

Estimating Dynamic Models

(Excerpted from a paper to be read to the Royal Statistical Society May 9, 2007)

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- Overview

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Two test bed problems

- The neural spike potential equations
- The tank reactor equations

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Simulated data results

- FitzHugh-Nagumo results
- Tank reactor results

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Fitting data with the nylon equations

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Overview

- We want to fit data by a solution to a system of nonlinear differential equations (DIFE's).
- We ignore DIFE's so simple that they can be solved, such as linear constant coefficient systems. These are already well taken care of.
- Our approach is a generalization of smoothing methods combined with a computational approach involving a modification of profiling.
- We will show results for simulated data from two test-bed problems.
- Data from a chemical reactor producing nylon is analyzed to estimate parameters defining equations for reaction kinetics.

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The FitzHugh-Nagumo model

- This simple two-component system is widely used to model properties of actual neural networks.
- They describe the reciprocal dependencies of the voltage V across an axon membrane and a recovery variable R reflecting outward currents, and
- the impact of a time-varying external excitation E .
- In the typical experiment only V will be measured, but we will consider both to be available.

The FitzHugh-Nagumo equations

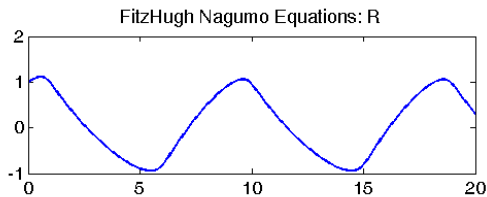
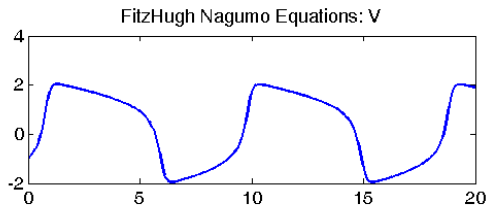
- Here is the system:

$$\begin{aligned}DV &= c \left(V - \frac{V^3}{3} + R \right) + E(t) \\ DR &= -\frac{1}{c} (V - a + bR)\end{aligned}$$

- V is voltage across axon membrane
- R reflects outward currents
- E reflects external excitation
- The dynamics of the system are controlled by parameters a , b and c .
- The system would be linear except for the V^3 term.

The neural spike potential equations

A FitzHugh-Nagumo solution



What we see

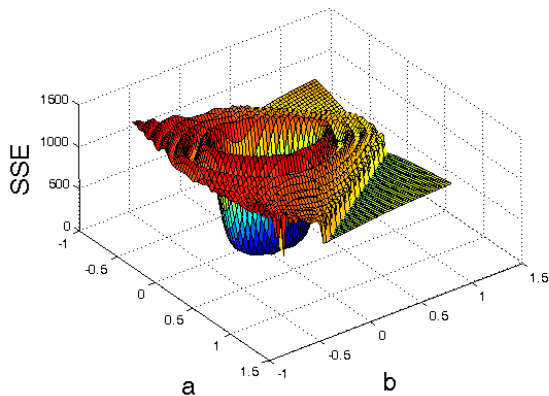
- The solution quickly reaches a steady state where it is periodic with an asymmetric pattern.
- The parameters control the amplitude and period of the response.
- The second order van der Pol equation is a closely related system.

The response surface can be complex

- Differential equations be simple, and yet define extremely complex behavior.
- This is reflected in the response surface of these equations as a functions of parameters a and b .

The neural spike potential equations

A FitzHugh-Nagumo response surface



The tank reactor model

- A continuously stirred tank reactor *CSTR* consists of a tank surrounded by cooling jacket and an impeller which stirs the contents.
- It is a basic piece of equipment for a chemical engineer.

The tank reactor variables

- A fluid is pumped into the tank containing a reagent with concentration C_{in} at a flow rate F_{in} and temperature T_{in} .
- Inside the tank a reaction takes place, producing a product that leaves the tank with concentration C_{out} and temperature T_{out} .
- A coolant enters the cooling jacket with temperature T_{cool} and flow rate F_{cool} .
- Temperature T_{out} is can be cheaply measured with little delay and considerable accuracy, but concentration C_{out} requires time and money.

The tank reactor equations

$$DC_{out} = -\beta_{CC}(T_{out})C_{out} + F_{in}C_{in}$$

$$DT_{out} = -\beta_{TT}(F_{cool}, F_{in})T_{out} + \beta_{TC}(T_{out})C_{out} \\ + F_{in}T_{in} + \alpha(F_{cool})T_{cool}.$$

- The concentration equation is linear and forced by C_{in} .
- The temperature equation is nonlinear because of the role of T_{out} in coefficient $\beta_{TC}(T_{out})$ multiplying C_{out} .

