

Analysis of pattern formation using numerical continuation

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Outline

- 1 Pattern formation: Turing instability
 - Domain size driven instability
- 2 Solution manifolds and numerical continuation
- 3 Critical wavelengths: primary bifurcation
- 4 Symmetries of steady states
- 5 Conclusions
- 6 Supplement: Dynamic simulation

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Problem

Consider reaction-diffusion system for two species \mathbf{u} and \mathbf{v} in 1D domain $x \in [0, \ell]$,

$$\begin{aligned}\mathbf{u}_t &= d_1 \mathbf{u}_{xx} + \bar{f}(\mathbf{u}, \mathbf{v}) \\ \mathbf{v}_t &= d_2 \mathbf{v}_{xx} + \bar{g}(\mathbf{u}, \mathbf{v})\end{aligned}$$

Context: A theory of biological pattern formation.
Self-organization in development biology, morphogenesis

Objective: **domain size** driven instability

V. Klika, M. Kozák and E.A. Gaffney: *Domain Size Driven Instability: Self-Organization in Systems with Advection*, SIAM J. Appl. Math., 2018, pp 2298–2322.

Domain can be scaled to the unit interval $0 \leq x \leq 1$ introducing parameter L . Hence, we consider

$$\begin{aligned} \mathbf{u}_t &= \frac{d_1}{L^2} \mathbf{u}_{xx} + f(\mathbf{u}, \mathbf{v}) \\ \mathbf{v}_t &= \frac{d_2}{L^2} \mathbf{v}_{xx} + g(\mathbf{u}, \mathbf{v}) \end{aligned}$$

in domain $0 \leq x \leq 1$. Here L is the length of the interval. We consider Neumann boundary conditions (zero flux)

$$\mathbf{u}_x(0, t) = \mathbf{u}_x(1, t) = 0, \quad \mathbf{v}_x(0, t) = \mathbf{v}_x(1, t) = 0.$$

We seek for *steady states*.

Homogeneous steady state: There exists $u^* \in \mathbb{R}^1$, $v^* \in \mathbb{R}^1$, such that

$$f(\mathbf{u}(x, 0), \mathbf{v}(x, 0)) = f(u^*, v^*) = g(\mathbf{u}(x, 0), \mathbf{v}(x, 0)) = g(u^*, v^*) = 0, \quad 0 \leq x \leq 1.$$

Note that, in this case, $\mathbf{u}_{xx} = 0$ and $\mathbf{v}_{xx} = 0$ in the domain $0 \leq x \leq 1$.

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Discretization of the model

Method of lines: Define the equidistant mesh on the interval $0 \leq x \leq 1$

$$x_j = jh, \quad h = \frac{1}{N+1}, \quad j = 1, \dots, N, \quad (2.1)$$

where N is the number of meshpoints.

The state variables \mathbf{u} , \mathbf{v} are approximated by discrete state variables

$$\mathbf{u} \approx [u_1, \dots, u_i, \dots, u_N]^T \in \mathbb{R}^N, \quad \mathbf{v} \approx [v_1, \dots, v_i, \dots, v_N]^T \in \mathbb{R}^N,$$

We seek for discrete steady states. They depend on the parameter L^2 .

We define

$$F : \mathbb{R}^{2N} \times \mathbb{R}^1 \longrightarrow \mathbb{R}^{2N} \quad (2.2)$$

and seek for the roots

$$F(w, L^2) = 0, \quad w \in \mathbb{R}^{2N}, \quad w_i = u_i, \quad w_{N+i} = v_i, \quad i = 1, \dots, N.$$

This set is called *solution manifold*.

We assume the existence of *homogeneous steady state*

$$F(w^*, L^2) = 0, \quad w^* \in \mathbb{R}^{2N}, \quad w_i^* = u^*, \quad w_{N+i}^* = v^*, \quad i = 1, \dots, N.$$

Primary bifurcation point

Definition. Consider the particular homogeneous steady state $w^* \in \mathbb{R}^{2N}$, $(L^*)^2 \in \mathbb{R}^1$,

$$F(w^*, (L^*)^2) = 0 \in \mathbb{R}^{2N}, \quad A \equiv F_w(w^*, (L^*)^2), \quad \dim \text{Ker } A = 1.$$

Let ξ and η be right and left eigenvectors corresponding to the zero eigenvalue

$$A\xi = 0 \in \mathbb{R}^{2N}, \quad \|\xi\| = 1, \quad A^T\eta = 0 \in \mathbb{R}^{2N}, \quad \|\eta\| = 1, \quad \eta^T\xi \neq 0,$$

with an algebraic multiplicity equal to one. Then the point $(w^*, (L^*)^2) \in \mathbb{R}^{2N+1}$ is called *primary bifurcation point*.

