

ESS101- Modeling and Simulation

Lecture 17

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Today (Chapters 8, 9)

- ☞ Implicit methods
 - ☞ Fixed-point method
 - ☞ Error constants
 - ☞ Predictor-correct method
 - ☞ Newton-Raphson method

Stiff systems

Linear systems

$$\dot{x}(t) = Ax(t), \quad \operatorname{Re}(\lambda_i) < 0, \quad \forall i$$

may have eigenvalue with the real part very much different in absolute value. I.e., high condition number

$$\left| \frac{\max_i \operatorname{Re}(\lambda_i)}{\min_i \operatorname{Re}(\lambda_i)} \right| \quad \textit{Stiff systems}$$

In order to avoid over accurate solutions due to the absolute stability requirements set by the fastest eigenvalue, A-stable (*implicit*) methods should be used

A-Stability

Definition (A-Stability). A method is *A-stable* if its stability region is the left half-plane

Theorem (Dahlquist's Second Barrier Theorem).

1. There's no A-stable explicit LMM
2. An A-stable LMM cannot have $p > 2$

In conclusion A-stable implicit methods allows efficiently selecting the step size to achieve the desired accuracy, without unnecessary further reduction because of stability

k-step LMMs

For the IVP problem

$$\dot{x}(t) = f(t, x(t)), \quad x(0) = x_0$$

A k-step LMM looks like

$$x_{n+k} + \alpha_{k-1}x_{n+k-1} + \cdots + \alpha_0x_n = h(\beta_k f_{n+k} + \beta_{k-1}f_{n+k-1} + \cdots + \beta_0f_n)$$

Recall that $f_{n+k} = f(t_{n+k}, x_{n+k})$

Hence, x_{n+k} is solution of the nonlinear equation

$$x_{n+k} = h\beta_k f(t_{n+k}, x_{n+k}) + \underbrace{h(\beta_{k-1}f_{n+k-1} + \cdots + \beta_0f_n) - \alpha_{k-1}x_{n+k-1} - \cdots - \alpha_0x_n}_{g_n}$$

Fixed-point method

Calculate x_{n+k} as solution of the iterative process

$$u^{[l+1]} = h\beta_k f(t_{n+k}, u^{[l]}) + g_n, \quad l = 0, 1, 2, \dots$$

1. How do we choose $u^{[0]}$?

1. $u^{[0]} = x_{k+n-1}$ makes sense

2. Does the sequence $u^{[1]}, u^{[2]}, \dots$ converge to x_{n+k} ? Yes, but..

Let $u^{[l]} = x_{n+k} + E^{[l]}$ Does $E^{[l]}$ converge to 0?

$$\begin{aligned} f(t_{n+k}, u^{[l]}) &= f(t_{n+k}, x_{n+k} + E^{[l]}) \\ &\approx f(t_{n+k}, x_{n+k}) + \frac{\partial f}{\partial x}(t_{n+k}, x_{n+k}) E^{[l]} \end{aligned}$$

Fixed-point method

Substitute $f(t_{n+k}, u^{[l]}) \approx f(t_{n+k}, x_{n+k}) + \frac{\partial f}{\partial x}(t_{n+k}, x_{n+k}) E^{[l]}$

in $u^{[l+1]} = h\beta_k f(t_{n+k}, u^{[l]}) + g_n, \quad l = 0, 1, 2, \dots$

From $u^{[l+1]} = h\beta_k f(t_{n+k}, x_{n+k}) + h\beta_k \underbrace{\frac{\partial f}{\partial x}(t_{n+k}, x_{n+k})}_B E^{[l]} + g_n$

Subtract $x_{n+k} = h\beta_k f(t_{n+k}, x_{n+k}) + g_n$

$$\underbrace{E^{[l+1]}}_{u^{[l+1]} - x_{n+k}} = h\beta_k B E^{[l]}$$

The error $E^{[l]}$ converge if the eigenvalues of B are within the unitary circle. ***(Again!!). Not for stiff problems***

Error constants

Consider the *consistency equation* written for 2-step LMMs

$$x(t+2h) + \alpha_1 x(t+h) + \alpha_0 x(t) = h[\beta_2 \dot{x}(t+2h) + \beta_1 \dot{x}(t+h) + \beta_0 \dot{x}(t)]$$

