

Introduction to Simulation - Lecture 15

Methods for Computing Periodic Steady-State

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Thanks to Deepak Ramaswamy, Michal Rewienski, and
Karen Veroy

Outline

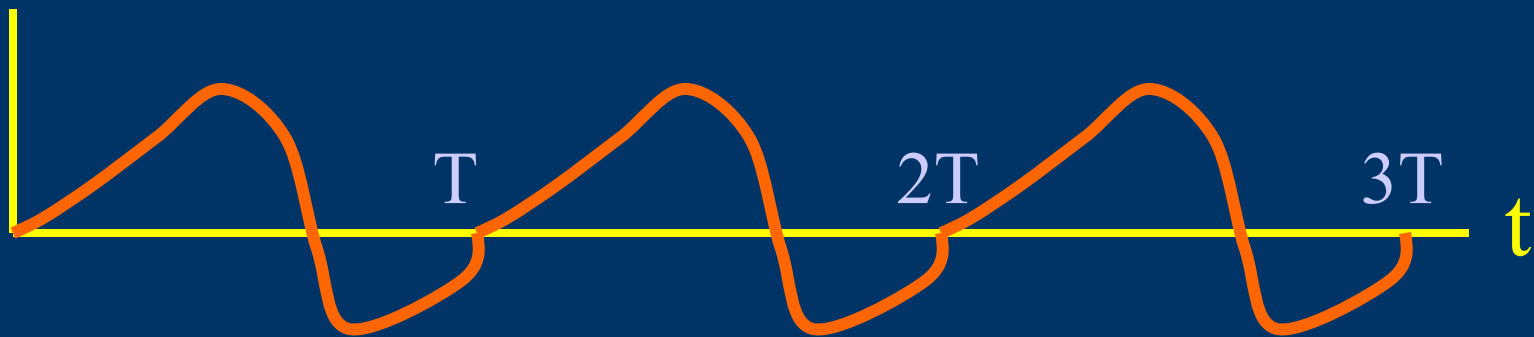
- Periodic Steady-state problems
 - Application examples and simple cases
- Finite-difference methods
 - Formulating large matrices
- Shooting Methods
 - State transition function
 - Sensitivity matrix
- Matrix Free Approach

Periodic Steady-State Basics

Basic Definition

$$\frac{dx(t)}{dt} = F \left(\underbrace{x(t)}_{\text{state}} + \underbrace{u(t)}_{\text{input}} \right)$$

- Suppose the system has a periodic input



- Many Systems eventually respond periodically

$$x(t+T) = x(t) \quad \text{for } t \gg 0$$

- If x satisfies a differential equation which has a unique solution for any initial condition

$$\frac{dx(t)}{dt} = F(x(t)) + u(t)$$

- Then if u is periodic with period T and
 $x(t_0 + T) = x(t_0)$ for some t_0
 $\Rightarrow x(t + T) = x(t)$ for all $t > t_0$

Swaying Bridge

- Periodic Input
 - Wind
- Response
 - Oscillating Platform
- Desired Info
 - Oscillation Amplitude

Periodic Steady-State Basics

Application Examples

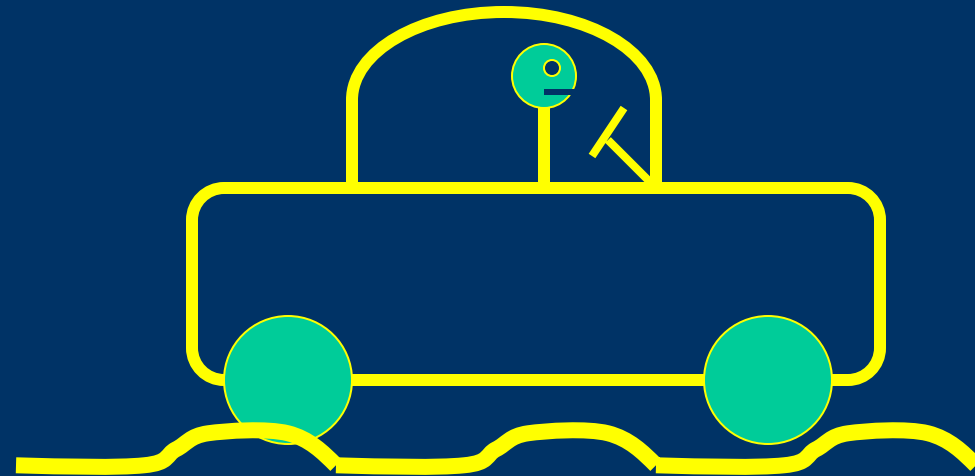
Communication Integrated Circuit

- Periodic Input
 - Received Signal at 900Mhz
- Response
 - filtered demodulated signal
- Desired Info
 - Distortion