... Lyapunov-Schmidt reduction, bifurcation equation

M. Golubitsky, I. Stewart and D.G. Schaeffer: *Singularities and groups in bifurcation theory, Vol II*, Springer, 1988

Example. Consider the Schnackenberg model for the parameter setting $a = 0.1$, $b = 0.9$, $\gamma = 10$, $d_1 = 0.1$, $d_2 = 1.6$ and $N = 20$.

Homogeneous state state w^* : $u^* = a + b = 1$, $v^* = b/(a + b)^2 = 0.9$.

The aim is to compute the branch of inhomogeneous steady states emanating from a particular primary bifurcation point.

The primary bifurcation point w^* , $(L^*)^2$ with least $(L^*)^2 > 0$ is $(L^*)^2 = 0.153969537228066$.

J. Schnakenberg: *Simple chemical reaction systems with limit cycle behaviour*, J. Theoret. Biol., Vol 81, 1979, pp 389–400.

Solution manifold via numerical continuation

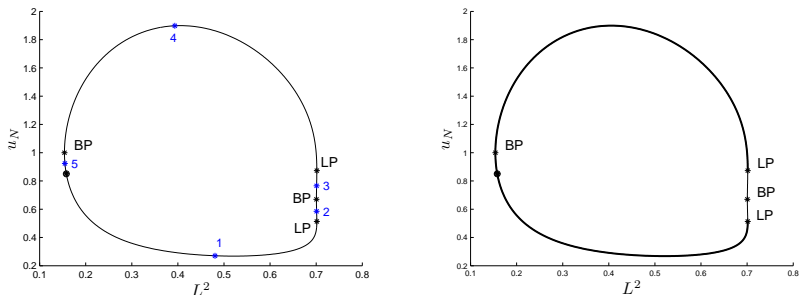


Figure: On the left: Branch of inhomogeneous steady states projected onto pairs (u_N, L^2) . It is oriented anticlockwise. The branch emanates from the **primary bifurcation point** $u_N = 1, (L^*)^2 \approx 0.1539$ labeled as BP. The circle on the branch marks the initial point of continuation procedure. In points 1, \dots , 5 we test stability. The indicated bifurcation points are (in clockwise directions) LP, secondary bifurcation point BP, LP and the primary bifurcation point BP. On the right: thick and thin segments of curves indicate **stable** and **unstable** steady states.

A. Dhooge, W. Govaerts and Yu.A. Kuznetsov: *MATCONT*: a MATLAB package for numerical bifurcation analysis of ODEs, ACM Transactions on Mathematical Software Vol 29, No.2., 2003, pp 141–164.

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Dispersion equation

Let $u^* \in \mathbb{R}^1$, $v^* \in \mathbb{R}^1$ be a homogeneous steady state i.e.,

$$f(u^*, v^*) = g(u^*, v^*) = 0, \quad 0 \leq x \leq 1.$$

In particular, in the model Schnakenberg model,

$$u^* = a + b, \quad v^* = b/(a + b)^2, \quad a > 0, b > 0.$$

We define Jacobian at the steady state $u^* \in \mathbb{R}^1$, $v^* \in \mathbb{R}^1$:

$$\mathbf{J} = \begin{bmatrix} f_u & f_v \\ g_u & g_v \end{bmatrix}_{u,v:=u^*,v^*}.$$

In particular, in the model Schnakenberg model,

$$\mathbf{J} = \begin{bmatrix} 2\gamma b/(a + b) - 1 & (a + b)^2 \\ -2b/(a + b) & -(a + b)^2 \end{bmatrix}, \quad a > 0, b > 0, \gamma > 0,$$

Let d_1 and d_2 be diffusion parameters. Let \mathbf{J} be Jacobian corresponding to a steady state. The equation

$$\det \left(\mathbf{J} - k^2 \begin{bmatrix} d_1 & 0 \\ 0 & d_1 \end{bmatrix} - \lambda \mathbf{I} \right) = 0, \quad \mathbf{I} = \mathbf{I}_{2 \times 2} \in \mathbb{R}^{2 \times 2}$$

is called *dispersion relation*. It depends on wavenumber k^2 and frequency λ . Dispersion relation implicitly defines the relationship $\lambda = \lambda(k^2)$.

