# N -site phosphorylation systems with $2 \mathrm{~N}-1$ steady states 

Dietrich Flockerzi<br>Katharina Holstein, Carsten Conradi<br>Max Planck Institute for Dynamics of Complex Technical Systems Magdeburg - Germany

Berlin - April 2014

## Contents

1 Introduction

- 1.1 The Origin (L. Wang \& E.D. Sontag)
- 1.2 The Network
- 1.3 The Mass Action ODE-System
- 1.4 Multistationarity General Reduction Results
- 2.1 Characterization of Multiststionarity
- 2.2 Scalar Determining Equation

3 Computational Aspects - Counterexamples

- 3.1 Triple phosphorylation $(n=3)$
- 3.2 The Case $n=4$

4 Geometry of Multistationarity

- 4.1 Relations to Sign Patterns/Orthants
- 4.2 Geometric Constraints and Reconstructions
-4. A Graphical Test
5 Literature


## Introduction 1.1: The Origin

## 1. Introduction

### 1.1 The Origin: JMB-Paper by L. Wang \& E.D. Sontag

On the number of steady states in a multiple futile cycle

$$
\text { Journal of Math. Biology 57:29-52, } 2008
$$

For N -site phosphorylation systems, there are no more than $2 \mathrm{~N}-1$ steady states.
'We do not expect the number of steady states to exceed $N+1$ if $N$ is even and $N$ if $N$ is odd.'
'So a natural conjecture would be that the number of steady states never exceeds $N+1$ under any condition.'

### 1.2 The Network



The network for the sequential distributive phosphorylation and dephosphorylation of protein $A$ at $n$-sites by a kinase $E_{1}$ a phosphatase $E_{2}$.
The phosphorylated forms of $A$ are denoted by the subscript $n P$ denoting the number of phosphorylated sites $\left(A=A_{0 . P}\right)$.

$$
\begin{align*}
& E_{1}+A_{i-1 P} \stackrel{k_{3 i-2}}{\stackrel{k_{3 i-1}}{\rightleftharpoons}} A_{i-1 P} E_{1} \xrightarrow{k_{3 i}} E_{1}+A_{i P}, \quad i=1, \ldots, n \\
& E_{2}+A_{i P} \stackrel{I_{3 i-2}}{\rightleftharpoons} A_{i P} E_{2} \xrightarrow{l_{3 i-1}} E_{2}+A_{i-1 P}, \quad i=1, \ldots, n . \tag{1.1}
\end{align*}
$$

## 1.2 cont.

With

$$
\begin{array}{rll}
x_{1}=E_{1}, & x_{2}=A=A_{0 P}, & x_{3}=E_{2},  \tag{1.2}\\
x_{1+3 i}=A_{(i-1) P} E_{1}, & x_{2+3 i}=A_{i P}, & x_{3+3 i}=A_{i P} E_{2}
\end{array}
$$

## The network

$$
\begin{align*}
& x_{1}+x_{3 i-1} \stackrel{k_{3 i-1}}{\stackrel{k_{3 i-2}}{\rightleftharpoons}} x_{3 i+1} \xrightarrow{k_{3 i}} x_{1}+x_{3 i+2}, \\
& x_{2}+x_{3 i+2} \stackrel{l_{3 i-2}}{\rightleftharpoons}  \tag{1.3}\\
& l_{3 i-1}
\end{align*} x_{3 i+3} \xrightarrow{l_{3 i}} x_{2}+x_{3 i-1},
$$

for $i=1, \ldots, n$ and for $\kappa_{(i)}:=\left(k_{3 i-2}, k_{3 i-1}, k_{3 i}, l_{3 i-2}, l_{3 i-1}, l_{3 i}\right)^{T}$. Define

$$
\begin{equation*}
\kappa:=\operatorname{col}\left(\kappa_{(1)}, \ldots, \kappa_{(n)}\right) \in \mathbb{R}_{>0}^{6 n} . \tag{1.4}
\end{equation*}
$$

### 1.3 The Mass Action ODE-System

From (1.1), one can derive for every $n$ the

- stoichiometric matrix $S \in \mathbb{R}^{(3+3 n) \times 6 n}$ and the
- rate exponent matrix $\mathcal{Y}=\left(y_{1}, \ldots, y_{6 n}\right) \in \mathbb{R}^{(3+3 n) \times 6 n}$.

