

Global Stability for Delayed Neural Network Models

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1. Boundedness of solutions

$$\dot{y}(t) = f(t, y_t)$$

2. Global stability

$$\dot{y}_i(t) = f_i(y_t), \quad i = 1, \dots, n$$

$$\dot{x}_i(t) = -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), \quad i = 1, \dots, n$$

3. Exponential stability

$$\dot{x}_i(t) = -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), \quad i = 1, \dots, n$$

4. Neural Network Models

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_{j,t}) \right), \quad i = 1, \dots, n$$

Notation

► $n \in \mathbb{N}$, $x = (x_1, \dots, x_n) \in \mathbb{R}^n$,

$$|x|_\infty = \max_{1 \leq i \leq n} |x_i|;$$

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► $\tau \in \mathbb{R}^+$, $C_n := C([- \tau, 0]; \mathbb{R}^n)$

$$\|\varphi\|_\infty = \sup_{\theta \in [-\tau, 0]} |\varphi(\theta)|_\infty;$$

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$$\|\varphi\|_\infty = \sup_{\theta \in [-\tau, 0]} |\varphi(\theta)|_\infty;$$

- $A = [a_{ij}] \in \mathbb{R}^{n \times n}$ is a **non-singular M-matrix** if $a_{ij} \leq 0$, $i \neq j$ and $\operatorname{Re} \sigma(A) > 0$.

$$\dot{y}(t) = f(t, y_t)$$

1. Boundedness of solutions

► FDE in C_n

$$\dot{y}(t) = f(t, y_t), \quad t \geq t_0, \quad (1)$$

$$t_0 \in \mathbb{R},$$

$$f = (f_1, \dots, f_n) : [t_0, +\infty) \times C_n \rightarrow \mathbb{R}^n \text{ continuous,}$$

$$y_t \in C_n, y_t(\theta) = y(t + \theta), \theta \in [-\tau, 0].$$

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$$y_t \in C_n, y_t(\theta) = y(t + \theta), \theta \in [-\tau, 0].$$

- $y(t) = y(t, t_0, \varphi)$ denote the solution of (1) such that $y_{t_0} = \varphi \in C_n$.

► Proposition 1

Assume that, $f = (f_1, \dots, f_n)$ satisfies

(H) $\forall t \geq t_0, \forall \varphi \in C_n, \forall i \in \{1, \dots, n\},$

$$\|\varphi\|_\infty = |\varphi(0)|_\infty = |\varphi_i(0)| > 0 \Rightarrow \varphi_i(0)f_i(t, \varphi) < 0;$$

Then, the solution $y(t) = y(t, t_0, \varphi)$ of (1) is defined and bounded on $[t_0, +\infty)$, and

$$|y(t)|_\infty \leq \|\varphi\|_\infty, \quad \text{for } t \geq t_0.$$

► Proof [1].

[1] T. Faria, J. J. Oliveira, Local and global stability for Lotka-Volterra systems with distributed delays and instantaneous negative feedbacks, *J. Differential Equations* 244 (2008) 1049-1079.

$$\begin{aligned}\dot{y}_i(t) &= f_i(y_t), & i &= 1, \dots, n \\ \dot{x}_i(t) &= -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), & i &= 1, \dots, n\end{aligned}$$

2. Global stability

► FDE in C_n

$$\dot{y}_i(t) = f_i(y_t), \quad t \geq 0, \quad i = 1, \dots, n, \quad (2)$$

$f_i : C_n \rightarrow \mathbb{R}$ are continuous, for $i \in \{1, \dots, n\}$

Hypotheses:

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► **(H1)** $\forall \varphi \in C_n, \forall i \in \{1, \dots, n\},$

$$\|\varphi\|_\infty = |\varphi(0)|_\infty = |\varphi_i(0)| > 0 \Rightarrow \varphi_i(0)f_i(\varphi) < 0;$$

(H2) f_i are bounded on bounded sets of C_n .

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- **(H1)** $\Rightarrow y \equiv 0$ is the unique equilibrium of (2).

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► Theorem 1

Assume **(H1)** and **(H2)**

Then $y \equiv 0$ is globally asymptotically stable.

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► Proof (idea)

Let $y(t) = (y_1(t), \dots, y_n(t))$ be a solution of (2).

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Let $y(t) = (y_1(t), \dots, y_n(t))$ be a solution of (2).

