

Stochastic Modeling in Systems Biology



Yang Cao

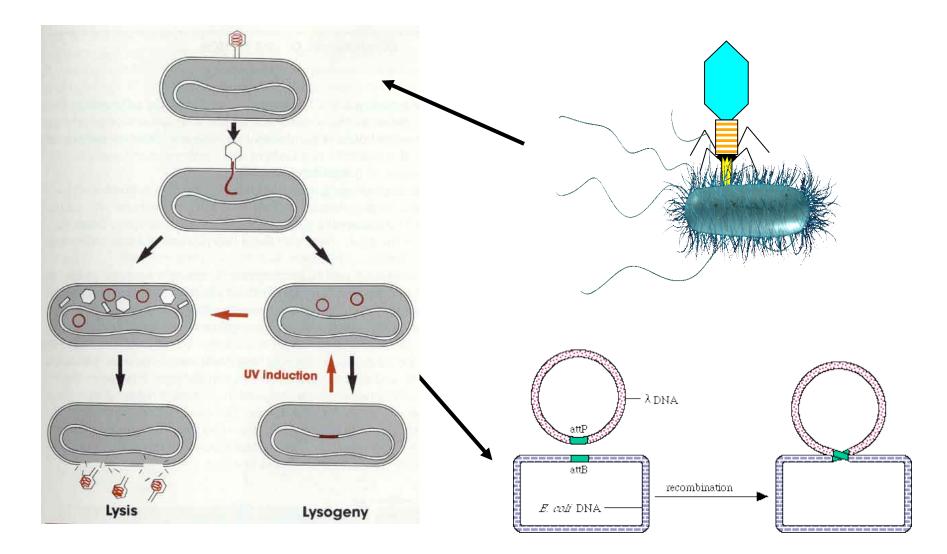


Department of Computer Science

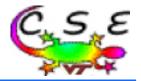


Lambda-phage affected E. Coli

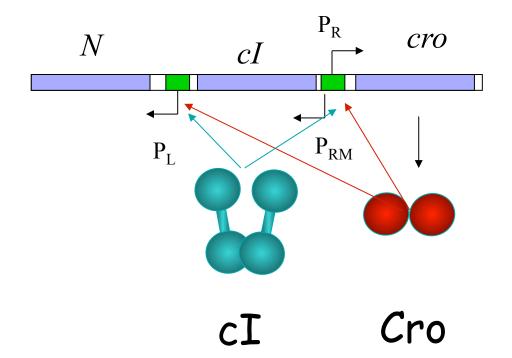




Highlight the lambda phage regulation



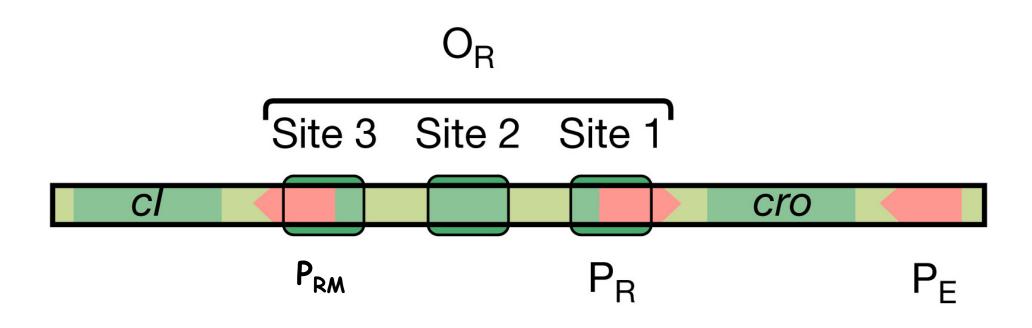
Computational Science and Engineering



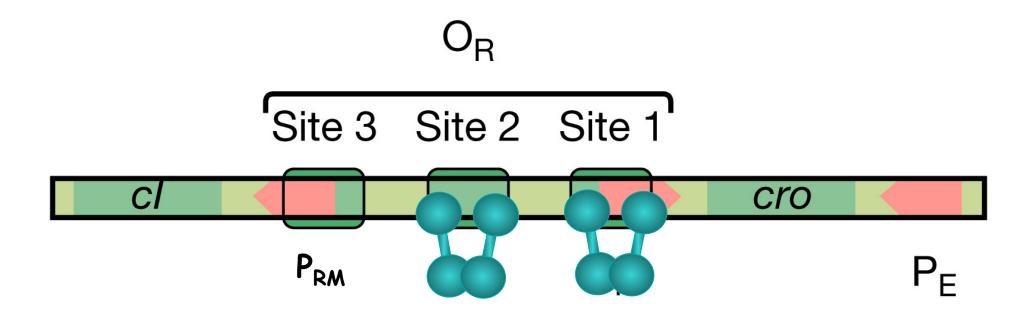
If cI wins, P_R and P_L are repressed and the cell enters lysogeny If Cro wins, P_{RM} is repressed and the cells enters the lytic cycle



A close up on the right promoter- operator region

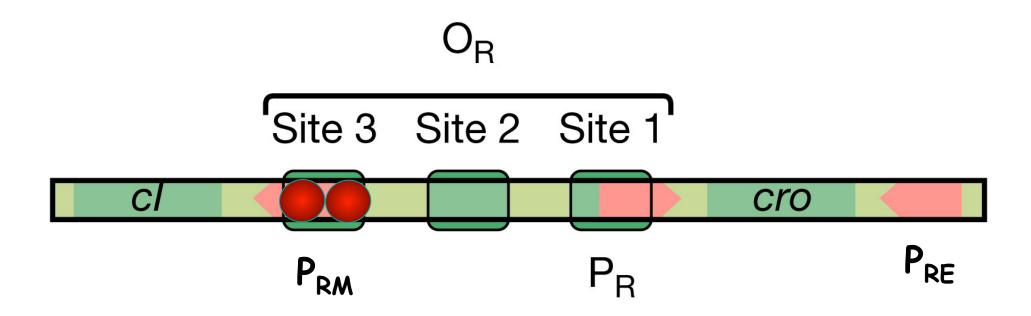






cI represses P_R – shuts off *cro* cI activates P_{RM} – expression of *cI*





Cro represses P_{RM} - shuts off *cI* expression

Lambda-phage affected E. Coli **Computational Science and Engineering** Lysis AN NUMBER Lysogeny а Cro₂ Cro2 R1 CI2 = deg **Stochastic** Cro₂ Cro deg т_{R1} 50% effects play an PRM PRE P RI important role λ "switch" O_{E2} N 4 in lytic/ CII R4 P2 lysogenic к₈ P1•CII ^k10 ▶ P1 R5 deg 🚽 k₇ decision СШ Cro₂ CI2 k13 1.011 P1 network CIII 0_{L1} 0_{L2} cIII т_{L1} 80% Arkin et al. b nucleotides from the cohesive end site (cos) 1997, 1998 35,000 40,000 PRE PRM To *int, xis* To S + tail & head genes cro icll 0 *cl* T_{R1} T_{R2} n T_{L1}



A Chemically Reacting System

• Molecules of N chemical species S_1, \ldots, S_N .

- In a volume $\boldsymbol{\Omega}$, at temperature T.

- Different conformations or excitation levels are considered different species if they behave differently.

• *M* "elemental" *reaction channels* R_1, \ldots, R_M .

- each R_j describes a *single instantaneous physical event*, which changes the population of at least one species. Thus, R_j is either

 $\emptyset \to S_i,$ or $S_i \to \text{ something else},$ or $S_i + S_{i'} \to \text{ something else}.$

A General Question



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<u>Question</u>: How does this system evolve in time?

The traditional answer, for *spatially homogeneous* systems:

"According to the *reaction rate equation* (RRE)."

- A set of coupled, first-order ODEs.
- Derived using ad hoc, phenomenological reasoning.
- Implies the system evolves *continuously* and *deterministically*.
- Empirically accurate for large systems.
- Often not adequate for small systems.

* * *

The question deserves a more carefully considered answer.