These define two monomial functions $\Phi: \mathbb{R}^{3+3 n} \rightarrow \mathbb{R}^{6 n}$ and $R(\kappa, \cdot): \mathbb{R}^{3+3 n} \rightarrow \mathbb{R}^{6 n}$ via

$$
\begin{equation*}
\Phi(x):=x^{\mathcal{Y}^{\top}} \equiv \operatorname{col}\left(x^{y_{1}}, \ldots, x^{y_{6 n}}\right) \quad \text { and } \quad R(\kappa, x):=\operatorname{diag}(\kappa) \Phi(x) \tag{1.5}
\end{equation*}
$$

and the

## Dynamical system with mass action kinetics

$$
\begin{equation*}
\dot{x}=S R(\kappa, x)=S \operatorname{diag}(\kappa) x^{\mathcal{Y}^{\boldsymbol{T}}} \tag{1.6}
\end{equation*}
$$

The $6 n$-dimensional vector $R(\kappa, x)$ is called the reaction rate vector.

$$
\begin{aligned}
& e^{\mu}=\operatorname{col}\left(e^{\mu_{\boldsymbol{i}}}\right), \ln (\mu)=\operatorname{col}\left(\ln \left(\mu_{i}\right)\right), \quad a^{\ell^{\boldsymbol{T}}}:=\prod_{i=1}^{m} a_{i}^{\ell_{\boldsymbol{i}}}=e^{\ell^{\boldsymbol{T}} \ln (a)}, \\
& g^{L}=\operatorname{col}\left(g^{\left.L_{\text {row } \mathbf{~}}\right) \text { for } g \in \mathbb{R}_{>0}^{m}, L \in \mathbb{Z}^{n \times m} .}\right.
\end{aligned}
$$

## For $n=3$

The stoichiometric matrix $S$ and the rate exponent matrix $\mathcal{Y}^{T}$ :


$$
\mathcal{Y}^{\boldsymbol{T}}=\left[\begin{array}{lll|lll|lll|lll}
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
\hline 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
\hline 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
\hline 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right]
$$

### 1.4 Multistationarity, e.g. for Switching

A matrix $Z$ of conservation laws, providing a basis for the left kernel of $S$, is given by

$$
Z=\left[\begin{array}{rrr|lll}
1 & 0 & 0  \tag{1.7}\\
-1 & 1 & -1 & 1 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 \\
0 & 0 & 1
\end{array}|\cdots| \begin{array}{lll}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{array}\right] \in \mathbb{R}^{3 \times(3+3 n)} .
$$

## Definition of Multistationarity

The system $\dot{x}=S R(\kappa, x)$ from (1.6) is said to exhibit multistationarity if and only if there exist a positive vector $\kappa \in \mathbb{R}_{>0}^{6 n}$ and at least two distinct positive vectors $a$ and $b$ in $\mathbb{R}_{>0}^{3+3 n}$ with

$$
\begin{align*}
S R(\kappa, a) & =0,  \tag{1.8a}\\
S R(\kappa, b) & =0,  \tag{1.8b}\\
Z a & =Z b . \tag{1.8c}
\end{align*}
$$

(1.8a) and (1.8b) describe the steady state property of $a$ and $b$ whereas (1.8c) asks for these steady states to belong to the same coset of the stoichiometric matrix $S$.

### 2.1 Characterization (Generator matrix E)

## 2. General Reduction Results

Consider the

## Mass Action Network

$$
\begin{equation*}
\dot{x}=S R(\kappa, x)=S \operatorname{diag}(\kappa) x^{\mathcal{Y}^{\mathrm{T}}} \tag{2.1}
\end{equation*}
$$

- with positive pointed polyhedral cone $\mathcal{C}=\operatorname{ker}(S) \bigcap \mathbb{R}_{>0}^{3 n+3}$ and its generator matrix $E \in \mathbb{R}_{>0}^{6 n \times 3 n}$ given below,
- and left kernel basis matrix $Z$ (conservation laws, $Z S=0$ ).