Periodic Steady-State Basics

Application Examples

Automobile Vibration



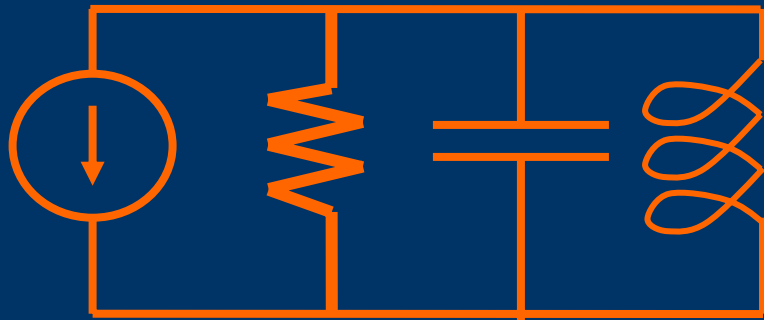
- **Periodic Input**
 - Regularly Spaced Road Bumps
- **Response**
 - Car Shakes
- **Desired Info**
 - Shake amplitude

Periodic Steady-State Basics

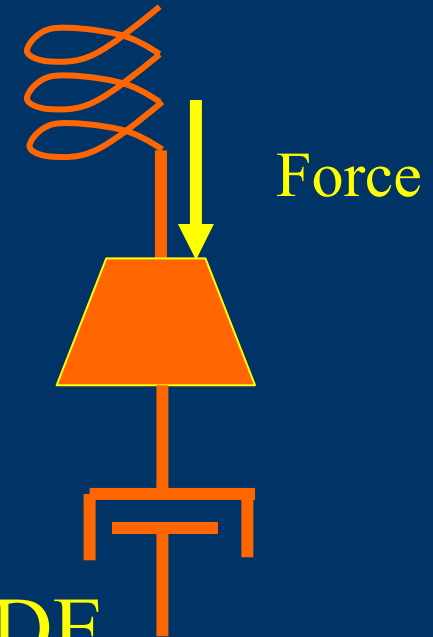
Simple Example

RLC Filter,
Spring+Mass+Dashpot

RLC Circuit



Spring-Mass-Dashpot



- Both Described by Second-Order ODE

$$M \frac{d^2 x}{dt^2} + D \frac{dx}{dt} + x = \underbrace{u(t)}_{input}$$

Periodic Steady-State Basics

Simple Example

RLC Filter,
Spring+Mass+Dashpot Cont.

- Both Described by Second-Order ODE

$$M \frac{d^2 x}{dt^2} + D \frac{dx}{dt} + x = u(t)$$

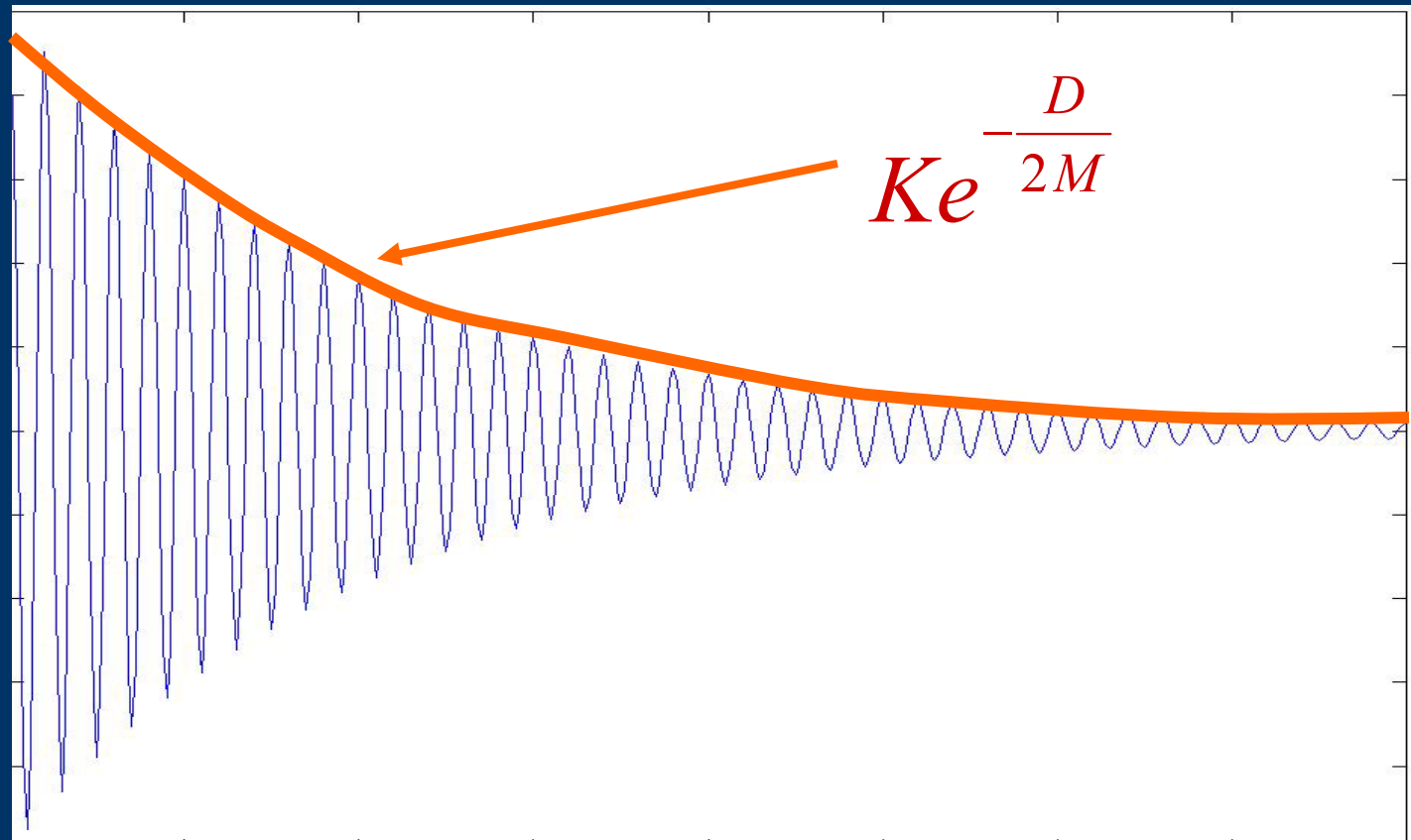
- $u(t) = 0$ lightly damped ($D \ll M$) Response

