

Development and Experimental Validation of Piecewise Affine Models of Carbon Starvation Response in *Escherichia coli*

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HYGEIA PhD school on
hybrid systems biology



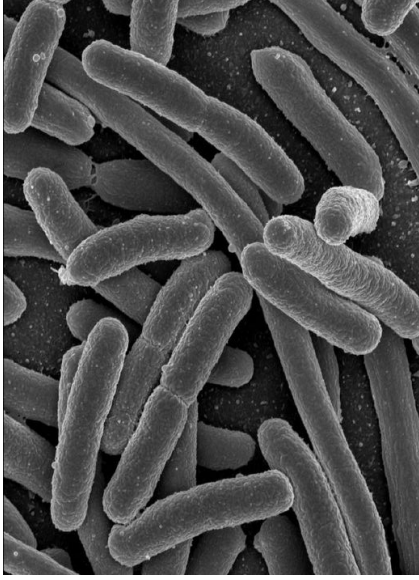
Overview

1. Carbon starvation response of *Escherichia coli*
2. Modeling and simulation: objective and constraints
3. Qualitative modeling and simulation of carbon starvation
4. Experimental validation of carbon starvation model
5. Conclusions

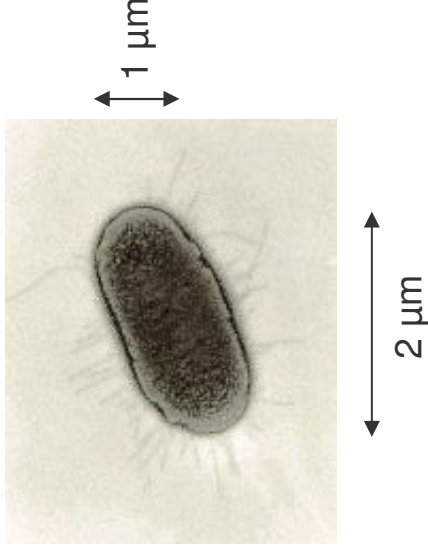
Escherichia coli

❖ The average **human gut** contains about **1 kg of bacteria**

- Normally, approximately 0.1% are *E. coli*



Rocky Mountain Laboratories, NIAID, NIH

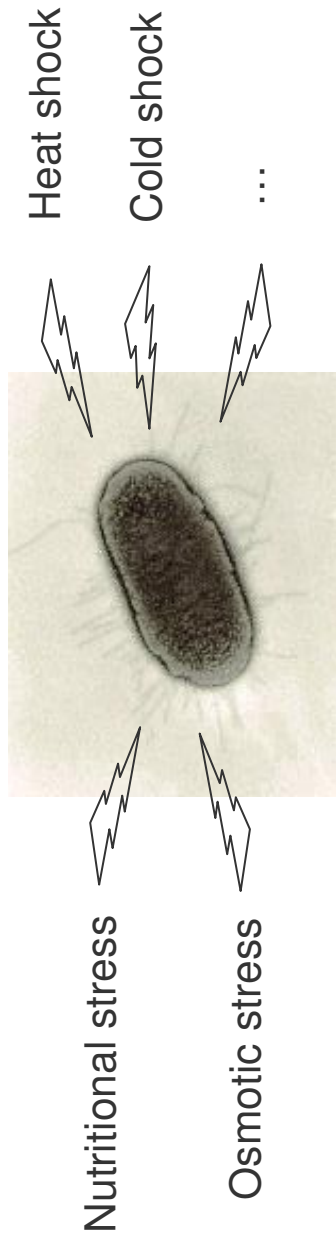


- *E. coli*, along with other enterobacteria, synthesize **vitamins** which are absorbed by our body (e.g., vitamin K, B-complex vitamins)

Escherichia coli stress responses

- ❖ *E. coli* is able to adapt and respond to a variety of stresses from its environment

Storz and Hengge-Aronis (2000), *Bacterial Stress Responses*, ASM Press

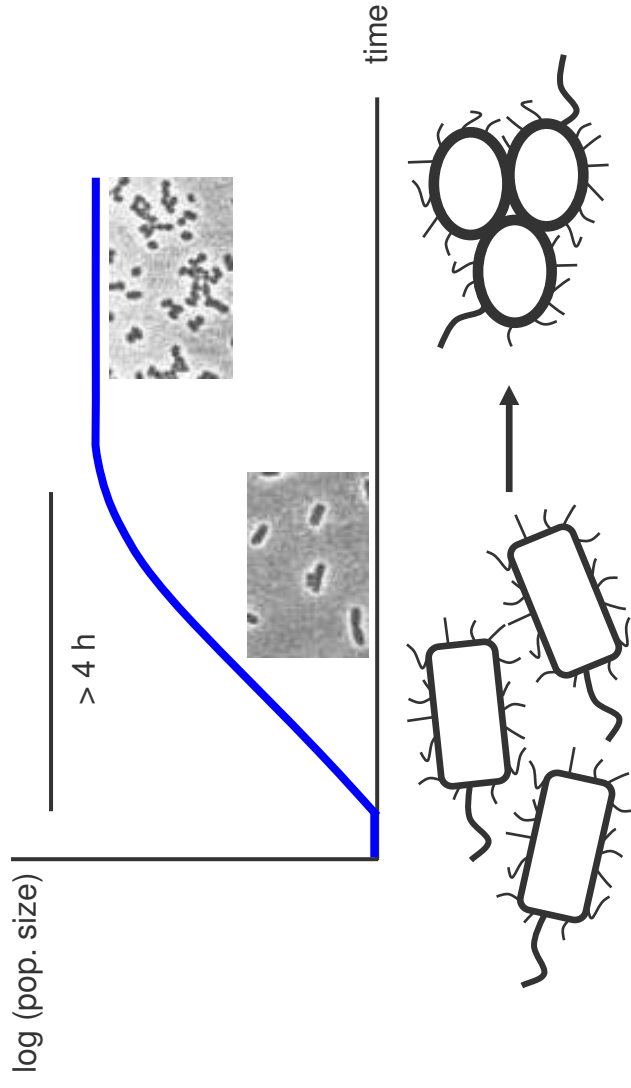


- ❖ Model organism for understanding adaptation of pathogenic bacteria to their host
-

Nutritional stress response in *E. coli*

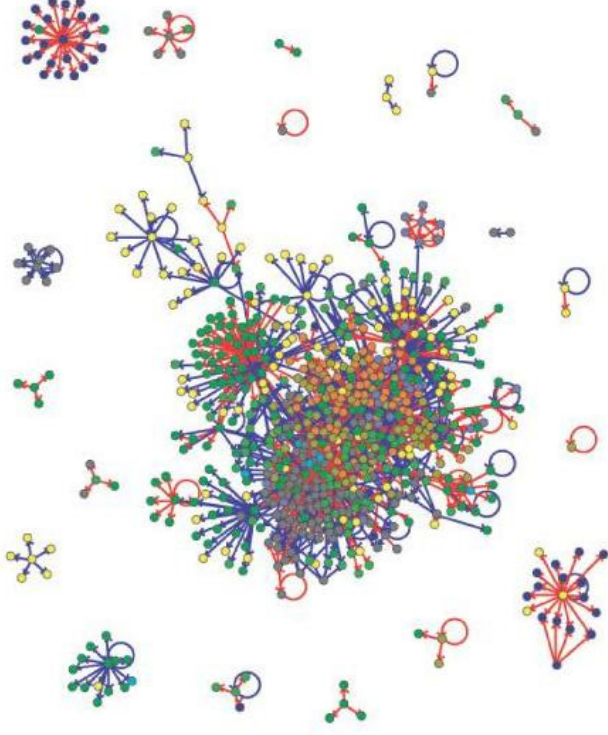
- ❖ Response of *E. coli* to nutritional stress conditions: transition from **exponential phase** to **stationary phase**

Changes in morphology, metabolism, gene expression, ...



Network controlling stress response

- ❖ Response of *E. coli* to nutritional stress conditions controlled by large and complex **genetic regulatory network**



Cases et de Lorenzo (2005),
Nat. Microbiol. Rev., 3(2):105-118

- ❖ **No global view of functioning** of network available, despite abundant knowledge on network components
-

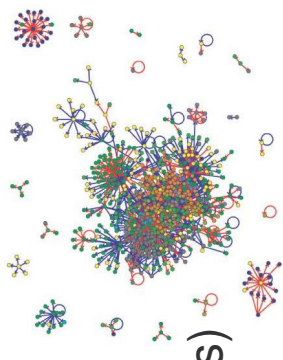
Analysis of carbon starvation response

❖ **Modeling** and **experimental** studies directed at understanding how network controls carbon starvation response

❖ Which network components and which interactions to take into account?

