


Today (July 16th, 2020) :

- Recap State-space representation and equilibrium points
- Linearization of non-linear Systems

Yesterday:

We introduced general State model:

$$\left\{ \begin{array}{l} \dot{x}_1(t) = f_1(x_1(t), \dots, x_n(t), u_1(t), \dots, u_m(t)) \\ \vdots \\ \dot{x}_n(t) = f_n(x_1(t), \dots, x_n(t), u_1(t), \dots, u_m(t)) \end{array} \right.$$

Or, more compactly:

$$\dot{x}(t) = f(x(t), u(t))$$

$$x(t) \in X$$

$$u(t) \in U$$

Often

$$X = \mathbb{R}^n$$

$$U = \mathbb{R}^m$$

Typically when written in this form, state and control spaces are defined if not clear from context

When the system is Linear

$$\dot{x}(t) = \underbrace{\begin{matrix} A & x(t) \\ n \times n & \end{matrix}}_{\uparrow} + \underbrace{\begin{matrix} B & u(t) \\ n \times m & \end{matrix}}_{\uparrow}$$

Equilibrium Points:

For systems with no inputs

$$\dot{x}(t) = f(x(t))$$

Set of all equilibrium points

$$X_{\text{eq}} := \{x \in X \mid f(x) = 0\}$$

For systems with inputs

$$\dot{x}(t) = f(x(t), u(t))$$

Assume a constant input $u \in U$

$$X_{\text{eq}}(u) := \{x \in X \mid f(x, u) = 0\}$$

For linear systems:

$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$X_{\text{eq}}(u) := \{x \in X \mid Ax + Bu = 0\}$$

- IF A is invertible, for each input u , there is a unique equilibrium point, $X = -A^{-1}Bu$

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- If A is not invertible:

1. No equilibria exist

2. If Bu is in the column space of A , there exist a continuum of equilibria for that particular input u .

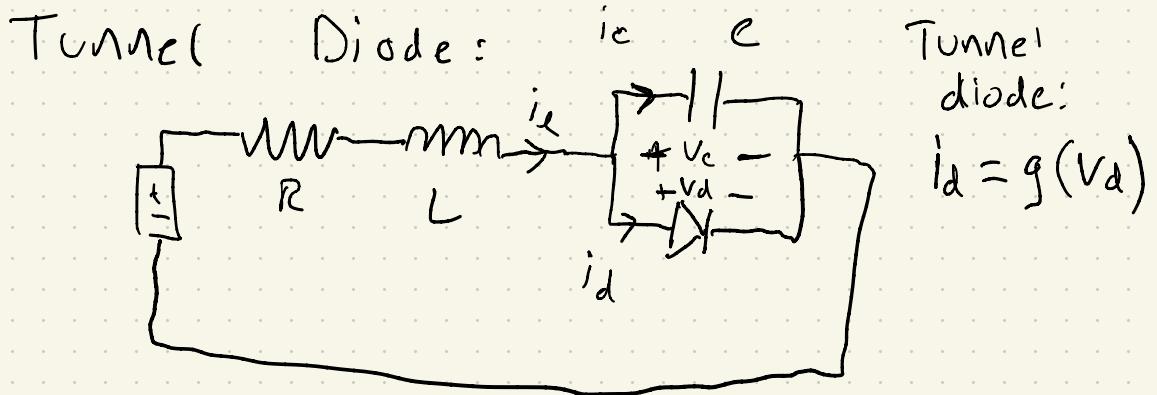
$$A = \begin{bmatrix} | & | & | \\ u_1 & u_2 & \dots \\ | & | & | \end{bmatrix} \begin{bmatrix} \vdots \\ \sigma_1 & \dots & \sigma_r \\ \vdots & \dots & \sigma_n \\ | & \dots & | \end{bmatrix} \begin{bmatrix} -v_1^T \\ \vdots \\ -v_r^T \\ | & \dots & | \\ -v_n^T \end{bmatrix}$$

$U \qquad S \qquad V^T$

First "r" columns of U in SVD of A form orthonormal basis for the column space of A