$$x(t) \approx K e^{-\frac{D}{2M} t} \cos\left(\frac{t}{\sqrt{M}} + \phi\right)$$

Periodic Steady-State Basics

Simple Example

RLC Filter,
Spring+Mass+Dashpot Cont.



- A lightly damped system oscillates many times before settling to a steady-state

- Sinusoidally excited linear time-invariant system

$$\frac{dx(t)}{dt} = Ax(t) + \underbrace{e^{i\omega t}}_{\text{input}}$$

- Steady-State Solution simple to determine

$$x(t) = (i\omega - A)^{-1} e^{i\omega t}$$

Not useful for nonlinear or time-varying systems

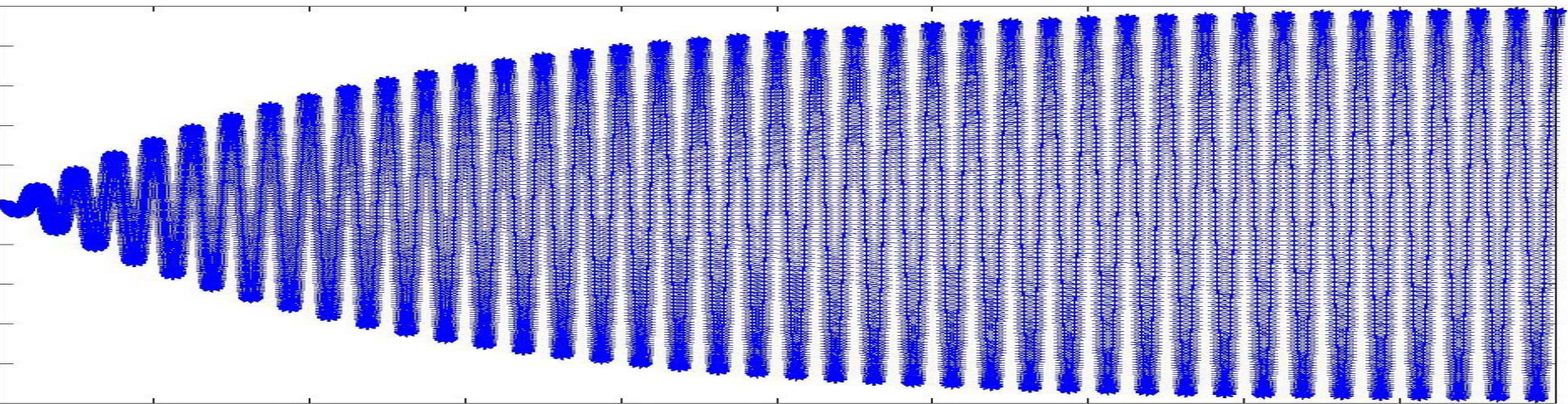
Periodic Steady-State Basics

Time Integration Method

- Time-Integrate Until Steady-State Achieved

$$\frac{dx(t)}{dt} = F(x(t)) + u(t) \Rightarrow \hat{x}^l = \hat{x}^{l-1} + \Delta t \left(F(\hat{x}^l) + u(l\Delta t) \right)$$

- Need many timepoints for lightly damped case!