- Impossible to model the whole network

E. coli genome: ~4500 genes (~150 transcription factor genes)

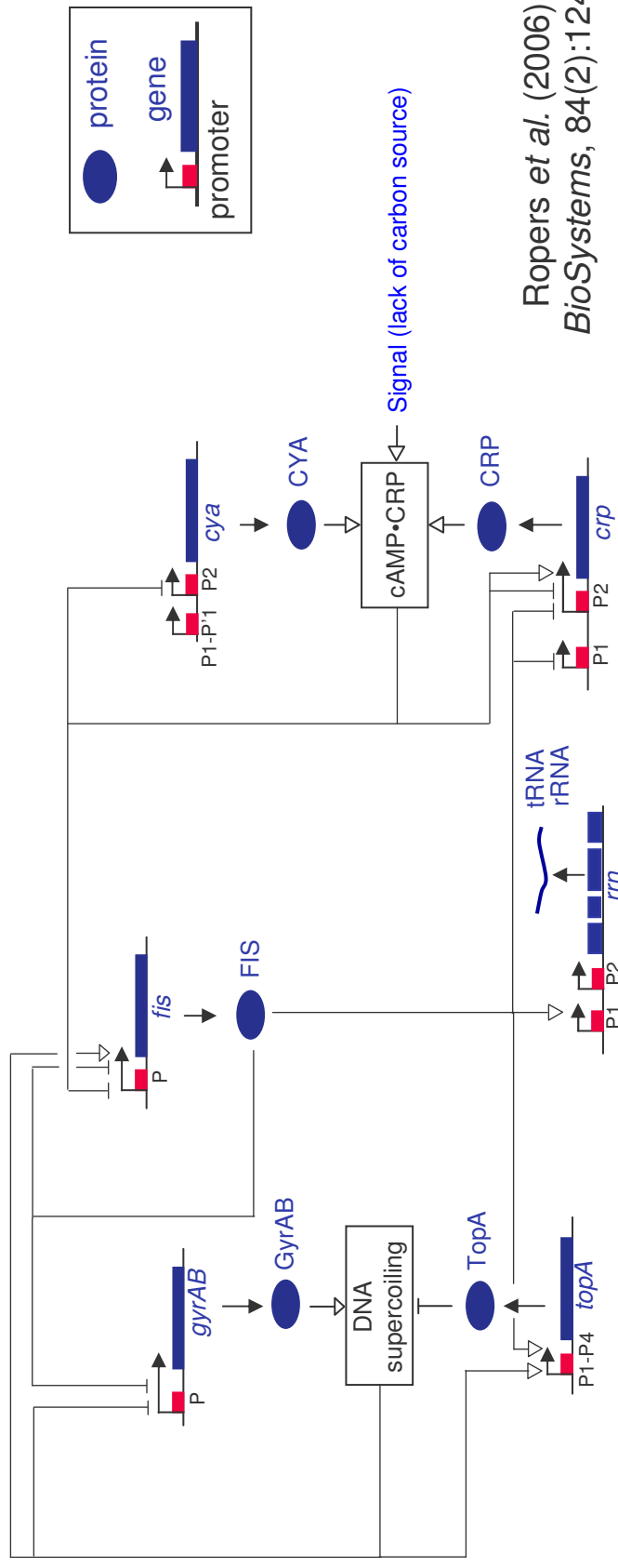


- Start with the **simplest possible representation** of the carbon starvation response in *E. coli*

Analysis of carbon starvation response

- ❖ **Modeling** and **experimental** studies directed at understanding how network controls carbon starvation response
- ❖ Bottom-up strategy:

1) Initial model of carbon starvation response

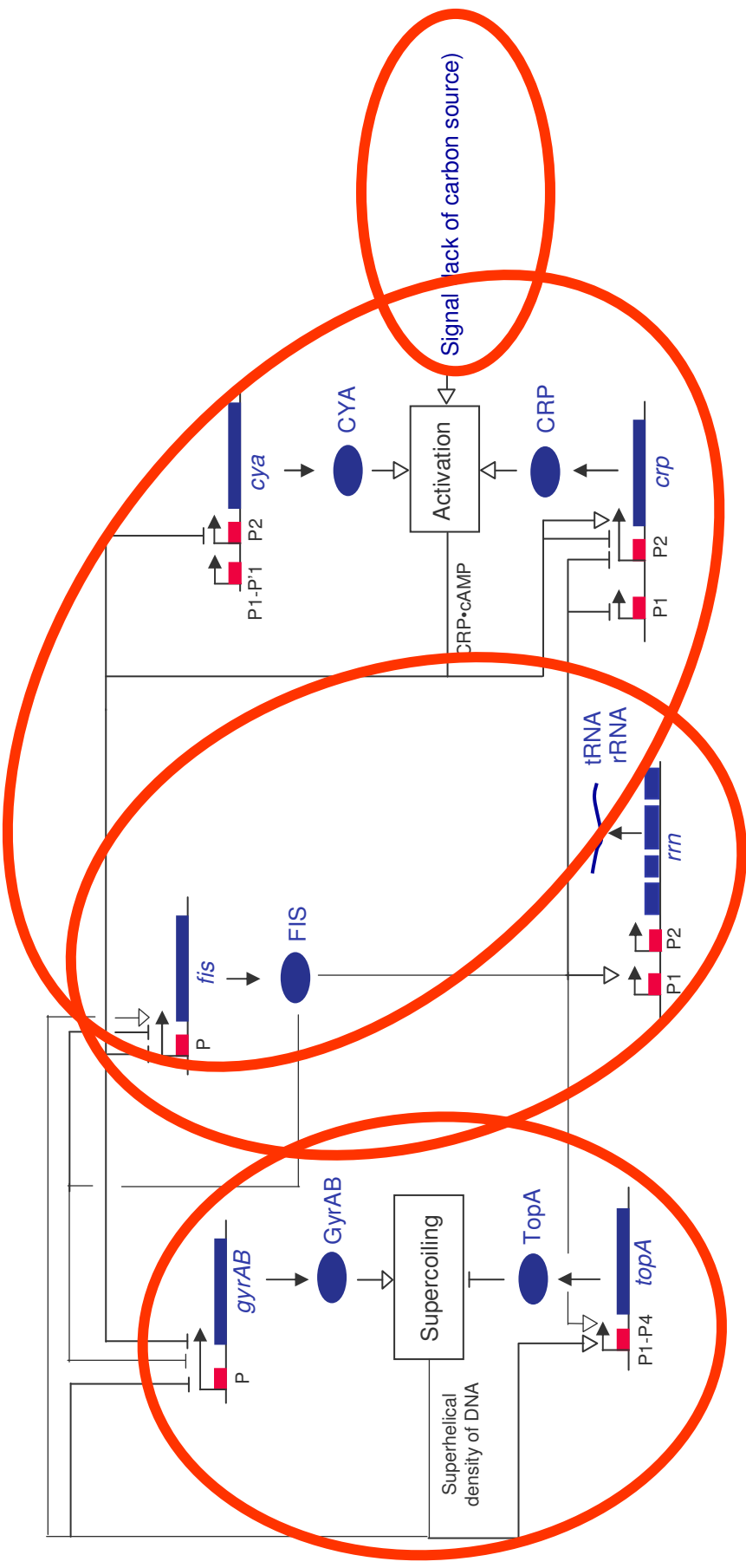


Analysis of carbon starvation response

- ❖ **Modeling** and **experimental** studies directed at understanding how network controls carbon starvation response
 - ❖ Bottom-up strategy:
 - 1) Initial model of the carbon starvation response
 - Search and curate data available in the literature and databases
 - 2) Experimental verification of model predictions
 - 3) Extension of model to take into account wrong predictions
 - Additional global regulators: IHF, HNS, ppGpp, FNR, LRP, ArcA, ...
-

Modeling of carbon starvation network

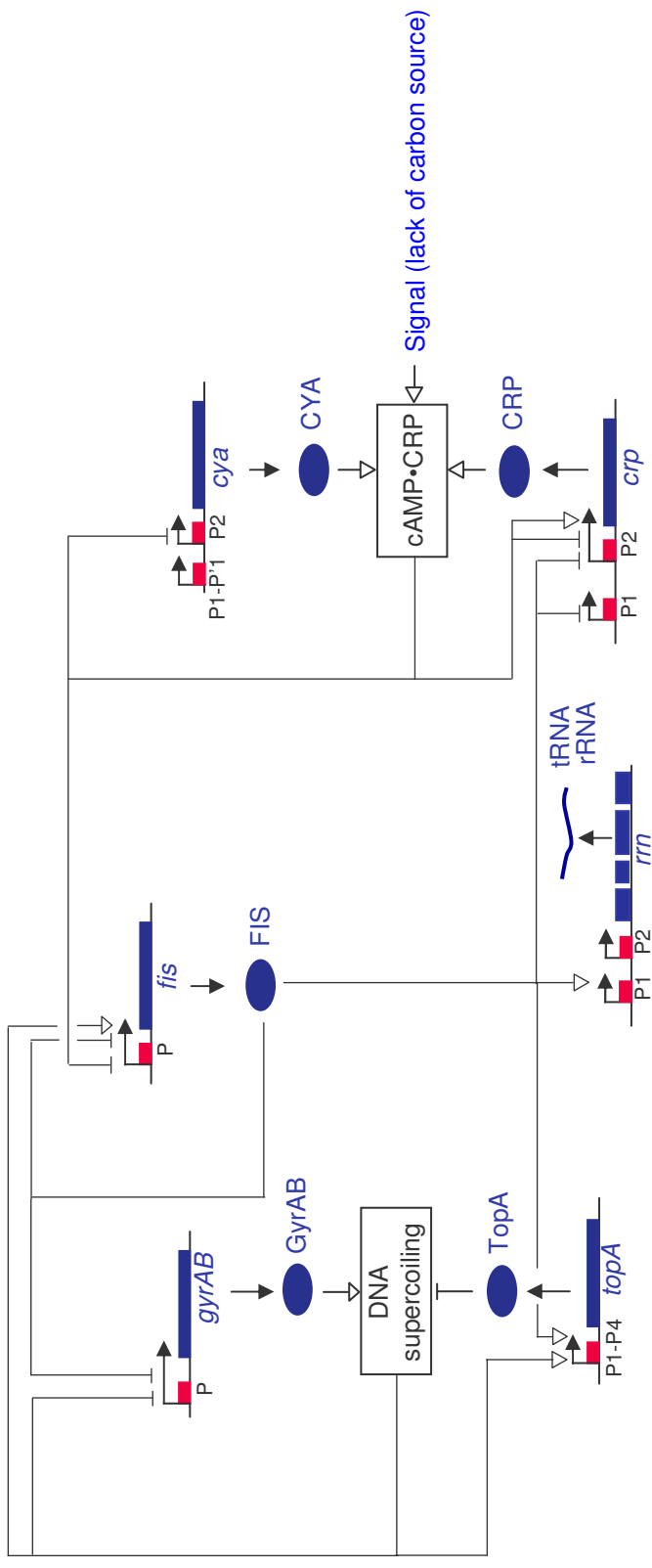
❖ Modular structure of carbon starvation network



Ropers et al. (2006),
BioSystems, 84(2):124-152

Modeling of carbon starvation network

- ❖ Can the initial model explain the carbon starvation response of *E. coli* cells?