Instead of analyzing roots of dispersion relation we analyse the spectrum of the following matrix

$$\mathbf{H} \equiv \mathbf{J} - k^2 \begin{bmatrix} d_1 & 0 \\ 0 & d_1 \end{bmatrix}.$$

The spectrum $\sigma(\mathbf{H})$ consists of two eigenvalues $\{\lambda_1(k^2), \lambda_2(k^2)\}$. These can be numerically computed as a function of k^2 . We use Matlab function `eig(H)`. Note that generally $\sigma(\mathbf{H})$ consists of either two real eigenvalues or a complex conjugate pair.

Given k^2 , we define

$$\Re(\lambda_*(k^2)) = \max \{ \Re(\lambda_i(k^2)) \}_{i=1,2}$$

which is the right-most eigenvalue of $\sigma(\mathbf{H})$. We call $\Re(\lambda_*(k^2))$ *maximal growth rate*.

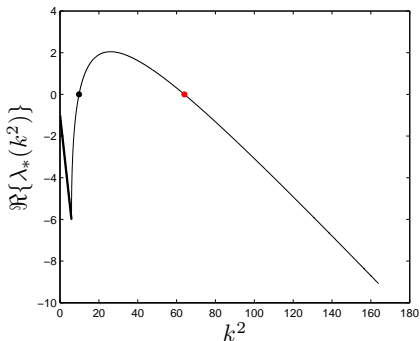


Figure: Maximal growth rate $k^2 \mapsto \Re(\lambda_*(k^2))$: thin and thick curve segments refers to two real eigenvalues and complex conjugate pairs, respectively. Case: Schnakenberg model, $a = 0.1$, $b = 0.9$, $\gamma = 10$, $d_1 = 0.1$, $d_2 = 1.6$.

Let k_-^2 and k_+^2 , $k_-^2 \leq k_+^2$, be the roots of function $k^2 \mapsto \Re(\lambda_*(k^2))$. We can get the closed-form expressions

$$k_-^2 = \frac{d_2 f_u + d_1 g_v - \sqrt{\Delta}}{2d_1 d_2}, \quad k_+^2 = \frac{d_2 f_u + d_1 g_v + \sqrt{\Delta}}{2d_1 d_2}, \quad (3.3)$$

where $\Delta = (d_2 f_u + d_1 g_v)^2 - 4d_1 d_2 \det \mathbf{J}$, and \mathbf{J} , f_u , g_v are related to Jacobian.

The open interval (k_-^2, k_+^2) is called *range of growing wavenumbers*. For a given k^2 , $k_-^2 < k^2 < k_+^2$, the maximal growth rate is positive.

Spatial pattern: linear stability analysis

Linearization about a homogeneous steady state $u^* \in \mathbb{R}^1$, $v^* \in \mathbb{R}^1$:

$$\begin{bmatrix} \mathbf{u}_t \\ \mathbf{v}_t \end{bmatrix} = \mathbf{J} \begin{bmatrix} \mathbf{u} \\ \mathbf{v} \end{bmatrix} + \frac{1}{L^2} \begin{bmatrix} d_1 & 0 \\ 0 & d_1 \end{bmatrix} \begin{bmatrix} \mathbf{u}_{xx} \\ \mathbf{v}_{xx} \end{bmatrix} \quad (3.4)$$

in domain $0 \leq x \leq 1$. We employ Fourier analysis, setting

$$\begin{bmatrix} \mathbf{u}(x, t) \\ \mathbf{v}(x, t) \end{bmatrix} = \sum_{j=1}^{+\infty} \mathbf{c}_j e^{\lambda t} W_j(x), \quad 0 \leq x \leq 1, \quad t \geq 0, \quad (3.5)$$

where $\mathbf{c}_j \in \mathbb{R}^2$ are coefficients to be determined, $\lambda \in \mathbb{R}^1$ defines temporal growth.

J.D. Murray: *Mathematical biology. II*, Springer-Verlag, New York, 2003.

