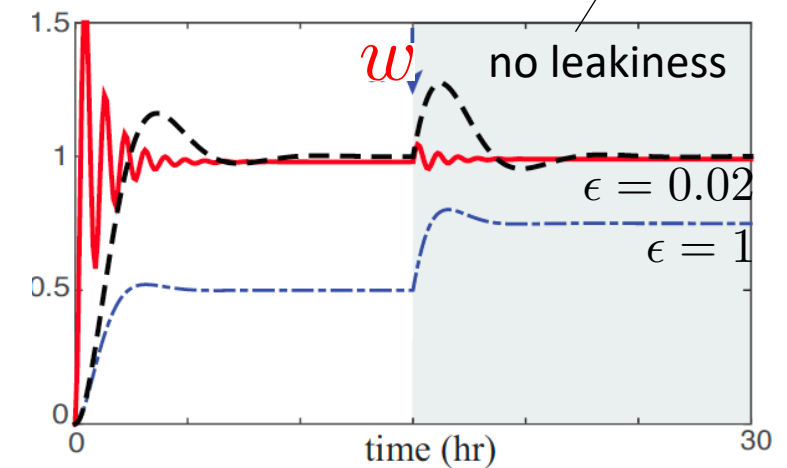
high RNA transcription rates (we can tune)

$$z = m - s$$

$$\epsilon \dot{z} = (v - y) - \epsilon \gamma z \quad (\text{QIC})$$

closed loop system when $\gamma = 0$
is LES

then $y(\epsilon) \rightarrow v$ as $\epsilon \rightarrow 0$
independent of disturbance



Tracking performance of quasi-integral control: a SSP problem

Problem: With time-varying inputs, can we still attenuate effect of disturbance as timescale separation between controller and plant increases ($\epsilon \rightarrow 0$) ?

Not obvious - tempting observation:

$$\begin{aligned} \dot{y} &= R(w)m - \delta y \\ \epsilon \dot{m} &= v(t) - \theta ms - \epsilon \gamma m \\ \epsilon \dot{s} &= y - \theta ms - \epsilon \gamma s \end{aligned} \xrightarrow{\epsilon=0} \begin{aligned} y(t) &= v(t) \\ &\text{independent of } w \end{aligned}$$

Boundary layer dynamics
 $m' = v(t) - \theta ms$
 $s' = y - \theta ms$
Jacobian is singular everywhere

→ Singular singular perturbation (SSP) problem

$$\dot{y} = f(y, x, t), \quad y \in \mathbb{R}^q$$

$$\epsilon \dot{x} = g(y, x, \epsilon), \quad x \in \mathbb{R}^p$$

$$\begin{aligned} y' &= \epsilon f(y, x, t) \\ x' &= g(y, x, \epsilon) \end{aligned}$$

$$J = \begin{pmatrix} 0 & 0 \\ \frac{\partial g}{\partial y} & \frac{\partial g}{\partial x} \end{pmatrix} \Big|_{\epsilon=0}$$

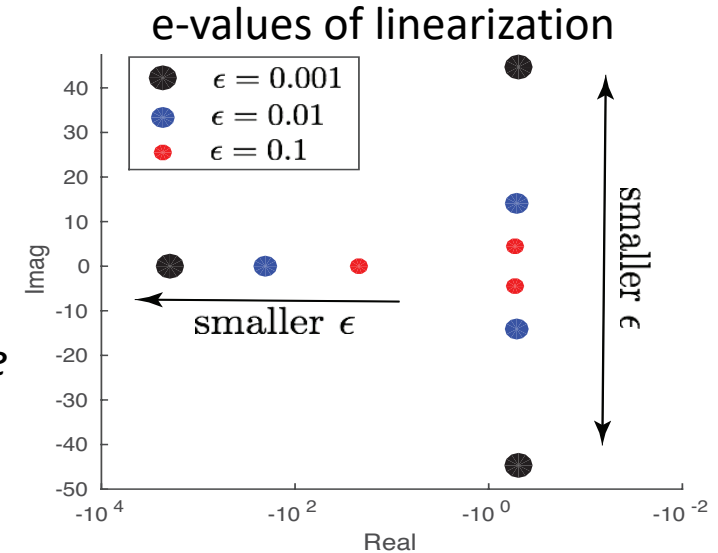
J has more than q zero e-values

If zero e-value of J has algebraic multiplicity (am) = geometric multiplicity (gm) → system can be taken to standard SP form by ϵ -independent coordinate change with less than p fast variables (Gu, Nefedov and O'Malley (1989); Sobolev (2005))

- not applicable here since $gm=1$ and $am=2$ ($am < gm$)
- Marino & Kokotovic (1988): there is no ϵ -independent diffeomorphism to standard SP form

Asymptotic expansion (with fractional exponents) can address some SSP problems assuming a limiting solution exists as $\epsilon \rightarrow 0$ (O'Malley & Jameson (1975); O'Malley (1979))

- not applicable – no limiting solution exists as $\epsilon \rightarrow 0$



Solving the SSP problem

$$\begin{aligned} \dot{y} &= A_1 \begin{bmatrix} y \\ x \end{bmatrix} + B_1 w(t), \quad y \in \mathbb{R}^q \\ \epsilon \dot{x} &= A_2^\epsilon \begin{bmatrix} y \\ x \end{bmatrix} + B_2 v(t), \quad x \in \mathbb{R}^p \end{aligned} \quad \text{assume } J = \begin{pmatrix} 0 & 0 \\ A_{21}^0 & A_{22}^0 \end{pmatrix} \left\{ \begin{array}{l} - \text{zero e-value has am} = q+1 \text{ and gm} = q \\ - \text{all other e-values have negative real part} \end{array} \right.$$

→ There is an ϵ -independent coordinate change with S Hurwitz

$$\begin{aligned} \dot{y} &= A_1 \begin{bmatrix} y \\ x \end{bmatrix} + B_1 w(t) \quad \text{slow} \\ \epsilon \dot{z}_1 &= Ry + B_2 v(t) + \epsilon Dz \quad \text{one-dimensional} \\ \epsilon \dot{z}_2 &= Sz_2 + B + 3v(t) + \epsilon E \begin{bmatrix} y \\ z_1 \end{bmatrix} \quad \text{fast} \end{aligned} \quad \xrightarrow{\text{set } \epsilon = 0 \text{ in the fast dynamics}}$$

ϵ -dependent reduced system

$$\begin{aligned} \dot{\bar{y}} &= \bar{A}_{11}\bar{y} + \bar{A}_{12}\bar{z}_1 + \bar{B}_1 w(t) + \bar{B}_4 v(t) \\ \epsilon \dot{\bar{z}}_1 &= R\bar{y} + \bar{B}_2 v(t) + \epsilon \bar{D}\bar{z}_1 \end{aligned}$$

Theorem (SSP): Assume that:

A1. inputs and their first derivatives bounded

A2. the reduced system is such that $\bar{D} < 0$, $(\bar{A}_{11}, \bar{A}_{12})$ controllable, $R\bar{A}_{12} > 0$ } Then: $\limsup_{t \rightarrow \infty} \|y(t) - \bar{y}(t)\| = \mathcal{O}(\sqrt{\epsilon})$

Proof : - decompose the error system into a slow and a fast subsystem

- S Hurwitz → fast subsystem is ISS with gain $\mathcal{O}(\epsilon)$
 - A2. → slow subsystem is ISS with gain $\mathcal{O}(1/\sqrt{\epsilon})$ } result follows from ISS small gain theorem for ϵ sufficiently small

Solving the robust tracking problem

original system

$$\begin{aligned}\dot{y} &= A_1 \begin{bmatrix} y \\ x \end{bmatrix} + B_1 w(t), \quad y \in \mathbb{R}^q \\ \epsilon \dot{x} &= A_2 \begin{bmatrix} y \\ x \end{bmatrix} + B_2 v(t), \quad x \in \mathbb{R}^p\end{aligned}$$

ϵ -dependent reduced system

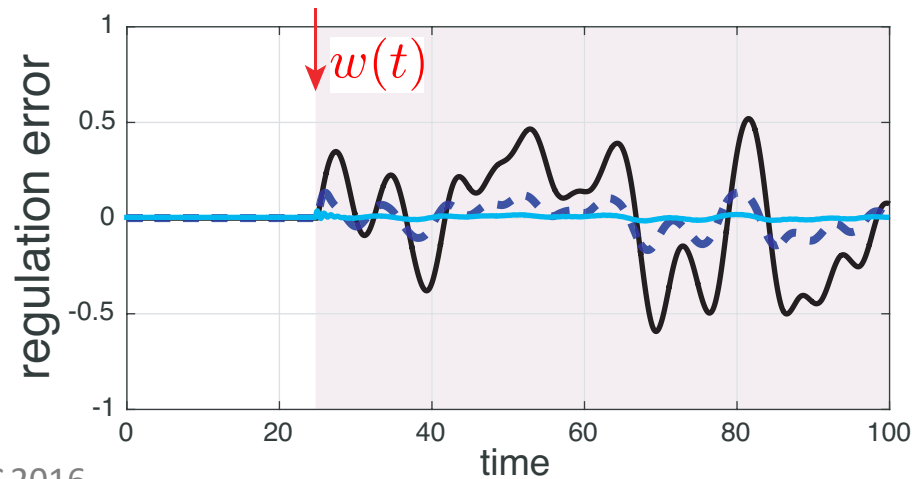
$$\begin{aligned}\dot{\bar{y}} &= \bar{A}_{11}\bar{y} + \bar{A}_{12}\bar{z}_1 + \bar{B}_1 w(t) + \bar{B}_4 v(t) \\ \epsilon \dot{\bar{z}}_1 &= R\bar{y} + \bar{B}_2 v(t) + \epsilon \bar{D}\bar{z}_1\end{aligned} \quad \limsup_{t \rightarrow \infty} \|y(t) - \bar{y}(t)\| = \mathcal{O}(\sqrt{\epsilon})$$