- Isolated equilibria for linear systems can not exist

* Fully characterize the equilibria for linear systems *



Tunnel diode:
 $i_d = g(V_d)$

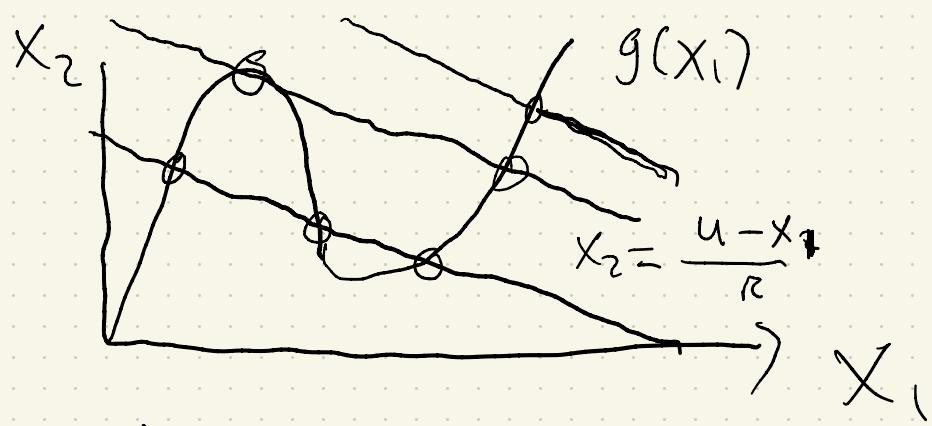
$$C \frac{dV_C(t)}{dt} = i_C(t) = i_L(t) - i_d(t) = i_L(t) - g(V_d)$$

$$L \frac{di_L(t)}{dt} = V_L(t) = -V_C - R i_L(t) + V_{in}(t)$$

$$X(t) := \begin{bmatrix} V_C(t) \\ i_L(t) \end{bmatrix} \quad U(t) := V_{in}(t)$$

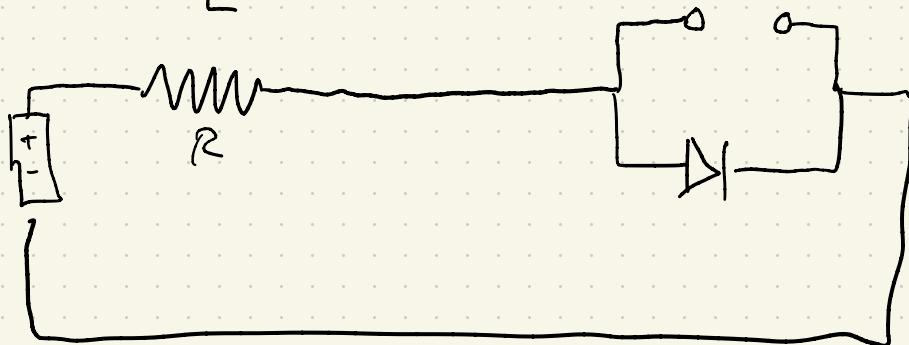
$$\dot{X}(t) = \begin{bmatrix} \underline{\frac{X_2(t) - g(X_1(t))}{C}} \\ \underline{\frac{1}{L}(-X_1(t) - RX_2(t) + U(t))} \end{bmatrix}$$

$$X_{eq}(u) := \left\{ X \mid \begin{array}{l} X_2 = g(X_1) \\ X_2 = \frac{u - X_1}{R} \end{array} \right\}$$



$$\frac{dV_C}{dt} = \frac{i_C}{C} = 0$$

$$\frac{di_L}{dt} = \frac{V_L}{L} = 0$$



Linearization

So far we have seen that linear systems have some nice properties

- Equilibria can be fully characterized
- Analytic Solutions to linear differential equations can be found
- easy-to-characterize Stability properties
- easy to design controllers for

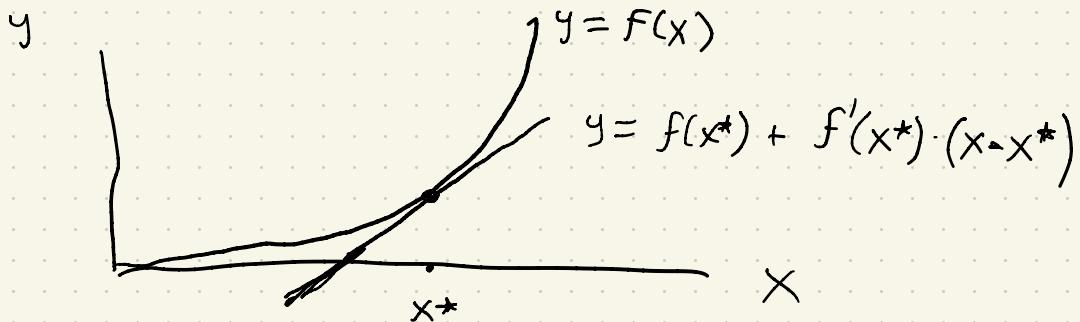
Non-linear systems do not share these properties in general

