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Control SystemsPart III: Stability

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$$\begin{cases} \dot{x} = f(x, u, t) \\ y = g(x, u, t) \end{cases} \qquad u(t) = \bar{u}, t \ge 0$$

$$\qquad \qquad \downarrow \qquad 0 = f(x, \bar{u}) \qquad \qquad \bar{x}$$

Consider a **perturbation of the initial state** set on the equilibrium state \bar{x} :

$$\begin{cases} u(t) = \bar{u}, t \ge 0 \\ x(0) = \bar{x} + \delta \bar{x} \end{cases}$$
 perturbed state trajectory

• The equilibrium state \bar{x} is **stable** if $\forall \varepsilon > 0$, $\exists \delta(\varepsilon) > 0$ such that:

$$\forall x(0): \|\delta \bar{x}\| < \delta(\varepsilon) \implies \|x(t) - \bar{x}\| < \varepsilon, \, \forall \, t \ge 0$$

- The equilibrium state \bar{x} is **asymptotically stable** if:
 - it is stable, that is, if $\forall \varepsilon > 0$, $\exists \delta(\varepsilon) > 0$ such that:

$$\forall x(0): \|\delta \bar{x}\| < \delta(\varepsilon) \implies \|x(t) - \bar{x}\| < \varepsilon, \, \forall \, t \ge 0$$

and

$$\lim_{t \to \infty} ||x(t) - \bar{x}|| = 0$$

• The equilibrium state \bar{x} is **unstable** if it is not stable

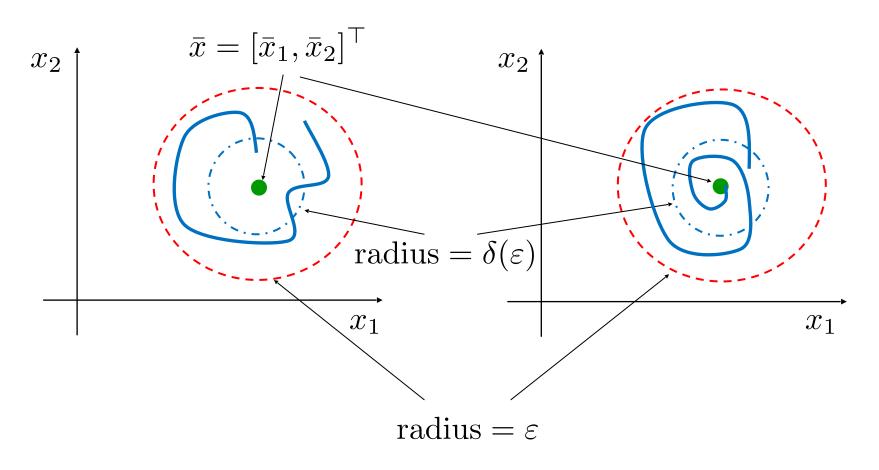
Stability of Equilibrium - Geometric Interpretation

$$f(\bar{x}, \bar{u}) = 0$$

$J\left(\omega,\omega ight)$

stability

asymptotic stability



Stability of Linear Systems

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases}$$

• a) In equilibrium conditions:

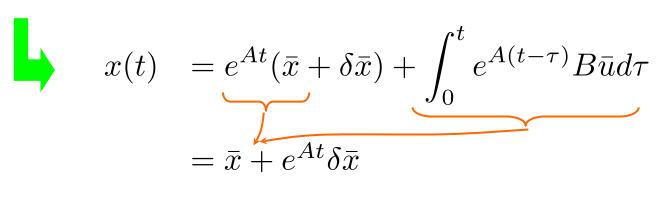
$$\begin{cases} u(t) = \bar{u}, t \ge 0 \\ x(0) = \bar{x} \end{cases}$$

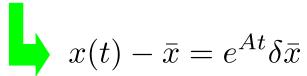
$$x(t) = e^{At}\bar{x} + \int_0^t e^{A(t-\tau)}B\bar{u}d\tau = \bar{x}, \ \forall t \ge 0$$

Stability of Linear Systems (contd.)

• **b)** After a perturbation of the equilibrium state:

$$\begin{cases} u(t) = \bar{u}, t \ge 0 \\ x(0) = \bar{x} + \delta \bar{x} \end{cases}$$
 $x(t) \ne \bar{x}, t \ge 0$ perturbed state trajectory





$$\begin{cases} u(t) = \bar{u}, t \ge 0 \\ x(0) = \bar{x} + \delta \bar{x} \end{cases}$$



$$x(t) - \bar{x} = e^{At} \delta \bar{x}$$

deviation of the perturbe $x(t) - \bar{x} = e^{At} \delta \bar{x} \quad \text{state trajectory from the}$ deviation of the perturbed equilibrium state