Aside Reviewing Integration Methods

Solve with Backward-Euler

- Nonlinear System

$$\frac{dx(t)}{dt} = F \left(\underbrace{x(t)}_{\text{state}} \right) + \underbrace{u(t)}_{\text{input}} \quad \underbrace{x(0) = x_0}_{\text{Initial Condition}}$$

- Backward Euler Equation for timestep l

$$\hat{x}^l - \hat{x}^{l-1} = \Delta t \left(F \left(\hat{x}^l \right) + u(l\Delta t) \right)$$

How do we solve the backward-Euler Equation?

Aside Reviewing Integration Methods

Implicit Methods

Backward-Euler Example

Forward-Euler

$$x(t_1) \square \hat{x}^1 = x(0) + \Delta t f(x(0), u(0))$$

$$x(t_2) \square \hat{x}^2 = \hat{x}^1 + \Delta t f(\hat{x}^1, u(t_1))$$

⋮

$$x(t_L) \square \hat{x}^L = \hat{x}^{L-1} + \Delta t f(\hat{x}^{L-1}, u(t_{L-1}))$$

Requires just function
Evaluations

Backward-Euler

$$x(t_1) \square \hat{x}^1 = x(0) + \Delta t f(\hat{x}^1, u(t_1))$$

$$x(t_2) \square \hat{x}^2 = \hat{x}^1 + \Delta t f(\hat{x}^2, u(t_2))$$

⋮

$$x(t_L) \square \hat{x}^L = \hat{x}^{L-1} + \Delta t f(\hat{x}^L, u(t_L))$$

Nonlinear equation
solution at each step

Stepwise Nonlinear equation solution needed whenever $\beta_0 \neq 0$

Aside Reviewing Integration Methods

Implicit Methods

Solution with Newton

Rewrite the multistep Equation

$$\alpha_0 \hat{x}^l - \Delta t \beta_0 f(\hat{x}^l, u(t_l)) + \underbrace{\sum_{j=1}^k \alpha_j \hat{x}^{l-j} - \Delta t \sum_{j=1}^k \beta_j f(\hat{x}^{l-j}, u(t_{l-j}))}_{b} = 0$$

Solve with Newton

b Independent of \hat{x}^l

$$\underbrace{\left(\alpha_0 I - \Delta t \beta_0 \frac{\partial f(\hat{x}^{l,j}, u(t_l))}{\partial x} \right)}_{\text{Jacobian}} (\hat{x}^{l,j+1} - \hat{x}^{l,j}) = - \underbrace{\left(\alpha_0 \hat{x}^{l,j} - \Delta t \beta_0 f(\hat{x}^{l,j}, u(t_l)) + b \right)}_{F(x^{l,j})}$$

Here j is the Newton iteration index

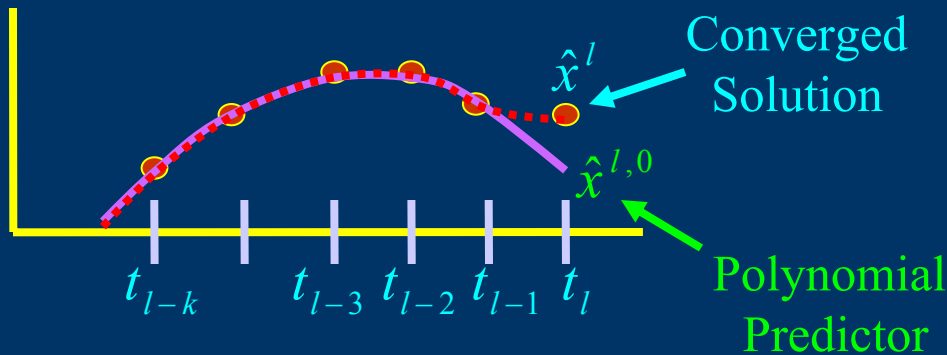
Aside Reviewing Integration Methods

Implicit Methods

Solution with Newton Cont.

Newton Iteration:
$$\left(\alpha_0 I - \Delta t \beta_0 \frac{\partial f(\hat{x}^{l,j}, u(t_l))}{\partial x} \right) (\hat{x}^{l,j+1} - \hat{x}^{l,j}) = -F(x^{l,j})$$

