

Singular A Matrix

if A_i singular

① Make A_i Non-singular

↗ change circuit model

↘ change A_i directly to make it more stable

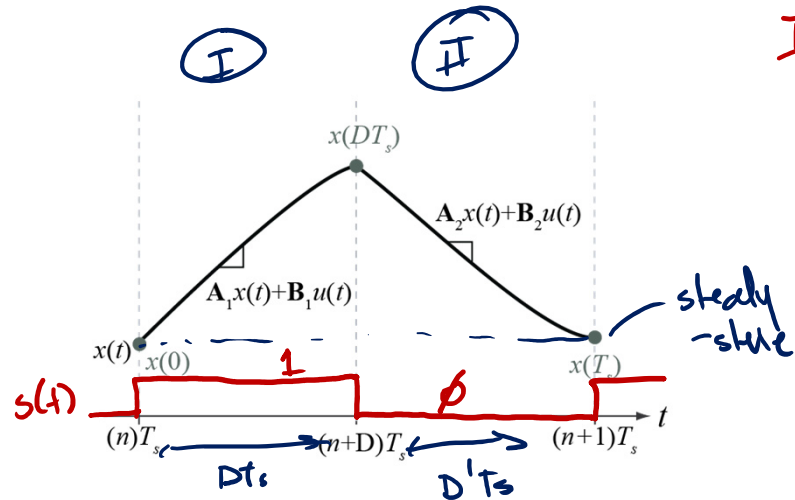
② calculate $x(t)$ a
different way

↗ numerically calculate convolution integral

↘ Augmented state space

Application to Switching Converters

In both **I** & **II** converter is modeled by LTI subinterval

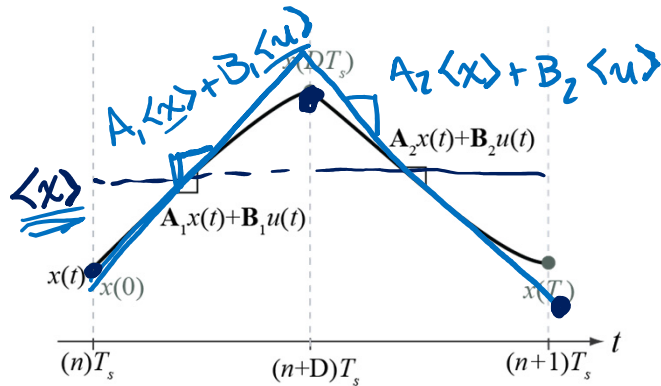


$$\text{Define } s(t) = \begin{cases} 0 & (n+D)T_s < t < (n+1)T_s \\ 1 & nT_s < t < nT_s + DT_s \end{cases}$$

$$\dot{x}(t) = \underbrace{\left[A_1 s(t) + A_2 (1-s(t)) \right]}_{A_{eq}(t)} x(t) + \left[B_1 s(t) + B_2 (1-s(t)) \right] u(t)$$

$$\dot{x}(t) = A_{eq}(t) x(t) + B_{eq}(t) u(t) \rightarrow \text{time-varying system}$$

State Space Averaging



lets just average the two state spaces together

$$A_{av} = \underline{DA_1 + D'A_2}$$

$$B_{av} = \underline{DB_1 + D'B_2}$$

$$\langle \dot{x} \rangle_{T_s} = A_{av} \langle x \rangle_{T_s} + B_{av} \langle u \rangle_{T_s}$$

In steady-state $\langle \dot{x} \rangle_{av} = \phi$

so, in steady-state

$$\phi = A_{av} \langle x \rangle + B_{av} \langle u \rangle$$

$$\langle x \rangle = -A_{av}^{-1} B_{av} \langle u \rangle$$

$$\langle x \rangle = - \left(\sum_{i=1}^k A_i \frac{t_i}{T_s} \right)^{-1} \left(\sum_{i=1}^k B_i \frac{t_i}{T_s} \right) \langle u \rangle$$

for k switching subintervals

Exact Solution

in ① $x(DTs) = e^{A_1 DTs} x_0 + A_1^{-1} (e^{A_1 DTs} - I) B_1 u$

then, in ② $x(Ts) = e^{A_2 DTs} x(DTs) + A_2^{-1} (e^{A_2 DTs} - I) B_2 u$

then, combining both

$$x(Ts) = e^{A_2 DTs} \left[e^{A_1 DTs} x_0 + A_1^{-1} (e^{A_1 DTs} - I) B_1 u \right] + A_2^{-1} (e^{A_2 DTs} - I) B_2 u$$