Theorem (robust tracking for reduced system):

If, in addition, all input derivatives are bounded, then $\limsup_{t \rightarrow \infty} \|R\bar{y}(t) + \bar{B}_2 v(t)\| = \mathcal{O}(\sqrt{\epsilon})$

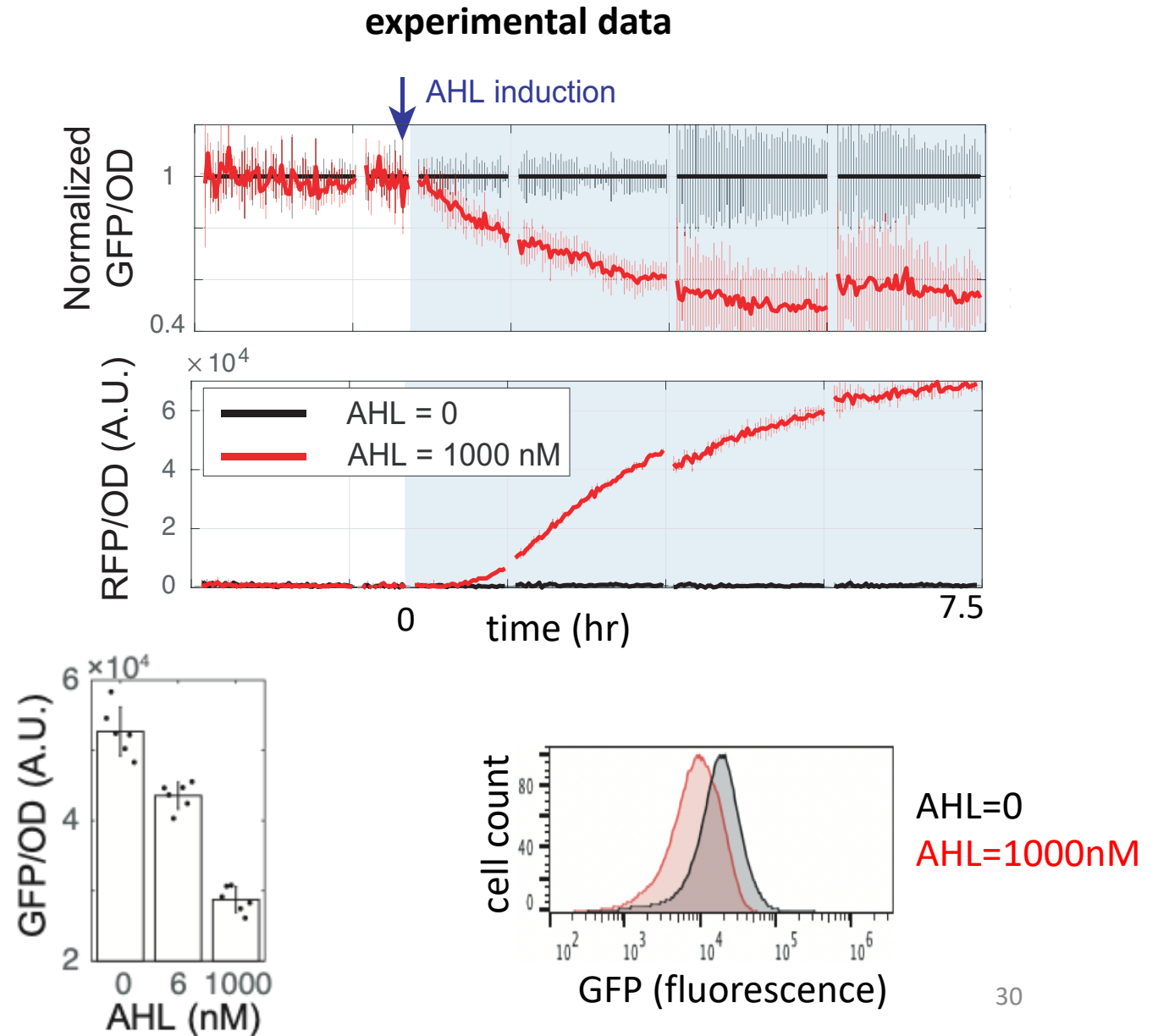
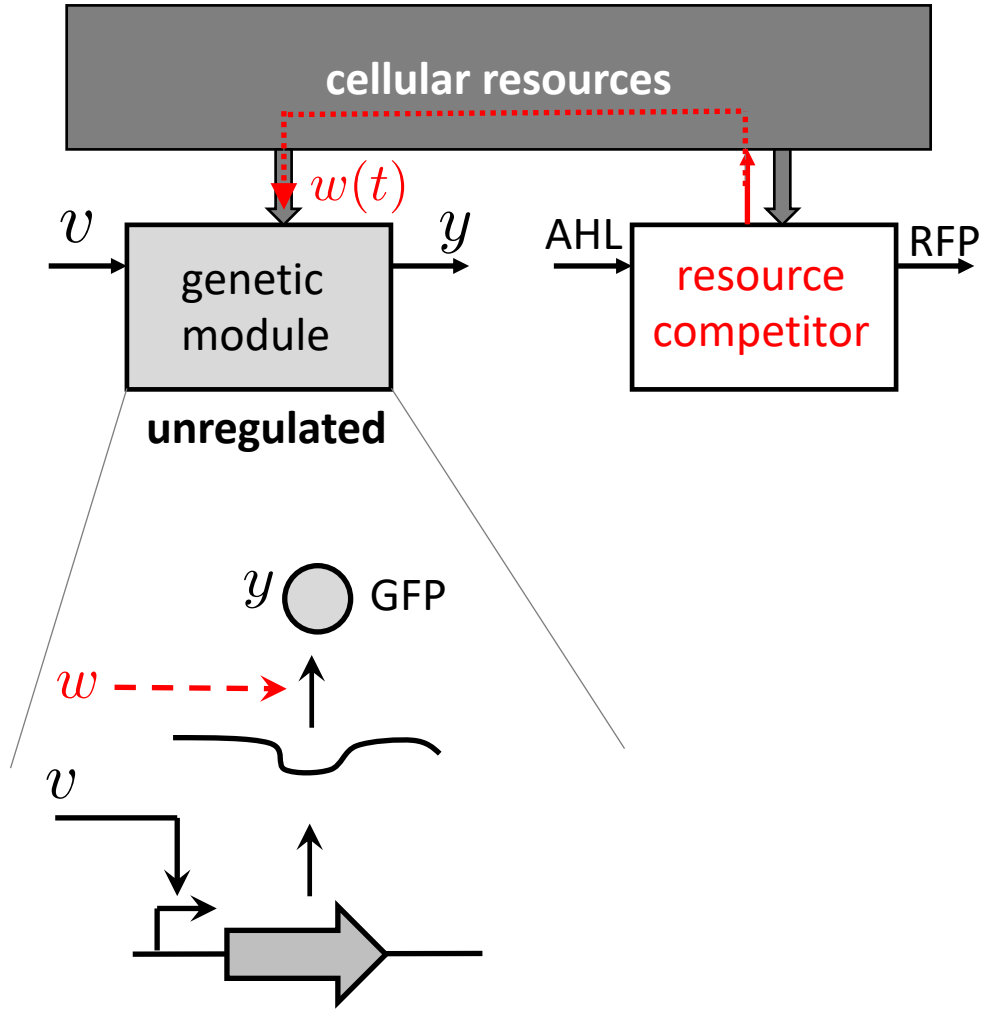
$\rightarrow \limsup_{t \rightarrow \infty} \|y(t) + R^{-1}\bar{B}_2 v(t)\| = \mathcal{O}(\sqrt{\epsilon}) \quad \rightarrow y(t) \text{ independent of } w(t) \text{ as } \epsilon \rightarrow 0$

$$\begin{aligned}\dot{y} &= R(w)m - \delta y \\ \epsilon \dot{m} &= v(t) - \theta m s - \epsilon \gamma m \\ \epsilon \dot{s} &= y - \theta m s - \epsilon \gamma s\end{aligned}$$