The tank reactor coefficients

- The dynamics of the system are controlled by these four coefficient functions:

$$\beta_{CC}(T_{out}, F_{in}) = \kappa \exp[-10^4 \tau (1/T_{out} - 1/T_{ref})] + F_{in}$$

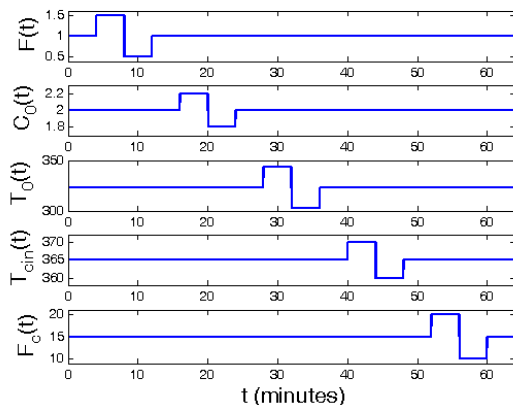
$$\beta_{TT}(F_{cool}, F_{in}) = \alpha(F_{cool}) + F_{in}$$

$$\beta_{TC}(T_{out}) = 130 \beta_{CC}(T_{out}, F_{in})$$

$$\alpha(F_{cool}) = a F_{cool}^{b+1} / (F_{cool} + a F_{cool}^b / 2),$$

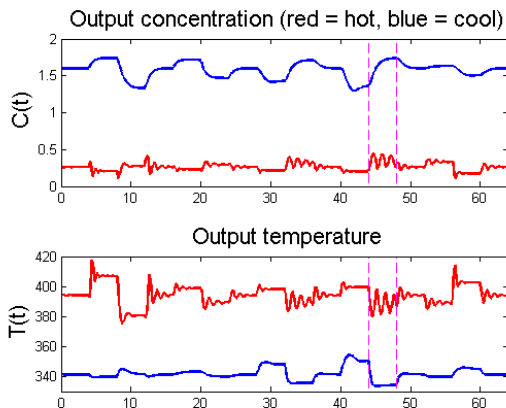
- These functions depend on two paired unknown parameters:
 - κ and τ
 - a and b

Tank reactor inputs



Each input in turn is stepped up, down and back to baseline.

Tank reactor outputs



The experiment is run at two coolant temperatures: hot and cool.

What we see

- When temperatures are moderate, the reactor responds smoothly to changes in input.
- But when temperatures are higher, sharp high frequency oscillations emerge, and are particularly troublesome for a change in coolant temperature.
- Can we predict reactor response at high temperatures from data collected and parameters estimated under the safer cool regime?
- Can we do this using only temperature measurements?

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Results for the Fitzhugh-Nagumo equations

- The solution to be estimated was determined by $\{a, b, c\} = \{0.2, 0.2, 3\}$ and initial values $\{V(0), R(0)\} = \{-1, 1\}$.
- The paths were measured at 0.05 time units on the interval $[0, 20]$.
- Noise was then added to these values with standard deviation 0.5.
- 500 simulated samples were analyzed.

Summary statistics for parameter estimates

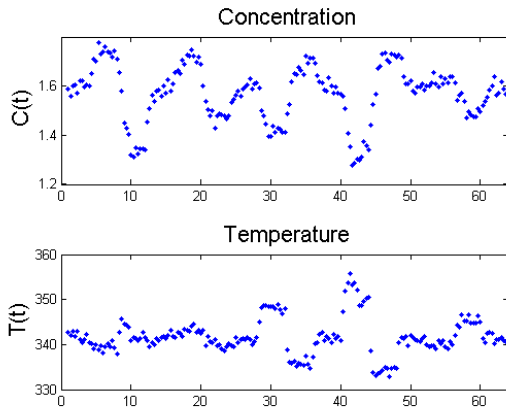
	<i>a</i>	<i>b</i>	<i>c</i>
True value	0.2000	0.2000	3.0000
Mean value	0.2005	0.1984	2.9949
Std. Dev.	0.0149	0.0643	0.0264
Est. Std. Dev.	0.0143	0.0684	0.0278
Bias	0.0005	-0.0016	-0.0051
Std. Err.	0.0007	0.0029	0.0012

Simulations for the tank reactor equations

- Parameters and initial values for paths were set to those provided by a well known text on control engineering, T. E. Marlin (2000) *Process Control*. New York: McGraw-Hill.
- Parameter b is impossible to estimate because of its correlation with a , and therefore was fixed 0.5.
- 1000 simulated samples were analyzed.