The Fourier functions W_j are related to 1 – D Laplacians with Neumann boundary conditions

$$W_j'' + k^2 W_j = 0, \quad 0 \leq x \leq 1, \quad W_j'(0) = W_j'(1) = 0. \quad (3.6)$$

The relevant eigenvalues and eigenvectors are $k^2 = (j\pi)^2$ and $W_j = \sqrt{2} \cos(j\pi x)$, for $j = 1, 2, \dots$

We conclude that

$$\det \left(\mathbf{J} - \frac{k^2}{L^2} \begin{bmatrix} d_1 & 0 \\ 0 & d_1 \end{bmatrix} - \lambda \mathbf{I} \right) = 0, \quad \mathbf{I} = \mathbf{I}_{2 \times 2} \in \mathbb{R}^{2 \times 2}. \quad (3.7)$$

This equation is analogous to the dispersion relation. It depends on frequency λ , particular eigenvalue $k^2 = (j\pi)^2$, $j = 1, 2, \dots$ and wavelength L^2 .

The roots of the above dispersion relation are related to the spectrum of the matrix

$$\mathbf{H} \equiv \mathbf{J} - \frac{k^2}{L^2} \begin{bmatrix} d_1 & 0 \\ 0 & d_1 \end{bmatrix}. \quad (3.8)$$

Its spectrum $\sigma(\mathbf{H})$ consists of two eigenvalues $\left\{ \lambda_1 \left(\frac{k^2}{L^2} \right), \lambda_2 \left(\frac{k^2}{L^2} \right) \right\}$.

We define the maximal growth rate as function

$$\frac{k^2}{L^2} \mapsto \Re \left(\lambda_* \left(\frac{k^2}{L^2} \right) \right) \equiv \max \left\{ \Re \left(\lambda_i \left(\frac{k^2}{L^2} \right) \right) \right\}_{i=1,2}. \quad (3.9)$$

We ask for $\frac{k^2}{L^2}$ when $\Re \left(\lambda_* \left(\frac{k^2}{L^2} \right) \right)$ is positive.

We observe that for parameters $k^2 = (j\pi)^2$ and L^2 which satisfy

$$k_-^2 < \frac{k^2}{L^2} < k_+^2$$

we can expect the existence of an inhomogeneous steady state.

In terms of wavelength L^2 , we arrive at the restriction

$$\frac{k^2}{k_+^2} < L^2 < \frac{k^2}{k_-^2}, \quad k^2 = (j\pi)^2. \quad (3.10)$$

The estimate (3.10) of the stable wavelength range is related to the partial differential equation (3.4). The state variables are functions $\mathbf{u}(x, t)$ and $\mathbf{v}(x, t)$, see (3.5).

However, when it comes to the discrete model (2.2) of reality, we must consistently consider **Laplacian on an equidistant grid** (2.1):

Definition.

$$[e_val, e_vec] = Lap_neum(N, No)$$

$$e_val = \frac{2}{h^2} \left[1 - \cos \left(\frac{j\pi}{N} \right) \right], \quad No = j \in \{1, \dots, N-1\}, \quad h = \frac{1}{N+1},$$

$e_vec \in \mathbb{R}^N$, the sampled eigenfunction of W_j , see (3.6).

Discrete Laplacian on an equidistant grid

Properties. $[e_val, e_vec] = Lap_neum(N, No)$

- N is number of meshpoints
- No is serial number of eigenmode, $No = j \in \{1, \dots, N - 1\}$

The function Lap_neum returns corresponding eigenvalue $e_val \in \mathbb{R}^1$ and eigenvector $e_vec \in \mathbb{R}^N$. By definition: If $No = 0$ then $e_val = 0$. Positive eigenvalues are arranged: $No \in \{1, \dots, N - 1\}$ from the smallest to the largest.

We formulate appropriate discrete analogies of (3.7), (3.8), (3.9) and (3.10). In particular, we set

$$k^2 = e_val = Lap_neum(N, No), \quad No = j \in \{1, \dots, N - 1\} \quad (3.11)$$

In order to simplify notation, e_val and e_vec are generic value variables.

Critical wavelengths

Definition. Given a mode number $No = j \in \{1, \dots, N-1\}$, we define interval

$$\frac{e_val}{k_+^2} < L^2 < \frac{e_val}{k_-^2} \quad (3.12)$$

and call it *stable wavelength range*. We define

$$L2_No_up = \frac{e_val}{k_+^2}, \quad L2_No_down = \frac{e_val}{k_-^2} \quad (3.13)$$

as *critical wavelengths* related to mode number $No = j \in \{1, \dots, N-1\}$.