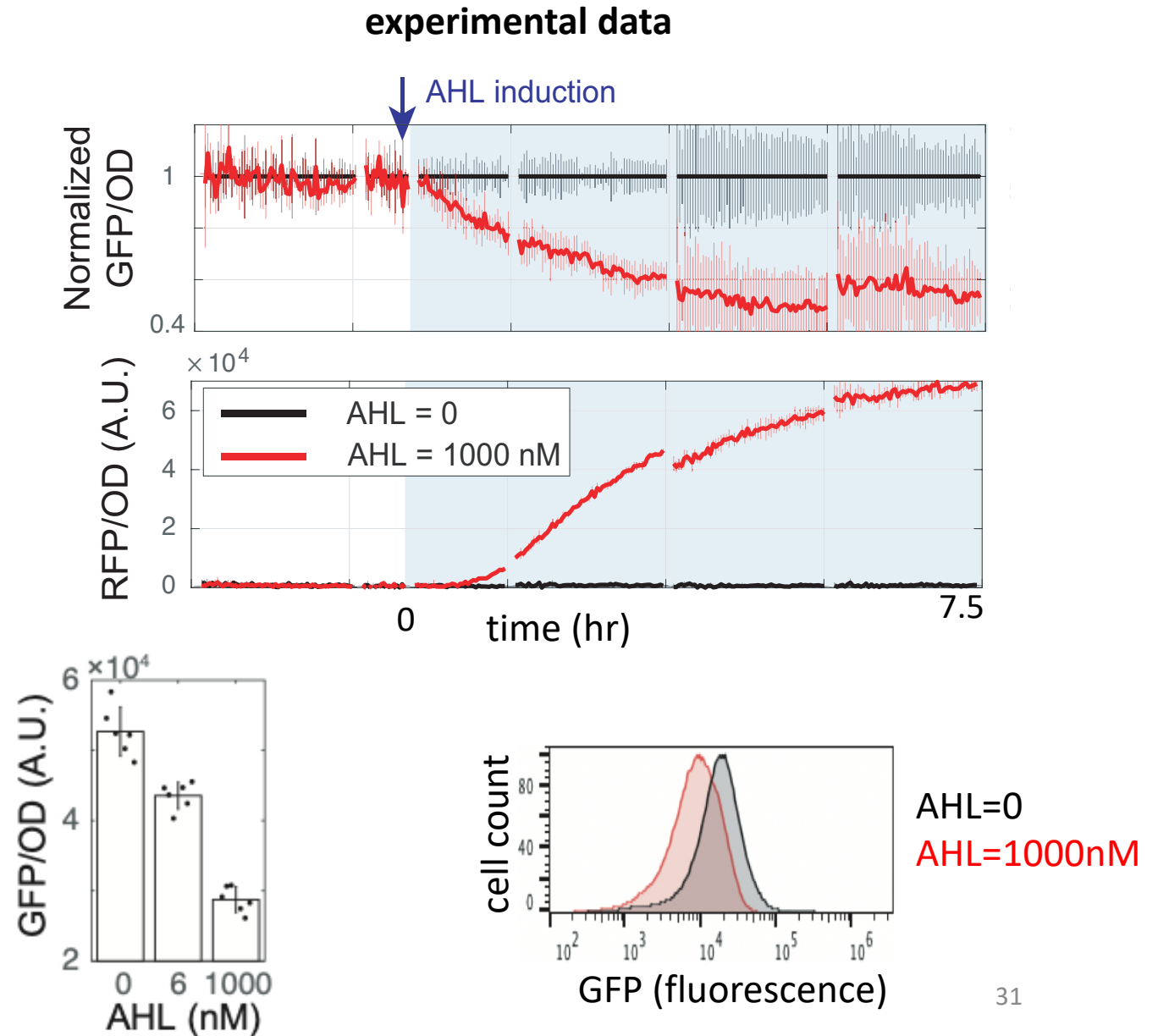
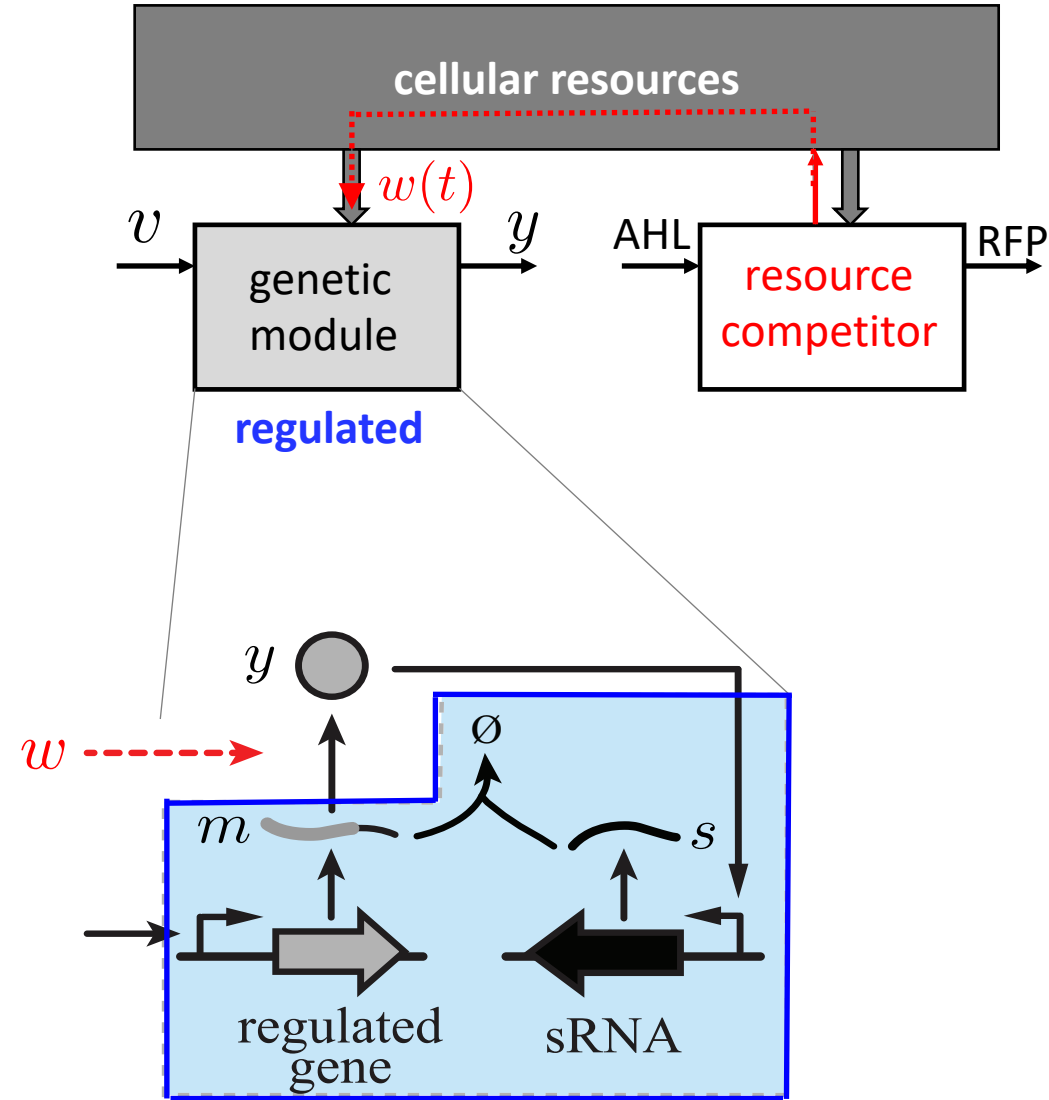