$$
E:=\left[\begin{array}{lll}
E_{0} & &  \tag{2.2}\\
& \ddots & \\
& & E_{0}
\end{array}\right] \in \mathbb{R}_{>0}^{6 n \times 3 n} \text { with } E_{0}:=\left[\begin{array}{ccc}
1 & 0 & 1 \\
1 & 0 & 0 \\
0 & 0 & 1 \\
0 & 1 & 1 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{array}\right]
$$

where that the columns of $E$ also form a basis of ker (S).
The steady state relations for the cone $\mathcal{C}$ are of the form

$$
\operatorname{diag}(\kappa) a^{\mathcal{Y}^{\mathrm{T}}}=E \lambda, \quad \operatorname{diag}(\kappa) b^{\mathcal{Y}^{\mathrm{T}}}=E \nu \quad \text { for } \lambda, \nu \in \mathbb{R}_{\geq 0}^{3 n} .
$$

### 2.1 Characterization (3D Reduction)

For a given positive steady state a one has the rate constant vector(s)

$$
\begin{equation*}
\kappa=\kappa(a, \lambda):=\operatorname{diag}\left(a^{-\mathcal{Y}^{\boldsymbol{T}}}\right) E \lambda . \tag{2.3}
\end{equation*}
$$

A further positive steady state $b$ for this $\kappa=\kappa(a, \lambda)$ can be written as

$$
b=\operatorname{diag}\left(e^{\mu}\right) a=\operatorname{diag}\left(\frac{1}{\kappa(a, \lambda)}\right) E \nu \quad\left(\mu \in \mathbb{R}^{3 n+3}\right)
$$

with

$$
\begin{equation*}
\mathcal{Y}^{T} \mu=\ln \left[\frac{E \nu}{E \lambda}\right] . \tag{2.4}
\end{equation*}
$$

## Two Facts

- The right hand side of (2.4) is in a 2-dimensional subspace (by Fredholm).
- The right kernel of $\mathcal{Y}^{\top}$ is 1 -dimensional.


## Consequence

$$
\begin{equation*}
\mu=L \ln (g) \text { for } g=\left(g_{1}, g_{2}, g_{3}\right)^{T} \in \mathbb{R}_{>0}^{3} \tag{2.5}
\end{equation*}
$$

for the matrix $L \in \mathbb{Z}^{(3+3 n) \times 3}$ given below and $b=\operatorname{diag}\left(e^{\mu}\right) a=\operatorname{diag}\left(g^{L}\right) a$.

### 2.1 Characterization (Matrix L)

We choose the matrix $L$ in an (obviously) clever way as

$$
L \equiv\left(L_{1}, L_{2}, L_{3}\right):=\left[\begin{array}{c}
L(0)  \tag{2.6a}\\
L(1) \\
\vdots \\
L(n)
\end{array}\right] \in \mathbb{Z}^{(3+3 n) \times 3}
$$

for

$$
L(0):=\left[\begin{array}{rcr}
1 & n-1 & -1  \tag{2.6b}\\
-1 & -n & 0 \\
1 & n-2 & -1
\end{array}\right], L(i):=\left[\begin{array}{rcr}
0 & i-2 & -1 \\
-1 & i-n & 0 \\
0 & i-2 & -1
\end{array}\right]
$$

In the expression $b=\operatorname{diag}\left(g^{L}\right) a$, the $g_{1}$-exponents are given by the 1 st column of $L$ and hence $\pm 1$ (or 0 ), the $g_{3}$-exponents are given by the 3 rd column of $L$ and hence -1 (or 0 ), the $g_{2}$-exponents are given by the 2 nd column of $L$.

One has: $\operatorname{ker}\left(\mathcal{Y}^{T}\right)=\left[L_{1}\right]$.

### 2.1 Characterization (Coset Condition)

With the parameter $a \in \mathbb{R}_{>0}^{3 n+3}$ :

## 3D Multistationarity Condition/Coset Condition

$$
\begin{gather*}
\Theta(g, a):=Z\left(\operatorname{diag}\left(g^{L}\right)-I d\right) a=0,  \tag{2.7}\\
\Theta=\left(\Theta_{1}, \Theta_{2}, \Theta_{3}\right)^{T}, \quad g=\left(g_{1}, g_{2}, g_{3}\right)^{T} \in \mathbb{R}_{>0}^{3}
\end{gather*}
$$

## 3D Reduction

For $g \neq \underline{1}$ satisfying the rational $3 \times 3$-system (2.7), the steady states

$$
a \text { and } b:=\operatorname{diag}\left(g^{L}\right) a
$$

are distinct positive steady states for the network $\dot{x}=S R(\kappa(a, \lambda), x)$ within one coset of the stoichiometric matrix $S$.