- stability properties do not depend on the specific value taken on by \bar{x}
 - stability is not a property of the equilibrium state (as in the general case) but it is a structural property of the system as a whole
- stability properties depend on the time-behaviour of e^{At} :
 - stability



$$e^{At}$$
 bounded $\forall t \geq 0$

asymptotic stability



$$\lim_{t \to \infty} e^{At} = 0$$

instability



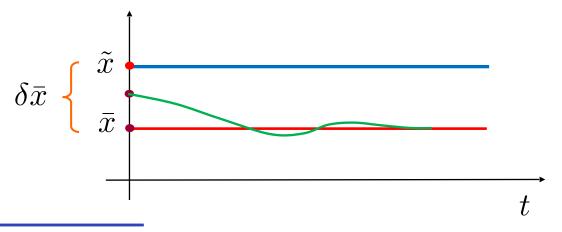
 e^{At} unbounded

Properties of Asymptotically Stable Linear Systems

- The system state moved from equilibrium "tends" getting back to it
- Given a specific **constant input** $u(t) = \bar{u}, t \ge 0$ the corresponding equilibrium state \bar{x} is **unique**:

asymptotic stability \bar{x} unique $\det(A) \neq 0$

In fact, suppose that, for a given \bar{u} , two different equilibrium states $\bar{x}, \, \tilde{x}$ would exist:



contradiction with the asymptotic stability assumption!!!

The perturbed state trajectory asymptotically only depends on the input trajectory u(t):

$$x(t) = x_l(t) + x_f(t)$$

For example:

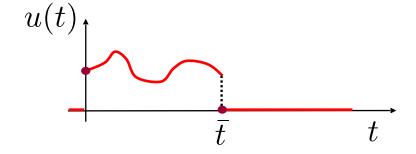
•
$$u(t) = 0, t \ge 0$$

$$\lim_{t \to \infty} x(t)$$

•
$$u(t) = 0, t \ge 0$$

$$\lim_{t \to \infty} x(t) = 0; \lim_{t \to \infty} y(t) = 0, \ \forall x_0$$

•
$$u(t) = \begin{cases} \text{any function} & 0 \le t < \bar{t} \\ 0 & t \ge \bar{t} \end{cases}$$

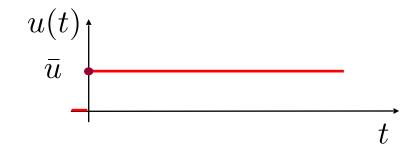




$$\lim_{t \to \infty} x(t) = 0; \lim_{t \to \infty} y(t) = 0, \ \forall x_0$$

• If:

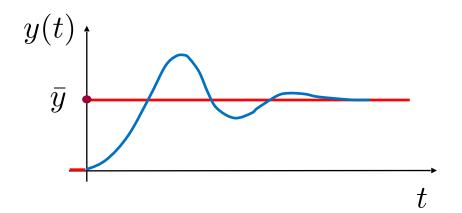
$$u(t) = \begin{cases} 0 & t < 0 \\ \bar{u} & t \ge 0 \end{cases}$$





$$\lim_{t \to \infty} y(t) = \bar{y}, \ \forall x_0$$

$$\lim_{t\to\infty}y(t)=\bar{y},\ \forall\,x_0\qquad\text{where}\qquad \bar{y}=\mu\bar{u}=\left(-CA^{-1}B+D\right)\bar{u}$$
 static gain

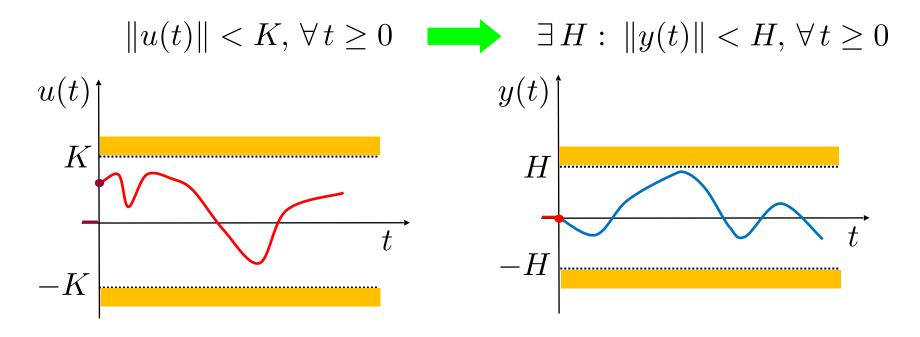


Properties of Asymptotically Stable Linear Systems (contd.)

It holds that:

that is:

u(t) bounded y(t) bounded



- This property is named Bounded Input Bounded Output (BIBO) Stability
- Asymptotic Stability
 BIBO Stability but NOT viceversa

Stability of Linear Systems: Summing Up

Stability properties depend on the asymptotic time-behaviour of the free state trajectories or, equivalently, of the matrix exponential:

$$x_l(t) = e^{At}x(0)$$

- stability
- asymptotic stability
- instability



 e^{At} bounded $\forall t \geq 0$

$$\lim_{t \to \infty} e^{At} = 0$$



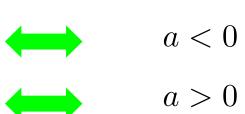
 e^{At} unbounded

$$x_l(t) = e^{at} x(0), \quad a \in \mathbb{R}$$

- stability
- asymptotic stability
- instability



$$a \leq 0$$







The stability property just depends on the **sign** of $a \in \mathbb{R}$

Consider the following cases:

- 1. Matrix A is diagonal
- 2. Matrix A has real and distinct eigenvalues
- 3. Matrix A has complex and distinct eigenvalues
- 4. Matrix A has eigenvalues with multiplicity larger than 1
 - 1. Matrix A can be transformed into a diagonal matrix
 - 2. Matrix *A* cannot be transformed into a diagonal matrix