Molecular Dynamics

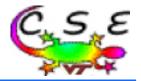


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Molecular Dynamics (MD)

- The most exact way of describing the system's evolution.
- Tracks the position and velocity of *every* molecule in the system.
- Simulates *every* collision, *non-reactive* as well as *reactive*.
- Shows changes in species populations and their spatial distributions.
- But . . . it's unfeasibly slow for nearly all realistic systems.

Some Facts about Cell (got from Mark Paul)



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Characteristic Length Scales

The radius of a single cell,

 $R_{cell} \approx 5 \mu \mathrm{m}$

The radius of a water molecule,

 $R_{water} \approx 0.3$ nm

The volume of a single cell,

$$V_{cell} \approx \frac{1}{2} \mathrm{pL}$$

If a cell only contained water, there would be,

$$N_{water} \approx 4 \times 10^{15}$$
 molecules

Characteristic Time Scales

Mean time for cell division,

 $t_{cell} \approx 100 \text{min}$

At room temperature the equipartition of energy yields the mean velocity of a molecule to be,

$$\frac{3}{2}k_BT = \frac{1}{2}mv^2$$

Using this, the mean time between collisions is,

 $t_c \lesssim 1 \mathrm{ps}$

The number of collisions to occur per cell cycle is then,

 $N \approx 3 \times 10^{31}$

Molecular dynamics is out!



- A great simplification occurs *if* successive *reactive* collisions tend to be separated in time by *very many non-reactive* collisions.
- The overall effect of the non-reactive collisions is to *randomize* the positions of the molecules (and also maintain thermal equilibrium).
- The non-reactive collisions merely serve to keep the system **wellstirred** or **spatially homogeneous** for the reactive collisions.
- Can describe the *state* of the system by $\mathbf{X}(t) \triangleq (X_1(t), \dots, X_N(t))$,

 $X_i(t) \triangleq$ the *number* of S_i molecules at time t.



But this *well-stirred simplification*, which . . .

- ignores the non-reactive collisions,
- *truncates* the definition of the system's state,

. . . comes at a price:

 $\mathbf{X}(t)$ must be viewed as a stochastic process.

- In fact, *the system was never deterministic to begin with!* Even if molecules moved according to classical mechanics . . .
 - monomolecular reactions always involve QM.
 - bimolecular reactions require collisions, whose extreme sensitivity to initial conditions renders them essentially random.
 - bimolecular reactions usually involve QM too.
- But stochastic processes can be handled.



For well-stirred systems, each R_j is completely characterized by:

- a *propensity function* $a_i(\mathbf{x})$: Given the system in state \mathbf{x} ,
 - $a_i(\mathbf{x}) dt \triangleq$ the *probability* that one R_i event will occur in the next dt.
 - The existence and form of $a_i(\mathbf{x})$ follow from kinetic theory.

- $a_i(\mathbf{x})$ is roughly equal to, but is *not* derived from, the RRE "rate".

• a state change vector $\boldsymbol{\nu}_j \equiv (\boldsymbol{\nu}_{1j}, \dots, \boldsymbol{\nu}_{Nj})$: $\boldsymbol{\nu}_{ij} \triangleq$ the change in the number of S_i molecules caused by one R_j event.

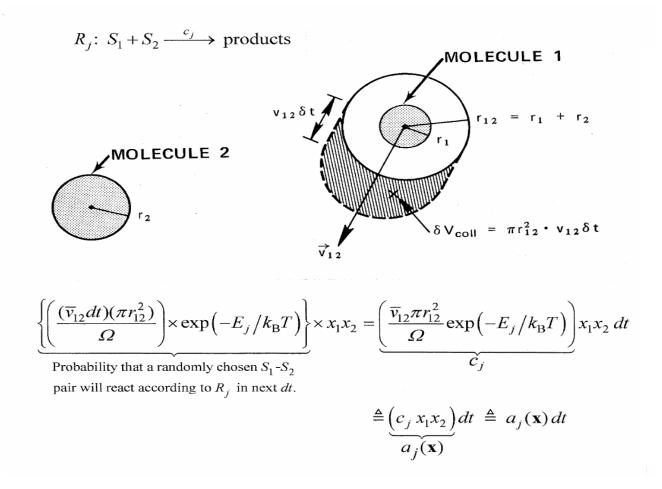
- R_j induces $\mathbf{x} \to \mathbf{x} + \boldsymbol{\nu}_j$. $\{\boldsymbol{\nu}_{ij}\} \equiv$ the "stoichiometric matrix."