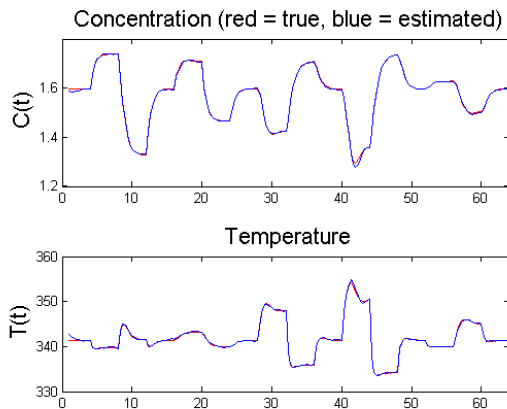
Tank reactor results

A typical set of tank reactor data

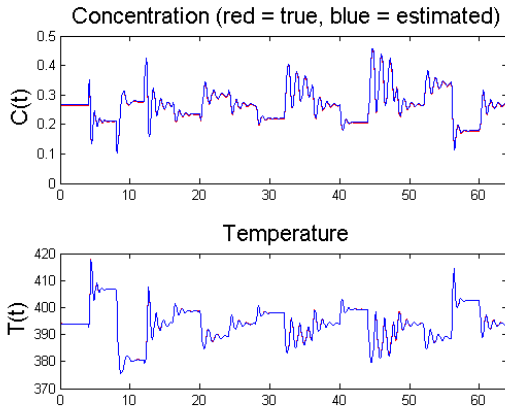


Tank reactor results

Path estimations, cool mode



Path estimations, hot mode



Data for only temperature collected in the cool mode were used.

Summary statistics for parameter estimates

	κ	τ	a
True value	0.4610	0.8330	1.6780
Mean value	0.4610	0.8349	1.6745
Std. Dev.	0.0034	0.0057	0.0188
Est. Std. Dev.	0.0035	0.0056	0.0190
Bias	0.0000	0.0000	-0.0001
Std. Err.	0.0002	0.0004	0.0012

Outline

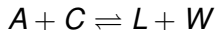
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The nylon experiment

- Nylon and other polymers are created by a chemical reaction in which molecules with two special types of endings chain together to form long molecules.
- The reaction requires water to form the molecules.
- The long molecules can also be broken up, releasing water.
- Temperature and water are critical control variables.
- There were five runs of the experiment at different temperature settings.
- These data were collected in the laboratory of Prof. K. MacAuley of the Dept. of Chemical Engineering at Queen's University, Kingston, Canada.
- The concentration measurements for variables A and C cost about \$30,000 to obtain.

The variables in the nylon equations

- A: molecules with an amine group end (measured)
- C: molecules with a carboxyl group end (measured)
- L: Nylon, a long chain of molecules (a polymer) (not measured)
- W: Water, indirectly adjusted in the experiment
- The variables are related by the mass balance equation



Nylon equations

$$DA = DC = -k_p(T) \left(CA - \frac{LW}{K_a(T)} \right)$$

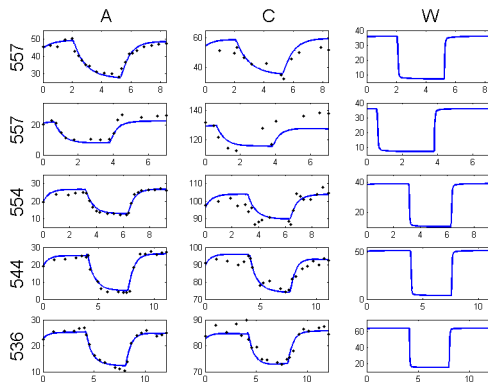
$$DW = k_p(T) \left(CA - \frac{LW}{K_a(T)} \right) - k_m \left(W - W_{eq} \right)$$

$$k_p(T) = k_{p0} \exp \left[-\frac{E}{R} \left(\frac{1}{T} - \frac{1}{T_0} \right) \right]$$

$$K_a(T) = \left[\frac{1 + \alpha W_{eq}}{\gamma_w / \gamma_{w0}} \right] K_{a0} \exp \left[-\frac{\Delta H}{R} \left(\frac{1}{T} - \frac{1}{T_0} \right) \right]$$

- variables and known constants are black
- parameters to be estimated are in red
- experimentally manipulated and measured constants and variables are in blue

Fits to the data



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Software and resources

- All the results were computed in Matlab.
- Matlab functional data analysis software was also used. These and a set of software routines that may be applied to any differential equation is available from the URL:
<http://www.functionaldata.org>.
- A paper is available from the URL:
<http://www.functionaldata.org>.
- J. O. Ramsay and B. W. Silverman (2005) *Functional Data Analysis*, Second Edition. New York: Springer.