Case 1: Matrix A is Diagonal

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$$A = \left[\begin{array}{ccc} s_1 & \cdots & 0 \\ & \ddots & \\ 0 & \cdots & s_n \end{array} \right]$$

$$s_1, s_2, \dots, s_n \in \mathbb{R}$$
 eigenvalues of A

$$e^{At} = \begin{bmatrix} e^{s_1 t} & \cdots & 0 \\ & \ddots & \\ 0 & \cdots & e^{s_n t} \end{bmatrix}$$

The matrix e^{At} is a square $n \times n$ $e^{At} = \begin{bmatrix} e^{s_1 \iota} & \cdots & 0 \\ & \ddots & \\ 0 & \cdots & e^{s_n t} \end{bmatrix}$ matrix whose elements $e^{s_i t}$ are functions of time

Hence:

stability



 $s_i \le 0, i = 1, \dots, n$

asymptotic stability



 $s_i < 0, i = 1, \ldots, n$

instability



 $\exists i \in \{1, \ldots, n\} \text{ such that } s_i > 0$

Case 2: Matrix A has real and distinct eigenvalues

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$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}$$

$$s_1, s_2, \dots, s_n \in \mathbb{R}, \, s_1 \neq s_2 \neq \dots \neq s_n$$
 eigenvalues of A

 $A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad \begin{array}{l} s_1, s_2, \ldots, s_n \in \mathbb{R}, \, s_1 \neq s_2 \neq \cdots \neq s_n \\ \text{eigenvalues of } A \\ \\ \text{Find matrix } T \in \mathbb{R}^{n \times n}, \, \det(T) \neq 0 \, : \, A = T\tilde{A}T^{-1} \,, \quad \tilde{A} = \begin{bmatrix} s_1 & \cdots & 0 \\ & \ddots & \\ 0 & \cdots & s_n \end{bmatrix} \\ & = I + At + \frac{1}{2}A^2t^2 + \cdots \\ & = I + T\tilde{A}T^{-1}t + \frac{1}{2}(T\tilde{A}T^{-1}t)(T\tilde{A}T^{-1}t) + \cdots \\ & = T\left(I + \tilde{A}t + \frac{1}{2}(\tilde{A}t)^2 + \cdots\right)T^{-1} \\ & = Te^{\tilde{A}t}T^{-1} \\ \end{array} \quad \begin{array}{l} e^{s_1t} & \cdots & 0 \\ & \ddots & \\ 0 & \cdots & e^{s_nt} \end{bmatrix} T^{-1} \\ \end{array}$

$$= I + At + \frac{1}{2}A^{2}t^{2} + \cdots$$

$$= I + T\tilde{A}T^{-1}t + \frac{1}{2}(T\tilde{A}T^{-1}t)(T\tilde{A}T^{-1}t) + \cdots$$

$$= T\left(I + \tilde{A}t + \frac{1}{2}(\tilde{A}t)^{2} + \cdots\right)T^{-1}$$

$$= At - T\tilde{A}T^{-1}t + \frac{1}{2}(\tilde{A}t)^{2} + \cdots$$

$$e^{At} = T \begin{bmatrix} e^{s_1 t} & \cdots & 0 \\ & \ddots & \\ 0 & \cdots & e^{s_n t} \end{bmatrix}$$

Hence:

- stability
- asymptotic stability
- instability



$$s_i \leq 0, i = 1, \dots, n$$



$$s_i < 0, i = 1, \dots, n$$



$$\exists i \in \{1, \dots, n\} \text{ such that } s_i > 0$$

Example

$$\begin{cases} \dot{x}_1 = -2x_1 + 6x_2 \\ \dot{x}_2 = -2x_1 + 5x_2 \end{cases} A = \begin{bmatrix} -2 & 6 \\ -2 & 5 \end{bmatrix}$$

Eigenvalues:

$$p_A(s) = \det(sI - A) = \det\begin{bmatrix} s+2 & -6\\ 2 & s-5 \end{bmatrix} = (s+2)(s-5) + 12$$
$$= s^2 - 3s + 2 = (s-2)(s-1)$$



$$s_1 = 1; \ s_2 = 2$$

 $s_1 = 1; \ s_2 = 2$ Unstable because both eigenvalues are positive

Eigenvectors:

$$Av = s_{1}v \qquad v = \begin{bmatrix} v_{1} \\ v_{2} \end{bmatrix}$$

$$\downarrow \begin{bmatrix} -2 & 6 \\ -2 & 5 \end{bmatrix} \begin{bmatrix} v_{1} \\ v_{2} \end{bmatrix} = 1 \cdot \begin{bmatrix} v_{1} \\ v_{2} \end{bmatrix} \qquad \begin{cases} -2v_{1} + 6v_{2} = v_{1} \\ -2v_{1} + 5v_{2} = v_{2} \end{cases}$$

$$Av = s_{2}v$$

$$\downarrow \begin{bmatrix} -2 & 6 \\ -2 & 5 \end{bmatrix} \begin{bmatrix} v_{1} \\ v_{2} \end{bmatrix} = 2 \cdot \begin{bmatrix} v_{1} \\ v_{2} \end{bmatrix} \qquad \begin{cases} -2v_{1} + 6v_{2} = 2v_{1} \\ -2v_{1} + 6v_{2} = 2v_{1} \\ -2v_{1} + 5v_{2} = 2v_{2} \end{cases}$$

$$v_1 = \frac{3}{2}v_2 \qquad \qquad v^{(2)} = \begin{bmatrix} 3\\2 \end{bmatrix}$$

Example (contd.)