— $\epsilon = 1$ $\epsilon = 0.1$ — $\epsilon = 0.01$

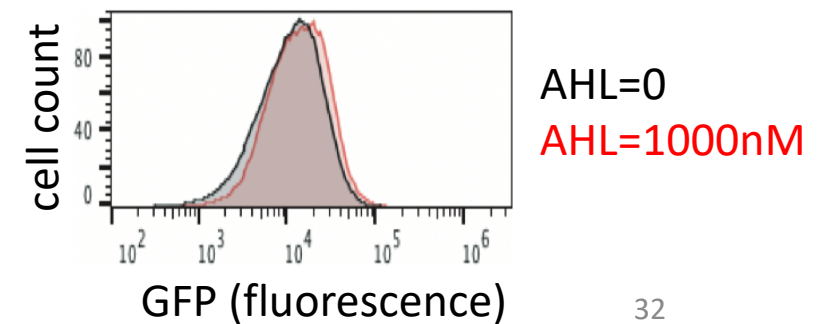
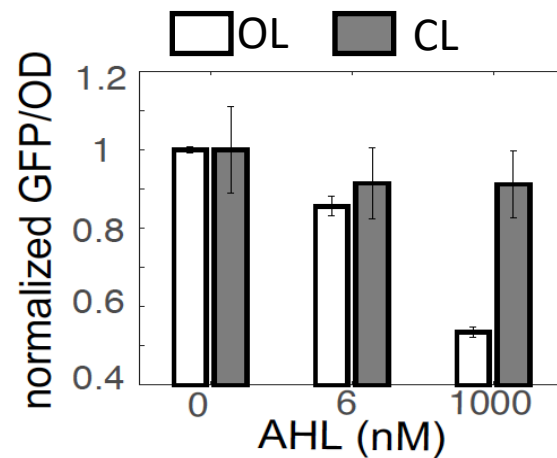
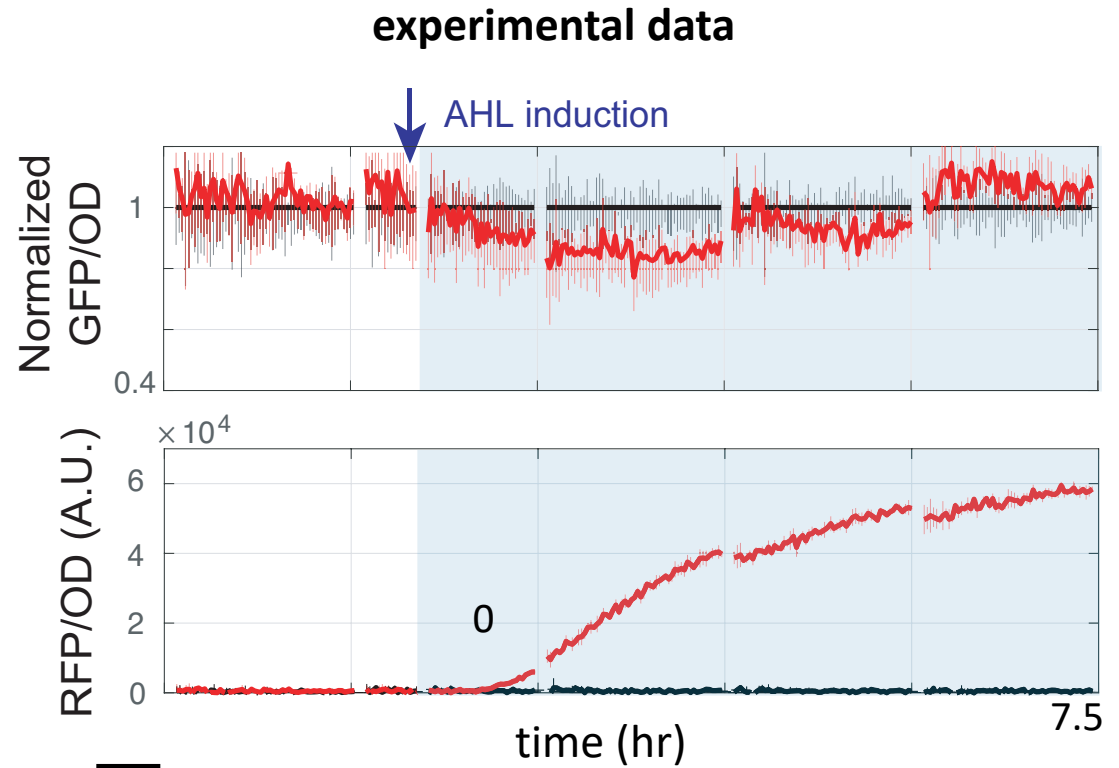
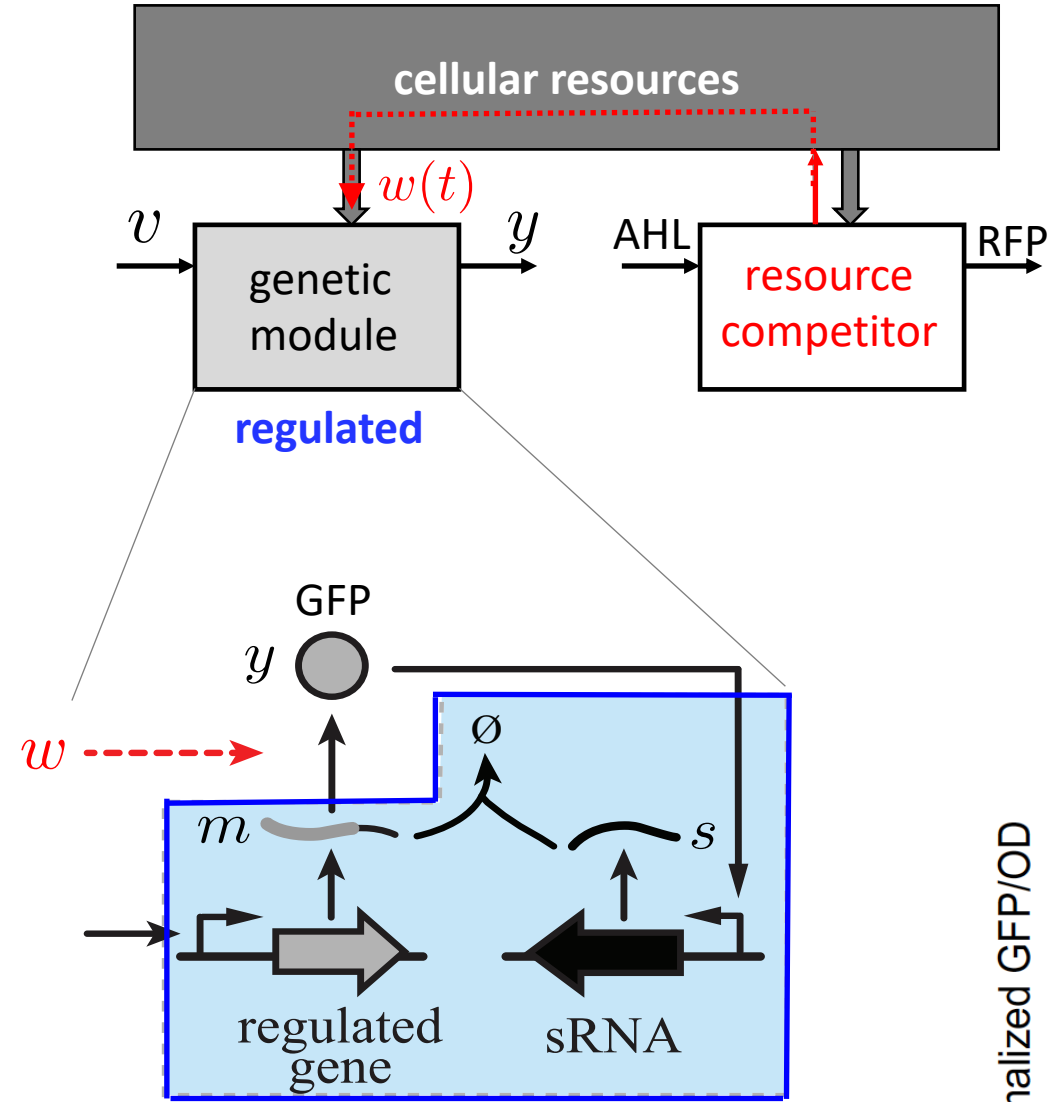
The *Resource Decoupler*: insulation via fast quasi-integral control



