

Boundedness and Global Exponential Stability for Delayed Differential Equations with Applications

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1. Boundedness of solutions

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

2. Exponential stability

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

3. 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

► $n \in \mathbb{N}$, $x, y \in \mathbb{R}^n$, $d = (d_1, \dots, d_n) > 0$, i.e. $d_i > 0$,

$$\langle x, y \rangle_d = \sum_{i=1}^n d_i x_i y_i, \quad |x|_{2,d} = \left(\sum_{i=1}^n d_i x_i^2 \right)^{1/2},$$

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

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

$$\|\varphi\|_{2,d} = \sup_{\theta \in [-\tau, 0]} |\varphi(\theta)|_{2,d}, \quad \|\varphi\|_{\infty,d} = \sup_{\theta \in [-\tau, 0]} |\varphi(\theta)|_{\infty,d};$$

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$$\|\varphi\|_{2,d} = \sup_{\theta \in [-\tau, 0]} |\varphi(\theta)|_{2,d}, \quad \|\varphi\|_{\infty,d} = \sup_{\theta \in [-\tau, 0]} |\varphi(\theta)|_{\infty,d};$$

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

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, for some $d = (d_1, \dots, d_n) > 0$, $f = (f_1, \dots, f_n)$ satisfies

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

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

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

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

Proof (idea)

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- ▶ Define

$$T = \min \left\{ t \in [t_0, t_1] : |y(t)|_{\infty, d} = \max_{s \in [t_0, t_1]} |y(s)|_{\infty, d} \right\}.$$

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- ▶ We have

$$|y_T(\theta)|_{\infty, d} = |y(T + \theta)|_{\infty, d} \leq |y(T)|_{\infty, d}, \quad -\tau \leq \theta \leq 0.$$

Choosing $i \in \{1, \dots, n\}$ such that $\|y_T\|_{\infty, d} = d_i |y_i(T)|$,

$$(\mathbf{H})_{\infty} \Rightarrow y_i(T) f_i(T, y_T) < 0.$$

If $y_i(T) > 0$ (analogous if $y_i(T) < 0$), then $\dot{y}_i(T) < 0$.

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- ▶ $d_i y_i(t) \leq |y(t)|_{\infty, d} < |y(T)|_{\infty, d} = d_i y_i(T)$, $t \in [t_0 - \tau, T)$,

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$$\Rightarrow \dot{y}_i(T) \geq 0.$$

- ▶ $|y(t, t_0, \varphi)|_{\infty, d} \leq \|\varphi\|_{\infty, d}$, $\forall t \geq t_0$.

► Proposition 2

Assume that, for some $d = (d_1, \dots, d_n) > 0$, f satisfies $(H)_2 \forall t \geq t_0, \forall \varphi \in C_n$,

$$\|\varphi\|_{2,d} = |\varphi(0)|_{2,d} > 0 \Rightarrow \langle \varphi(0), f(t, \varphi) \rangle_d < 0.$$

Then, the solution $y(t) = y(t, t_0, \varphi)$ of $\dot{y}(t) = f(t, y_t)$ is defined and bounded on $[t_0, +\infty)$, and

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- ▶ Proof: Similar to the proof of Proposition 1.

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

2. Exponential stability

- In applications,

$$\dot{x}_i(t) = -\rho_i(x_i(t))[b_i(x_i(t)) + f_i(x_t)], \quad t \geq 0, \quad i = 1, \dots, n, \quad (2)$$

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

Hypothesis:

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Hypothesis:

- **(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 $b_i(u) = \beta_i u$.]

► Definition

An equilibrium $x^* \in \mathbb{R}$ of (2) is said to be *globally exponentially stable* if there are $\varepsilon, M > 0$ such that

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

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► Theorem 1

Suppose that $0 < r \leq \rho_i(x)$, $\forall x \in \mathbb{R}$, $i = 1, \dots, n$ and assume **(A1)** and

(A2) $_{\infty}$ $\exists d = (d_1, \dots, d_n) > 0, \forall \varphi, \psi \in C_n$:

$$|f_i(\varphi) - f_i(\psi)| \leq l_i \|\varphi - \psi\|_{\infty, d},$$

with $\beta_i > d_i l_i$, $i = 1, \dots, n$.

Then there is a unique equilibrium x^* of (2) which is globally exponentially stable.

Proof (idea)

► Existence of equilibrium

Consider

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

H is injective and $|H(x)|_{\infty, d} \rightarrow +\infty$ as $|x|_{\infty, d} \rightarrow +\infty$ implying that H is a homeomorphism [1], then there exists $x^* \in \mathbb{R}^n$, $H(x^*) = 0$, i.e. x^* is an equilibrium of (2).

[1] M. Forti and A. Tesi, New conditions for global stability of neural networks with applications to linear and quadratic programming problems, *IEEE Trans. Circuits Syst.* 42 (1995) 354-366.

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- By translation we may suppose $x^* = 0$, $b_i(0) + f_i(t, 0) = 0$.

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- Consider $x(t) = x(t, 0, \varphi)$ a solution of (2).
- The change of variables

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

for $\varepsilon > 0$ small enough, transform (2) into

$$\dot{z}(t) = g(t, z_t), \quad (3)$$

$$g = (g_1, \dots, g_n) \text{ with}$$

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

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► **(A1)+(A2) $_{\infty} \Rightarrow$ (H) $_{\infty}$**

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

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

► Theorem 2

Suppose that $0 < r \leq \rho_i(x) \leq R, \forall x \in \mathbb{R}, i = 1, \dots, n$
 and assume **(A1)** and

(A2)₂ $\exists d = (d_1, \dots, d_n) > 0, \forall \varphi, \psi \in C_n$:

$$|f(\varphi) - f(\psi)|_{2,d} \leq l \|\varphi - \psi\|_{2,d},$$

with $\beta_i > l\sqrt{R/r}, i = 1, \dots, n$.