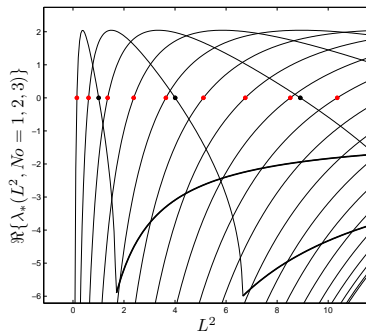
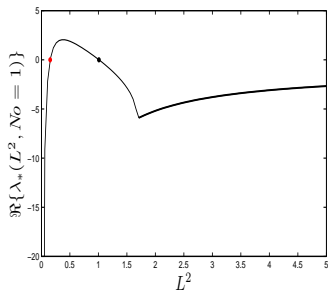


Figure: Critical wavelengths, see Example: On the left: $L2_1_up \approx 0.1542$, $L2_1_down \approx 1.0098$. On the right: sorted in ascending order: $L2_1_up$, $L2_2_up$, $L2_1_down$, $L2_3_up$, $L2_4_up$, $L2_5_up$, $L2_2_down$, $L2_6_up$, etc.

Critical wavelengths: primary bifurcation

Theorem. For a given $j \in \{1, \dots, N-1\}$, let $L2_j_up$ and $L2_j_down$ be the critical wavelengths. Then $L2_j_up$ and $L2_j_down$ are connected to the following **primary bifurcation points**:

- $F(w^*, L2_j_up) = 0 \in \mathbb{R}^N$,
 $F_w(w^*, L2_j_up) \begin{bmatrix} a_{up} \\ b_{up} \end{bmatrix} \otimes e_vec \in \mathbb{R}^{2N} = 0 \in \mathbb{R}^{2N}$
- $F(w^*, L2_j_down) = 0 \in \mathbb{R}^N$,
 $F_w(w^*, L2_j_down) \begin{bmatrix} a_{down} \\ b_{down} \end{bmatrix} \otimes e_vec \in \mathbb{R}^{2N} = 0 \in \mathbb{R}^{2N}$

The coefficients $a_{up} \in \mathbb{R}^1$, $b_{up} \in \mathbb{R}^1$ and $a_{down} \in \mathbb{R}^1$, $b_{down} \in \mathbb{R}^1$ are defined by a formula.

Therefore, we can identify the critical wavelength with the primary bifurcation point. We can compute and sort all $2(N-1)$ bifurcation points.

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Matrix representation

Consider abstract group $\Gamma = \mathbb{Z}_2 \oplus \mathbb{Z}_2 = \{I, \kappa_1, \kappa_2, \kappa_1\kappa_2\}$, $\kappa_1\kappa_2 = \kappa_2\kappa_1$. Here

- \mathbb{Z}_2 is a cyclic group of order 2
- $\mathbb{Z}_2 \oplus \mathbb{Z}_2$ is a direct sum of groups.

Γ is therefore an Abelian group.

Preliminaries

We consider the following matrices:

identity matrix and *zero matrix* and *exchange matrix*
of the proper size:

$$\mathbf{I}_{2N \times 2N} \in \mathbb{R}^{2N \times 2N}, \quad \mathbf{O}_{N \times N} \in \mathbb{R}^{N \times N}, \quad \mathbf{E} = \begin{bmatrix} 0 & & 1 \\ & \ddots & \\ 1 & & 0 \end{bmatrix} \in \mathbb{R}^{N \times N}$$

We define matrix representation of the group Γ in the state space \mathbb{R}^{2N} :

$$\mathbf{G}(\iota) = \mathbf{I}_{2N \times 2N} \in \mathbb{R}^{2N \times 2N}, \quad \mathbf{G}(\kappa_1) = -\mathbf{I}_{2N \times 2N} \in \mathbb{R}^{2N \times 2N},$$

$$\mathbf{G}(\kappa_2) = \begin{bmatrix} \mathbf{E} & \mathbf{O}_{N \times N} \\ \mathbf{O}_{N \times N} & \mathbf{E} \end{bmatrix} \in \mathbb{R}^{2N \times 2N},$$

$$\mathbf{G}(\kappa_1 \kappa_2) = \mathbf{G}(\kappa_1) \mathbf{G}(\kappa_2) = -\mathbf{G}(\kappa_2) = \mathbf{G}(\kappa_2 \kappa_1).$$

We conclude, that $\Gamma = \{\mathbf{G}(\iota), \mathbf{G}(\kappa_1), \mathbf{G}(\kappa_2), \mathbf{G}(\kappa_1 \kappa_2)\}$ is Abelian group with faithful representation on state space \mathbb{R}^{2N} . Each group element $\gamma \in \Gamma$ is identified with its action namely a linear transformation on \mathbb{R}^{2N} .