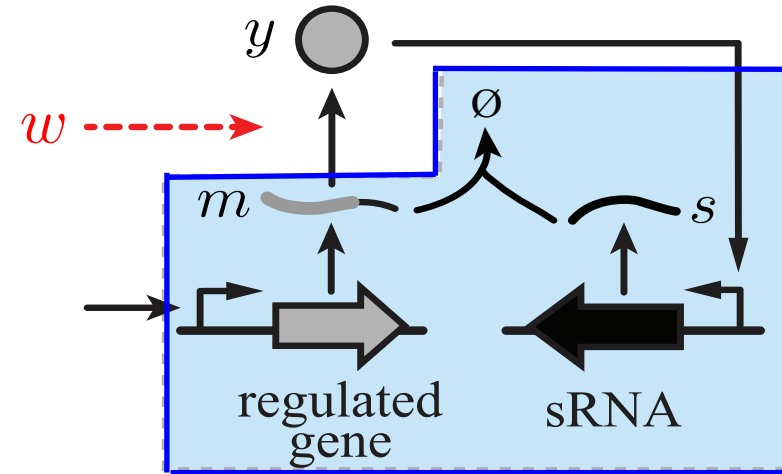
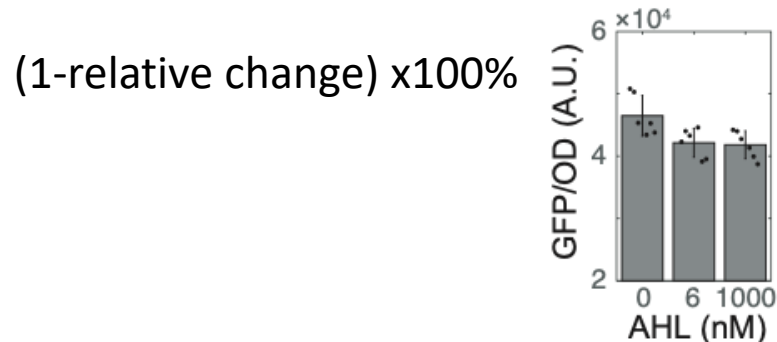
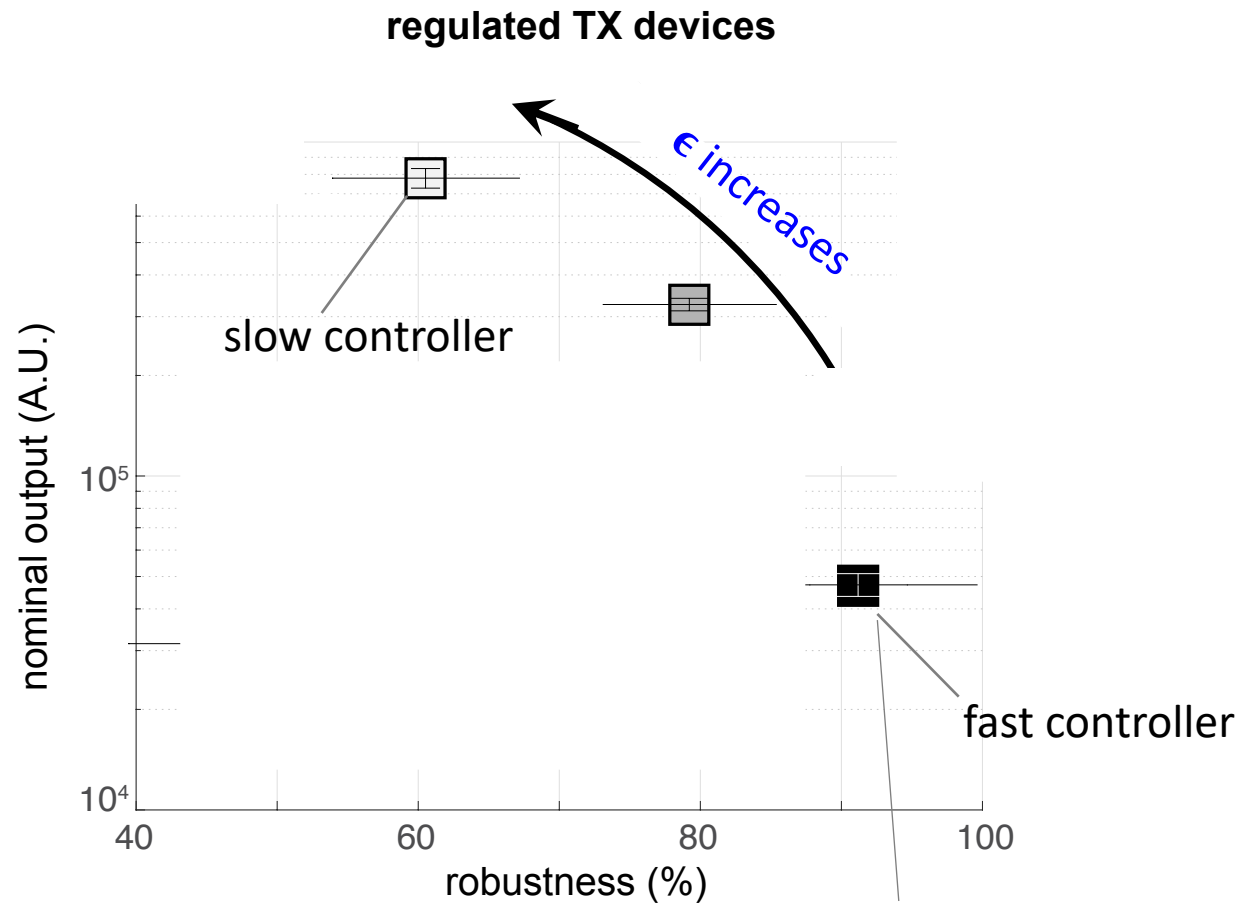
The *Resource Decoupler*: insulation via fast quasi-integral control



The *Resource Decoupler*: insulation via fast quasi-integral control



The *Resource Decoupler*: insulation via fast quasi-integral control



fast RNA interactions "free"

$$\dot{y} = R(w)m - \delta y$$

$$\dot{m} = T_m \cdot v - \frac{\theta}{\epsilon} m s - \gamma m$$

$$\dot{s} = T_s \cdot y - \frac{\theta}{\epsilon} m s - \gamma s$$

high RNA TX rates

T_s easily tunable by sRNA promoter

T_m GFP promoter strength

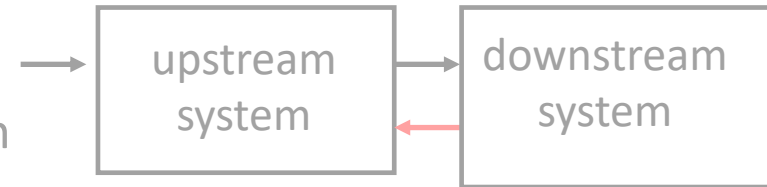
A journey towards modular composition

Engineering biology: Why and how

Modular composition: A grand challenge

Inter-module loads and the *load driver*

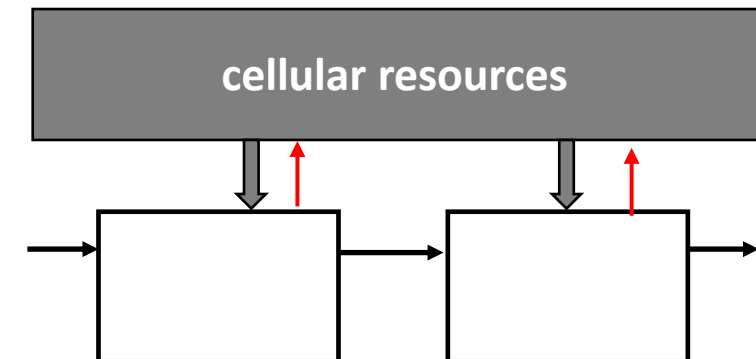
Disturbance attenuation via time scale separation



Resource loading and the *resource decoupler*

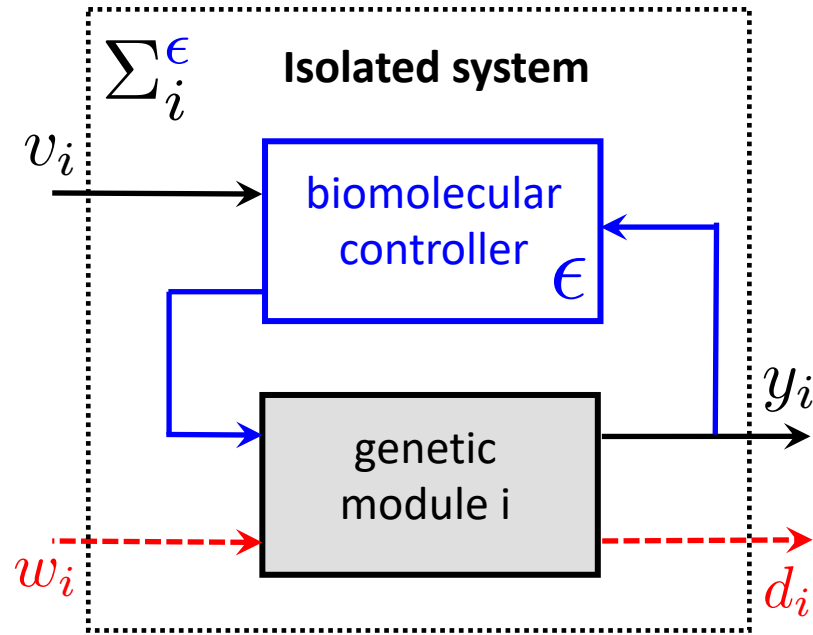
Disturbance rejection despite leaky integral actions

