

Lecture 12.
Error Control in
Transient Simulation

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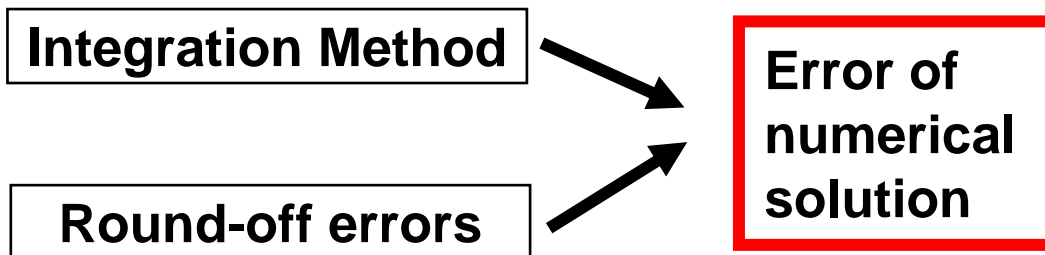
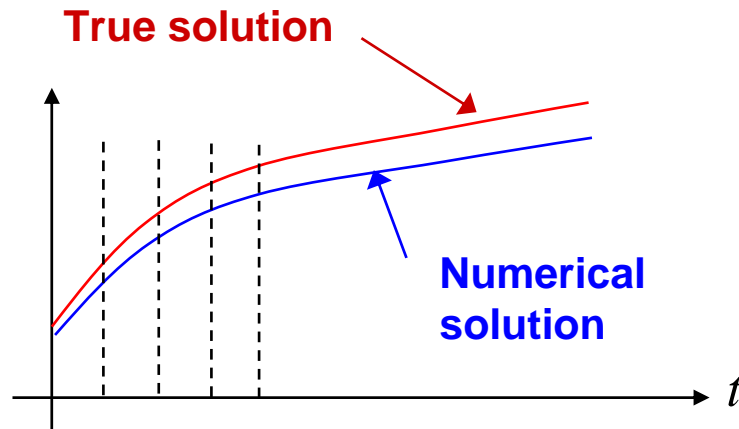
Shanghai Jiao Tong University

Fall 2010

Outline

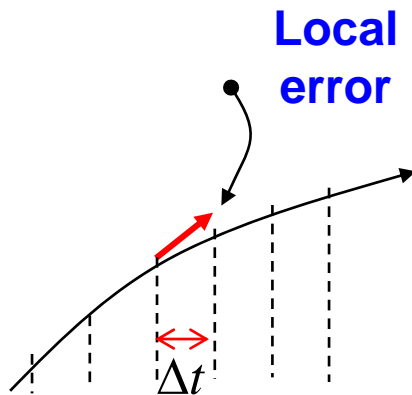
- **Truncation error**
- **Local Truncation Error (LTE)**
 - for FE/BE/TR
- **Local error of LMS methods**
- **Time step control**
 - Finite difference calculation

Error Analysis

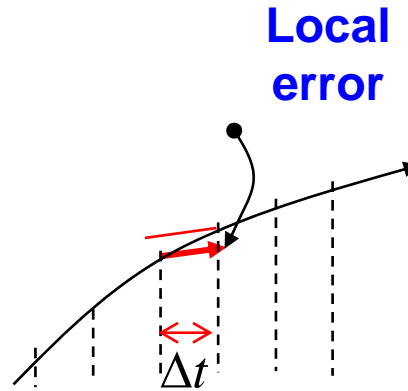


Local Error

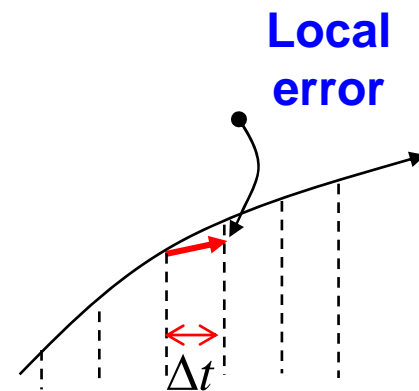
- Local error is the error that could happen in one time step Δt , assuming no error at the beginning.



F.E.