Solution with Newton is very efficient



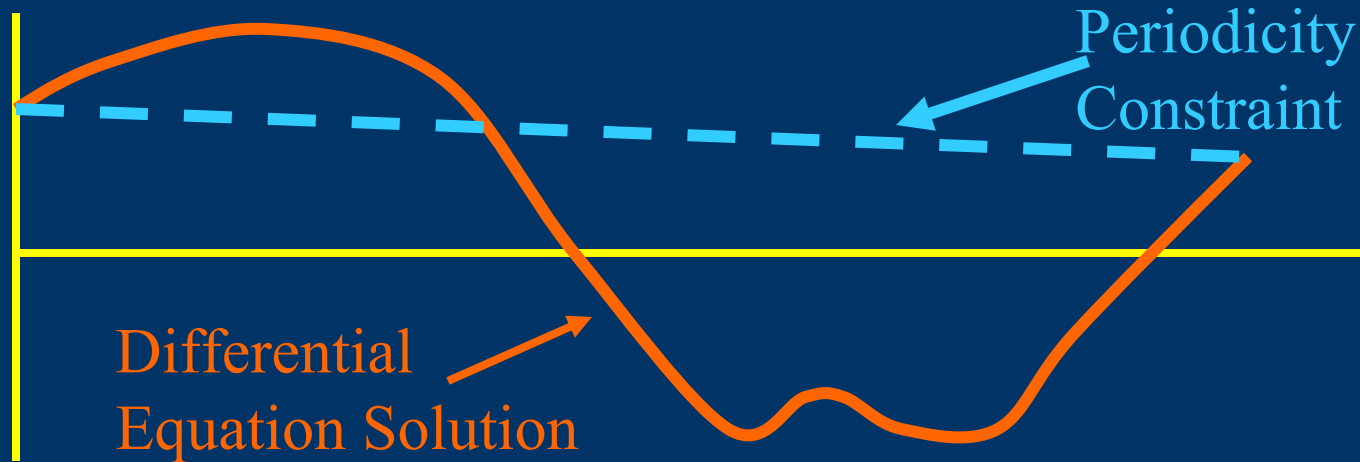
Easy to generate a good initial guess using polynomial fitting

$$\alpha_0 I - \Delta t \beta_0 \frac{\partial f(\hat{x}^{l,j}, u(t_l))}{\partial x} \Rightarrow \alpha_0 I \text{ as } \Delta t \rightarrow 0$$

Jacobian become easy to factor for small timesteps

Boundary-Value Problem

Basic Formulation



N Differential Equations:
$$\frac{d}{dt} x_i(t) = F_i(x(t))$$

N Periodicity Constraints:
$$x_i(T) = x_i(0)$$

Boundary-Value Problem

Finite Difference Methods

Linear Example Problem

$$\frac{dx(t)}{dt} = Ax(t) + \underbrace{u(t)}_{\text{input}} \quad t \in [0, T] \quad \underbrace{x(T) = x(0)}_{\text{periodicity constraint}}$$

Discretize with Backward-Euler

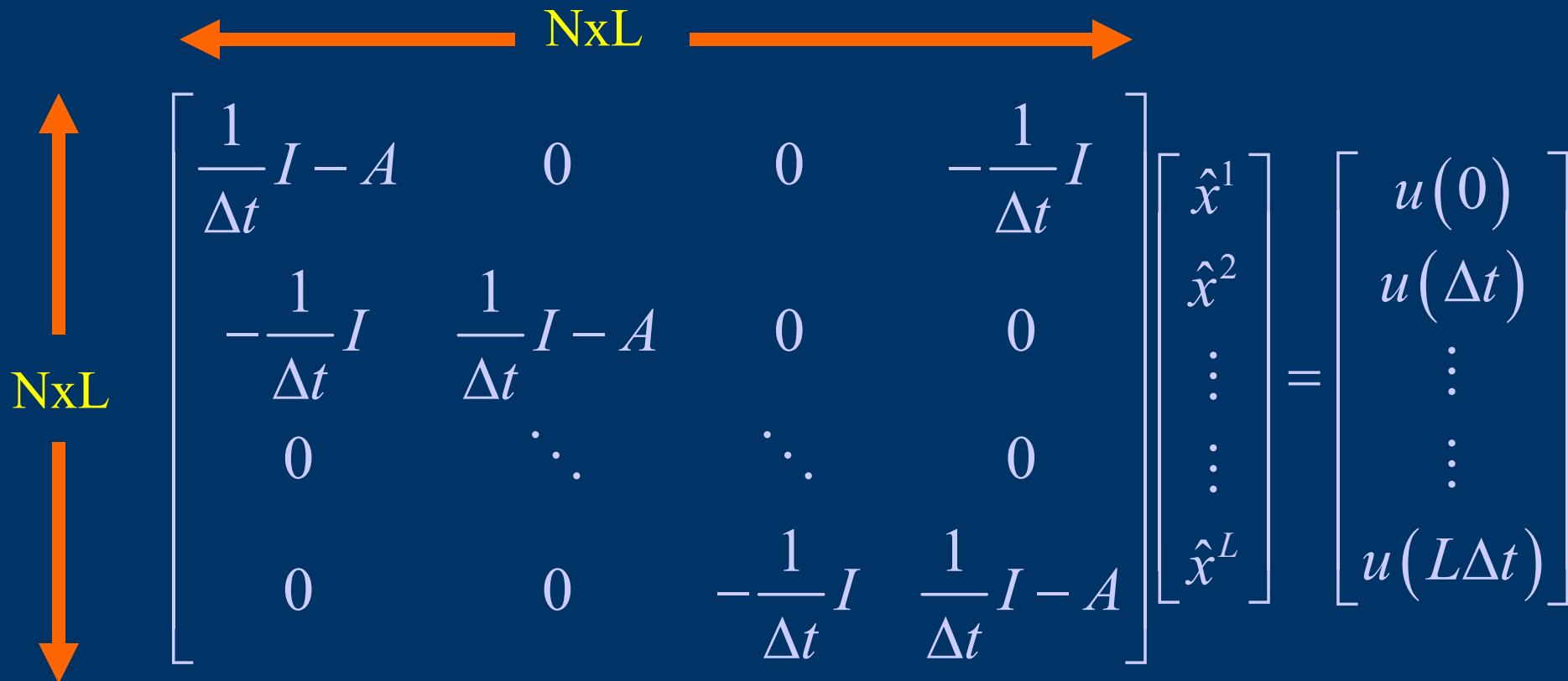
$$\begin{aligned} \hat{x}^1 &= \hat{x}^0 + \Delta t \left(A\hat{x}^1 + u(\Delta t) \right) \\ \hat{x}^2 &= \hat{x}^1 + \Delta t \left(A\hat{x}^2 + u(2\Delta t) \right) \\ &\vdots \\ \hat{x}^L &= \hat{x}^{L-1} + \Delta t \left(A\hat{x}^L + u(L\Delta t) \right) \end{aligned} \quad \Delta t = \frac{T}{L}$$