- ❖ Translation of biological data into a mathematical model
-

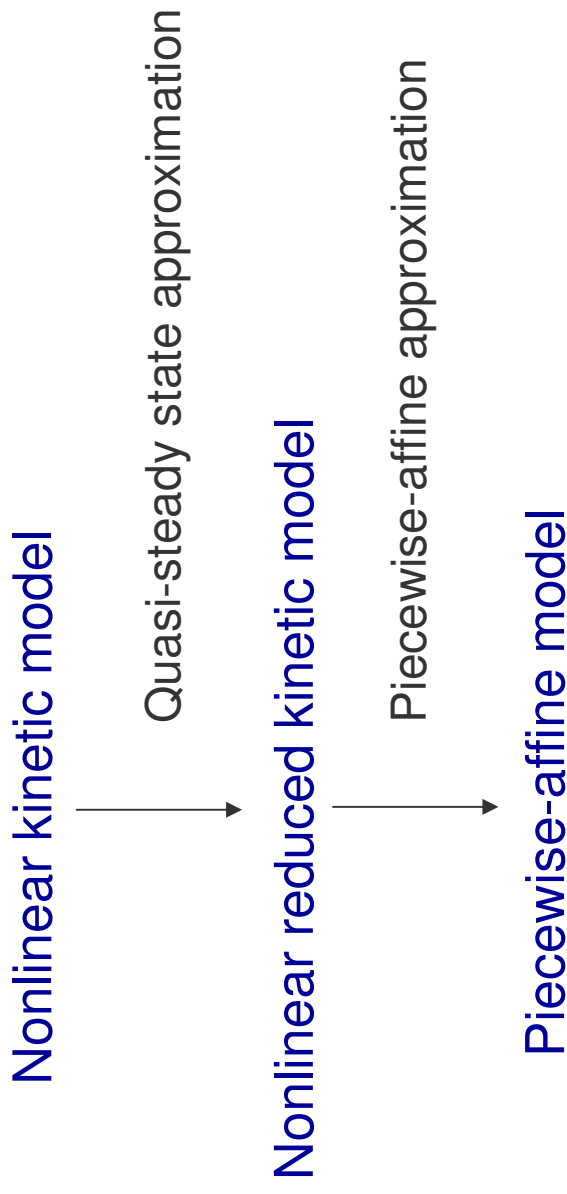
Constraints on modeling and simulation

- ❖ Current **constraints** on modeling and simulation:
 - Knowledge on molecular mechanisms rare
 - Quantitative information on kinetic parameters and molecular concentrations absent
- ❖ Possible strategies to overcome the constraints
 - Parameter estimation from experimental data
 - Parameter sensitivity analysis
 - Model simplifications
- ❖ Intuition: essential properties of system dynamics **robust** against moderate changes in kinetic parameters and rate laws

Stelling *et al.* (2004), *Cell*, 118(6):675-86

From nonlinear kinetic model to PA model

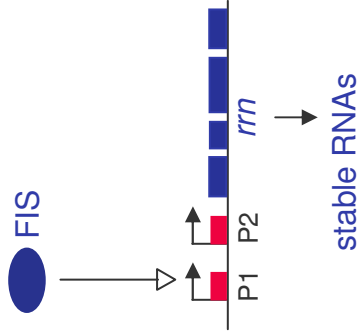
- ❖ Modeling process consists of reducing classical nonlinear kinetic model to PA model



Nonlinear kinetic model

❖ Nonlinear kinetic ODE model of 12 variables and 46 parameters

- Regulation of gene expression (Hill)



$$\dot{x}_n = \kappa_n^1 h^+(x_f, \theta_f, m_f) + \kappa_n^2 - \gamma_n x_n$$

R. Heinrich and S. Schuster (1996), *The regulation of cellular systems*, Chapman & Hall, New York.

Nonlinear kinetic model

- ❖ Nonlinear kinetic ODE model of 12 variables and 46 parameters
 - Regulation of gene expression (Hill)
 - Enzymatic reactions (Michaelis-Menten or mass action)



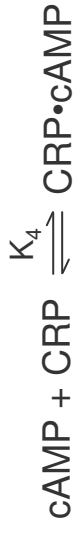
$$\dot{x}_{y \sim p} = k_1 x_{y \sim} x_p - (k_{-1} + k_2 h^+(u_s, \theta_s, m_s) + \gamma_y) x_{y \sim p}$$

$$\dot{x}_{m \sim} = k_2 h^+(u_s, \theta_s, m_s) x_{y \sim p} + k_{-4} x_{c \sim m} - k_3 x_{m \sim} - k_4 x_{c \sim} x_{m \sim}$$

R. Heinrich and S. Schuster (1996), *The regulation of cellular systems*, Chapman & Hall, New York.

Nonlinear kinetic model

- ❖ Nonlinear kinetic ODE model of 12 variables and 46 parameters
 - Regulation of gene expression (Hill)
 - Enzymatic reactions (Michaelis-Menten or mass action)
 - Formation of biochemical complexes (mass action)



$$\dot{x}_{c \sim m} = k_4 x_c x_m - (k_{-4} + \gamma_c) x_{c \sim m}$$

R. Heinrich and S. Schuster (1996), *The regulation of cellular systems*, Chapman & Hall, New York.

Modeling of carbon starvation network

Ordinary differential equations :

$$\dot{u}_s = 0 \quad (1)$$

$$\dot{x}_{y\sim} = \kappa_y^1 + \kappa_y^2 h^-(x_{c\sim m}, \theta_{c\sim m}^3, m_{c\sim m}) - \gamma_y x_{y\sim} + (k_{-1} + k_2 h^-(u_s, \theta_s, m_s)) x_{y\sim p} - k_1 x_{y\sim} x_p \quad (2)$$

$$\dot{x}_{y\sim p} = k_1 x_{y\sim} x_p - (k_{-1} + k_2 h^+(u_s, \theta_s, m_s) + \gamma_y) x_{y\sim p} \quad (3)$$

$$\dot{x}_{c\sim} = \kappa_c^1 + \kappa_c^2 h^-(x_f, \theta_f^2, m_f) h^+(x_{c\sim m}, \theta_{c\sim m}^1, m_{c\sim m}) + \kappa_c^3 h^-(x_f, \theta_f^1, m_f) - \gamma_c x_{c\sim} + k_{-4} x_{c\sim m} - k_4 x_{c\sim} x_{m\sim} \quad (4)$$

$$\dot{x}_{c\sim m} = k_4 x_{c\sim} x_{m\sim} - (k_{-4} + \gamma_c) x_{c\sim m} \quad (5)$$

$$\dot{x}_{m\sim} = k_2 h^+(u_s, \theta_s, m_s) x_{y\sim p} + k_{-4} x_{c\sim m} - k_3 x_{m\sim} - k_4 x_{c\sim} x_{m\sim} \quad (6)$$

$$\dot{x}_f = \kappa_f^1 h^-(x_{c\sim m}, \theta_{c\sim m}^1, m_{c\sim m}) h^-(x_f, \theta_f^5, m_f) + \kappa_f^2 h^+(SC, \theta_{SC}^1, m_{SC}) \times h^-(x_{c\sim m}, \theta_{c\sim m}^1, m_{c\sim m}) h^-(x_f, \theta_f^5, m_f) - \gamma_f x_f \quad (7)$$

$$\text{with } SC = a + b \frac{x_a}{x_t}$$

$$\dot{x}_a = \kappa_a h^-(SC, \theta_{SC}^2, m_{SC}) h^-(x_f, \theta_f^4, m_f) - \gamma_a x_a \quad (8)$$

$$\dot{x}_t = \kappa_t h^+(SC, \theta_{SC}^2, m_{SC}) h^+(x_f, \theta_f^4, m_f) - \gamma_t x_t \quad (9)$$

$$\dot{x}_n = \kappa_n^1 h^+(x_f, \theta_f^3, m_f) + \kappa_n^2 - \gamma_n x_n \quad (10)$$

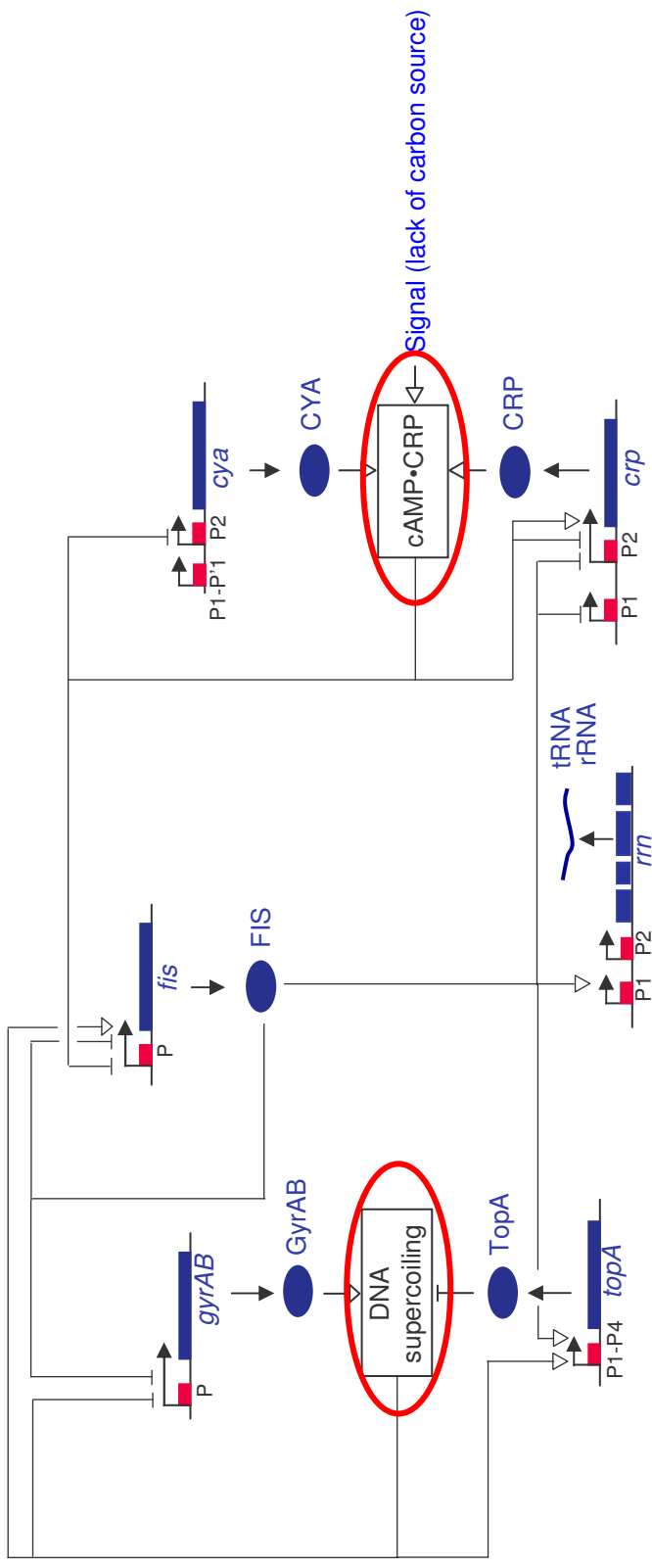
Conservation relations :