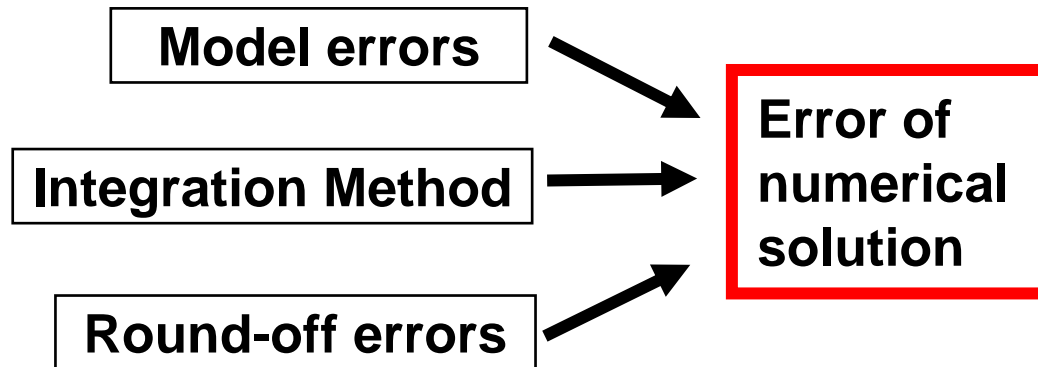
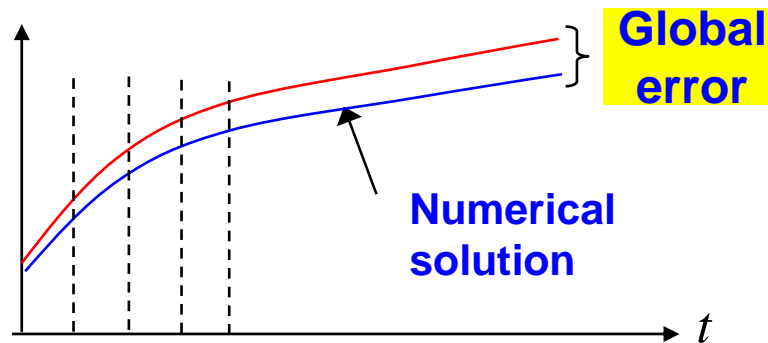
B.E.



T.R.

Global Error

- **Global error** is the accumulated error over the simulation period.



Global Truncation Errors

Global Truncation Error (GTE)

Assume initial condition known:

$$x(t_0) = x_0$$

The error at time point t_{k+1} :

$$e_k := \left\| \overset{\text{exact}}{\color{red}x(t_{k+1})} - \hat{x}_{k+1} \right\|$$

No available because the **exact solution $x(t_{k+1})$ is unknown.**

Local Truncation Errors

Local Truncation Error (**LTE**)

(one-step error)

Assume x_k is known exactly:

$$x(t_k) = \hat{x}_k$$

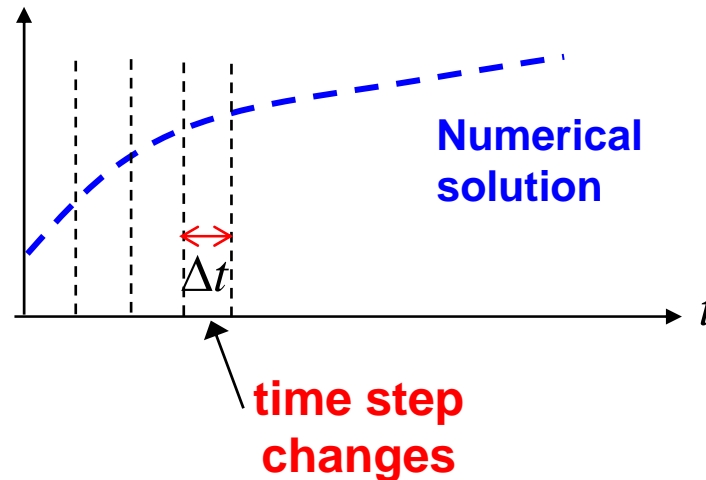
(for convenience)

Estimate the error at the **next time point t_{k+1}** :

$$e_k := \left\| x(t_{k+1}) - \hat{x}_{k+1} \right\|$$

- **Can be calculated approximately;**
- **Used to determine the next time step size (Δt) in SPICE**

Dynamic Time Step Control



- **Dynamic time step control** – increase or decrease time step (Δt) for accuracy control.
- Adopted by most SPICE simulators.
- Typically use **Local Truncation Error (LTE)**.