► Proposition 1 $\Rightarrow y(t)$ defined and bounded on $[-\tau, +\infty)$

$$-v_i = \liminf_{t \rightarrow +\infty} y_i(t), \quad u_i = \limsup_{t \rightarrow +\infty} y_i(t)$$

$$v = \max_i \{v_i\}, \quad u = \max_i \{u_i\},$$

$$u, v \in \mathbb{R}, \quad -v \leq u.$$

► We have to show $\max(u, v) = 0$.

$$\begin{aligned} \dot{y}_i(t) &= f_i(y_t), & i &= 1, \dots, n \\ \dot{x}_i(t) &= -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), & i &= 1, \dots, n \end{aligned}$$

- We suppose $|v| \leq u$. ($|u| \leq v$ is similar)
Let $i \in \{1, \dots, n\}$ such that $u_i = u$.

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- ▶ We have

$$\forall \epsilon > 0, \exists T > 0 : \|y_t\|_\infty < u + \epsilon, \quad t \geq T$$

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- ▶ We can show that exists $(t_k)_{k \in \mathbb{N}}$ such that

$$t_k \nearrow +\infty, \quad y_i(t_k) \rightarrow u, \quad \text{and} \quad f_i(y_{t_k}) \rightarrow 0.$$

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- ▶ **(H1)+(H2)** $\Rightarrow \dot{y}(t)$ is bounded $\Rightarrow \{y_{t_k}\}$ is bounded and equicontinuous $\Rightarrow \exists \varphi \in C_n$

$$y_{t_k} \rightarrow \varphi \text{ on } C_n,$$

with $\|\varphi\|_\infty \leq u$, $\varphi_i(0) = u$ and $f_i(\varphi) = 0$.

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- ▶ **(H1)** $\Rightarrow u = 0$. \square

$$\begin{aligned}\dot{y}_i(t) &= f_i(y_t), & i = 1, \dots, n \\ \dot{x}_i(t) &= -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), & i = 1, \dots, n\end{aligned}$$

► Applications to general neural network models

$$\dot{x}_i(t) = -\rho_i(x_i(t))[b_i(x_i(t)) + f_i(x_t)], \quad t \geq 0, \quad i = 1, \dots, n, \quad (3)$$

where $\rho_i : \mathbb{R} \rightarrow (0, +\infty)$, $b_i : \mathbb{R} \rightarrow \mathbb{R}$ and $f = (f_1, \dots, f_n) : C_n \rightarrow \mathbb{R}^n$ are continuous.

Hypotheses:

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Hypotheses:

- **(A1)** $\exists \beta_i > 0, \forall u, v \in \mathbb{R}, u \neq v$:

$$(b_i(u) - b_i(v))/(u - v) \geq \beta_i;$$

[In particular, for $b_i(u) = \beta_i u$.]

- **(A2)** $f_i : C_n \rightarrow \mathbb{R}$ are Lipschitz functions with Lipschitz constants l_i .

$$\begin{aligned}\dot{y}_i(t) &= f_i(y_t), & i &= 1, \dots, n \\ \dot{x}_i(t) &= -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), & i &= 1, \dots, n\end{aligned}$$

► Theorem 2

Assume **(A1)** and **(A2)**.

If $\beta_i > l_i, \forall i$, then (3) has an equilibrium point $x^* \in \mathbb{R}^n$, which is globally asymptotically stable.

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► Proof (idea)

Existence of equilibrium point

$$\begin{aligned} H: \mathbb{R}^n &\rightarrow \mathbb{R}^n \\ x &\mapsto (b_1(x_1) + f_1(x), \dots, b_n(x_n) + f_n(x)) \end{aligned}$$

is a homeomorphism.

Then there exists $x^* \in \mathbb{R}^n$, $H(x^*) = 0$, i.e. x^* is an equilibrium.

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► By translation, we may suppose $x^* = 0$, $b_i(0) + f_i(0) = 0, \forall i$.