In order to simplify notation, we identify the mentioned linear transformations with group elements $\Gamma = \{\iota, \kappa_1, \kappa_2, \kappa_1 \kappa_2\}$.

Maximal isotropy subgroups

The group Γ has proper subgroups

$\Sigma_{\kappa_1} = \{\iota, \kappa_1\}$, $\Sigma_{\kappa_2} = \{\iota, \kappa_2\}$, $\Sigma_{\kappa_1\kappa_2} = \{\iota, \kappa_1\kappa_2\}$ and $\Sigma_0 = \{\iota\}$.

We need to recall two notions of representation theory:

- the isotropy subgroup Σ
- the fixed point subspace $\text{Fix } \Sigma$ of a subgroup Σ .

It holds

$$\left\{ \begin{array}{ll} \text{Fix}_{\mathbb{R}^{2N}} \Sigma_{\kappa_1} &= \text{Fix}_{\mathbb{R}^{2N}} \Gamma = \mathbf{0} \in \mathbb{R}^{2N}, \\ \text{Fix}_{\mathbb{R}^{2N}} \Sigma_{\kappa_2} &= \{w \in \mathbb{R}^{2N} : w_i = w_{N-i+1}, w_{N+i} = w_{2N-i+1}, \\ &\quad i = 1, \dots, N\}, \\ \text{Fix}_{\mathbb{R}^{2N}} \Sigma_{\kappa_1\kappa_2} &= \{w \in \mathbb{R}^{2N} : w_i = -w_{N-i+1}, w_{N+i} = -w_{2N-i+1}, \\ &\quad i = 1, \dots, N\}, \\ \text{Fix}_{\mathbb{R}^{2N}} \Sigma_0 &= \mathbb{R}^{2N}. \end{array} \right.$$

Σ_{κ_2} , $\Sigma_{\kappa_1\kappa_2}$ and Σ_0 are isotropy subgroups of Γ . Moreover, Σ_{κ_2} and $\Sigma_{\kappa_1\kappa_2}$ are *maximal isotropy subgroups*.

The symmetry of the solution: how it manifests itself

A key feature of Schnackenberg's model is its Γ -equivariance:

$$F(\gamma w, L^2) = \gamma F(w, L^2)$$

for $(w, L^2) \in \mathbb{R}^{2N} \times \mathbb{R}^1$, for all $\gamma \in \{\iota, \kappa_1, \kappa_2, \kappa_1\kappa_2\}$.

Consider Schnackenberg model, see Example, assuming $N = 40$:

From the homogeneous steady state bifurcate the following inhomogeneous steady states (in ascending order)

$L2_1_up$, $L2_2_up$, $L2_1_down$, $L2_3_up$, $L2_4_up$, $L2_5_up$, $L2_2_down$, $L2_6_up$,
etc.

Consider the branches emanating from $L2_3_up$ and $L2_4_up$. We ask for a comparison.

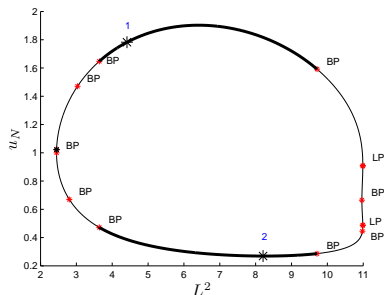
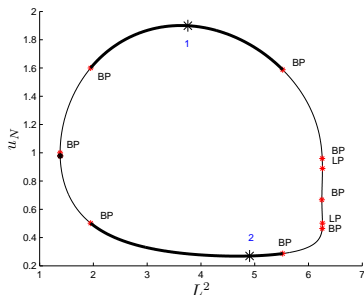


Figure: Schnakenberg model, see Example, $N = 40$. Branches of inhomogeneous steady states projected onto pairs (u_N, L^2) , emanating from $L2_3_up$ (on the left) and $L2_4_up$ (on the right). Thick and thin segments of curves indicate stable and unstable steady states. Placement of random test points * on stable segments.