Decentralized implementation



Outlook

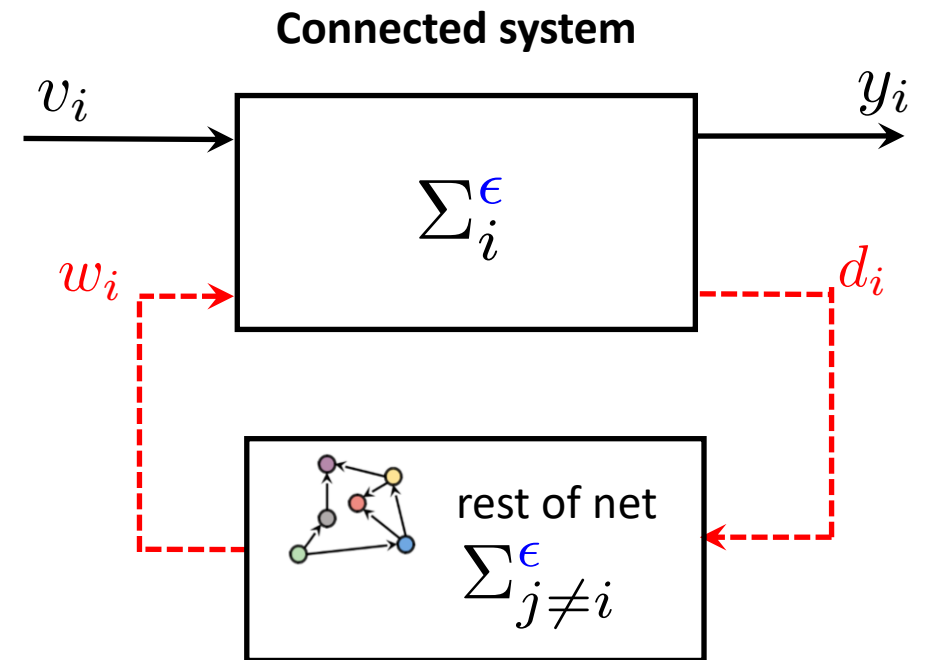
Network disturbance attenuation



We have: for constant w_i bounded independent of ϵ

$$\lim_{t \rightarrow \infty} \|y_i(t) - h(v_i)\| = \mathcal{O}(\sqrt{\epsilon}) \|w_i\|$$

$\rightarrow y_i$ independent of w_i



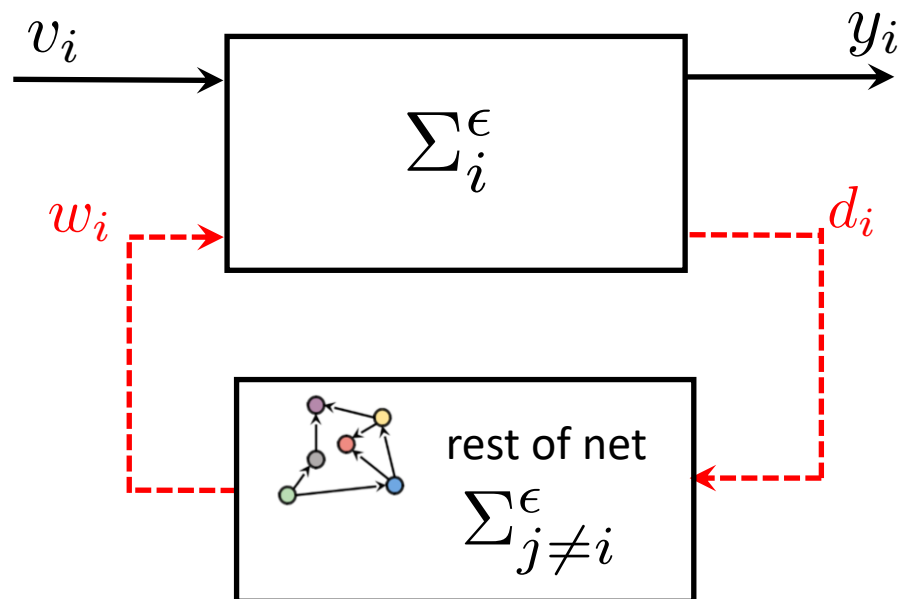
Problem: Can we guarantee that

$$\lim_{t \rightarrow \infty} \|y_i(t) - h(v_i)\| = \mathcal{O}(\sqrt{\epsilon})$$

- ensure that w_i steady state has ϵ -independent bound
- ensure closed loop system approaches steady state

Network disturbance attenuation

ensure that w_i has an ϵ -independent steady state bound



physics leads to steady state relationships:

(i) system i $d_i = g_i(v_i) + \hat{g}_i(v_i) \cdot w_i + \tilde{g}_i(w_i) \cdot O(\epsilon)$

linear term in w_i

HOT in w_i

(ii) interconnection $w_i = \sum_{j \neq i} d_j$

(iii) system

(i)+(ii) $\rightarrow A(v) \cdot w = g(v) + \tilde{g}(w)O(\epsilon)$

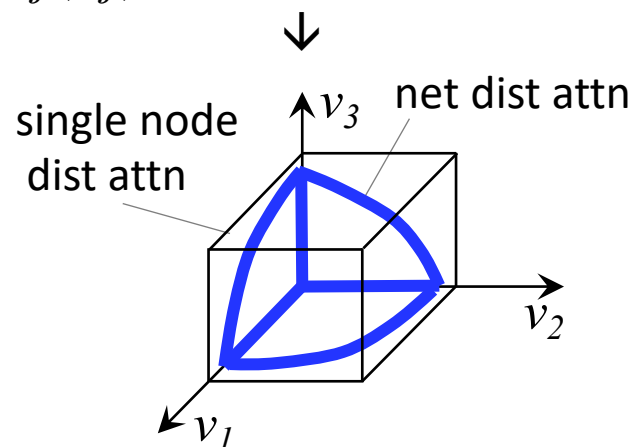
$$A(v) = \begin{bmatrix} 1 & -\hat{g}_2 & \cdot & \cdot & -\hat{g}_n \\ -\hat{g}_1 & 1 & -\hat{g}_2 & \cdot & -\hat{g}_n \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -\hat{g}_1 & -\hat{g}_2 & \cdot & -\hat{g}_{n-1} & 1 \end{bmatrix}$$

\rightarrow If $A(v)$ is invertible, then w has ϵ -independent bound

sufficient check: diagonal dominance

$$\sum_{j \neq i} \hat{g}_j(v_j) < 1, \quad \forall i$$

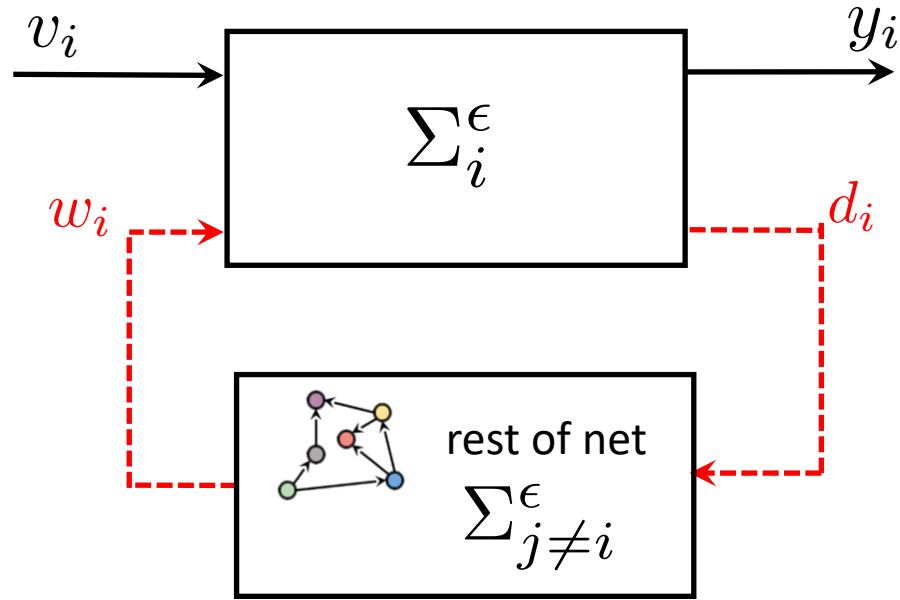
$\hat{g}_j(v_j)$ increasing function of v_j



*obtain constraints
on tunable parameters
as a function of the
number of nodes*

Network disturbance attenuation

ensure closed loop system approaches steady state



Assumption: Σ_i^ϵ is input-to-state/output monotone

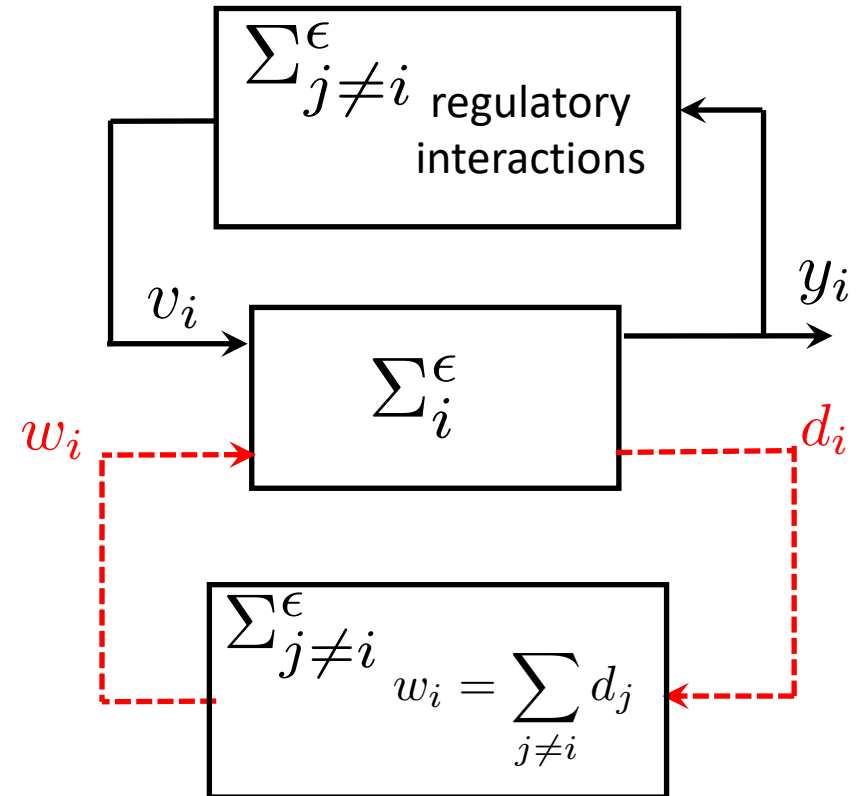
→ use Small Gain Theorem for Monotone Systems
(Angeli & Sontag, *IEEE TAC* 2003)