► $\beta_i > l_i, \forall i \Rightarrow$ **(H1)** and **(H2)**

From Theorem 1, we have the result. \square

$$\dot{x}_i(t) = -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), \quad i = 1, \dots, n$$

3. Exponential stability

- Consider again the FDE,

$$\dot{x}_i(t) = -\rho_i(x_i(t))[b_i(x_i(t)) + f_i(x_t)], \quad t \geq 0, \quad i = 1, \dots, n \quad (3)$$

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- **Definition**

An equilibrium $x^* \in \mathbb{R}$ of (3) is said to be *globally exponentially stable* if there are $\varepsilon, M > 0$ such that

$$\|x(t, 0, \varphi) - x^*\|_\infty \leq Me^{-\varepsilon t} \|\varphi - x^*\|_\infty, \quad t \geq 0, \quad \varphi \in C_n.$$

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$$\|x(t, 0, \varphi) - x^*\|_\infty \leq M e^{-\varepsilon t} \|\varphi - x^*\|_\infty, \quad t \geq 0, \quad \varphi \in C_n.$$

► Theorem 3

Suppose that $0 < r \leq \rho_i(x)$, $\forall x \in \mathbb{R}$, $i = 1, \dots, n$ and assume **(A1)** and **(A2)** with $\beta_i > l_i$, $i = 1, \dots, n$. Then there is a unique equilibrium x^* of (3) which is globally exponentially stable.

$$\dot{x}_i(t) = -\rho_i(x_i(t))(b_i(x_i(t)) + f_i(x_t)), \quad i = 1, \dots, n$$

► Proof (idea)

Assume $x^* = 0$ the equilibrium point and consider $x(t) = x(t, 0, \varphi)$ a solution of (3).

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Assume $x^* = 0$ the equilibrium point and consider $x(t) = x(t, 0, \varphi)$ a solution of (3).

► The change of variables

$$z(t) = e^{\varepsilon t} x(t),$$

for $\varepsilon > 0$ small enough, transform (3) into

$$\dot{z}(t) = g(t, z_t), \tag{4}$$

$g = (g_1, \dots, g_n)$ with

$$g_i(t, \varphi) =$$

$$\varepsilon \varphi_i(0) - \rho_i(t, e^{-\varepsilon(t+\cdot)} \varphi) e^{\varepsilon t} [b_i(e^{-\varepsilon t} \varphi_i(0)) + f_i(t, e^{-\varepsilon(t+\cdot)} \varphi)]$$

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► **(A1)+(A2) \Rightarrow (H)**

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► **(A1)+(A2) \Rightarrow (H)**

► From Proposition 1 $\|z(t)\|_\infty \leq \|z_0\|_\infty$, $t \geq 0$, and

$$\|x(t, 0, \varphi)\|_\infty = \|e^{-\varepsilon t} z(t, 0, e^{\varepsilon \cdot} \varphi)\|_\infty \leq e^{-\varepsilon t} \|\varphi\|_\infty. \square$$

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4. Neural Network Models

Cohen-Grossberg neural network with distributed delays

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left[b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_{j,t}) \right], \quad (5)$$

► $\rho_i : \mathbb{R} \rightarrow (0, +\infty)$ are continuous;

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- ▶ $f_{ij} : C_1 \rightarrow \mathbb{R}$ are Lipschitzian with

$$|f_{ij}(\varphi) - f_{ij}(\psi)| \leq l_{ij} \|\varphi - \psi\|, \quad \varphi, \psi \in C_1 = C([- \tau, 0]; \mathbb{R});$$

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- ▶ $b_i : \mathbb{R} \rightarrow \mathbb{R}$ are continuous satisfying **(A1)**;
- ▶ $N := \text{diag}(\beta_1, \dots, \beta_n) - [l_{ij}]$.

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j, t) \right), i = 1, \dots, n$$

► Theorem 4

If N is a non-singular M-matrix, then there is a unique equilibrium of (5), which is globally asymptotically stable.

If in addition $0 < r \leq \rho_i(x), \forall x \in \mathbb{R}, i = 1, \dots, n$, then the equilibrium of (5) is globally exponentially stable.

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), i = 1, \dots, n$$

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If N is a non-singular M-matrix, then there is a unique equilibrium of (5), which is globally asymptotically stable.

If in addition $0 < r \leq \rho_i(x)$, $\forall x \in \mathbb{R}$, $i = 1, \dots, n$, then the equilibrium of (5) is globally exponentially stable.