Local Truncation Error (LTE)

LTE \equiv One-step error, assuming perfect past data.

$$LTE := y(t_n) - y_n$$

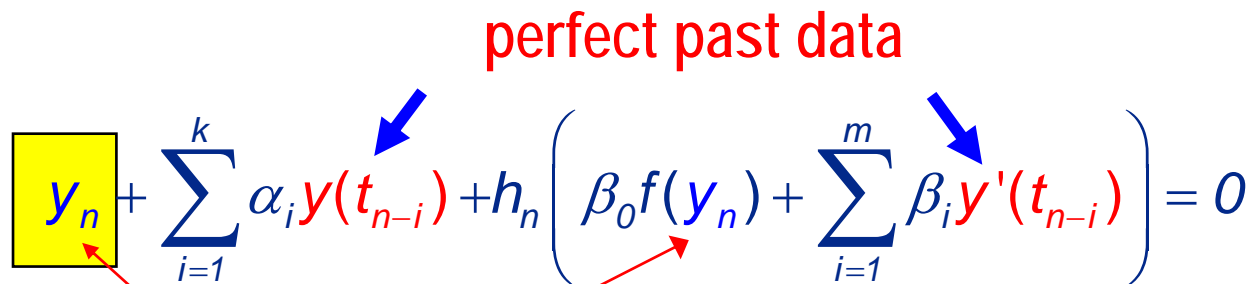
exact solution

simulated

If using a linear multi-step (**LMS**) method:

$$y_n + \sum_{i=1}^k \alpha_i y(t_{n-i}) + h_n \left(\beta_0 f(y_n) + \sum_{i=1}^m \beta_i y'(t_{n-i}) \right) = 0$$

perfect past data

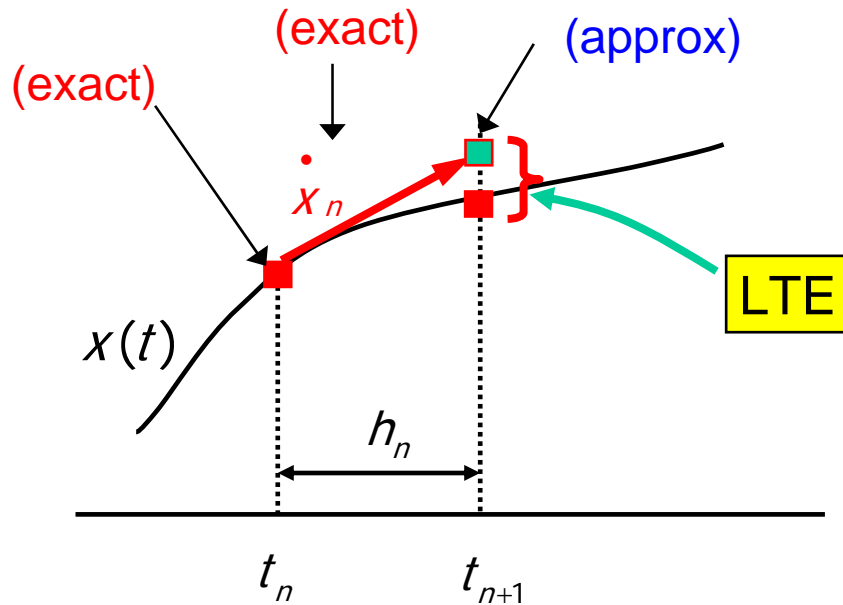


Approximation of $y(t_n)$

LTE for Typical Methods

- **We shall derive the LTE's of three basic methods**
 - **Forward Euler (FE)**
 - **Backward Euler (BE)**
 - **Trapezoidal Rule (TR)**
- **The key technique used – Taylor expansion**

Forward Euler (FE)



\dot{x}_n, x_n are assumed known exactly

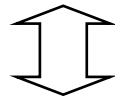
LTE of Forward Euler

x_n, \dot{x}_n are assumed known exactly

(assume exact)