E.g.,

$$S_{1} + S_{2} \underbrace{\xrightarrow{c_{1}}}_{c_{2}} 2S_{1} \implies \begin{cases} a_{1}(\mathbf{x}) = c_{1}x_{1}x_{2}, & \mathbf{\nu}_{1} = (+1, -1, 0, \dots, 0) \\ a_{2}(\mathbf{x}) = c_{2}\frac{x_{1}(x_{1} - 1)}{2}, & \mathbf{\nu}_{2} = (-1, +1, 0, \dots, 0) \end{cases}$$

One Reasoning (but not a proof)







Difference

- Propensity function describes the probability while reaction rate describes the changing rate.
- Propensity functions are defined based on population of species while the reaction rates are defined based on the concentration of species
- Connection
 - For simple system, they have similar format. For reaction like $A \rightarrow B$
 - Reaction rate: k[A]• Propensity function CX_A and we have c = k- For reaction like $A + B \rightarrow C$ • Reaction rate k[A][B]• : • Propensity function $CX_A X_B$ and we have c = k/V



Two exact, rigorously derivable consequences . . .

➤ 1. The *chemical master equation* (CME):

$$\frac{\partial P(\mathbf{x},t|\mathbf{x}_0,t_0)}{\partial t} = \sum_{j=1}^{M} \Big[a_j(\mathbf{x}-\boldsymbol{\nu}_j)P(\mathbf{x}-\boldsymbol{\nu}_j,t|\mathbf{x}_0,t_0) - a_j(\mathbf{x})P(\mathbf{x},t|\mathbf{x}_0,t_0) \Big].$$

- Gives $P(\mathbf{x}, t | \mathbf{x}_0, t_0) \triangleq \operatorname{Prob} \{ \mathbf{X}(t) = \mathbf{x}, \text{ given } \mathbf{X}(t_0) = \mathbf{x}_0 \}$ for $t \ge t_0$.
- The CME follows from the *probability* statement

$$P(\mathbf{x}, t+dt | \mathbf{x}_0, t_0) = P(\mathbf{x}, t | \mathbf{x}_0, t_0) \times \left[1 - \sum_{j=1}^{M} \left(a_j(\mathbf{x}) dt \right) \right]$$
$$+ \sum_{j=1}^{M} P(\mathbf{x} - \boldsymbol{\nu}_j, t | \mathbf{x}_0, t_0) \times \left(a_j(\mathbf{x} - \boldsymbol{\nu}_j) dt \right).$$

• But it's practically always *intractable* (analytically and numerically).

- > 2. The *stochastic simulation algorithm* (SSA):
 - A procedure for constructing *sample paths* or *realizations* of $\mathbf{X}(t)$.
 - Approach: Generate the time to the *next* reaction and the index of that reaction.
 - Theoretical justification: With $p(\tau, j | \mathbf{x}, t)$ defined by

 $p(\tau, j | \mathbf{x}, t) d\tau \triangleq$ prob, given $\mathbf{X}(t) = \mathbf{x}$, that the next reaction will occur in $[t + \tau, t + \tau + d\tau)$, and will be an R_i ,

can prove that

$$p(\tau, j | \mathbf{x}, t) = a_j(\mathbf{x}) \exp\left(-a_0(\mathbf{x})\tau\right), \text{ where } a_0(\mathbf{x}) \triangleq \sum_{j'=1}^M a_{j'}(\mathbf{x}).$$

This implies that the *time* τ to the next reaction event is an exponential random variable with mean $1/a_0(\mathbf{x})$, and the *index* j of that reaction is an integer random variable with prob $a_j(\mathbf{x})/a_0(\mathbf{x})$.