- ★ It is very useful to form a linear approximation of a non-linear system around points of interest and analyze the resultant linear system

Recall:

First-order Taylor approximation of a function $f(x)$

$$f(x) \approx f(x^*) + \nabla f(x^*) \cdot (x - x^*)$$



$$\nabla f := \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \cdots & \frac{\partial f_n}{\partial x_n} \end{bmatrix}$$

"Jacobian Matrix"

$\dot{x}(t) = f(x(t))$, let x^* be
a point we wish
to linearize around

$$\dot{x}(+) \approx f(x^*) + \nabla f(x^*)(x(+)-x^*)$$

Define $\delta x(+) := (x(+)-x^*)$

$$\dot{\delta x}(+) = \dot{x}(+) - \dot{x}^* \approx f(x^*) + \nabla f(x^*) \delta x(+)$$

$$\dot{\delta x}(+) \approx \underline{f(x^*) + \nabla f(x^*) \delta x(+)}$$

If x^* is an equilibrium point: $f(x^*) = 0$

$$\dot{\delta x}(+) \approx A \delta x(+)$$

$$A = \nabla f(x^*)$$

Now with inputs:

$$\dot{\bar{X}}(t) = f(x(t), u(t))$$

consider linearization (\bar{x}^*, \bar{u}^*)

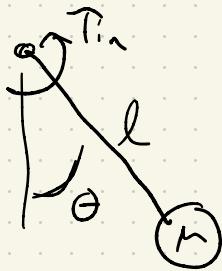
$$\begin{aligned}\dot{\bar{X}}(t) \approx & f(\bar{x}^*, \bar{u}^*) + \nabla_x f(\bar{x}^*, \bar{u}^*) \delta x(t) \\ & + \nabla_u f(\bar{x}^*, \bar{u}^*) \delta u(t)\end{aligned}$$

where $\delta x(t) := (x(t) - \bar{x}^*)$
 $\delta u(t) := (u(t) - \bar{u}^*)$

$$\nabla_x f := \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \dots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} \leftarrow n \times n$$

$$\nabla_u f := \begin{bmatrix} \frac{\partial f_1}{\partial u_1} & \dots & \frac{\partial f_1}{\partial u_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial u_1} & \dots & \frac{\partial f_n}{\partial u_m} \end{bmatrix} \leftarrow n \times m$$

$$\begin{aligned}\delta \dot{\bar{X}}(t) \approx & A \delta x(t) + B \delta u(t) \\ \nabla_x f(\bar{x}^*, \bar{u}^*) & \quad \nabla_u f(\bar{x}^*, \bar{u}^*)\end{aligned}$$



$$x(t) = \begin{bmatrix} \theta(t) \\ \dot{\theta}(t) \end{bmatrix} \quad u(t) = \ddot{\theta}(t)$$

$$\ddot{x}(t) = \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} x_2(t) \\ -\frac{k}{m}x_2(t) - \frac{g}{l}\sin x_1(t) + \frac{u(t)}{ml} \end{bmatrix}$$

Two equilibria

downward:

$$x_1^* = 0$$

$$x_2^* = 0$$

$$u^* = 0$$

Upward:

$$x_1 = \pi$$

$$x_2 = 0$$

$$u = 0$$

$$\nabla_x f(x^*, u^*) \equiv$$

$$\begin{bmatrix} 0 & 1 \\ -g/l & -k/m \end{bmatrix}$$

$$\nabla_x f = \begin{bmatrix} 0 & 1 \\ g/l & -k/m \end{bmatrix}$$

$$\nabla_u f(x^*, u^*) = \begin{bmatrix} 0 \\ 1/m \end{bmatrix}$$

$$\nabla_u f = \begin{bmatrix} 0 \\ -1/m \end{bmatrix}$$

$$g = 10, \quad l = 1, \quad m = 1, \quad k = 0.1$$

Eigenvalues of $\nabla_x f$:

$$\lambda = -0.05 \pm 3.162 i$$

$$\lambda = \begin{cases} 3.1127 \\ -3.2127 \end{cases}$$