► Proof (idea)

N non-singular M-matrix \Rightarrow

Exists $d = (d_1, \dots, d_n) > 0$ such that $Nd > 0$, i.e.

$$\beta_i > d_i^{-1} \sum_{j=1}^n l_{ij} d_j, \quad i = 1, \dots, n; \quad (6)$$

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► The change of variables

$$y_i(t) = d_i^{-1} x_i(t)$$

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), \quad i = 1, \dots, n$$

► transform (5) into

$$\dot{y}_i(t) = -\bar{\rho}_i(y_i(t)) [\bar{b}_i(y_i(t)) + \bar{f}_i(y_t)], \quad i = 1, \dots, n,$$

$$\bar{f}_i(\varphi) = d_i^{-1} \sum_{j=1}^n f_{ij}(d_j \varphi_j), \quad \varphi \in C_n$$

$$\bar{b}_i(u) = d_i^{-1} b_i(d_i u), \quad \bar{\rho}_i = \rho_i(d_i u), \quad u \in \mathbb{R}$$

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j, t) \right), \quad i = 1, \dots, n$$

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$$\bar{b}_i(u) = d_i^{-1} b_i(d_i u), \quad \bar{\rho}_i = \rho_i(d_i u), \quad u \in \mathbb{R}$$

- \bar{f}_i satisfies **(A2)**, $i \in \{1, \dots, n\}$:

$$|\bar{f}_i(\varphi) - \bar{f}_i(\psi)| \leq \left(d_i^{-1} \sum_{j=1}^n l_{ij} d_j \right) \|\varphi - \psi\|_\infty$$

and \bar{b}_i satisfies **(A1)** with, by (6),

$$\bar{\beta}_i = \beta_i > \bar{l}_i := d_i^{-1} \sum_{j=1}^n l_{ij} d_j,$$

and the result follows from Theorems 2 and 3. \square

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), i = 1, \dots, n$$

The Cohen-Grossberg model with time-varying delays

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left[b_i(x_i(t)) + \sum_{j=1}^n \sum_{p=1}^P h_{ijp}(x_j(t - \tau_{ijp}(t))) \right] \quad (7)$$

has an equilibrium globally asymptotically (**exponentially**) stable if

- $\tau_{ijp} : [0, +\infty) \rightarrow [0, +\infty)$ are continuous with $\tau_{ijp}(t) \leq \tau$;

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 $\exists \beta_i > 0, \forall u, v \in \mathbb{R}, u \neq v$:

$$(b_i(u) - b_i(v))/(u - v) \geq \beta_i;$$

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- ▶ h_{ijp} are Lipschitz functions with constant l_{ijp} ;
- ▶ N is a non-singular M-matrix, where

$$N = \text{diag}(\beta_1, \dots, \beta_n) - [l_{ij}], \quad \text{with} \quad l_{ij} := \sum_{p=1}^P l_{ijp}.$$

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), i = 1, \dots, n$$

In H. Jiang et al.[2], proved the exponential stability assuming:

- ▶ $\tau_{ijp} : [0, +\infty) \rightarrow [0, +\infty)$ are continuous with $\tau_{ijp}(t) \leq \tau$;
- ▶ $\rho_i(x)$ are **locally Lipschitzian** and $0 < r \leq \rho_i(x) \leq R < \infty$;
- ▶ $b_i \in C^1(\mathbb{R}, \mathbb{R})$ with $b'_i(x) \geq \beta_i > 0$;
- ▶ $h_{ijp}(x) = c_{ijp}g_{ijp}(x)$, with $c_{ijp} \in \mathbb{R}$ and g_{ijp} Lipschitz functions with constant μ_{ijp} ;
- ▶ $\exists \alpha_{ijp}, \gamma_{ijp} \in \mathbb{R}, \omega_i > 0, r > 1, \sigma > 0$ such that, $\forall i$

$$r\omega_i \underline{k}_i \beta_i - (r-1) \sum_{j=1}^n \sum_{p=1}^P \omega_j \bar{k}_i \mu_{ijp}^{\frac{r-\gamma_{ijp}}{r-1}} |c_{ijp}|^{\frac{r-\alpha_{ijp}}{r-1}} - \sum_{j=1}^n \sum_{p=1}^P \omega_j \bar{k}_i \mu_{ijp}^{\gamma_{ijp}} |c_{ijp}|^\alpha > \sigma. \quad (8)$$

Instead of (8), we only assume N non-singular M-matrix.