Transformation into diagonal form:

$$T = \begin{bmatrix} v^{(1)} \middle| v^{(2)} \end{bmatrix} = \begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix} \longrightarrow T^{-1} = \begin{bmatrix} 2 & -3 \\ -1 & 2 \end{bmatrix}$$

$$\tilde{A} = T^{-1}AT = \begin{bmatrix} 2 & -3 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} -2 & 6 \\ -2 & 5 \end{bmatrix} \begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$$

Example (contd.)

• Calculation of the matrix exponential e^{At} :

$$e^{At} = Te^{\tilde{A}t}T^{-1} = T\begin{bmatrix} e^t & 0\\ 0 & e^{2t} \end{bmatrix}T^{-1}$$

$$= \begin{bmatrix} 2 & 3\\ 1 & 2 \end{bmatrix}\begin{bmatrix} e^t & 0\\ 0 & e^{2t} \end{bmatrix}\begin{bmatrix} 2 & -3\\ -1 & 2 \end{bmatrix}$$

$$= \begin{bmatrix} 4e^t - 3e^{2t} & -6e^t + 6e^{2t}\\ 2e^t - 2e^{2t} & -3e^t + 4e^{2t} \end{bmatrix}$$



The matrix exponential contains elements (all, in this specific example) that are **asymptotically unbounded** which is consistent with the previous statement about **instability** based on the **positive sign of the eigenvalues**

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}$$

$$s_1, s_2, \dots, s_n \in \mathbb{C}, s_1 \neq s_2 \neq \cdots \neq s_n$$
 eigenvalues of A

For simplicity, consider the case: n=2; $s_1=\sigma+j\omega$; $s_2=\sigma-j\omega$



Hence, the matrix exponential e^{At} contains terms such as:

$$\gamma e^{(\sigma+j\omega)t} + \bar{\gamma} e^{(\sigma-j\omega)t}$$
 where $\gamma = \alpha + j\beta$; $\bar{\gamma} = \alpha - j\beta$



Then:

this is the term responsible for boundedness/convergence/divergence over time

Hence, generalising:

- stability
- asymptotic stability
- instability

$$Re(s_i) \le 0, i = 1, ..., n$$



Re
$$(s_i) < 0, i = 1, ..., n$$



 $\exists i \in \{1, \ldots, n\} \text{ such that } \operatorname{Re}(s_i) > 0$

• Example 1:

$$A = \left[\begin{array}{cc} \alpha & 0 \\ 0 & \alpha \end{array} \right] \quad s_1 = s_2 = \alpha$$

$$e^{At} = \begin{bmatrix} e^{\alpha t} & 0 \\ 0 & e^{\alpha t} \end{bmatrix}$$

Matrix A is already in diagonal form, hence no need for resorting to an equivalent state equation. This case is equivalent to Case 1

• Example 2:

$$A = \left[\begin{array}{cc} \alpha & 1 \\ 0 & \alpha \end{array} \right] \quad s_1 = s_2 = \alpha$$

In this case, there **does not exist** an equivalent state space transformation bringing matrix A into a diagonal form

$$e^{At} = I + At + \frac{1}{2}A^2t^2 + \cdots$$

$$A^{2} = \begin{bmatrix} \alpha^{2} & 2\alpha \\ 0 & \alpha^{2} \end{bmatrix} \qquad A^{3} = \begin{bmatrix} \alpha^{3} & 3\alpha^{2} \\ 0 & \alpha^{3} \end{bmatrix} \quad \cdots \quad A^{k} = \begin{bmatrix} \alpha^{k} & k\alpha^{k-1} \\ 0 & \alpha^{k} \end{bmatrix} \quad \cdots$$

Therefore:

$$A = \begin{bmatrix} \alpha & 1 \\ 0 & \alpha \end{bmatrix} \quad s_1 = s_2 = \alpha$$

$$e^{At} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} \alpha & 1 \\ 0 & \alpha \end{bmatrix} t + \begin{bmatrix} \alpha^2 & 2\alpha \\ 0 & \alpha^2 \end{bmatrix} \frac{t^2}{2!} + \cdots$$

$$+\cdots + \left[\begin{array}{cc} \alpha^k & k\alpha^{k-1} \\ 0 & \alpha^k \end{array}\right] \frac{t^k}{k!} + \cdots$$

$$= \begin{bmatrix} e^{\alpha t} & t + \alpha t^2 + \dots + \alpha^{k-1} \frac{t^k}{(k-1)!} + \dots \\ 0 & e^{\alpha t} \end{bmatrix} = \begin{bmatrix} e^{\alpha t} & te^{\alpha t} \\ 0 & e^{\alpha t} \end{bmatrix}$$



Hence:

- Concerning **Example 1**:

- stability
 - asymptotic stability $\qquad \qquad \alpha < 0$
- instability

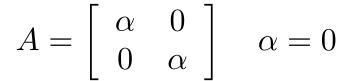


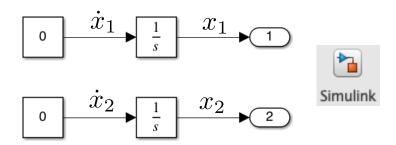
 $\alpha = 0$

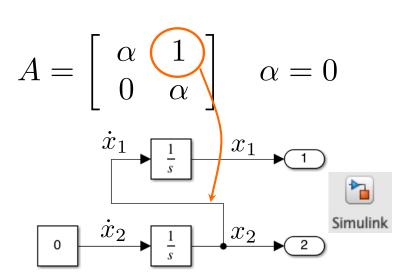
- Concerning **Example 2**:

- asymptotic stability $\qquad \qquad \alpha < 0$
- instability









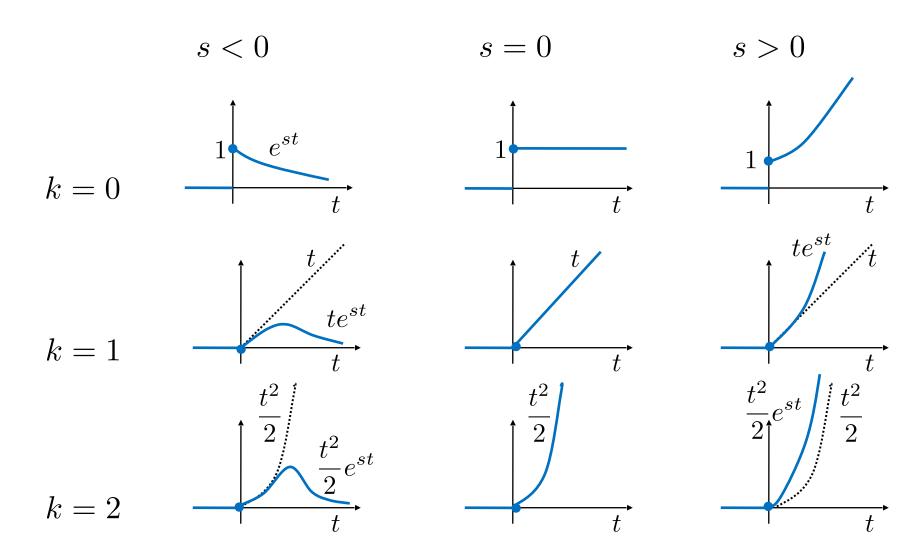
In general, consider a matrix A such that:

- A has eigenvalues with multiplicity $\nu > 1$
- matrix A cannot be transformed into equivalent diagonal form



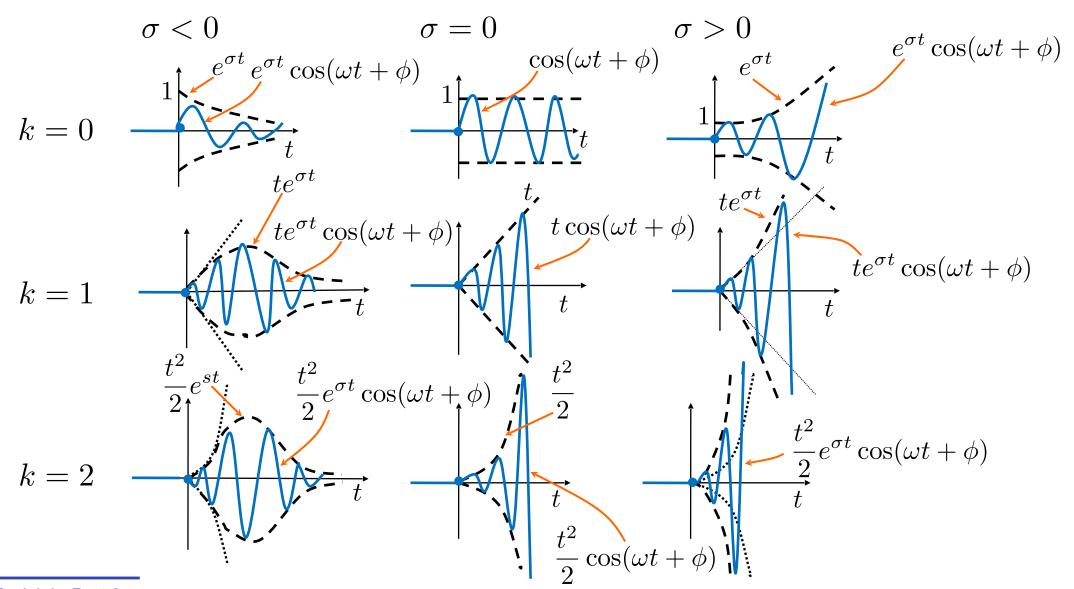
 e^{At} contains terms of the form $t^k e^{s_i t}, k = 1, 2, \dots, \nu - 1$

• Case 1: $s \in \mathbb{R}$



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• Case 2: $s \in \mathbb{C}, \, s_1 = \sigma + j\omega, \, s_2 = \sigma - j\omega$