By expanding in Taylor series

$$\begin{aligned} & x(t+2h) + \alpha_1 x(t+h) + \alpha_0 x(t) - h[\beta_2 \dot{x}(t+2h) + \beta_1 \dot{x}(t+h) + \beta_0 \dot{x}(t)] \\ &= C_0 x(t) + C_1 h \dot{x}(t) + \cdots + C_p h^p x^{(p)}(t) + O(h^{p+1}) \end{aligned}$$

we conclude that $C_0 = C_1 = \cdots = C_p = 0$ for a p -th order method

$$\begin{aligned} & x(t+2h) + \alpha_1 x(t+h) + \alpha_0 x(t) - h[\beta_2 \dot{x}(t+2h) + \beta_1 \dot{x}(t+h) + \beta_0 \dot{x}(t)] \\ &= C_{p+1} h^{p+1} x^{(p+1)}(t) + O(h^{p+2}) \end{aligned}$$

$$C_{p+1} \neq 0$$

Error constant

They will be used to
estimate the local errors

Example. Calculation of the error constants

Consider the 1-step LMM

$$x_{n+1} + \alpha_0 x_n = h(\beta_1 f_{n+1} + \beta_0 f_n)$$

Calculate the coefficients $\alpha_0, \beta_0, \beta_1$ such that the method has order 1. Calculate the error constant.

The corresponding consistency equation is

$$x(t+h) + \alpha_0 x(t) = h[\beta_1 \dot{x}(t+h) + \beta_0 \dot{x}(t)]$$

Since order must be 1, by expanding $x(t+h)$, $\dot{x}(t+h)$ up to the first order term and collecting terms

$$\begin{aligned} & x(t+h) + \alpha_0 x(t) - h[\beta_1 \dot{x}(t+h) + \beta_0 \dot{x}(t)] \\ &= (1 + \alpha_0) x(t) + [1 - (\beta_1 + \beta_0)] h \dot{x}(t) + O(h^2) \end{aligned}$$

Example. Calculation of the error constants

In order to have order 1

$$1 + \alpha_0 = 0 \Rightarrow \alpha_0 = -1$$

$$1 - \beta_1 - \beta_0 = 0 \Rightarrow \beta_1 = \theta, \quad \beta_0 = 1 - \theta$$

We have to calculate the error constant C_2

$$\begin{aligned} & x(t+h) + \alpha_0 x(t) - h[\beta_1 \dot{x}(t+h) + \beta_0 \dot{x}(t)] \\ &= C_2 h^2 \ddot{x}(t) + O(h^3) \end{aligned}$$

It's enough expanding $x(t+h)$, $\dot{x}(t+h)$ up to the second order term and collecting terms

$$x(t+h) + \alpha_0 x(t) - h[\beta_1 \dot{x}(t+h) + \beta_0 \dot{x}(t)] = \underbrace{\left(\frac{1}{2} - \theta\right)}_{C_2} h^2 \ddot{x}(t) + O(h^3)$$

Predictor-corrector methods

Idea. Evaluate f_{n+k} at x_{n+k} predicted with an explicit method

Consider an explicit and implicit LMM methods of the **same order**

$$x_{n+k} + \alpha_{k-1}^e x_{n+k-1} + \cdots + \alpha_0^e x_n = h \left(\beta_{k-1}^e f_{n+k-1} + \cdots + \beta_0^e f_n \right)$$

$$x_{n+k} + \alpha_{k-1}^i x_{n+k-1} + \cdots + \alpha_0^i x_n = h \left(\beta_k^i f_{n+k} + \beta_{k-1}^i f_{n+k-1} + \cdots + \beta_0^i f_n \right)$$

E.g, Forward+Backward Euler for 1st order,
AB(2)+trapezoidal for 2nd order, Adam-Bashforth+Adam-Moulton

Predictor-corrector methods

(P) Use the explicit LMM to calculate $x_{n+k}^{[0]}$

$$x_{n+k}^{[0]} = h \left(\beta_{k-1}^e f_{n+k-1} + \cdots + \beta_0^e f_n \right) - \alpha_{k-1}^e x_{n+k-1} - \cdots - \alpha_0^e x_n$$

(E) Evaluate f_{n+k} by using the system state update function

$$f_{n+k}^{[0]} = f \left(t_{n+k}, x_{n+k}^{[0]} \right)$$

(C) Calculate x_{n+k} as

$$x_{n+k} = h \left(\beta_k^i f_{n+k}^{[0]} + \beta_{k-1}^i f_{n+k-1} + \cdots + \beta_0^i f_n \right) - \alpha_{k-1}^i x_{n+k-1} - \cdots - \alpha_0^i x_n$$

Predictor-corrector methods

Error constants can be used to increase the accuracy

It can be shown that

$$\underbrace{e_n}_{\text{local error}} \approx \frac{C_{p+1}^i}{C_{p+1}^e - C_{p+1}^i} \left(x_{n+k} - x_{n+k}^{[0]} \right)$$