$A(v)$ diagonally dominant → unique/globally attractive equilibrium

Note: we can prove the controller makes Σ_i^ϵ SP - monotone
if its dynamics are much faster than the plant

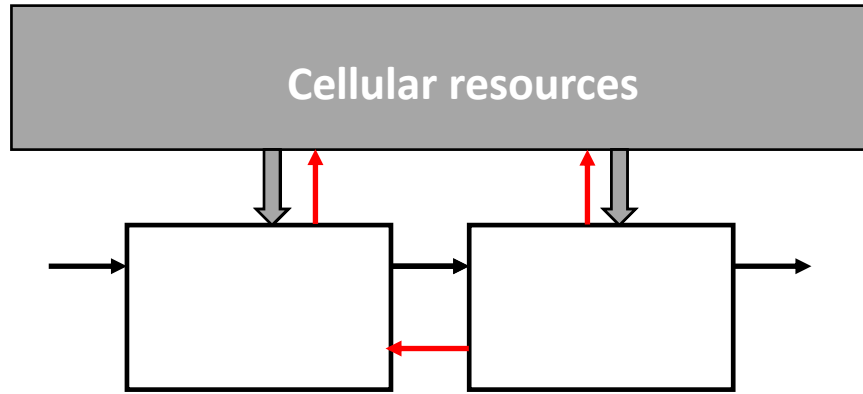
(Grunberg and Del Vecchio, *IEEE CDC* 2019)

on-going: time-varying inputs and regulatory interactions



In preparation – ingredients:
small-gain theorem for singularly perturbed monotone
systems (Christofides & Teel, *IEEE TAC* 1995;
Angeli & Sontag, *IEEE TAC* 2003)

Summary

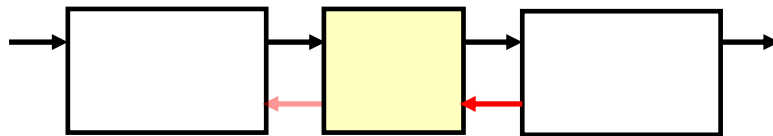


Loads applied by downstream modules change the behavior of upstream systems

Loads that modules apply to cellular resources cause subtle couplings among theoretically independent modules

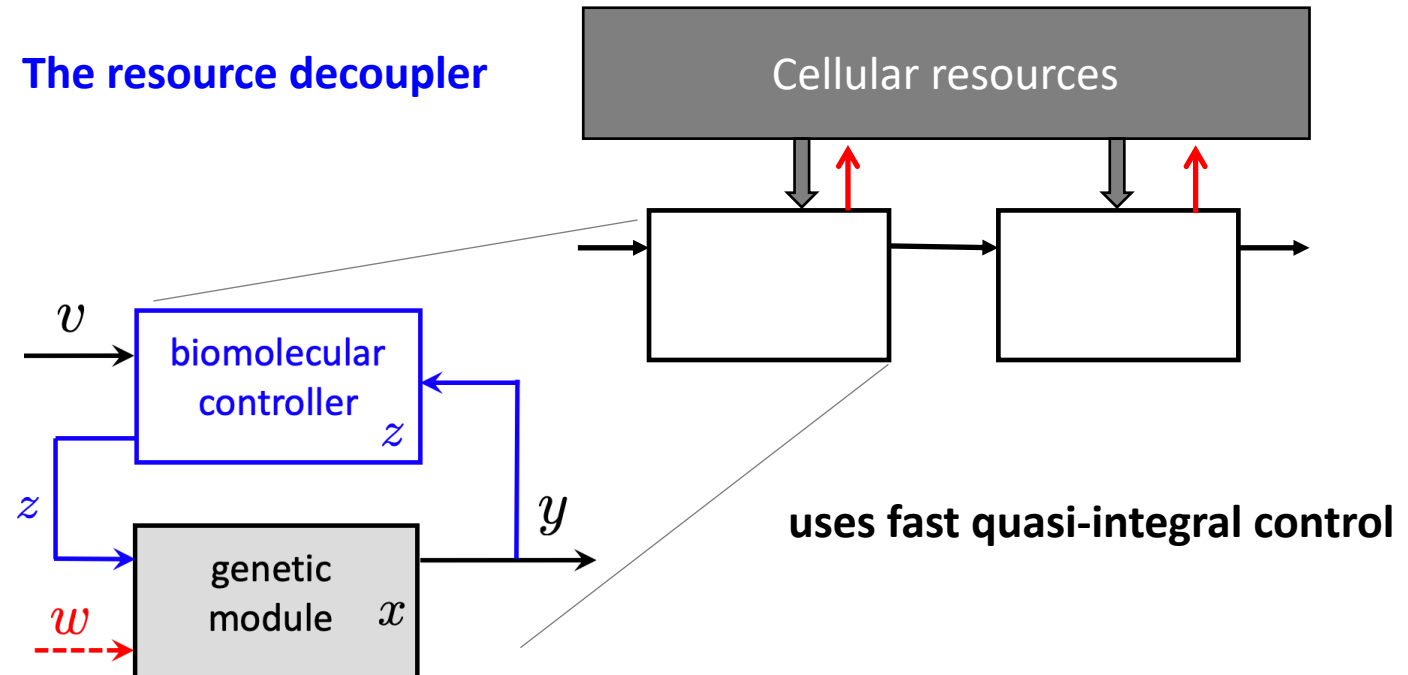
An engineering framework for insulating genetic modules from perturbations

The load driver

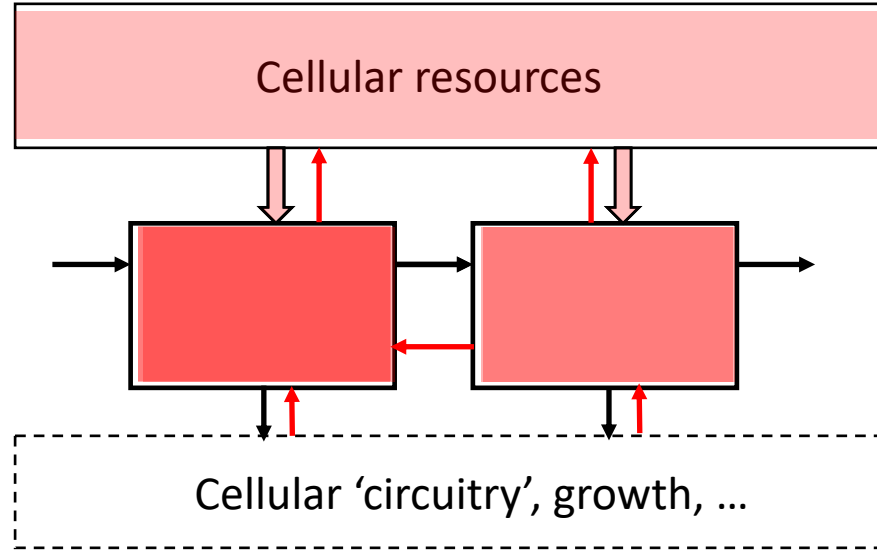


uses time scale separation in place of high-gain negative feedback

The resource decoupler



Some reasons why modularity is a challenge



Loads applied by downstream modules change the behavior of upstream systems

(Del Vecchio, Hespanha, Klavins, Papachristodoulou, Sontag, ...)