$$x_y = x_{y\sim} + x_{y\sim p} \quad (11)$$

$$x_c = x_{c\sim} + x_{c\sim m} \quad (12)$$

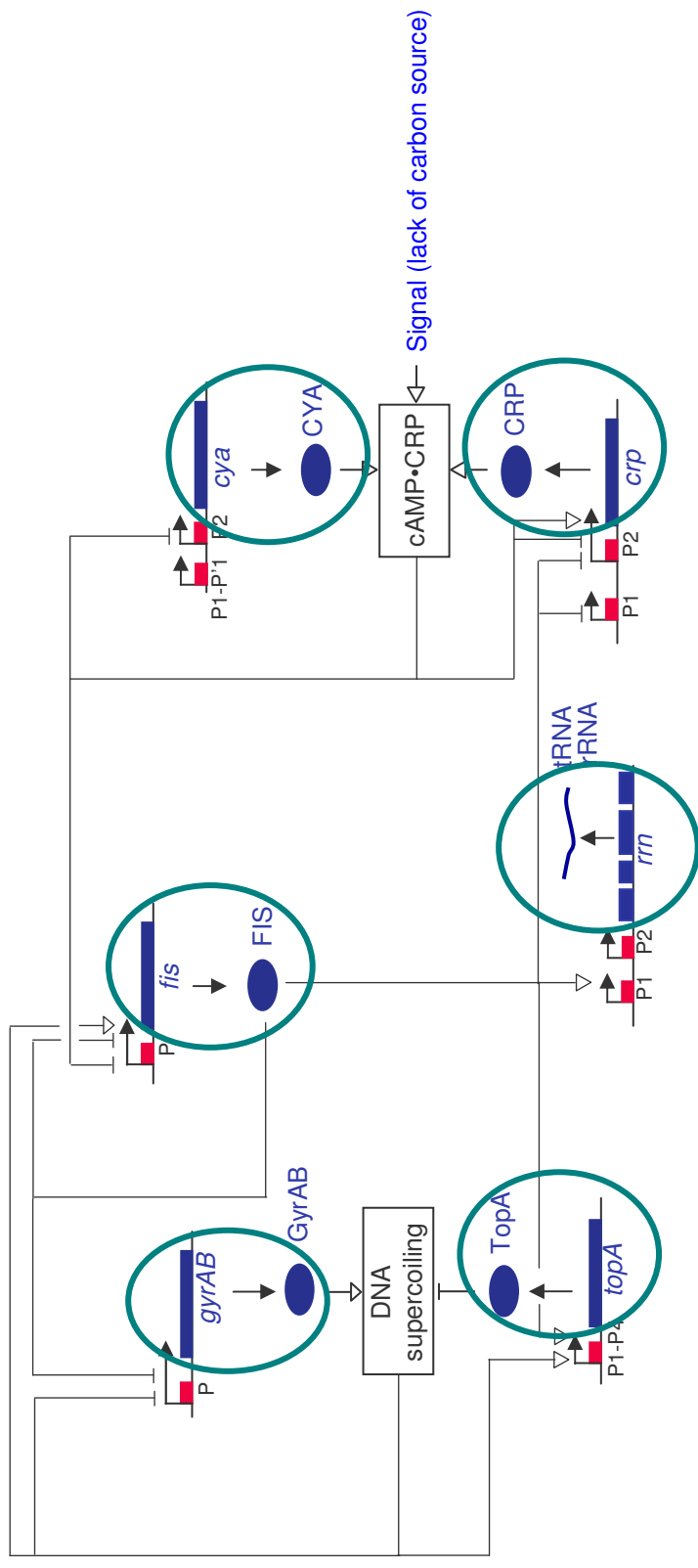
Quasi steady state approximation

❖ Identification of slow and **fast** processes in network



Quasi steady state approximation

❖ Identification of **slow** and fast processes in network



❖ Change of variables and quasi steady-state approximation

Heinrich and Schuster, 1996

Nonlinear reduced model

❖ QSSA model of 7 variables and 46 parameters

$$\dot{u}_s = 0 \quad (1)$$

$$\dot{x}_y = \kappa_y^1 + \kappa_y^2 h^-(x_{c\sim m}, \theta_{c\sim m}^2, m_{c\sim m}) - \gamma_y x_y \quad (2)$$

$$\dot{x}_c = \kappa_c^1 + \kappa_c^2 h^-(x_f, \theta_f^2, m_f) h^+(x_{c\sim m}, \theta_{c\sim m}^1, m_{c\sim m}) + \kappa_c^3 h^-(x_f, \theta_f^1, m_f) - \gamma_c x_c \quad (3)$$

$$\begin{aligned} \dot{x}_f = & \kappa_f^1 h^-(x_{c\sim m}, \theta_{c\sim m}^1, m_{c\sim m}) h^-(x_f, \theta_f^5, m_f) + \kappa_f^2 h^+(SC, \theta_{SC}^1, m_{SC}) \\ & \times h^-(x_{c\sim m}, \theta_{c\sim m}^1, m_{c\sim m}) h^-(x_f, \theta_f^5, m_f) - \gamma_f x_f \end{aligned} \quad (4)$$

$$\dot{x}_a = \kappa_a h^-(SC, \theta_{SC}^2, m_{SC}) h^-(x_f, \theta_f^4, m_f) - \gamma_a x_a \quad (5)$$

$$\dot{x}_t = \kappa_t h^+(SC, \theta_{SC}^2, m_{SC}) h^+(x_f, \theta_f^4, m_f) - \gamma_t x_t \quad (6)$$

$$\dot{x}_n = \kappa_n^1 h^+(x_f, \theta_f^3, m_f) + \kappa_n^2 - \gamma_n x_n \quad (7)$$

with

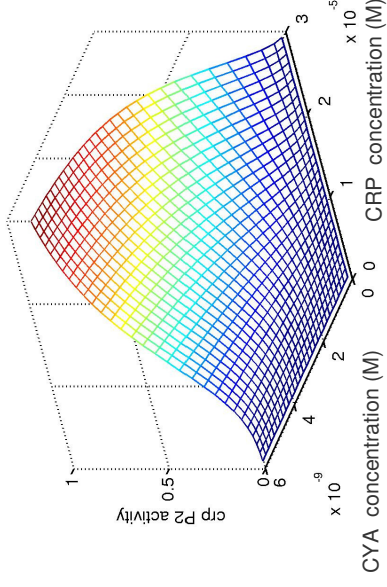
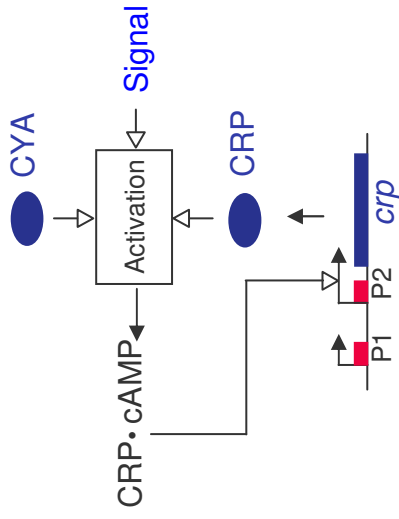
$$x_{y\sim p} = \frac{k_1 x_y x_p}{k_1 x_p + k_{-1} + k_2 h^+(u_s, \theta_s, m_s)}$$

$$x_{c\sim m} = \frac{k_2 h^+(u_s, \theta_s, m_s) x_c x_y}{K_4 k_3 + k_2 h^+(u_s, \theta_s, m_s) x_y}$$

$$SC = a + b \frac{x_a}{x_t}$$

Piecewise-affine approximation

- ❖ Approximation of Hill function with step function
- ❖ Approximation of sigmoidal surfaces with product of step functions



$$s^+(x_{CYA}, \theta_{CYA}^I) s^+(x_{CRP}, \theta_{CRP}^I) s^+(x_{SIGNAL}, \theta_{SIGNAL})$$

Model of carbon starvation network

❖ PADE model of 7 variables and 36 parameter inequalities

$$\dot{u}_s = 0 \quad (1)$$

$$\dot{x}_y = \kappa_y^1 + \kappa_y^2 (1 - s^+(x_c, \theta_c^3) s^+(x_y, \theta_y^3) s^+(u_s, \theta_s)) - \gamma_y x_y \quad (2)$$

$$\dot{x}_c = \kappa_c^1 + \kappa_c^2 s^-(x_f, \theta_f^2) s^+(x_c, \theta_c^1) s^+(x_y, \theta_y^1) s^+(u_s, \theta_s) + \kappa_c^3 s^-(x_f, \theta_f^1) - \gamma_c x_c \quad (3)$$

$$\begin{aligned} \dot{x}_f = & \kappa_f^1 (1 - s^+(x_c, \theta_c^1) s^+(x_y, \theta_y^1) s^+(u_s, \theta_s)) s^-(x_f, \theta_f^5) \\ & + \kappa_f^2 s^+(x_a, \theta_a^1) s^-(x_t, \theta_t^2) s^-(x_f, \theta_f^5) \end{aligned} \quad (4)$$