### 2.2 Scalar Determinig Equation

Exploiting the properties of our choice of $L$ and taking $g_{2} \equiv \xi$ : The system

$$
\Theta_{1}=0, \quad \Theta_{3}=0
$$

is linear wrt. $g_{1}$ and $g_{3}$. Suppressing the a-dependence:

$$
\begin{align*}
& g_{1}=g_{1}(\xi):=\quad \xi^{1-n} F_{1}(\xi) / \Delta(\xi) \stackrel{!}{>} 0  \tag{2.8a}\\
& g_{3}=g_{3}(\xi):=\quad \xi^{-1} F_{\mathbf{3}}(\xi) / \Delta(\xi) \stackrel{!}{>} 0 \tag{2.8b}
\end{align*}
$$

with linear

$$
\begin{equation*}
\Delta(\xi):=\frac{a_{1} \xi}{\omega_{1}}-\frac{a_{3}}{\omega_{3}}=\frac{a_{1}}{\omega_{1}}\left(\xi-\xi^{*}\right) \tag{2.8c}
\end{equation*}
$$

and with polynomials $F_{1}$ and $F_{3}$ in $\xi$ of degree $n-1$ and $n$ where $F_{3}$ is affine in $F_{1}$ :

$$
\begin{align*}
F_{\mathbf{3}}(\xi)=F_{\mathbf{3 1}}(\xi)+\frac{a_{\mathbf{1}} \xi}{\omega_{\mathbf{1}}} F_{1}(\xi)= & F_{\mathbf{3 3}}(\xi)+\frac{a_{3}}{\omega_{3}} F_{1}(\xi), \quad \omega:=Z a  \tag{2.8d}\\
& \text { Like } \quad \xi \boldsymbol{u}-\mathbf{v}=\xi \mathbf{v}-\mathbf{v}+\xi(\boldsymbol{u}-\boldsymbol{v})=\xi \boldsymbol{u}-\boldsymbol{u}+(\boldsymbol{u}-\boldsymbol{v}) .
\end{align*}
$$

The resulting $\Theta_{2} \stackrel{!}{=} 0$ can be written in polynomial form as

$$
Q(\xi):=J_{0}(\xi) F_{3}(\xi)-J_{1}(\xi)\left[F_{1}(\xi)\right]^{2}-J_{2}(\xi) F_{1}(\xi) F_{3}(\xi) \stackrel{!}{=} 0
$$

## 2.2 cont.

The resulting $\Theta_{2} \stackrel{!}{=} 0$ can be written in polynomial form as

$$
Q(\xi) \equiv Q_{1}(\xi):=Q_{10}(\xi) \Delta^{2}(\xi)-Q_{11}(\xi) \Delta(\xi) F_{1}(\xi)+Q_{12}(\xi) F_{1}^{2}(\xi) \stackrel{!}{=} 0
$$

or equivalently as

$$
Q(\xi) \equiv Q_{3}(\xi):=Q_{30}(\xi) \Delta^{2}(\xi)-Q_{31}(\xi) \Delta(\xi) F_{1}(\xi)+Q_{32}(\xi) F_{1}^{2}(\xi) \stackrel{!}{=} 0
$$

We now take linear combinations with nonnegative $h_{1}$ and $h_{3}, h:=\left(h_{1}, h_{3}\right) \neq(0,0)$, and define

$$
\begin{equation*}
P_{h}(\xi):=\omega_{2} h_{1} Q_{1}(\xi)+\omega_{2} h_{3} Q_{3}(\xi)=A_{h}(\xi) \Delta^{2}(\xi)+B_{h}(\xi) \Delta(\xi) F_{1}(\xi)-C_{h}(\xi) F_{1}^{2}(\xi) \tag{2.9}
\end{equation*}
$$

with certain polynomials $A_{h}(\xi), B_{h}(\xi)$ and $C_{h}(\xi)$. Note: $P_{h}$ is of degree $2 n+1$.
A zero $\xi_{0}$ of $P_{h}$ will be called admissible if it satisfies

$$
\left.\xi_{0}>0, \quad g_{1}\left(\xi_{0}\right)>0 \quad \text { (i.e., } \Delta\left(\xi_{0}\right) F_{1}\left(\xi_{0}\right)>0\right)
$$

and hence automatically $g_{3}\left(\xi_{0}\right)>0$.
Note: nonlinear a-dependence!