[2] H. Jiang, J. Cao and Z. Teng, Dynamics of Cohen-Grossberg neural networks with time-varying delays, *Phys.*

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j, t) \right), i = 1, \dots, n$$

► Example:

$$\begin{aligned} \dot{x}_1(t) = & -(8 + 2 \sin x_1(t)) [7x_1(t) - \tanh x_1(t) - 2 \tanh x_2(t) \\ & - \tanh(x_1(t - \tfrac{1}{3} \sin t - 1)) - \tanh(x_2(t - \tfrac{1}{4} e^{-\sin t} - 1)) + 2] \end{aligned}$$

$$\begin{aligned} \dot{x}_2(t) = & -(5 + 2 \cos x_2(t)) [10x_2(t) - 2 \tanh x_1(t) - \tanh x_2(t) \\ & - \tanh(x_1(t - \tfrac{1}{4} e^{-\sin t} - 1)) - 2 \tanh(x_2(t - \tfrac{1}{3} \sin t - 1)) + 3] \end{aligned}$$

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), i = 1, \dots, n$$

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► $N = \text{diag}(7, 10) - \begin{pmatrix} 2 & 3 \\ 3 & 3 \end{pmatrix}$ is a non-singular M-matrix.

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), i = 1, \dots, n$$

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► If (8) holds, then there are $\omega_1, \omega_2 > 0$ such that

$$\begin{cases} 22\omega_1 - 30\omega_2 > 0 \\ -21\omega_1 + 9\omega_2 > 0 \end{cases},$$

which is impossible.

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), i = 1, \dots, n$$

Static NNM with S-type distributed delays

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left[b_i(x_i(t)) + f_i \left(\sum_{j=1}^n \omega_{ij} \int_{-\tau}^0 x_j(t + \theta) d\eta_{ij}(\theta) + J_i \right) \right] \quad (9)$$

- ▶ $\tau > 0, J_i, \omega_{ij} \in \mathbb{R};$
- ▶ $\rho_i : \mathbb{R} \rightarrow (0, +\infty)$ continuous (with $\rho_i(x) \geq r > 0$);
- ▶ $b_i : \mathbb{R} \rightarrow \mathbb{R}$ continuous satisfying **(A1)**;
- ▶ $f_i : \mathbb{R} \rightarrow \mathbb{R}$ Lipschitz with Lipschitz constant l_i ;
- ▶ $\eta_{ij} : [-\tau, 0] \rightarrow \mathbb{R}$ are normalized bounded variation functions;

$$N := \text{diag}(\beta_1, \dots, \beta_n) - [l_i |\omega_{ij}|]$$

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_{j,t}) \right), i = 1, \dots, n$$

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▶ Theorem 5

If N is a non-singular M-matrix, then there is an equilibrium point of (9) which is globally asymptotically (exponentially) stable.

► Example:

$$\dot{x}_i(t) = -b_i x_i(t) + f_i \left(\sum_{j=1}^n \omega_{ij} \int_{-\tau}^0 x_j(t + \theta) d\eta_{ij}(\theta) + J_i \right) \quad (10)$$

- $b_i > 0, J_i, \omega_{ij} \in \mathbb{R};$
- $\eta_{ij} : [-\tau, 0] \rightarrow \mathbb{R}$ are normalized bounded variation functions;
- $f_i : \mathbb{R} \rightarrow \mathbb{R}$ Lipschitz with Lipschitz constant l_i ;

$$N = \text{diag}(b_1, \dots, b_n) - [l_i |\omega_{ij}|].$$

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$$N = \text{diag}(b_1, \dots, b_n) - [l_i |\omega_{ij}|].$$

► **Corollary**

If N is a non-singular M-matrix, then there is an equilibrium point of (10) which is globally exponentially stable.

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_j(t)) \right), i = 1, \dots, n$$

► Example:

$$\dot{x}_i(t) = -b_i x_i(t) + f_i \left(\sum_{j=1}^n \omega_{ij} \int_{-\tau}^0 x_j(t + \theta) d\eta_{ij}(\theta) + J_i \right) \quad (10)$$

- $b_i > 0, J_i, \omega_{ij} \in \mathbb{R};$
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► **Corollary**

If N is a non-singular M-matrix, then there is an equilibrium point of (10) which is globally exponentially stable.

► **Remark**

In 2006, M. Wang and L. Wang proved the global **asymptotic** stability with η_{ij} normalizing and **nondecreasing bounded variation functions** on $[-\tau, 0]$.

1. Boundedness of solutions
2. Global stability
3. Exponential stability
4. Neural Network Models

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left(b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_{j,t}) \right), i = 1, \dots, n$$

Thanks you

Obrigado