The "Direct" Version of the SSA

1. With the system in state **x** at time *t*, evaluate $a_0(\mathbf{x}) \triangleq \sum_{j'=1}^{M} a_{j'}(\mathbf{x})$.

2. Draw two unit-interval uniform random numbers r_1 and r_2 , and compute τ and *j* according to

•
$$\tau = \frac{1}{a_0(\mathbf{x})} \ln\left(\frac{1}{r_1}\right),$$

•
$$j = \text{the smallest integer satisfying } \sum_{j'=1}^{j} a_{j'}(\mathbf{x}) > r_2 a_0(\mathbf{x}).$$

- **3.** Replace $t \leftarrow t + \tau$ and $\mathbf{x} \leftarrow \mathbf{x} + \boldsymbol{\nu}_{j}$.
- 4. Record (\mathbf{x}, t) . Return to Step 1, or else end the simulation.

(Inverse Generation Method)



- A different but equivalent simulation method for SSA
- Generate a firing time for each reaction channel

$$\tau_j = \frac{1}{a_j(x)} \ln\left(\frac{1}{r_j}\right),$$

• Find the minimum of all the firing time and throw off all the others

$$\mu$$
 = the index satisfying

$$\boldsymbol{\tau}_{\mu} = \min_{j} \boldsymbol{\tau}_{j},$$

- In theory this method is equivalent to the DM
- The biggest concern is the computational cost



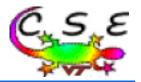
- Derived by Gibson and Bruck 2000
- Keep the randomly generated firing time if the corresponding propensity function is not changed (Use a dependent graph (DG) to achieve this goal)
- Use absolute time instead of relative time

$$\tau_{\alpha} = \frac{1}{a_{\alpha}(t)} \log\left(\frac{1}{r}\right) + t.$$

Reuse the unapplied uniform random number

$$\tau_{\alpha} \leftarrow (a_{\alpha,old}/a_{\alpha,new})(\tau_{\alpha}-t) + t.$$

- Use a priority tree (heap array) to conduct the search
- Only need to generate one uniform random number each step
- The computational cost to maintain the data structure can be hug!



- Analyze the time profile of DM and NRM. Conclude that the data structure maintaining cost is very high for most problems.
- Sort the reaction channel so that more frequent firing reaction channels have smaller index. (Run a few presimulation to collect info for the problem.)
- If necessary, use the dependent graph (DG) to avoid recalculating propensity functions for reaction channels that are not affected by the last reaction.
- Efficient for multiscale problem
- Among all test problems we tried, ODM is faster than NRM.



- The pro-simulation procedure is troublesome for an automatic code.
- The index should be changed dynamically during the simulation
- Bubble sorting technique
 If a reaction just fired, move its index one step up. After a
 while, the reaction index will be automatically well-sorted.
- Less (but almost the same) efficient than ODM but much easier to code and maintain.



The SSA ...

- Is *exact*.
- Is equivalent to (but is not derived from) the CME.
- Does *not* entail approximating "dt" by " Δt ".
- Is *procedurally simple*, even when the CME is intractable.
- *Remains too slow for most practical problems*: Simulating *every* reaction event, *one* at a time, is just too much work if any reactant is present in very large numbers.



A Model for Prokaryotic Gene Expression

- Computational Science and Engineering
- 1. Transcription Initiation (the binding and initiation)

P+RNAP \rightarrow P • RNAP $k_1 = 10^8 \,\mathrm{M}^{-1} s^{-1}$ P • RNAP \rightarrow P+RNAP $k_2 = 10 s^{-1}$ P • RNAP \rightarrow TrRNAP $k_3 = 1 s^{-1}$

2. Elongation (RBS is available before elongation terminates

 $TrRNAP \rightarrow RBS + P + EIRNAP$ $k_4 = 1s^{-1}$

3. Translation Initiation

Elongation

4.

Ribosome +RBS \rightarrow RibRBS $k_5 = 10^8 M^{-1} s^{-1}$ RibRBS \rightarrow Ribosome +RBS $k_6 = 2.25 s^{-1}$ RibRBS \rightarrow ElRib +RBS $k_7 = 0.5 s^{-1}$ RBS \rightarrow decay $k_8 = 0.3 s^{-1}$ ElRib \rightarrow Protein $k_9 = 0.015 s^{-1}$