## 2.2 cont.

In the 'symmetric' case $h=\left(\omega_{1}, \omega_{3}\right)$ one finds $A_{h}(\xi)>0$ and $C_{h}(\xi)>0$ for $\xi>0$ and thus

## Scalar determining equation for $\xi>0, \xi \neq \xi^{*}$

The determining equation for admissible solutions $g \in \mathbb{R}_{>0}^{3}$ of the coset condition (2.7) is given by

$$
\begin{align*}
& \theta(\xi, a):= \\
& 2 C_{h}(\xi, a) F_{1}(\xi, a)-\Delta(\xi, a)\left[B_{h}(\xi, a)+\left(B_{h}^{2}(\xi, a)+4 A_{h}(\xi, a) C_{h}(\xi, a)\right)^{1 / 2}\right]=0 . \tag{2.10}
\end{align*}
$$

Any positive zero $\xi=\xi(a)$ of $\theta(\xi, a)$, different from $\xi^{*}(a)$, defines a positive steady state

$$
b=\operatorname{diag}\left(g^{L}\right) a \neq a
$$

of the network (1.6) for $g=\left(g_{1}(\xi(a), a), \xi(a), g_{3}(\xi(a), a)\right)^{T}$ from (2.8).
In the 'unsymmetric' cases $h=\left(0, \omega_{3}\right)$ or $h=\left(\omega_{1}, 0\right)$ one has to check whether $A_{h}(\xi)>0$ and $C_{h}(\xi)>0$ hold for $\xi>0$ in order to establish (2.10).

Remark: There are at most $2 n-1$ admissible zeros for $P_{h}$.

### 3.1 Computational Aspects for $n=3$

## 3. Computational Aspects - Counterexamples

In the 'unsymmetric' case $h=\left(0, \omega_{3}\right)$ we denote $A_{\left(0, \omega_{3}\right)}$ by $A_{0}$ etc. $A_{0}$ and $C_{0}$ turn out to be positive for $\xi>0$ so that (2.10) applies. Recalling (2.8c),

$$
\Delta(\xi)=\frac{a_{1} \xi}{\omega_{1}}-\frac{a_{3}}{\omega_{3}}
$$

and suppressing the a-dependencies one has (2.10) in the form

$$
\begin{aligned}
2 C_{0}(\xi) F_{1}(\xi) & +a_{3} \omega_{1}\left[B_{0}(\xi)+\left(B_{0}^{2}(\xi)+4 A_{0}(\xi) C_{0}(\xi)\right)^{1 / 2}\right] \\
& =a_{1} \omega_{3} \xi\left[B_{0}(\xi)+\left(B_{0}^{2}(\xi)+4 A_{0}(\xi) C_{0}(\xi)\right)^{1 / 2}\right]
\end{aligned}
$$

where the $n$ parameters

$$
a_{3 j+1} \quad \text { for } \quad j=1,2, \ldots, n
$$

appear just on the left-hand side and in a linear way. So they might be tuned to fulfill some prescribed constraints.

## 3.1 cont. $(n=3)$

For the triple phosphorylation $(n=3)$ :

- We choose a positive $a \in \mathbb{R}_{>0}^{3 \cdot 3+3}$ and fix the rate constant vector

$$
\kappa=\kappa(a)=\operatorname{diag}\left(a^{-\mathcal{Y}^{\boldsymbol{T}}}\right) E \lambda \text { with } \lambda=\underline{1}
$$

so that $a$ is a positive steady state of the network (1.6).