$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}$$

$$\begin{array}{c} s_1, s_2, \dots, s_n \in \mathbb{C} \\ \text{eigenvalues of } A \end{array}$$

$$s_1, s_2, \dots, s_n \in \mathbb{C}$$
 eigenvalues of A

Result 1:

$$Re(s_i) < 0, i = 1, ..., n$$
 Asymptotic Stability

Result 2:

 $\exists i \in \{1,\ldots,n\} \text{ such that } \operatorname{Re}(s_i) > 0 \longrightarrow \text{Instability}$

Result 3:

$$\left\{\begin{array}{ll} \mathrm{Re}(s_i) \leq 0\,,\, i=1,\ldots,n\\ \\ \exists\, \widetilde{i} \in \{1,\ldots,n\} \text{ such that } \mathrm{Re}(s_{\widetilde{i}})=0 \end{array}\right. \quad \text{No Asymptotic Stability}$$

- If multiplicity of all $s_{\widetilde{i}}$ such that $\operatorname{Re}(s_{\widetilde{i}}) = 0$ is equal to 1
 - Stability (Non-Asymptotic, also called Marginal)
- If $\exists \widetilde{i} \in \{1, \ldots, n\}$ such that $\operatorname{Re}(s_{\widetilde{i}}) = 0$ with multiplicity > 1
 - Instability or Stability (non asymptotic anyway)

Stability of Linear Systems: Other Criteria/Tools

- So far, the stability analysis has been carried out by evaluating the eigenvalues of matrix A and their location in the complex plane
- Other criteria can be devised not requiring the calculation of the eigenvalues of matrix A but based on the:
 - analysis of the **elements** of matrix A
 - analysis of the **characteristic polynomial** of matrix A:

$$\varphi_A(s) = \det(sI - A) = \varphi_0 s^n + \varphi_1 s^{n-1} + \dots + \varphi_{n-1} s + \varphi_n$$

Criterion 1:

If matrix A is triangular:



$$a_{ii} < 0, i = 1, \dots, n$$



 $a_{ii} < 0, i = 1, \dots, n$ Asymptotic Stability

Criterion 2:

Letting
$$\operatorname{tr}(A) := \sum_{i=1}^{n} a_{ii}$$
:

Asymptotic Stability $\operatorname{tr}(A) < 0$







 $\operatorname{tr}(A) > 0$ Instability

Criterion 3:

Asymptotic Stability \rightarrow det $(A) \neq 0$



• Criterion 4 (valid for second-order systems n=2):

Asymptotic Stability
$$\longleftrightarrow$$
 Re $(s_i) < 0$, $i = 1, 2$ \longleftrightarrow $\begin{cases} \varphi_0, \varphi_1, \varphi_2 \end{cases}$ same sign

Criterion 5:

Asymptotic Stability \leftarrow Re $(s_i) < 0, i = 1, 2$ \neq 0 \neq 0 same sign

$$\varphi(s) = s^3 + 3s^2 + 2s$$

Not Asymptotically Stable

$$\varphi(s) = s^3 + 2s + 5$$

Not Asymptotically Stable

$$\varphi(s) = s^3 + 5s^2 - 2s + 4$$

Not Asymptotically Stable

$$\varphi(s) = s^3 + 5s^2 + 2s + 4$$

???

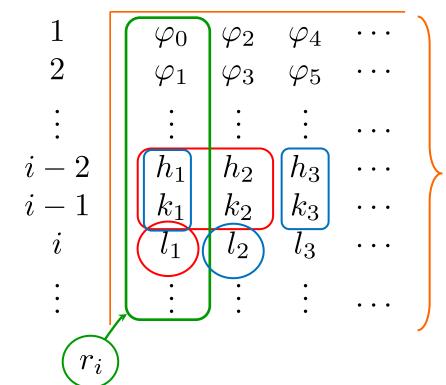


In the general case, a **necessary** and sufficient condition is needed

Routh Table

For a given system matrix A the characteristic polynomial $\varphi_A(s)$ is:

$$\varphi_A(s) = \varphi_0 s^n + \varphi_1 s^{n-1} + \dots + \varphi_{n-1} s + \varphi_n$$



 $\mathsf{maximum}\ n+1\ \mathsf{rows}$

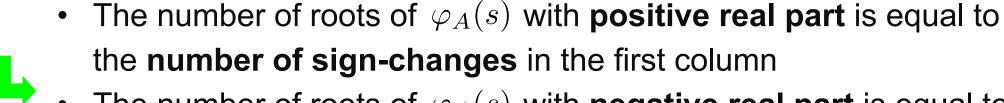
$$\begin{bmatrix}
l_1 \neq -\frac{1}{k_1} \det \begin{bmatrix} h_1 & h_2 \\ k_1 & k_2 \end{bmatrix} \end{bmatrix} \underbrace{l_2 \neq -\frac{1}{k_1}} \det \begin{bmatrix} h_1 & h_3 \\ k_1 & k_3 \end{bmatrix} \dots \quad l_j = -\frac{1}{k_1} \det \begin{bmatrix} h_1 & h_{j+1} \\ k_1 & k_{j+1} \end{bmatrix}$$

General Routh-Hurwitz Stability Criterion

Consider a given system matrix A and its characteristic polynomial $\varphi_A(s)$:

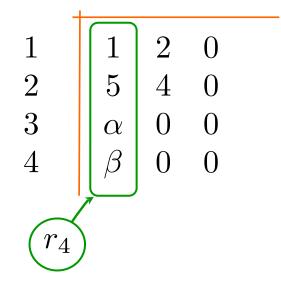
$$\varphi_A(s) = \varphi_0 s^n + \varphi_1 s^{n-1} + \dots + \varphi_{n-1} s + \varphi_n$$

- If the Routh Table cannot be completed no asymptotic stability
- If the Routh Table can be completed (n + 1 rows)



- The number of roots of $\varphi_A(s)$ with **negative real part** is equal to the **number of sign-permanencies** in the first column r_i
- No sign-changes in the first column r_i \longleftrightarrow asymptotic stability

$$\varphi_A(s) = s^3 + 5s^2 + 2s + 4$$



$$\alpha = -\frac{1}{5} \det \begin{bmatrix} 1 & 2 \\ 5 & 4 \end{bmatrix} = \frac{6}{5}$$

$$\beta = -\frac{1}{\alpha} \det \begin{bmatrix} 5 & 4 \\ \alpha & 0 \end{bmatrix} = 4$$



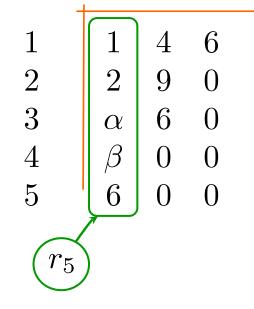
No sign-changes in r_4



asymptotic stability

Example 2

$$\varphi_A(s) = s^4 + 2s^3 + 4s^2 + 9s + 6$$



$$\alpha = -\frac{1}{2} \det \begin{bmatrix} 1 & 4 \\ 2 & 9 \end{bmatrix} = -\frac{1}{2}$$

$$\beta = -\frac{1}{\alpha} \det \begin{bmatrix} 2 & 9 \\ \alpha & 6 \end{bmatrix} = 33$$



Two sign-changes in r_5



instability

$$\varphi_A(s) = s^4 + 6s^3 + 11s^2 + 6s + K$$

1	1	11	K
2	6	6	0
3	10	K	0
4	$\mid \alpha \mid$	0	0
5	$\lfloor K \rfloor$	0	0
r_5			

$$\alpha = -\frac{1}{10} \det \begin{bmatrix} 6 & 6 \\ 10 & K \end{bmatrix} = \frac{3}{5} (10 - K)$$

If K > 0 and K < 10



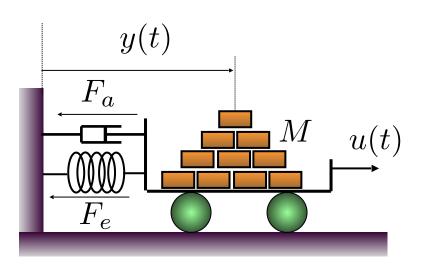
No sign-changes in r_5



asymptotic stability

Example 4

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$$\left\{ \begin{array}{l} x_1 := y \\ x_2 := \dot{y} \end{array} \right., \ x := \left[\begin{array}{l} x_1 \\ x_2 \end{array} \right]$$

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\frac{k}{M} x_1 - \frac{h}{M} x_2 + \frac{1}{M} u \\ y = x_1 \end{cases}$$

$$\dot{x} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{k}{M} & -\frac{h}{M} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \longrightarrow A = \begin{bmatrix} 0 & 1 \\ -\frac{k}{M} & -\frac{h}{M} \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ \frac{h}{M} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$



$$A = \begin{bmatrix} 0 & 1 \\ -\frac{k}{M} & -\frac{h}{M} \end{bmatrix}$$

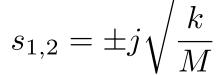
$$\varphi_A(s) = \det(sI - A) = \det\begin{bmatrix} s & -1 \\ \frac{k}{M} & s + \frac{h}{M} \end{bmatrix} = s^2 + \frac{h}{M}s + \frac{k}{M}$$

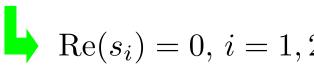
where $M>0, k\geq 0, h\geq 0$

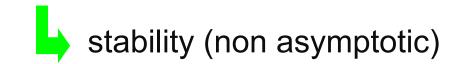
Example 4 (contd.)

- k > 0, h > 0Case 1 (both elastic and friction forces active):
 - $\operatorname{Re}(s_i) < 0, i = 1, 2$ asymptotic stability
- Case 2 (only elastic force active): k > 0, h = 0

$$\varphi_A(s) = s^2 + \frac{k}{M} \qquad \Longrightarrow \qquad s_{1,2} = \pm j\sqrt{\frac{k}{M}}$$







Case 3 (only friction force active): k = 0, h > 0

$$\varphi_A(s) = s^2 + \frac{h}{M}s \quad \Longrightarrow \quad s_1 = 0 \; ; \; s_2 = -\frac{h}{M}$$

Re
$$(s_1) = 0$$
, Re $(s_2) < 0$

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\frac{h}{M} x_2 \longrightarrow x_2(t) = x_{20} e^{-\frac{h}{M}t} \longrightarrow 0 \end{cases}$$

$$\downarrow \dot{x}_1 = x_{20} e^{-\frac{h}{M}t}$$



stability (non asymptotic)