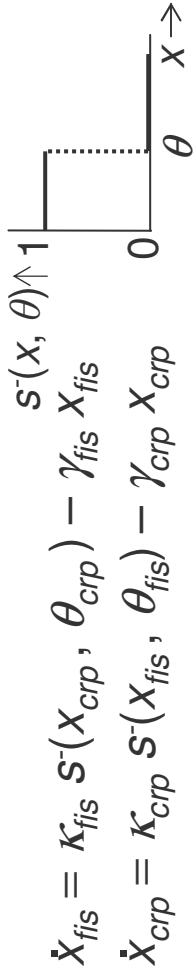
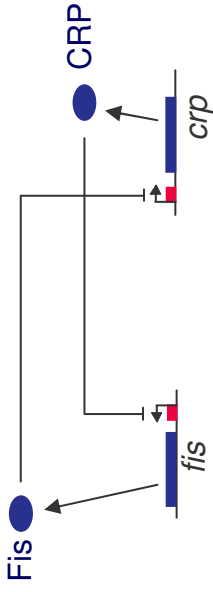
$$\times (1 - s^+(x_c, \theta_c^1) s^+(x_y, \theta_y^1) s^+(u_s, \theta_s)) - \gamma_f x_f \quad (4)$$

$$\dot{x}_a = \kappa_a (1 - s^+(x_a, \theta_a^2) s^-(x_t, \theta_t^1)) s^-(x_f, \theta_f^4) - \gamma_a x_a \quad (5)$$

$$\dot{x}_t = \kappa_t s^+(x_a, \theta_a^2) s^-(x_t, \theta_t^1) s^+(x_f, \theta_f^4) - \gamma_t x_t \quad (6)$$

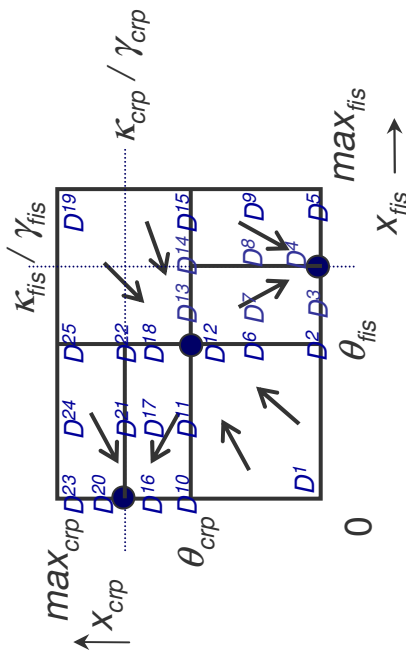
$$\dot{x}_n = \kappa_n^1 s^+(x_f, \theta_f^3) + \kappa_n^2 - \gamma_n x_n \quad (7)$$

Outline of qualitative simulation

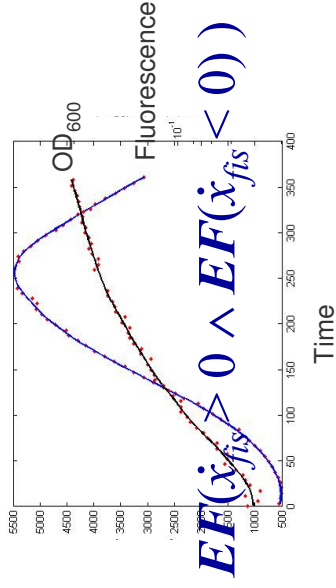


$$\dot{X}_{fis} = \kappa_{fis} S(X_{crp}, \theta_{crp}) - \gamma_{fis} X_{fis}$$

$$\dot{X}_{crp} = \kappa_{crp} S(X_{fis}, \theta_{fis}) - \gamma_{crp} X_{crp}$$

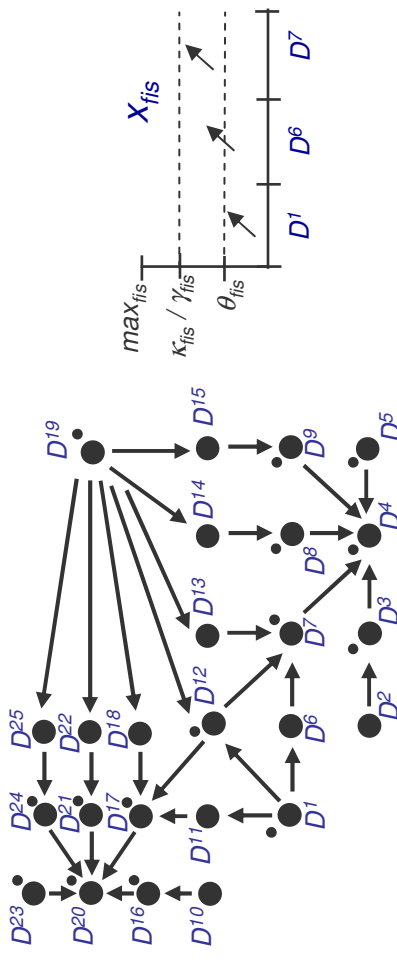


Models using step functions



Model-checking for verification of model predictions

Network dynamics easy to analyze



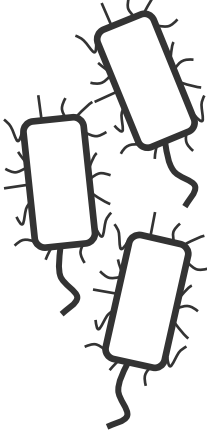
Qualitative predictions of dynamics, robust for large variations in parameter values

Attractors of stress response network

❖ Analysis of attractors of PA model: two **steady states**

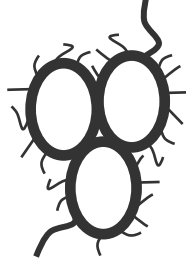
- **Stable** steady state, corresponding to exponential-phase conditions

```
Crp = k_Crp_1/g_Crp
Cya = (k_Cya_1+k_Cya_2)/g_Cya
Fis = l_Fis_4
GyrAB = l_GyrAB_1
z_Signal <= Signal < l_Signal
TopA = z_TopA
rrn = (k_rrn_2+k_rrn_1)/g_rrn
```



- **Stable** steady state, corresponding to stationary-phase conditions

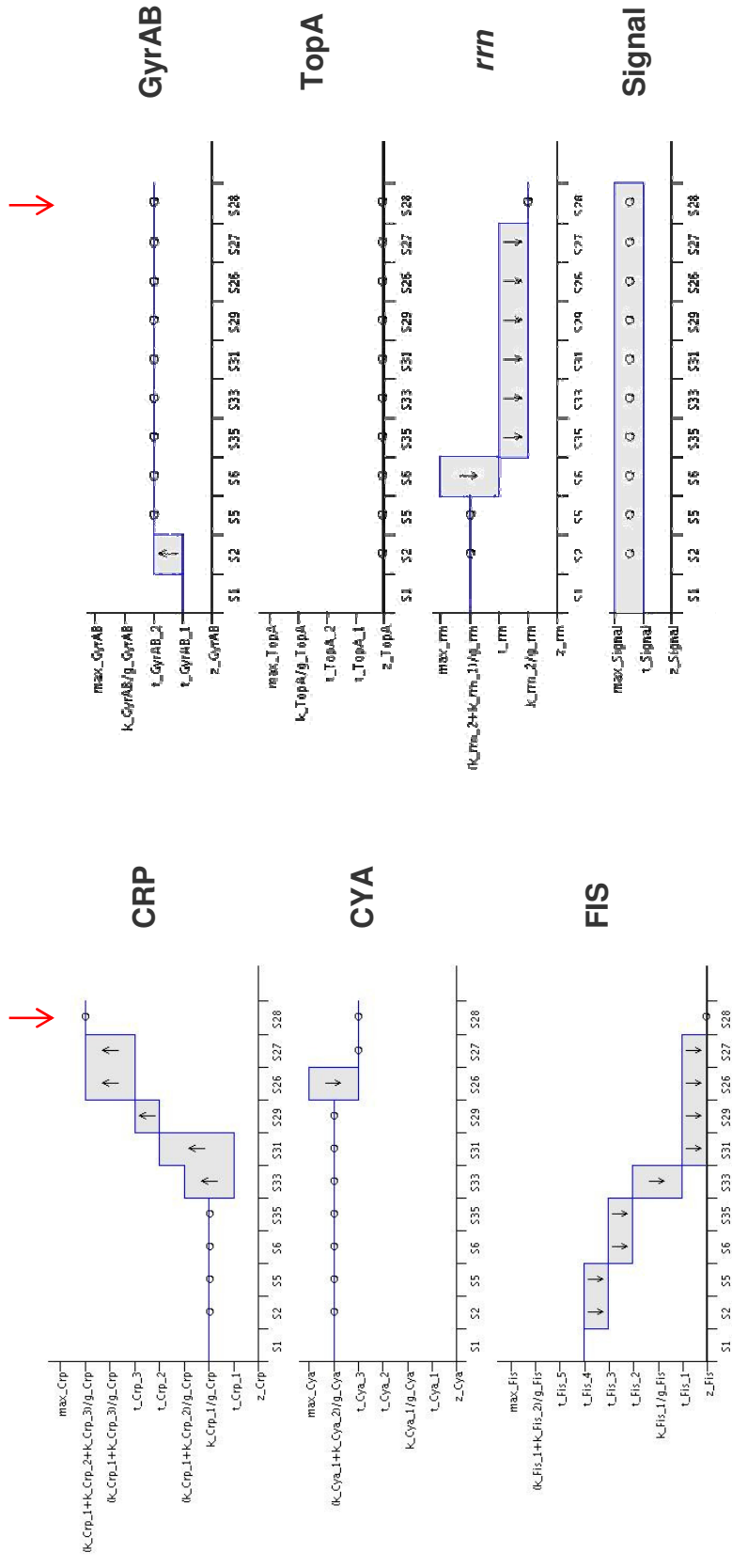
```
Crp = (k_Crp_1+k_Crp_2+k_Crp_3)/g_Crp
Cya = l_Cya_3
Fis = z_Fis
GyrAB = l_GyrAB_2
l_Signal < Signal <= max_Signal
TopA = z_TopA
rrn = k_rrn_2/g_rrn
```