- Obviously, one has $\theta_{0}(1, a)=0$.
- In particular, we choose a of the form

$$
\begin{equation*}
a^{*}=\left(1,1,1\left|a_{4}, 1,1\right| a_{7}, 1,0.1 \mid a_{10}, 0.32,60\right)^{T} \in \mathbb{R}_{>0}^{12} \tag{3.1}
\end{equation*}
$$

and compute analytically the remaining $n=3$ parameters $a_{4}, a_{7}$ and $a_{10}$ so that $\theta_{0}\left(\xi, a^{*}\right)$ has the triple zero $\xi=1$ and a further zero $\xi=\frac{1}{2}$. The resulting numerical values (up to 4 decimals) are given by

$$
\begin{equation*}
a_{4}:=a_{4}^{*}=5.9026(84) \ldots, a_{7}:=a_{7}^{*}=2.1344(85) \ldots, a_{10}:=a_{10}^{*}=248.9413(34) \ldots . \tag{3.2}
\end{equation*}
$$

The rate constant vector $\kappa=\kappa\left(a^{*}\right)$ is positive.

- Finally, we vary the 10th component:

$$
a=a^{*}+\delta e_{10}, \quad-.05<\delta<.05
$$

in (3.1), leading to the bifurcation diagram in Figure 1 in the $(\delta, \xi)$-plane.

### 3.1 Bifurcation diagram



Figure: 4.1 Numerical continuation of $\theta_{0}(\xi, a)=0$ from (2.10) with the data (3.1)\&(3.2).

Pitchfork bifurcation at $\left(\delta_{0}, \xi_{0}\right)=(0,1)(\mathrm{BP})$ and two saddle node bifurcations (LP) at $\left(\delta_{-}, \xi_{-}\right)=(-.04488 \ldots, .66691(4) \ldots)$ and $\left(\delta_{+}, \xi_{+}\right)=(.03352 \ldots, .41262(522) \ldots)$. For $\delta=0$ one encounters the prescribed triple zero $\xi=1$, the zero $\xi=\frac{1}{2}$ and an additional zero near .36222(562)....
Solid lines correspond to $\xi$ 's yielding exponentially stable steady states, dashed lines to $\xi$ 's yielding unstable steady states.

### 3.1 Numerical values

For $\delta=-.03$, the numerical values for the five admissible zeros $\xi^{(j)}$ of (2.10) and the five admissible steady states $b^{(j)}$ of (1.6) can be found below.

| Phos. \# | $b^{(1)}$ | $b^{(2)}$ | $b^{(3)}$ | $b^{(4)} \equiv a$ | $b^{(5)}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 1.4730 | 1.2198 | 1.0793 | 1 | 0.9618 |
|  | 4.7498 | 2.4000 | 1.4726 | 1 | 0.7700 |
|  | 4.2424 | 2.1440 | 1.3722 | 1 | 0.8246 |
|  | 41.3012 | 17.2813 | 9.3826 | 5.9026 | 4.3718 |
|  | 1.6493 | 1.3655 | 1.1583 | 1 | 0.8980 |
|  | 6.9970 | 2.9277 | 1.5895 | 1 | 0.7406 |
|  | 5.1859 | 3.5554 | 2.6688 | 2.1344 | 1.8438 |
| 2 | 0.5726 | 0.7768 | 0.9112 | 1 | 1.0474 |
|  | 0.2429 | 0.1665 | 0.1250 | .1 | 0.0863 |
| 3 | 209.9882 | 235.8919 | 244.8175 | 248.9113 | 250.7710 |
|  | 0.0636 | 0.1414 | 0.2293 | .32 | 0.3909 |
|  | 50.6175 | 56.8616 | 59.0132 | 60 | 60.4482 |
| $\xi$ | 0.3472 | 0.5689 | 0.7866 | 1 | 1.1662 |

Table: The five admissible steady states $b^{(\boldsymbol{j})}$ of (1.6) for $\delta=-.03$ and the corresponding zeros $\xi^{(j)}$ of (2.10) up to 4 decimals: the numerical values of the rate constant vectors $\kappa=\kappa(a)$ and $\kappa\left(a^{*}\right)$ coincide up to the first 4 decimals, but $\kappa_{14}(a)=\kappa_{15}(a)=0.00401749 \ldots$ and $\kappa_{14}\left(a^{*}\right)=\kappa_{15}\left(a^{*}\right)=0.00401701 \ldots$. differ.

### 3.2 Case $n=4$

- For $n \geq 3$, the above argument can be applied to an $n$-site phosphorylation to create networks with $n+1$ steady states for (1.6) by tuning the $n$ parameters $a_{3 j+1}$ so that

$$
n+1 \text { steady states may be prescribed. }
$$

- For odd $n$, one is then generically expecting $n+2$ such steady states.