Hence, x_{t+k} at step 3 can be updated as

$$\hat{x}_{n+k} \approx x_{n+k} + \frac{C_{p+1}^i}{C_{p+1}^e - C_{p+1}^i} \left(x_{n+k} - x_{n+k}^{[0]} \right)$$

with accuracy of order $O(h^{p+1})$

Example

Simulate the system

$$\dot{x}(t) = (1 - 2t)x(t), \quad x(0) = 1$$

over the time interval $0 \leq t \leq 0.9$

Recall the *exact solution* $x(t) = e^{\frac{1}{4} - \left(\frac{1}{2} - t\right)^2}$

Let's use the forward and backward Euler methods (order 1) with $h=0.1$

(P) (FE Method)	$x_1^{[0]} = x_0 + 0.1f_0 = 0.232$
(E) (sys dyn)	$f_1^{[0]} = f\left(t_1, x_1^{[0]}\right) = 0.35635$
(C) (BE Method)	$x_1 = x_0 + 0.1f_1^{[0]} = 0.23564$
(E) (sys dyn)	$f_1^{[0]} = f\left(t_1, x_1^{[0]}\right) = 0.36023$

Example

The error constants are

$$C_2^i = -1/2, \quad C_2^e = 1/2$$

Hence, the accuracy of x_1 can be improved as follows

$$\begin{aligned} \hat{x}_1 &\approx x_1 + \frac{C_2^i}{C_2^e - C_2^i} (x_1 - x_1^{[0]}) \\ &= 0.23372 \end{aligned}$$

while the exact value is

$$x(t_1) = 0.23392$$

Newton-Raphson method

Consider the equation $F(u) = 0$ with

$$F(u) = u - h\beta_k f(t_{n+k}, u) - g_n$$

with solution $u = x_{t+k}$

Define $E^{[l]} = u^{[l]} - x_{t+k}$ and expand in Taylor series $F(x_{t+k})$

$$F(x_{n+k}) = 0$$

$$= F(u^{[l]} - E^{[l]})$$

$$\approx F(u^{[l]}) - \frac{\partial F}{\partial x}(u^{[l]})E^{[l]}$$

Assume a non-singular
Jacobian and calculate

$$\hat{E}^{[l]} = \left[\frac{\partial F}{\partial x}(u^{[l]}) \right]^{-1} F(u^{[l]})$$

Newton-Raphson method

Update $u^{[l]}$ as

$$u^{[l+1]} = u^{[l]} - \hat{E}^{[l]}$$

It can be show that the convergence is **quadratic**, that is the number of corrected digits double at every iteration

Example

Solve the IVP

$$\dot{x}(t) = -2y(t)^3$$

$$\dot{y}(t) = 2x(t) - y(t)^3$$

$$x(0) = 1, \quad y(0) = 1$$

with the backward Euler method and $h=0.1$

$$\text{Define } u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad F(u) = \begin{bmatrix} u_1 - x_n + 2hu_2^3 \\ u_2 - y_n + h(2u_1 - u_2^3) \end{bmatrix} = 0$$

$$\text{The Jacobian is } \frac{\partial F}{\partial x}(u) = \begin{bmatrix} 1 & 6hu_2^2 \\ -2h & 1 + 3hu_2^2 \end{bmatrix}$$

Example

A generic iteration looks like

$$u^{[l+1]} = u^{[l]} - \overbrace{\begin{bmatrix} 1 & 6h(u_2^{[l]})^2 \\ -2h & 1 + 3h(u_2^{[l]})^2 \end{bmatrix}}^{\hat{E}^{[l]}} \times \underbrace{\begin{bmatrix} u_1^{[l]} - x_n + 2h(u_2^{[l]})^3 \\ u_2^{[l]} - y_n + h\left(2u_1^{[l]} - (u_2^{[l]})^3\right) \end{bmatrix}}_{F(u^{[l]})} \times$$

To calculate $x(t_l)$, $y(t_l)$ we can set $u^{[0]} = \begin{bmatrix} x(0) \\ y(0) \end{bmatrix}$

Example

ℓ	0	1	2	3
$\mathbf{u}^{[\ell]}$	1.00	0.774 647 887	0.773 901 924	0.773 901 807
	1.00	1.042 253 521	1.041 731 347	1.041 731 265
$\hat{\mathbf{E}}^{[\ell]}$	2.2535×10^{-1}	7.4596×10^{-4}	1.1711×10^{-7}	2.9131×10^{-15}
	-4.2254×10^{-2}	5.2217×10^{-4}	8.1975×10^{-8}	1.9628×10^{-15}
$\mathbf{E}^{[\ell]}$	2.2610×10^{-1}	7.4608×10^{-4}	1.1711×10^{-7}	2.8866×10^{-15}
	-4.1731×10^{-2}	5.2226×10^{-4}	8.1975×10^{-8}	1.9984×10^{-15}