$$\sum_{\kappa_1 \kappa_2}$$

discrete odd functions = antisymmetric

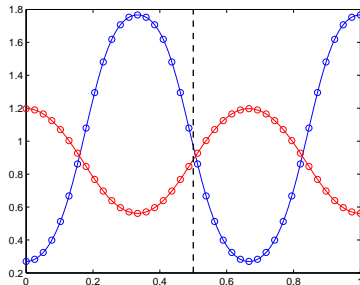
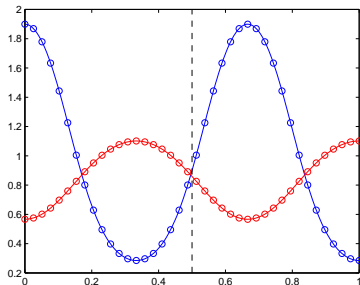


Figure: Schnakenberg model, see Example, $N = 40$, the branch $L2_3_up$: Consider the steady states $[u_1, \dots, u_N, v_1, \dots, v_N] \in \mathbb{R}^{2N}$ related the two marked test points * in the branch $L2_3_up$. Both steady states $[u_1, \dots, u_N]$ (in blue), and $[v_1, \dots, v_N]$ (in red) have rotational symmetry with respect to the center line $x = 1/2$.

activator/inhibitor = red/blue

\sum_{κ_2} discrete even functions = symmetric

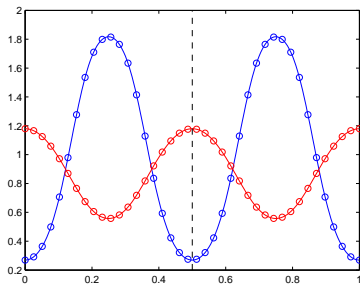
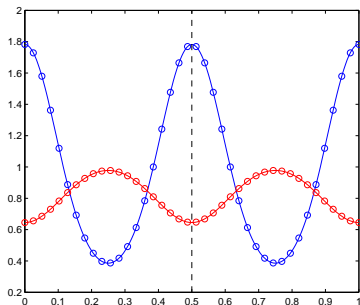


Figure: Schnakenberg model, see Example, $N = 40$, the branch $L2_4_up$: Consider the steady states $[u_1, \dots, u_N, v_1, \dots, v_N] \in \mathbb{R}^{2N}$ related the two marked test points * in the branch $L2_4_up$. Both steady states $[u_1, \dots, u_N]$ (in blue), and $[v_1, \dots, v_N]$ (in red) have symmetry of reflection with respect to the center line $x = 1/2$.

activator/inhibitor = red/blue

$$L^2, \quad \text{asym} \equiv \frac{u_1 - u_N}{2}, \quad \text{sym} \equiv \frac{u_1 + u_N}{2}.$$

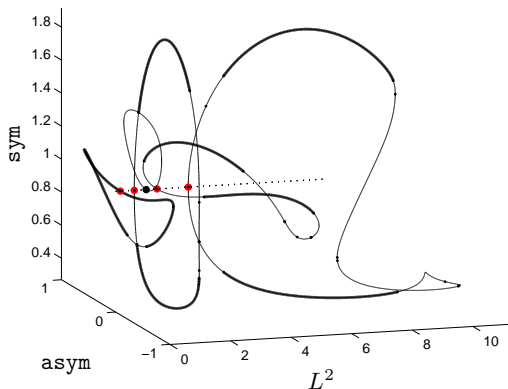


Figure: Schnakenberg model, see Example. Homogeneous steady states (dashed). Branches of inhomogeneous steady states emanating from $L2_1_up$, $L2_2_up$, $L2_1_down$, $L2_3_up$, $L2_4_up$.

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Conclusions

Algorithmic contribution to the continuation algorithm: a) initialization of the branch (via Taylor expansion of the bifurcation equation), b) segmenting the branch, distinguishing **stable and unstable branch segments**.