Using this rationale for even $n=4$, we have constructed a phosphorylation network with a determining equation (2.10) with 5 prescribed zeros at $0.5,1,1.03,1.05$ and 1.07 by choosing $a \in \mathbb{R}_{>0}^{15}$ as

$$
\begin{array}{llllll}
a_{1}=1, & a_{2}=1, & a_{3}=1, & a_{4}=1.983448, & a_{5}=1, & a_{6}=1, \\
a_{7}=469.6162955, & a_{8}=1, & a_{9}=400, & a_{10}=73.8036, & a_{11}=.32, & a_{12}=60, \\
a_{13}=.5807998, & a_{14}=7, & a_{15}=1.8 . & & &
\end{array}
$$

As it turns out, this determining equation has two additional positive zeros, one near .59 and one near 51.07. By judicious guessing - see next figure.

## 3.2 cont. $(n=4)$



Figure: 4.2 Numerical continuation of $\theta_{0}(\xi, a)=0$ from (2.10) with the above data - zoom on the right

There are 6 zeros $0.5,0.5910929 \ldots, 1,1.03,1.05$ and 1.07 and there is a 7 th zero near $\xi=51.07286$.
Solid lines correspond to $\xi$ 's yielding exponentially stable steady states, dashed lines to $\xi$ 's yielding unstable steady states. The label LP denotes saddle-node bifurcation points, the label BP transcritical bifurcation points.

### 4.1 Relations to sign patterns/orthants

## 4. Geometry of Multistationarity

## Relations to sign patterns/orthants

- For the steady states of the 3 -site phosphorylation system we observe that the sign vector for $\ln \left(b^{(j+1)} / b^{(j)}\right)$ is given by

$$
\operatorname{sign}\left(\ln \left(b^{(j+1)} / b^{(j)}\right)\right)=\left(-,-,-|-,-,-|-,+,-|+,+,+)^{T}=: s_{2}\right.
$$

for $j=1,2,3,4$ so that these steady states are ordered with respect to $s_{2}$.

- The steady states of our 4-site phosphorylation system are not ordered in such a way.


### 4.2 Geometric constraints on multistationarity

Let $\kappa \in \mathbb{R}_{>0}^{6 n}$ be given and assume network (1.1) admits two distinct positive vectors $a$ and $b$ with $S R(\kappa, a)=S R(\kappa, b)=0, Z(b-a)=0$.

## Geometry and Reconstruction

Then the steady state concentrations $a_{1}$ and $b_{1}$ of the kinase together with the steady state concentrations $a_{3}$ and $b_{3}$ of the phosphatase and the steady state concentrations $a_{2}$ and $b_{2}$ of the unphosphorylated protein allow the reconstruction of the ratios

$$
\left(g^{L}\right)_{i}=\frac{b_{i}}{a_{i}}, \quad i=4, \ldots, 3+3 n
$$

in the following way:

$$
\Gamma_{(0)}^{T}=\left(\Gamma_{E_{1}}, \Gamma_{A}, \Gamma_{E_{2}}\right)=\left(\frac{b_{1}}{a_{1}}, \frac{b_{2}}{a_{2}}, \frac{b_{3}}{a_{3}}\right) \text { and } \xi=\frac{\Gamma_{E_{1}}}{\Gamma_{E_{2}}}=\frac{b_{1} / a_{1}}{b_{2} / a_{3}},
$$

with $\Gamma_{(\mathbf{1})}^{\boldsymbol{T}}=\left(\Gamma_{\mathbf{A}} \Gamma_{\boldsymbol{E}_{1}}, \xi \Gamma_{\mathbf{A}}, \xi \Gamma_{\mathbf{A}} \Gamma_{\mathbf{E}_{\mathbf{2}}}\right)=\left(\frac{\boldsymbol{b}_{\mathbf{4}}}{\mathbf{a}_{4}}, \frac{\boldsymbol{b}_{\mathbf{5}}}{\mathbf{a}_{5}}, \frac{\boldsymbol{b}_{6}}{\mathbf{a}_{6}}\right)$ and