Periodicity implies $\hat{x}^L = \hat{x}^0$

Boundary-Value Problem

Finite Difference Methods

Linear Example Matrix Form


$$\begin{array}{c} \text{← } N \times L \text{ →} \\ \begin{array}{c} \text{↑ } N \times L \\ \text{↓ } N \times L \end{array} \end{array} \begin{bmatrix} \frac{1}{\Delta t} I - A & 0 & 0 & -\frac{1}{\Delta t} I \\ -\frac{1}{\Delta t} I & \frac{1}{\Delta t} I - A & 0 & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & 0 & -\frac{1}{\Delta t} I & \frac{1}{\Delta t} I - A \end{bmatrix} \begin{bmatrix} \hat{x}^1 \\ \hat{x}^2 \\ \vdots \\ \hat{x}^L \end{bmatrix} = \begin{bmatrix} u(0) \\ u(\Delta t) \\ \vdots \\ u(L\Delta t) \end{bmatrix}$$

Matrix is almost lower triangular

Boundary-Value Problem

Finite Difference Methods

Nonlinear Problem

$$\frac{dx(t)}{dt} = F(x(t)) + \underbrace{u(t)}_{\text{input}} \quad t \in [0, T] \quad \underbrace{x(T) = x(0)}_{\text{periodicity constraint}}$$

Discretize with Backward-Euler

$$H_{FD} \begin{pmatrix} \hat{x}^1 \\ \hat{x}^2 \\ \vdots \\ \hat{x}^L \end{pmatrix} = \begin{pmatrix} \hat{x}^1 - \hat{x}^L - \Delta t \left(F(\hat{x}^1) + u(\Delta t) \right) \\ \hat{x}^2 - \hat{x}^1 - \Delta t \left(F(\hat{x}^2) + u(2\Delta t) \right) \\ \vdots \\ \hat{x}^L - \hat{x}^{L-1} - \Delta t \left(F(\hat{x}^L) + u(L\Delta t) \right) \end{pmatrix} = \mathbf{0}$$

Solve Using Newton's Method

Boundary-Value Problem

Shooting Method

Basic Definitions

Start with $\frac{dx(t)}{dt} = F(x(t)) + u(t)$

And assume $x(t)$ is unique given $x(0)$.