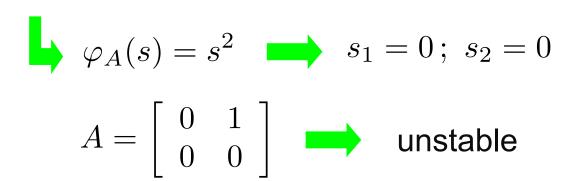
$$\dot{x}_1 = x_{20}e^{-\frac{h}{M}t}$$

$$x_1(t) = x_{10} + x_{20} \int_0^t e^{-\frac{h}{M}\tau} d\tau$$

$$= x_{10} - x_{20} \frac{M}{h} \left(e^{-\frac{h}{M}t} - 1 \right) \longrightarrow x_{10} + x_{20} \frac{M}{h}$$

Example 4 (contd.)

• Case 4 (no elastic nor friction force acting): $k=0,\ h=0$



$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = 0 \end{cases} \longrightarrow x_2(t) = x_{20}, \forall t$$

$$x(0) = \begin{bmatrix} x_{10} \\ x_{20} \end{bmatrix} \longrightarrow x_1(t) = x_{10} + x_{20}t \underset{t \to \infty}{\longrightarrow} \infty$$

Stability of Equilibrium of a Nonlinear System via the Linearised System

Imperial College London

Recall from Part 2:

Stability of equilibrium is a **local property** (see Definitions in Part 2, slide 3).



We can take advantage of the linearised system on the specific equilibrium state to analyse its stability

(contd.)

Main Result:

Denoting by s_i , i = 1, ..., n the eigenvalues of matrix A:

- (A) Re $(s_i) < 0$, i = 1, ..., n \bar{x} asymptotically stable equilibrium state
- (B) $\exists i \text{ such that } \operatorname{Re}(s_i) > 0 \implies \bar{x} \text{ unstable stable equilibrium state}$

(contd.)

Critical Case:

$$\operatorname{Re}(s_i) \leq 0, i = 1, \dots, n$$

 $\exists i \text{ such that } \operatorname{Re}(s_i) = 0$

 \bar{x} asymptotically stable equilibrium state

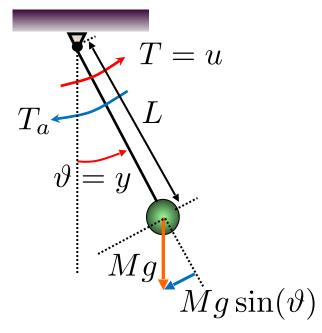
 \bar{x} stable equilibrium state

 $ar{x}$ unstable stable equilibrium state

In this case, <u>no decision</u> can be made on the stability of the equilibrium state based on the linearised system

Example

Recall from Part 2, slides 45, 46:



$$\begin{cases} x_1 := \vartheta \\ x_2 := \dot{\vartheta} \end{cases}, x := \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\begin{cases} \dot{x}_1 = \dot{\vartheta} = x_2 \\ \dot{x}_2 = -\frac{MgL}{J} \sin(x_1) - \frac{h}{J} x_2 + \frac{1}{J} u \\ y = x_1 \end{cases}$$

$$u(t) = \bar{u} = 0, \forall t$$

$$u(t) = \bar{u} = 0, \forall t \qquad \qquad \begin{cases} 0 = x_2 \\ 0 = -\frac{MgL}{J} \sin(x_1) - \frac{h}{J} x_2 \end{cases}$$

We pick the two "physical" solutions:

$$\begin{cases} \bar{x}_2 = 0 \\ \sin(\bar{x}_1) = \frac{1}{MqL} \bar{u} \end{cases} \longrightarrow \begin{cases} \bar{x}_2 = 0 \\ \bar{x}_1 = k\pi, \ \forall k \in \mathbb{Z} \end{cases}$$

$$\begin{cases} \bar{x}_2 = 0 \\ \bar{x}_1 = k\pi, \ \forall k \in \mathbb{Z} \end{cases}$$

$$\bar{x} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \; ; \; \tilde{x} = \begin{bmatrix} \pi \\ 0 \end{bmatrix}$$

Example (contd.)

The state matrices of the linearised system on the two equilibrium states are:

$$f_x(\bar{x}, \bar{u}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \\ \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_2} \end{bmatrix}_{\bar{x}, \bar{u}} = \begin{bmatrix} 0 & 1 \\ -\frac{MgL}{J}\cos(x_1) & -\frac{h}{J} \end{bmatrix}_{\bar{x}, \bar{u}} = \begin{bmatrix} 0 & 1 \\ -\frac{MgL}{J} & -\frac{h}{J} \end{bmatrix} = \bar{A}$$



$$f_x(\tilde{x}, \bar{u}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix}_{\tilde{x}, \bar{u}} = \begin{bmatrix} 0 & 1 \\ -\frac{MgL}{J}\cos(x_1) & -\frac{h}{J} \end{bmatrix}_{\tilde{x}, \bar{u}} = \begin{bmatrix} 0 & 1 \\ +\frac{MgL}{J} & -\frac{h}{J} \end{bmatrix} = \tilde{A}$$