$$
\Gamma_{(i)}^{T}=\left(\left\ulcorner_{A_{(i-1) P}} E_{1}, \Gamma_{A_{i P}}, \Gamma_{A_{i P} E_{2}}\right)=\xi^{i-1}\left(\frac{b_{4}}{a_{4}}, \frac{b_{5}}{a_{5}}, \frac{b_{6}}{a_{6}}\right)=\left(\frac{b_{1+3 i}}{a_{1+3 i}}, \frac{b_{2+3 i}}{a_{2+3 i}}, \frac{b_{3+3 i}}{a_{3+3 i}}\right)\right.
$$

for $\boldsymbol{i}=\mathbf{1}, \ldots, \boldsymbol{n}$. In particular one has for $\boldsymbol{i}=\mathbf{1}, \ldots, \boldsymbol{n}-1$

$$
\begin{equation*}
\xi=\frac{\Gamma_{E_{1}}}{\Gamma_{E_{2}}}=\frac{\Gamma_{\boldsymbol{A}_{P}}}{\Gamma_{\boldsymbol{A}}}=\frac{\Gamma_{\boldsymbol{A}_{(i+1) P}}}{\Gamma_{\boldsymbol{A}_{i P}}}=\frac{\Gamma_{\boldsymbol{A}_{i P} E_{1}}}{\Gamma_{\boldsymbol{A}_{(i-1) P}} E_{1}}=\frac{\Gamma_{\boldsymbol{A}_{(i+1) P}} \boldsymbol{E}_{\mathbf{2}}}{\Gamma_{\boldsymbol{A}_{i P} E_{2}}} . \tag{4.1}
\end{equation*}
$$

## 4.2 cont.

Consider the experimental investigation of a specific multisite phosphorylation system (1.1) whereby the rate constants $\kappa$ and the total concentrations are fixed, but might not (all) be known. Suppose we know a priori that the system exhibits multistationarity.

Then steady state data of the concentration of kinase, phosphatase and protein in two different steady states $a$ and $b$ (for these total concentrations) are sufficient to reconstruct all fractions $\frac{b_{i}}{a_{i}}$ of the two steady states. That is:

## Measurements and Reconstruction

It suffices to measure $a_{1}, a_{2}, a_{3}$ and $b_{1}, b_{2}, b_{3}$ to reconstruct all the ratios
$\frac{b_{i}}{a_{i}}, i=1, \ldots, 3+3 n$.

### 4.4 A graphical test to exclude multistationarity

Suppose for the phosphoforms $A, A_{P}, \ldots, A_{n}$ two different sets of steady state values have been measured, i.e., there exists data for $a_{2}, a_{5}, \ldots, a_{2+3 n}$ and $b_{2}, b_{5}, \ldots, b_{2+3 n}$.

If these belong to two steady states within one and the same coset, then the points

$$
\alpha_{i}:=\frac{a_{3 i+2}}{a_{3 i-1}}, \quad \beta_{i}:=\frac{b_{3 i+2}}{b_{3 i-1}}, \quad i=1, \ldots, n,
$$

are collinear. Hence:

## Exclusion of multistationarity

Measurement of two steady state values for $A, \ldots, A_{n} P$ suffices to exclude multistationarity in case the points $\left(\alpha_{i}, \beta_{i}\right)$ are not collinear.

## Literature

- D. Flockerzi and C. Conradi: Subnetwork Analysis for Multistationarity in Mass Action Kinetics, Journal of Physics Conference Series 138, 012006, 2008.
- L. Wang and E. Sontag: On the number of steady states in a multiple futile cycle. Journal of Mathematical Biology, 57:29-52, 2008.
- C. Conradi and D. Flockerzi: Multistationarity in mass action networks with applications to ERK activation, Journal of Mathematical Biology 65, 1, 107-156, 2012.
- C. Conradi and D. Flockerzi: Switching in mass action networks based on linear inequalities, SIAM Journal on Applied Dynamical Systems 11, 1, 110-134, 2012.
- K. Holstein, D. Flockerzi, and C. Conradi: Multistationarity in sequential distributed multisite phosphorylation networks. Bulletin of Mathematical Biology, 75: 2028-2058, 2013.
- D. Flockerzi, K. Holstein and C. Conradi:

N -site phosphorylation systems with $2 \mathrm{~N}-1$ steady states, arXiv:1312.4774v1.