Results

- classification of model symmetries
- construction of a global bifurcation diagram

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Supplement: Dynamic simulation

Recall

$$F : \mathbb{R}^{2N} \times \mathbb{R}^1 \longrightarrow \mathbb{R}^{2N}$$

$$F(w, L^2) = 0, \quad w \in \mathbb{R}^{2N}, \quad w_i = u_i, \quad w_{N+i} = v_i, \quad i = 1, \dots, N.$$

Dynamic simulation. Define the initial value problem

$$w'(t) = F(w(t), L^2),$$

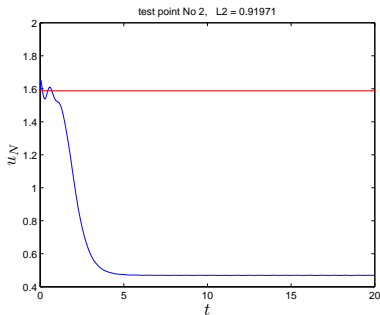
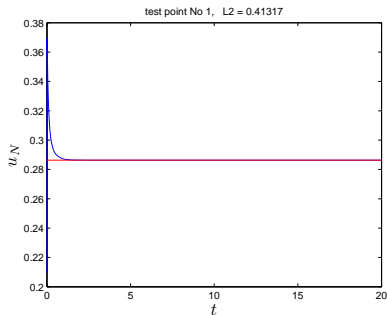
$$t \in \mathbb{R}^1 \longmapsto w(t) = [u_1(t), \dots, u_N(t), v_1(t), \dots, v_N(t)]^T \in \mathbb{R}^{2N}.$$

L is fixed. The initial condition $w^0 \in \mathbb{R}^{2N}$ is usually considered to be randomly perturbed *homogeneous steady state*.

It is expected that $w(t) \in \mathbb{R}^{2N} \longmapsto [u_1, \dots, u_N, v_1, \dots, v_N]^T \in \mathbb{R}^{2N}$ as $t \in \mathbb{R}^1 \longmapsto \infty$. Thus, in the case of convergence, the vector $[u_1, \dots, u_N, v_1, \dots, v_N]^T$ can be an *inhomogeneous* steady state related to the selected parameter L .

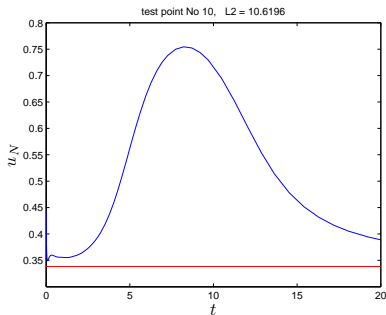
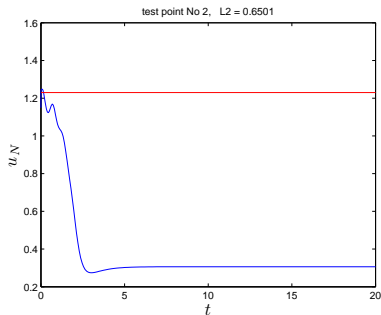
We are going to illustrate that

- 1 dynamic simulations can converge to steady states that are not unique,
- 2 it may not converge at all.
- 3 in principle, the dynamic simulation can only provide stable steady states.



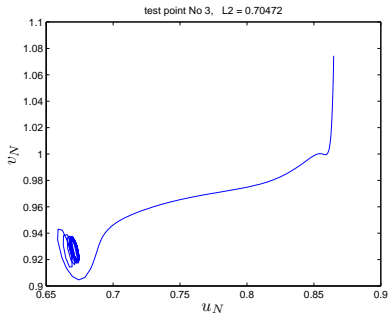
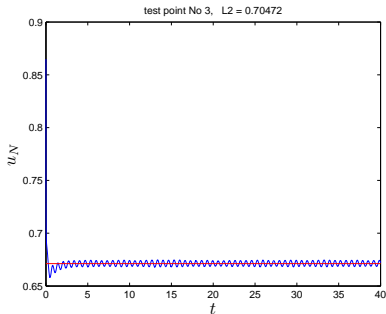
On the left: Consider the branch $L2_1_up$. Dynamic simulation: random perturbation at stable test point No 1. Steady state (red), resulting trajectory (blue).

On the right: Consider the branch $L2_1_down$. Dynamic simulation: random perturbation at an unstable test point No 2. Steady state (red), resulting trajectory (blue).



On the left: Consider the branch $L2_2_up$. Dynamic simulation: random perturbation at unstable test point No 2. Steady state (red), resulting trajectory (blue).

On the right: Consider the branch $L2_5_up$. Dynamic simulation: random perturbation at stable test point No 10. Steady state (red), resulting trajectory (blue). Observe the *Transient growth*.



The branch $L2_1_up$. Dynamic simulation: random perturbation at unstable test point No 3.
 On the left: Steady state (red), resulting oscillation (blue).
 On the right: Phase portrait of the oscillations.