$$x(Ts) = e^{A_2 DTs} e^{A_1 DTs} x_0 + e^{A_2 DTs} A_1^{-1} (e^{A_1 DTs} - I) B_1 u + A_2^{-1} (e^{A_2 DTs} - I) B_2 u$$

for k subintervals

$$x(Ts) = \prod_{i=k}^1 (e^{A_i t_i}) x_0 + \sum_{i=1}^k \left[\prod_{j=h}^{i+1} e^{A_j t_j} \right] A_i^{-1} (e^{A_i t_i} - I) B_i u_i$$

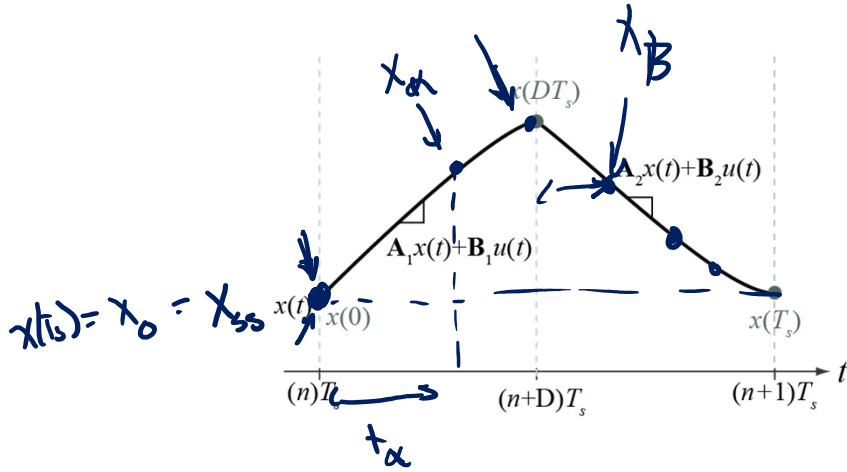
Steady-State Solution

in steady-state

$$x(T_s) = x_0 = x_{ss}$$

$$\underline{x_{ss}} = \left(\mathbf{I} - \prod_{i=h}^1 e^{A_i t_i} \right)^{-1} \sum_{i=1}^h \left[\prod_{j=h}^{i+1} e^{A_j t_j} \right] A_i^{-1} (e^{A_i t_i} - \mathbf{I}) B_i u_i$$

Waveform Reconstruction



$$x_\alpha = e^{A_i t_\alpha} x_{ss} + A_i^{-1} (e^{A_i t_\alpha} - I) B_i u$$

can reconstruct states at any time point by re-applying solution

Comparison to Averaging

$$X_{ss} = \left(\mathbf{I} - \prod_{i=k} e^{A_i t_i} \right)^{-1} \sum_{i=1}^k \left(\prod_{j=k}^{i+1} e^{A_j t_j} \right) A_i^{-1} \left(e^{A_i t_i} - \mathbf{I} \right) B_i u$$

If we let $e^{A_i t_i} \approx \mathbf{I} + A_i t_i$

$$X_{ss} = \left(\mathbf{I} - \left(\mathbf{I} + A_1 t_1 + A_2 t_2 + \dots + A_1 t_1 A_2 t_2 + A_1 t_1 A_3 t_3 + \dots \right) \right)^{-1} \dots$$

$$\cdot \sum_{i=1}^k \left(\prod_{j=k}^{i+1} e^{A_j t_j} \right) A_i^{-1} \left(\mathbf{I} + A_i t_i - \mathbf{I} \right) B_i u$$

$$\sum_{i=1}^k \left(\prod_{j=k}^{i+1} e^{A_j t_j} \right) \cdot B_i t_i u$$

Also neglect any terms with two $A_k t_k$ factors
 & eliminate the product term in the forced response

$$X_{ss} = - \left(\sum_{i=1}^k A_i t_i \right)^{-1} \left(\sum_{i=1}^k B_i t_i \right) u = \langle X_{av} \rangle \rightarrow \text{same as state space averaging}$$