Modules apply a load the cellular resources: creates subtle couplings

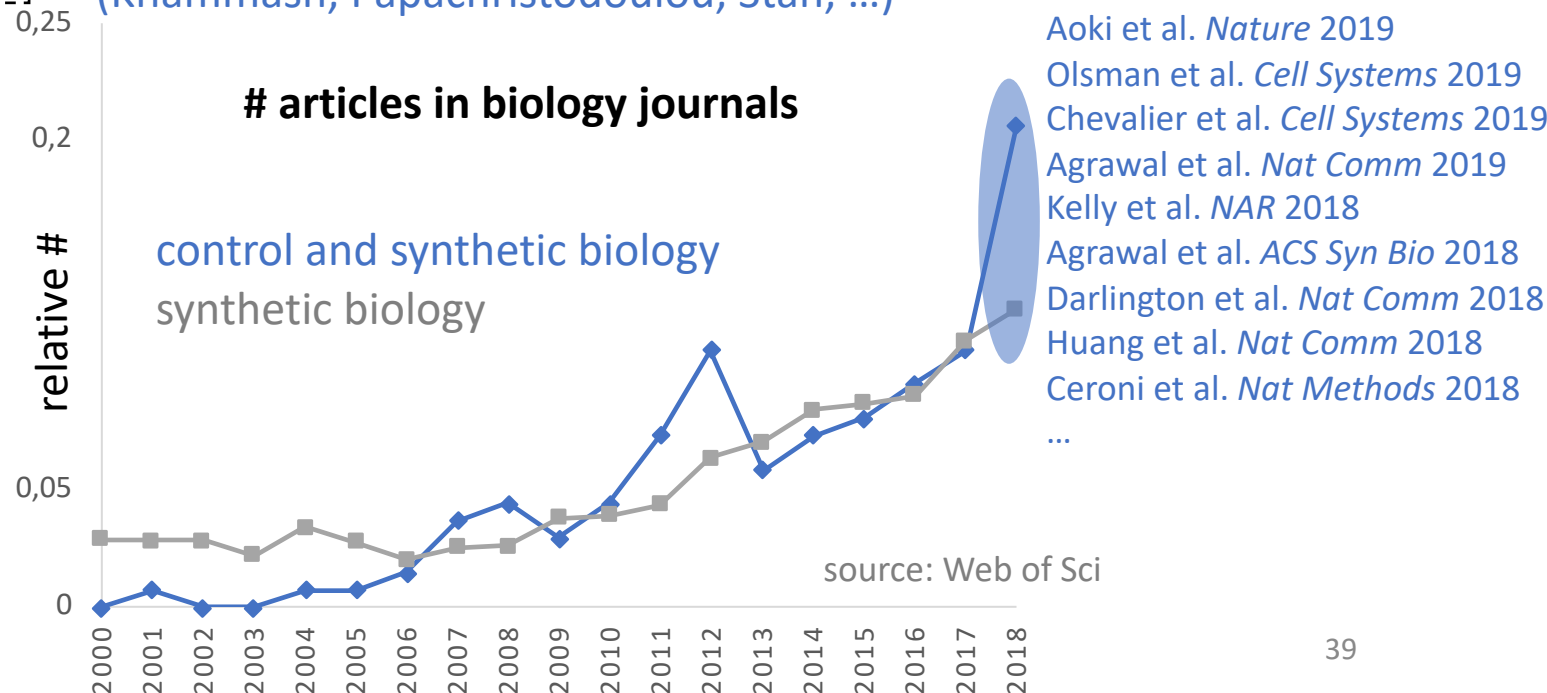
(Bates, Del Vecchio, Murray, Stan, ...)

Modules often have “off-target” interactions, affect growth rate, and this, in turn, has global effects on a module’s dynamics

(Khammash, Papachristodoulou, Stan, ...)

and many more...

- **lab conditions:** temperature, nutrients, Ph,...
- **cell type/strain**
- **growth phase**
- **mutations**



Former Students/
Post-docs:

Andras Gyorgy
(NYU, Abu Dhabi)

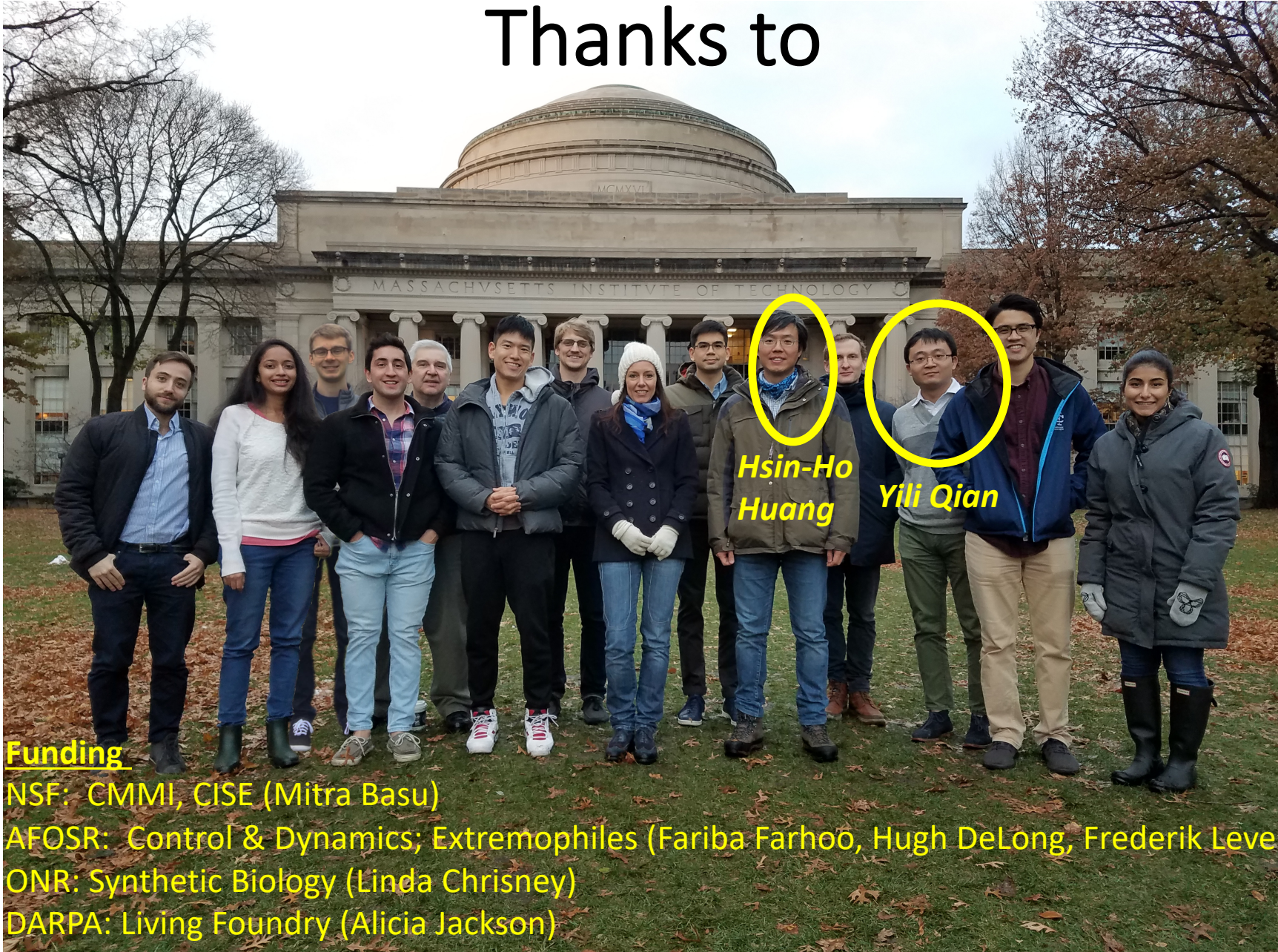
Hattie Chang
(Harvard)

Jose Jimenez
(U. of Surrey)

John Yazbek



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ONR: Synthetic Biology (Linda Chrisney)

DARPA: Living Foundry (Alicia Jackson)

Collaborators:

Eduardo Sontag
(NEU)

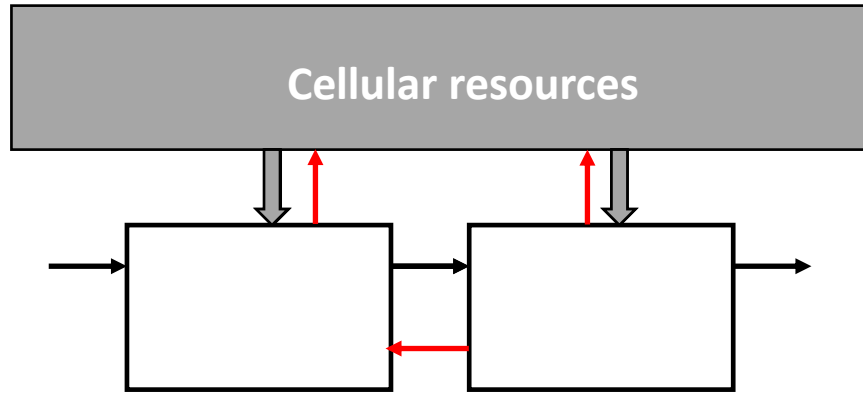
Ron Weiss
(MIT)

Jim Collins
(MIT)

Richard Murray
(Caltech)



Summary

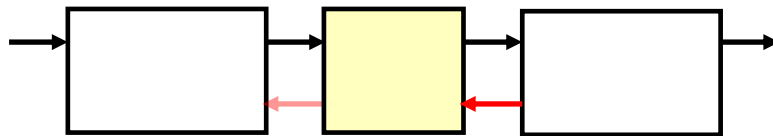


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