Simulation of stress response network

❖ Simulation of transition from exponential to stationary phase

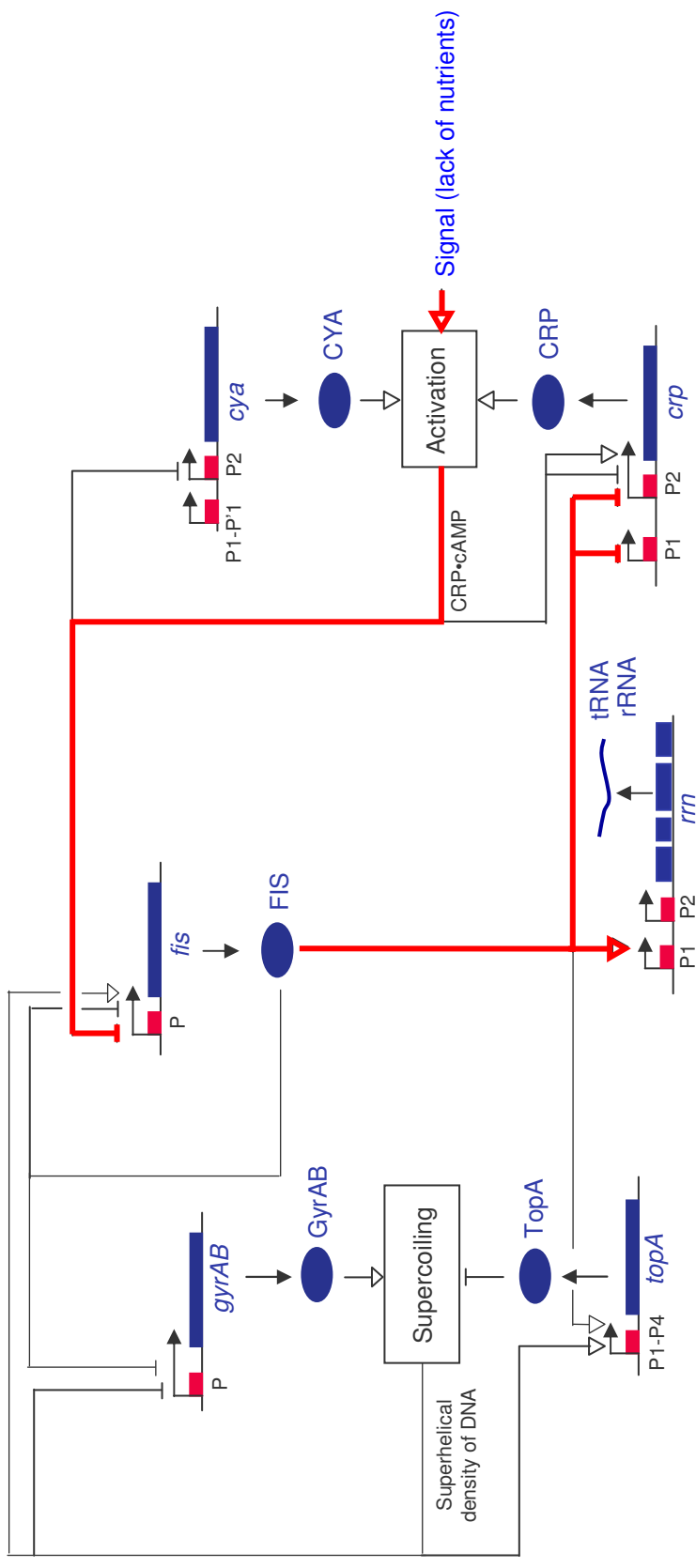
State transition graph with 27 states, **1 stable steady state**



Insight into nutritional stress response

- ❖ Sequence of **qualitative events** leading to adjustment of growth of cell after nutritional stress signal

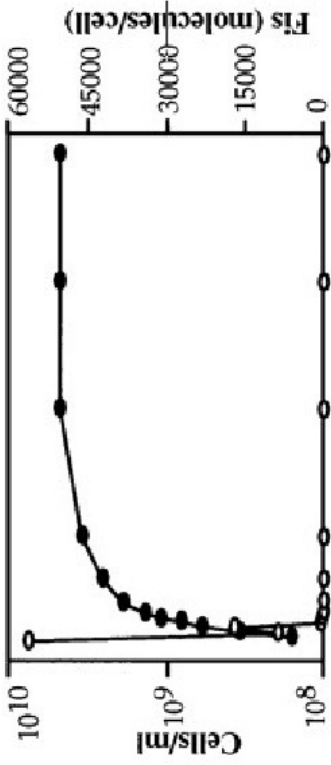
Role of the mutual inhibition of Fis and CRP•cAMP



Validation of carbon starvation response model

❖ Validation of model using model checking

- “Fis concentration decreases and becomes steady in stationary phase”



$$EF(\dot{x}_{fis} < 0 \wedge EF(\dot{x}_{fis} = 0 \wedge x_{rrn} < \theta_{rrn}))$$

True

- “*cya* transcription is negatively regulated by the complex cAMP-CRP”

Kawamukai *et al.* (1985), *J. Bacteriol.*, 164(2):872-877

$$AG(x_{crp} > \theta_{crp} \wedge x_{cya} > \theta_{cya} \wedge x_s > \theta_s \rightarrow EF \dot{x}_{cya} < 0) \quad \text{True}$$

- “DNA supercoiling decreases during transition to stationary phase”

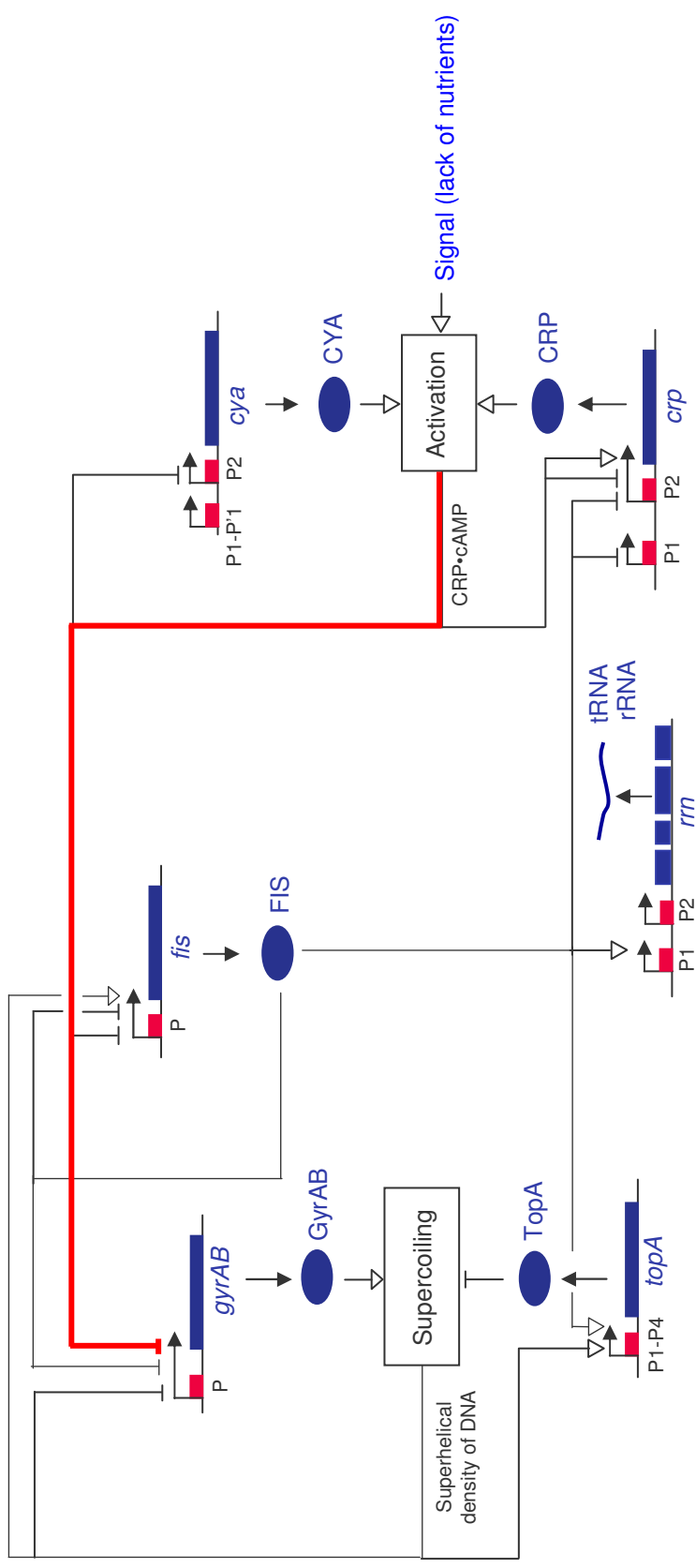
Balke, Gralla (1987), *J. Bacteriol.*, 169(10):4499-4506

$$EF(\dot{x}_{gyrAB} < 0 \vee \dot{x}_{topA} > 0) \wedge x_{rrn} < \theta_{rrn}) \quad \text{False}$$

Suggestion of missing interaction

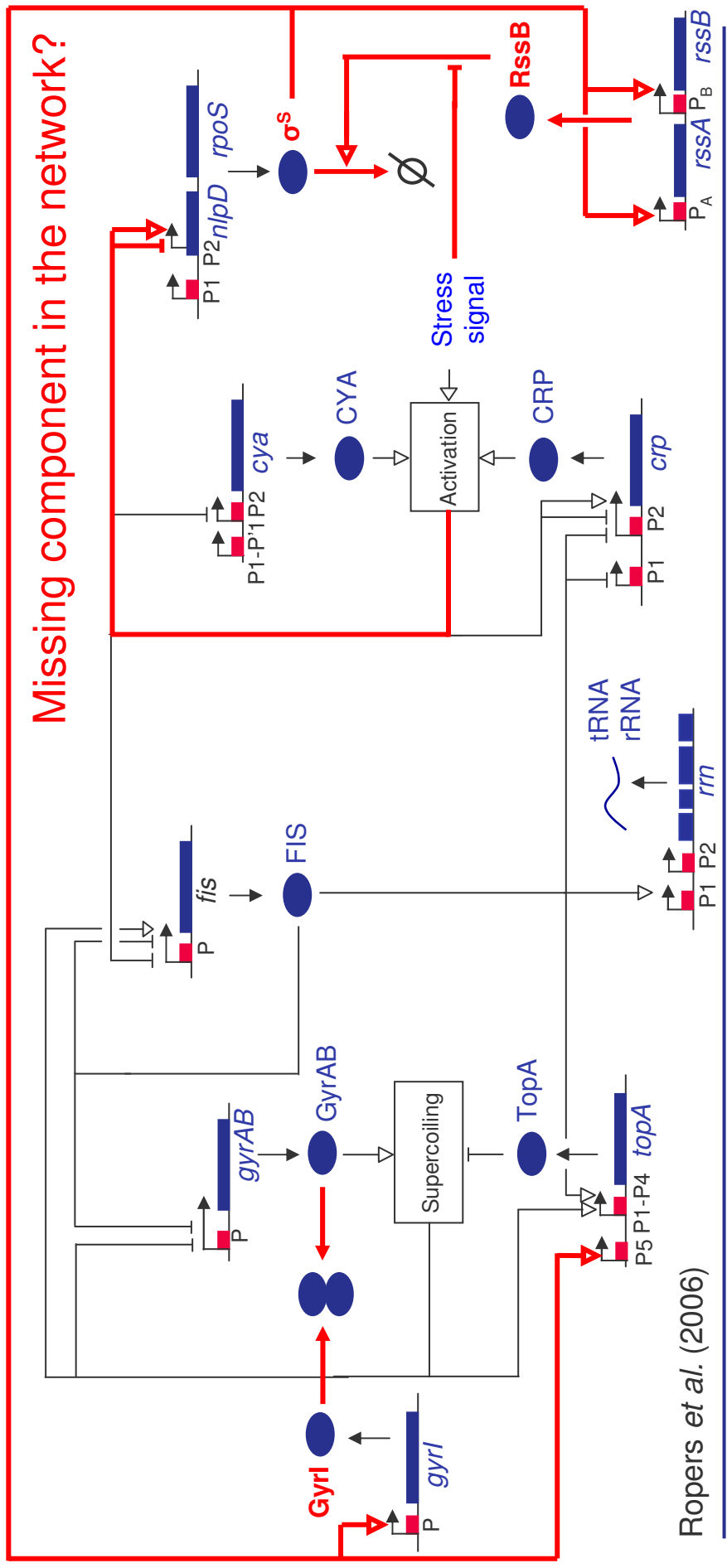
- ❖ Model does not reproduce observed downregulation of negative supercoiling