Then there a unique equilibrium x^* of (2) which is globally exponentially stable.

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► Remark

Assuming the existence of an equilibrium point, similar results can be obtained for the non-autonomous case

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

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

3. Neural Network Models

Cohen-Grossberg neural network with distributed delays

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left[b_i(x_i(t)) + \sum_{j=1}^n f_{ij}(x_{j,t}) \right], \quad (4)$$

► $\rho_i : \mathbb{R} \rightarrow (0, +\infty)$ are continuous and $\rho_i(x) \geq r > 0$;

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

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

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► Proposition 3

If N is a non-singular M-matrix, then there is a unique equilibrium of (4), which is globally exponentially stable.

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For $f_i(\varphi) := \sum_{j=1}^n f_{ij}(\varphi_j)$, $\varphi = (\varphi_1, \dots, \varphi_n) \in C_n$, (4) has the form of (2).

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► N non-singular M-matrix \Rightarrow

Exists $c = (c_1, \dots, c_n) > 0$ such that $Nc > 0$,

$$\beta_i > c_i^{-1} \sum_{j=1}^n l_{ij} c_j, \quad i = 1, \dots, n; \quad (5)$$

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► Proposition 3

If N is a non-singular M-matrix, then there is a unique equilibrium of (4), which is globally exponentially stable.

► Proof (idea)

For $f_i(\varphi) := \sum_{j=1}^n f_{ij}(\varphi_j)$, $\varphi = (\varphi_1, \dots, \varphi_n) \in C_n$, (4) has the form of (2).

► N non-singular M-matrix \Rightarrow

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► The result follows from Theorem 1.

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► Denote $f = (f_1, \dots, f_n) : C_n \rightarrow \mathbb{R}^n$

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► **Proposition 4**

Assume **(A1)** and suppose

$$0 < r \leq \rho_i(x) \leq R \quad \forall x \in \mathbb{R}, i = 1, \dots, n,$$

$$\|f(\varphi) - f(\psi)\|_{2,d} \leq l \|\varphi - \psi\|_{2,d} \quad \forall \varphi, \psi \in C_n,$$

with $\beta_i > l\sqrt{R/r}$, $\forall i$.

Then there is an equilibrium of (4), which is globally exponentially stable.

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Then there is an equilibrium of (4), which is globally exponentially stable.

- Proof: Similar to the proof of Proposition 3.

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

- Example 1: Consider the 2-neuron network

$$\dot{x}_1(t) = -b_1 x_1(t) + a_{11} f_1(x_1(t - \tau)) + a_{12} f_2(x_2(t - \tau)) \quad (6)$$

$$\dot{x}_2(t) = -b_2 x_2(t) + a_{21} f_1(x_1(t - \tau)) + a_{22} f_2(x_2(t - \tau))$$

where, for $i = 1, 2$, $\tau, b_i > 0$, $a_{ij} \in \mathbb{R}$, $a_{ii} \neq 0$, and $f_i : \mathbb{R} \rightarrow \mathbb{R}$ such that $|f_i(u) - f_i(v)| \leq |u - v|$, $u, v \in \mathbb{R}$.

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- If $N = \text{diag}(b_1, b_2) - [a_{ij}]$ is a non-singular M-matrix, i.e

$$b_1 > a_{11} \text{ and } (b_1 - a_{11})(b_2 - a_{22}) > |a_{12}a_{21}|, \quad (7)$$

then, from Proposition 3, (6) has an equilibrium x^* , which is globally exponentially stable.

- For the situation $a_{12}a_{21} < 0$, define

$$f(\varphi) = A \begin{pmatrix} f_1(\varphi_1(-\tau)) \\ f_2(\varphi_2(-\tau)) \end{pmatrix}, \text{ for } A = [a_{ij}], \varphi = (\varphi_1, \varphi_2) \in C_2.$$

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- Choosing $d = (d_1, d_2) > 0$ such that $d_1 a_{11} a_{12} + d_2 a_{21} a_{22} = 0$,

$$|f(\varphi) - f(\psi)|_{2,d} \leq \left(\max \left\{ \frac{a_{11}}{a_{22}}, \frac{a_{22}}{a_{11}} \right\} \det A \right)^{1/2} \|\varphi - \psi\|_{2,d}$$

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Example 2: The Cohen-Grossberg model with time-varying delays

$$\dot{x}_i(t) = -\rho_i(x_i(t)) \left[b_i(x_i(t)) + \sum_{j=1}^n \sum_{p=1}^P h_{ijp}(x_j(t - \tau_{ijp}(t))) \right] \quad (9)$$

has an equilibrium point globally exponentially stable if

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

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- ▶ $b_i : \mathbb{R} \rightarrow \mathbb{R}$ are continuous satisfying **(A1)**, i.e.,
 $\exists \beta_i > 0, \forall u, v \in \mathbb{R}, u \neq v$:

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

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In H. Jiang et al.[2], the same result was proved 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, $\forall i$

$$r\omega_i \underline{k}_i \beta_i - (r-1) \sum_{j=1}^n \sum_{p=1}^P \omega_j \bar{k}_i \mu_{ijp}^{\frac{r-\gamma_{ijp}}{r-1}} |c_{ijp}|^{\frac{r-\alpha_{ijp}}{r-1}} - \sum_{j=1}^n \sum_{p=1}^P \omega_j \bar{k}_i \mu_{ijp}^{\gamma_{ijp}} |c_{ijp}|^{\alpha_{ijp}} > \sigma. \quad (10)$$

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

Lett. A 354 (2006) 414-422.

► Example 3:

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

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► If (10) 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.

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

Thanks you

Obrigado