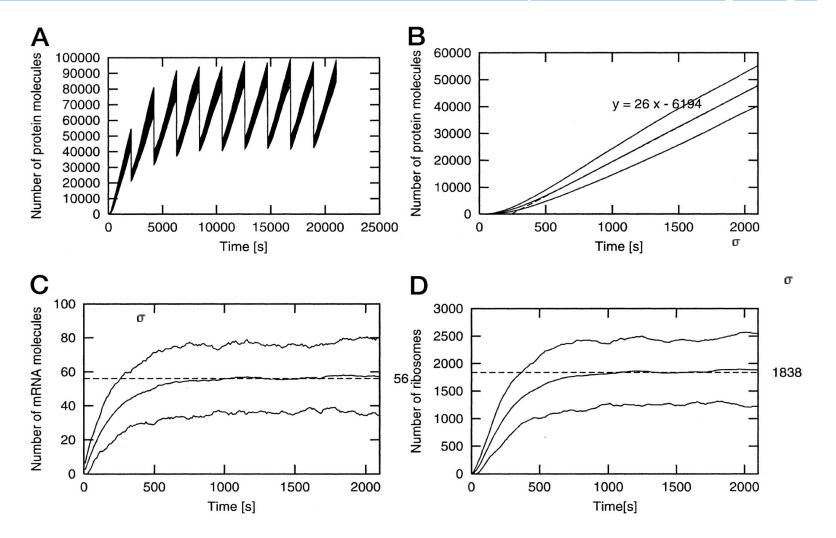
Protein → decay

 $k_9 = 0.013s$ $k_{10} = 6.42 \times 10^{-5} s^{-1}$



Simulation Results

Computational Science and Engineering



Kierzek, A. M. et al. J. Biol. Chem. 2001;276:8165-8172



Reactions:

$$B_{1} + 2X \stackrel{c_{1}}{\underset{c_{2}}{\longleftrightarrow}} 3X$$
$$B_{2} \stackrel{c_{3}}{\underset{c_{4}}{\longleftrightarrow}} X$$

• Propensity functions:

$$a_{1}(x) = \frac{c_{1}}{2} N_{1} x(x-1),$$

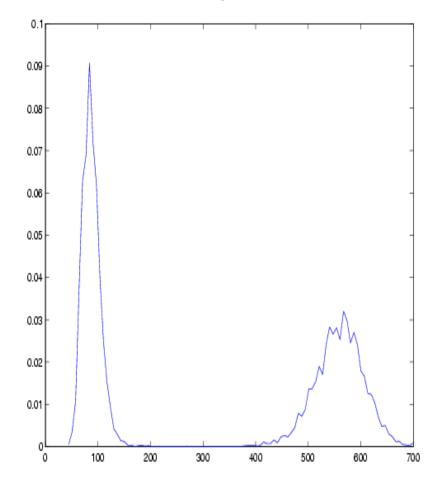
$$a_{2}(x) = \frac{c_{2}}{6} x(x-1)(x-2),$$