Missing interaction in the network?



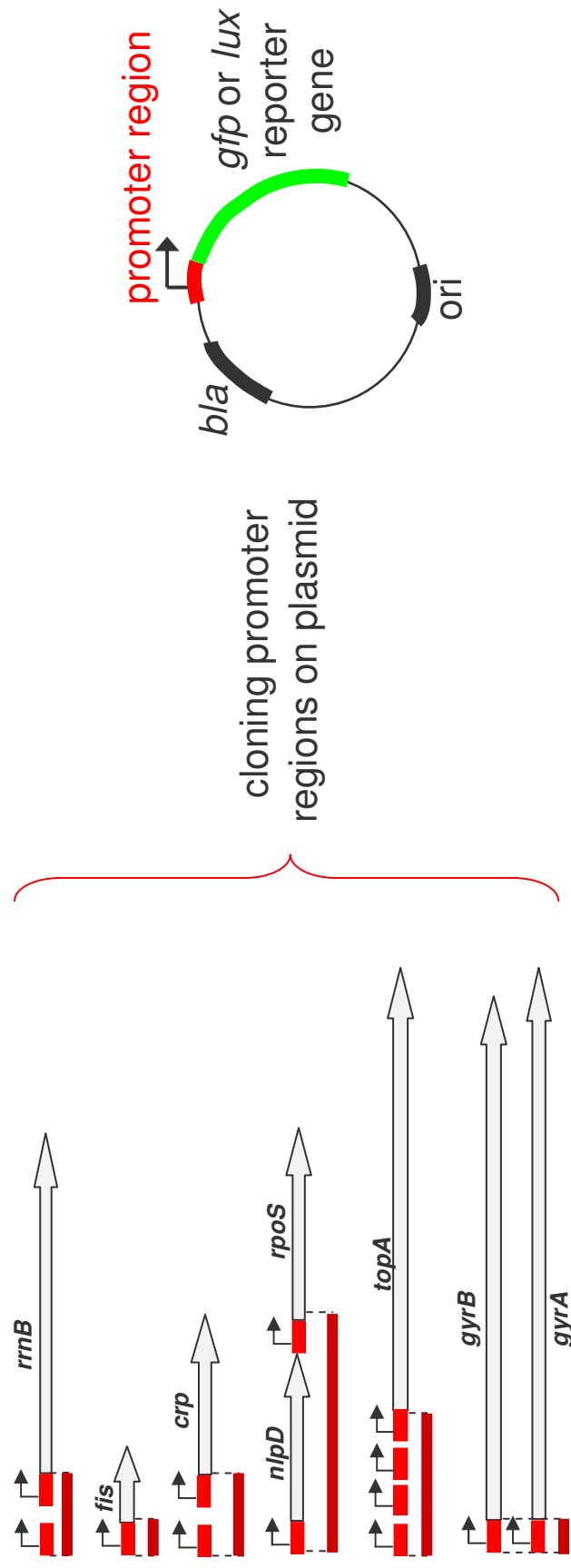
Extension of stress response network

- ❖ Model does not reproduce observed downregulation of negative supercoiling



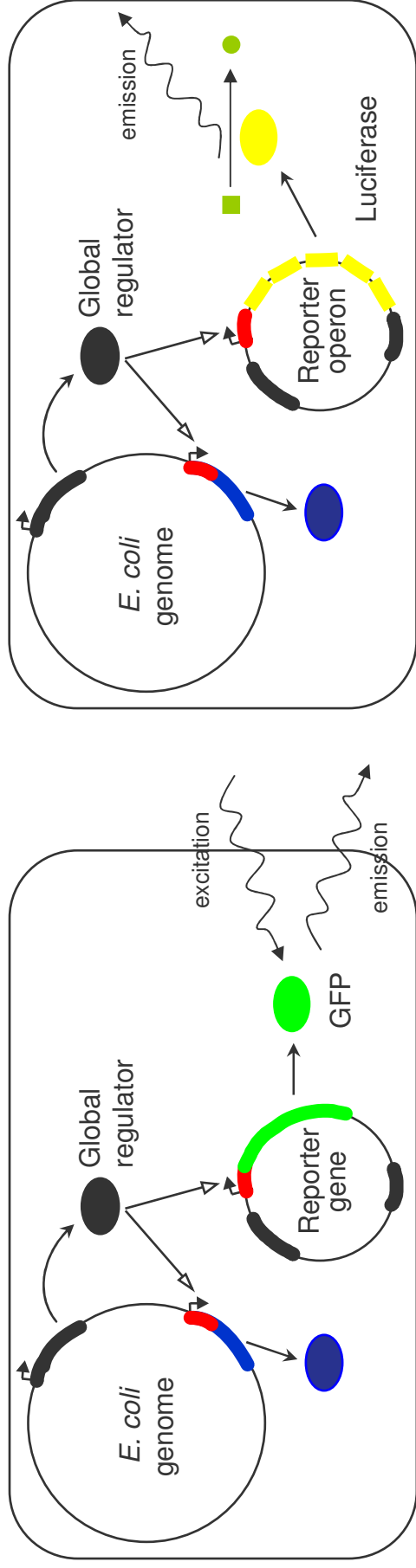
Reporter gene systems

- ❖ Simulations yield predictions that cannot be verified with currently available experimental data
- ❖ Use of **reporter gene systems** to monitor gene expression



Monitoring of gene expression

- ❖ Integration of fluorescent or luminescent reporter gene systems into bacterial cell

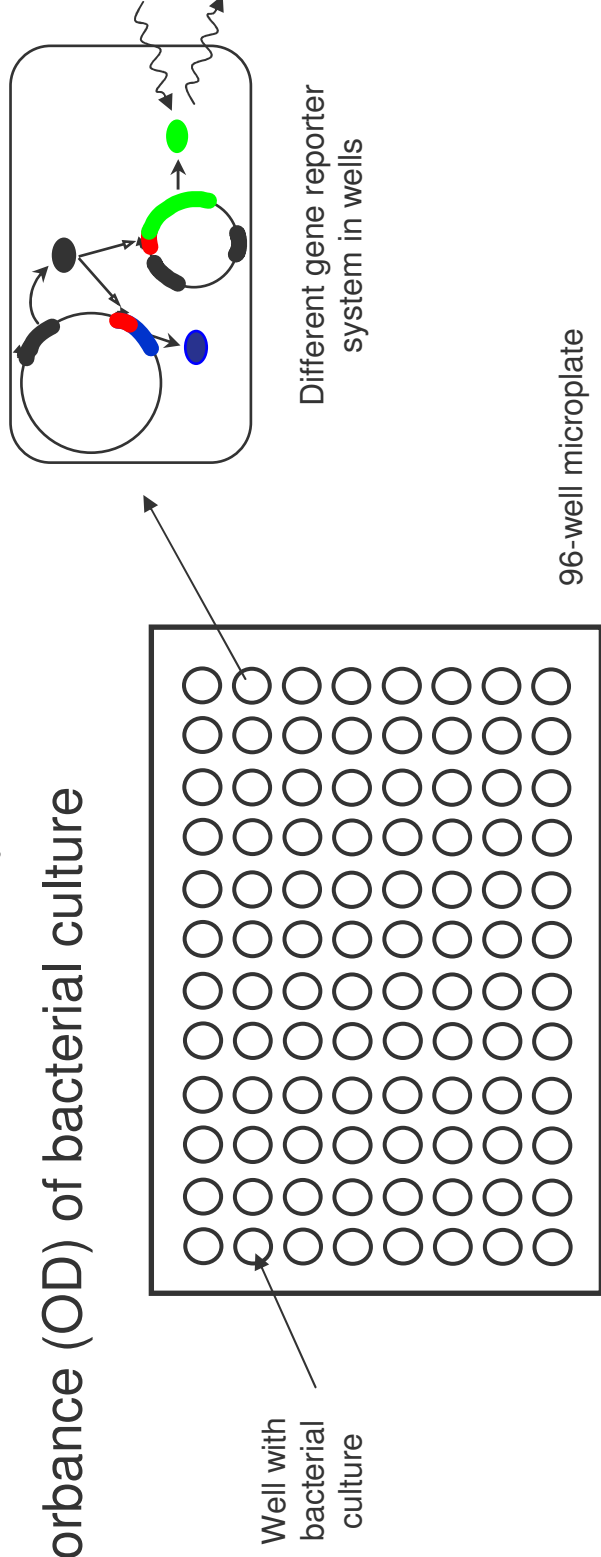


- ❖ Expression of reporter gene reflects expression of host gene of interest
-

Real-time monitoring: microplate reader

❖ Use of automated microplate reader to monitor in parallel in single experiment expression of different reporter genes