D.E. defines a State-Transition Function

$$\Phi(y, t_0, t_1) \equiv x(t_1)$$

where $x(t)$ is the D.E. solution given $x(t_0) = y$

Boundary-Value Problem

Shooting Method

State Transition function Example

$$\frac{dx(t)}{dt} = \lambda x(t)$$

$$\Phi(y, t_0, t_1) \equiv e^{\lambda(t_1 - t_0)} y$$

Boundary-Value Problem

Shooting Method

Abstract Formulation

Solve

$$H(x(0)) = \underbrace{\Phi(x(0), 0, T)}_{x(T)} - x(0) = 0$$

Use Newton's method

$$J_H(x) = \frac{\partial \Phi(x, 0, T)}{\partial x} - I$$

$$J_H(x^k)(x^{k+1} - x^k) = -H(x^k)$$

Boundary-Value Problem

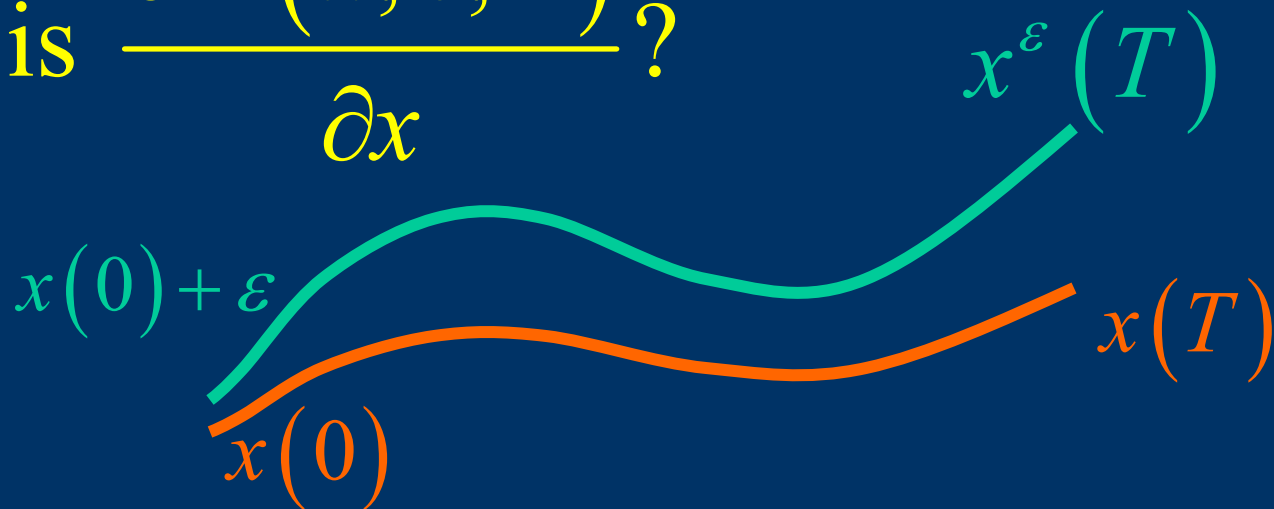
Shooting Method

Computing Newton

To Compute $\Phi(x(0), 0, T)$

Integrate $\frac{dx(t)}{dt} = F(x(t)) + u(t)$ on $[0, T]$

What is $\frac{\partial \Phi(x, 0, T)}{\partial x}$?



Indicates the sensitivity of $x(T)$ to changes in $x(0)$

Boundary-Value Problem

Shooting Method

Sensitivity Matrix by Perturbation

$$\frac{\partial \Phi(x, 0, T)}{\partial x} \approx$$

$$\begin{bmatrix} \frac{x_1^{\varepsilon_1}(T) - x_1(T)}{\varepsilon_1} & \dots & \dots & \frac{x_1^{\varepsilon_N}(T) - x_1(T)}{\varepsilon_N} \\ \vdots & \dots & \dots & \vdots \\ \vdots & \dots & \dots & \vdots \\ \frac{x_N^{\varepsilon_1}(T) - x_N(T)}{\varepsilon_1} & \dots & \dots & \frac{x_N^{\varepsilon_N}(T) - x_N(T)}{\varepsilon_N} \end{bmatrix}$$

Boundary-Value Problem

Shooting Method

Efficient Sensitivity Evaluation

Differentiate the first step of Backward-Euler

$$\frac{\partial}{\partial x(0)} \left(\hat{x}^1 - x(0) - \Delta t \left(F(\hat{x}^1) + u(\Delta t) \right) = 0 \right)$$
$$\Rightarrow \frac{\partial \hat{x}^1}{\partial x(0)} - \frac{\partial x(0)}{\partial x(0)} - \Delta t \frac{\partial F(\hat{x}^1)}{\partial x} \frac{\partial \hat{x}^1}{\partial x(0)} = 0$$
$$\Rightarrow \left(I - \Delta t \frac{\partial F(\hat{x}^1)}{\partial x} \right) \frac{\partial \hat{x}^1}{\partial x(0)} = \cancel{\frac{\partial x(0)}{\partial x(0)}} I$$

Applying the same trick on the l -th step

$$\Rightarrow \left(I - \Delta t \frac{\partial F(\hat{x}^l)}{\partial x} \right) \frac{\partial \hat{x}^l}{\partial x(0)} = \frac{\partial \hat{x}^{l-1}}{\partial x(0)}$$

$$\frac{\partial \Phi(x, 0, T)}{\partial x} \approx \prod_{l=1}^L \left(I - \Delta t \frac{\partial F(\hat{x}^l)}{\partial x} \right)^{-1}$$

Boundary-Value Problem

Shooting Method

Observations on Sensitivity Matrix

Newton at each timestep uses same matrices

$$\frac{\partial \Phi(x, 0, T)}{\partial x} \approx \prod_{l=1}^L \underbrace{\left(I - \Delta t \frac{\partial F(\hat{x}^l)}{\partial x} \right)^{-1}}_{\substack{\text{Timestep Newton} \\ \text{Jacobian}}}$$