$$a_{3}(x) = c_{3} N_{2},$$

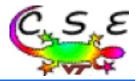
$$a_{4}(x) = c_{4} x.$$

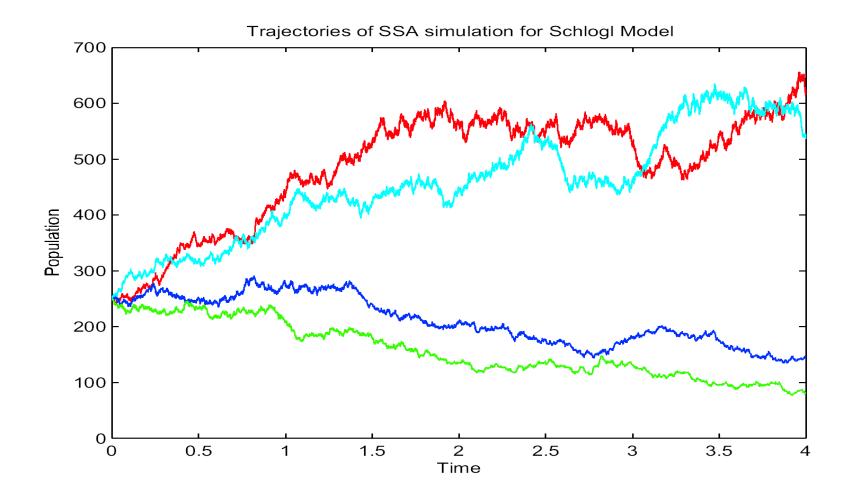
• Bistable distribution

Histogram plot of the state in Schlögl model



Single Simulation Results

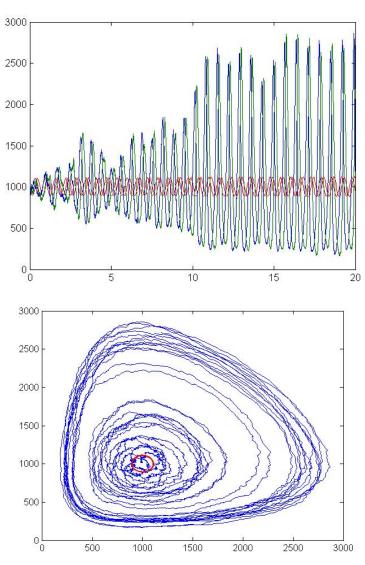




Stochastic Modeling



Computational Science and Engineering



Lotka reactions:

$$A + X \xrightarrow{c_1} 2X$$
$$X + Y \xrightarrow{c_2} 2Y$$
$$Y \xrightarrow{c_3} Z$$

Lead to ODEs

$$\begin{cases} \dot{x} = (c_1 A - c_2 y)x\\ \dot{y} = (-c_3 + c_2 x)y \end{cases}$$

The stochastic simulation generates interestin

$$c_1 A = 10,$$

 $c_2 = 0.01,$
 $c_3 = 10$

Brusselator

$\begin{array}{ll} A & \xrightarrow{c_1} X \\ B + X & \xrightarrow{c_2} Y + C \\ 2X + Y & \xrightarrow{c_3} 3Y \\ Y & \xrightarrow{c_4} D \end{array} \begin{array}{ll} c_1 A = 5000, \\ c_2 B = 50, \\ c_3 = 0.00005, \\ c_4 = 5. \end{array}$

Lead to ODEs

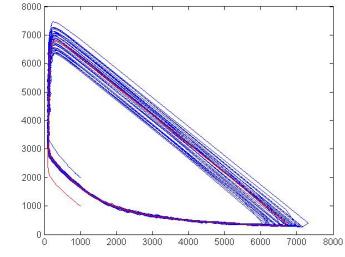
$$\begin{cases} \dot{x} = c_1 A - c_2 B y + \frac{c_3}{2} x^2 y - c_4 x \\ \dot{y} = c_2 B y - \frac{c_3}{2} x^2 y \end{cases}$$

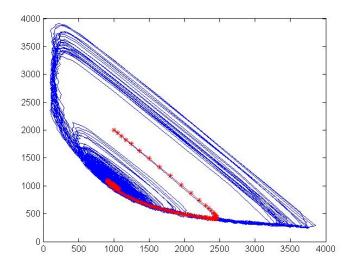
Bifurcation happens
around the condition:
$$\frac{2c_2B}{c_3} = \frac{(c_1A)^2}{c_4^2} + \frac{2c_4}{c_3}$$

J. Tyson's 1973, 1974 paper

$$c_1 A = 5000,$$

 $c_2 B = 50,$
 $c_3 = 0.0001,$
 $c_4 = 5.$









Spatially Inhomogeneous Systems

- Spatial homogeneity does *not* require that all equal-size subvolumes of Ω contain the same number of molecules!
- The CME and SSA require only that the center of a *randomly* chosen S_i molecule be found with *equal probability* at any point inside Ω .
- A system consisting of only one molecule can be "well-stirred".

> But the well-stirred assumption can't always be made.

In that case, we must do something different; however, the traditional *reaction-diffusion equation* (RDE) is *not always* the answer:

- The RDE (like the RRE) is *continuous* and *deterministic*.
- It assumes that each $d\Omega$ contains a spatially homogeneous mixture of *infinitely* many molecules.
- Not the case in most cellular systems, where spatial inhomogeneity arises not from slow mixing but rather from compartmentalization caused by highly heterogeneous structures within the cell.