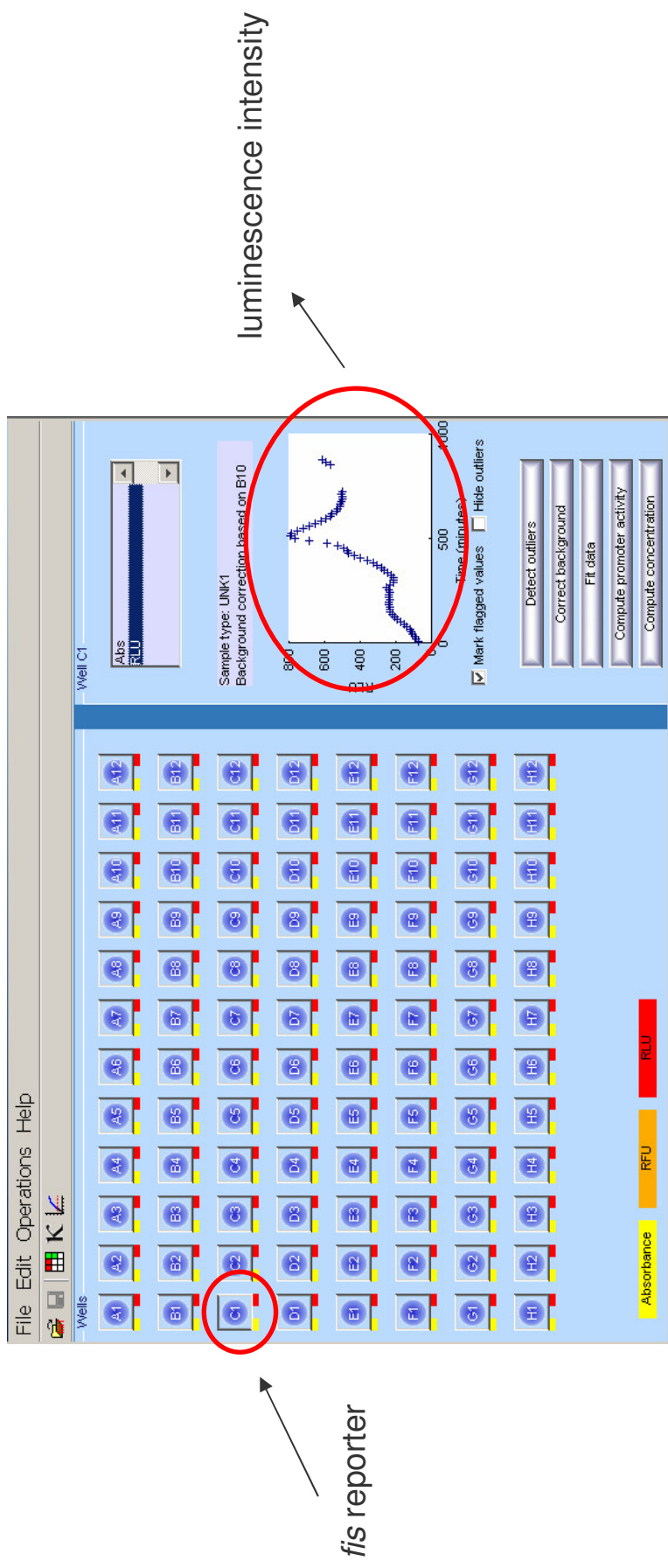
- fluorescence/luminescent intensity
- absorbance (OD) of bacterial culture



❖ Upshift experiments in M9/glucose medium

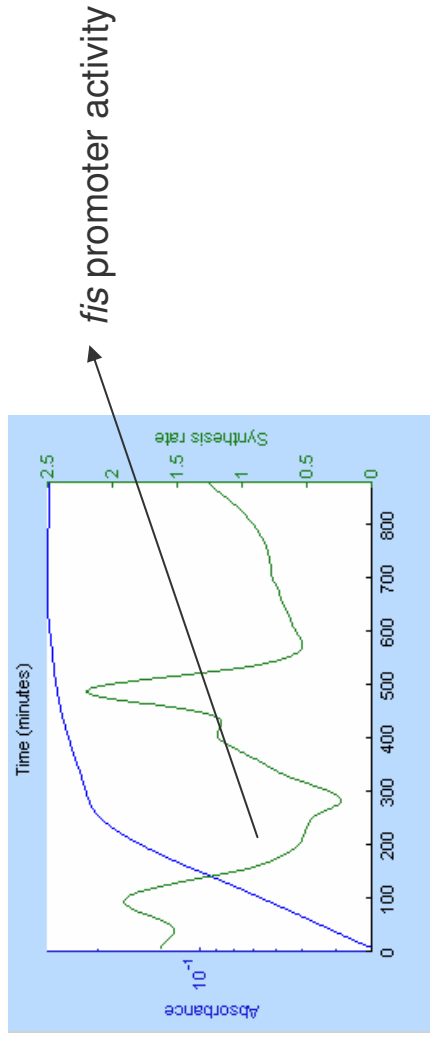
Analysis of reporter gene expression data

❖ **Wellreader:** Matlab program for analysis of reporter gene expression data



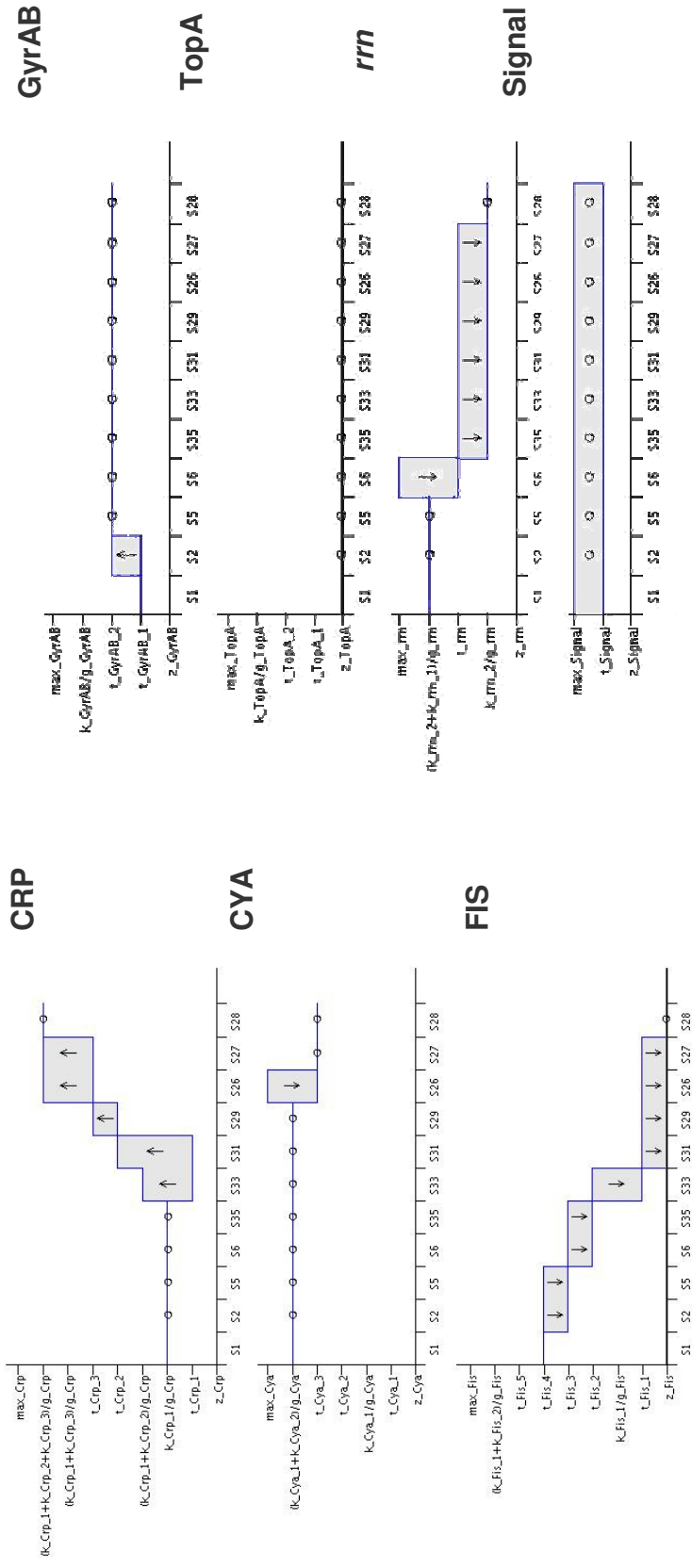
Data analysis issues

- ❖ Outlier detection and background subtraction
- ❖ Data smoothing and interpolation by means of cubic smoothing splines
- ❖ Computation of reporter concentration, promoter activity, host protein concentration
- ❖ Computation of confidence intervals



Validation of carbon starvation model

❖ Model predictions verified by experimental data?



❖ Preliminary results: partly yes, partly no

Perspectives

- ❖ Refining model validation by monitoring gene expression in single cells
Collaboration with Irina Mihalcescu, Université Joseph Fourier

- ❖ Inference of regulatory networks from gene expression data
Use hybrid system identification methods adapted to PA models

Drulhe *et al.* (2006), *Hybrid Systems: Computation and Control*, LNCS 3927, 184-99

- ❖ Composite models of *E. coli* stress response on genetic and metabolic level
Collaboration with Daniel Kahn, INRA

Conclusions

- ❖ Understanding of functioning and development of living organisms requires **analysis of genetic regulatory networks**
 - From structure to behavior of networks
- ❖ Need for **mathematical methods and computer tools well-adapted to available** experimental data
 - Coarse-grained models and qualitative analysis of dynamics
- ❖ **Biological relevance** attained through **integration of modeling and experiments**
 - Models guide experiments, and experiments stimulate models**

Contributors and sponsors

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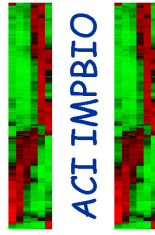
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Ministère de la Recherche,
IMPBIO program



European Commission,
FP6, NEST program



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INRIA, ARC program



Agence Nationale de la
Recherche, BioSys program