Formula simplifies in the linear case

$$\frac{\partial \Phi(x, 0, T)}{\partial x} \approx \left(I - \Delta t A \right)^{-L}$$

Shooting Method

Matrix-Free Approach

Basic Setup

Start with $\frac{dx(t)}{dt} = F(x(t)) + u(t)$

$$H(x(0)) = \Phi(x(0), 0, T) - x(0) = 0$$

Use Newton's method

$$J_H(x) = \frac{\partial \Phi(x, 0, T)}{\partial x} - I$$

$$J_H(x^k) (x^{k+1} - x^k) = -H(x^k)$$

Shooting Method


Matrix-Free Approach

Matrix-Vector Product

Solve Newton equation with Krylov-subspace method

$$\underbrace{\left(\frac{\partial \Phi(x^k, 0, T)}{\partial x} - I \right)}_A \underbrace{(x^{k+1} - x^k)}_x = \underbrace{x^k - \Phi(x^k, 0, T)}_b$$

Matrix-Vector Product Computation

$$\left(\frac{\partial \Phi(x^k, 0, T)}{\partial x} - I \right) p^j \approx \frac{\Phi(x^k + \varepsilon p^j, 0, T) - \Phi(x^k, 0, T)}{\varepsilon} - p^j$$


Krylov method search direction

Shooting Method

Matrix-Free Approach

Convergence for GCR

Example

$$\frac{dx}{dt} - Ax = 0 \quad \text{eig}(A) \text{ real and negative}$$

Shooting-Newton Jacobian

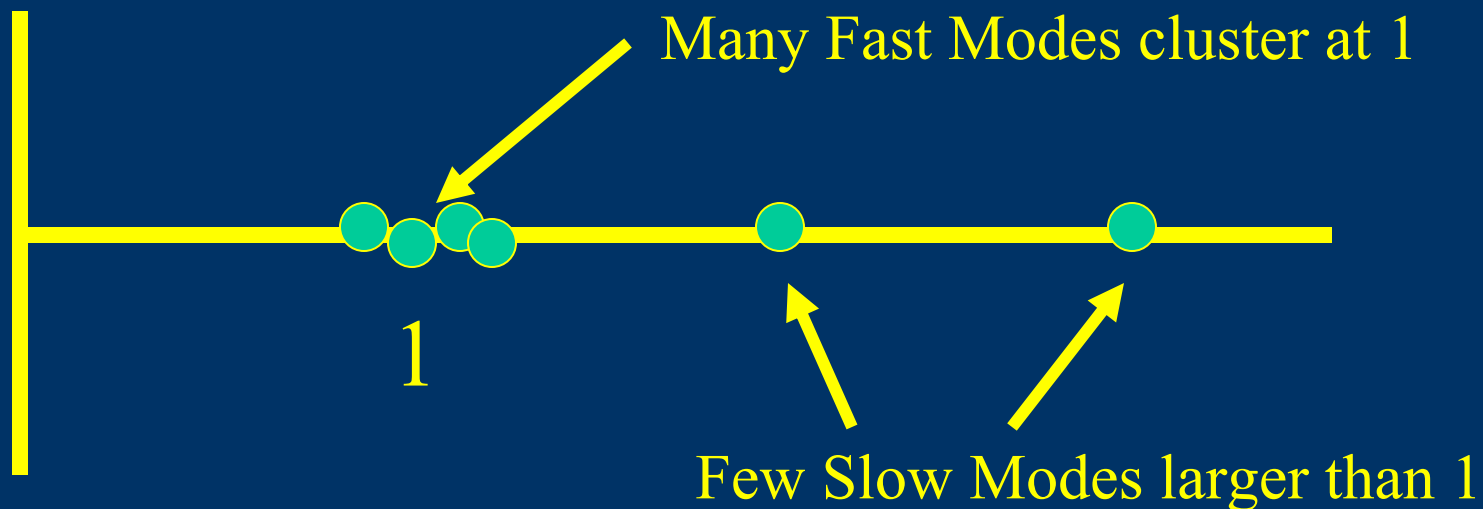
$$\frac{\partial \Phi(x, 0, T)}{\partial x} - I = e^{AT} - I$$

Shooting Method

Matrix-Free Approach

Convergence for GCR-evals

$$e^{AT} - I = S \begin{bmatrix} e^{\lambda_1 T} - 1 & & & \\ & \ddots & & \\ & & e^{\lambda_N T} - 1 & \\ & & & \ddots & \\ & & & & e^{\lambda_N T} - 1 \end{bmatrix} S^{-1}$$



Summary

- Periodic Steady-state problems
 - Application examples and simple cases
- Finite-difference methods
 - Formulating large matrices
- Shooting Methods
 - State transition function
 - Sensitivity matrix