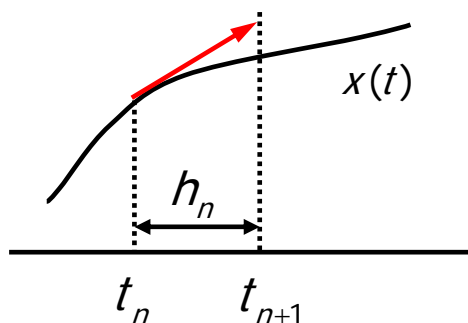
Forward Euler:

$$x_{n+1} = x_n + h_n \dot{x}_n$$



$$x(t_n) + h_n \dot{x}(t_n) = x_{n+1} \approx x(t_{n+1})$$

$$\begin{aligned} x_n &= x(t_n) \\ \dot{x}_n &= \dot{x}(t_n) \end{aligned}$$



The error at t_{n+1} is the LTE:

$$LTE := x(t_{n+1}) - x_{n+1} = ?$$

LTE of Forward Euler

Taylor expanding $x(t)$ at $t = t_{n+1}$:

$$x(t_{n+1}) = x(t_n) + h_n \dot{x}(t_n) + \frac{h_n^2}{2} \ddot{x}(t_n) + O(h_n^3)$$

(assume exact)

$$\begin{aligned} x_n &= x(t_n) \\ \dot{x}_n &= \dot{x}(t_n) \end{aligned}$$

$$\Rightarrow x(t_{n+1}) = \left[x_n + h_n \dot{x}_n \right] + \frac{h_n^2}{2} \ddot{x}_n + O(h_n^3)$$

$$x_{n+1} = x_n + h_n \dot{x}_n = x_{n+1} + \frac{h_n^2}{2} \ddot{x}_n + O(h_n^3)$$

**Forward Euler
formula**

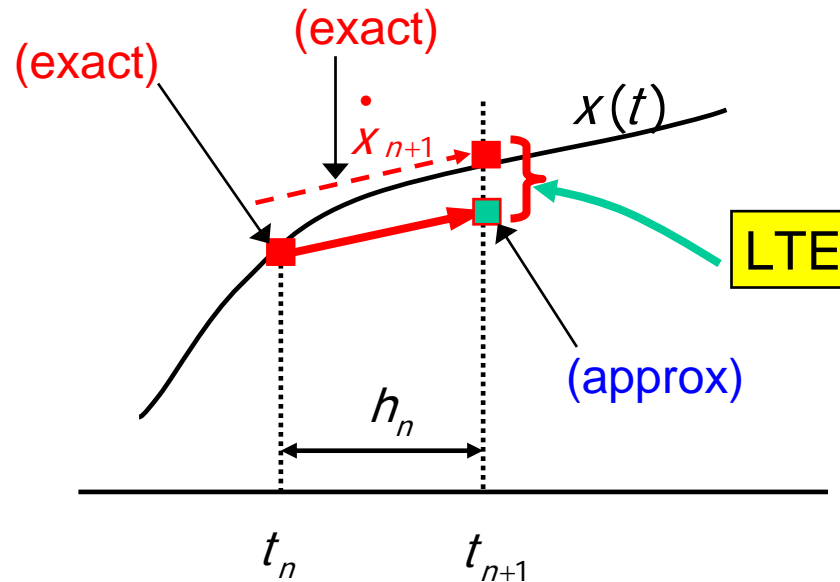
LTE of Forward Euler (cont'd)

Ignore the high-order terms.

$$LTE := x(t_{n+1}) - x_{n+1} = \underbrace{\frac{h_n^2}{2} \ddot{x}_n}_{\text{LTE}} + \mathcal{O}(h_n^3)$$

\Rightarrow $LTE_{FE} = \frac{h_n^2}{2} \ddot{x}_n$

Backward Euler (BE)



\dot{x}_n, \dot{x}_{n+1} are assumed known exactly

LTE of Backward Euler

(assuming)

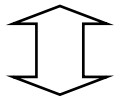
$$x_n = x(t_n)$$

$$\dot{x}_{n+1} = \dot{x}(t_{n+1})$$

approx.

perfect

$$x_{n+1} = x_n + h_n \dot{x}_{n+1}$$

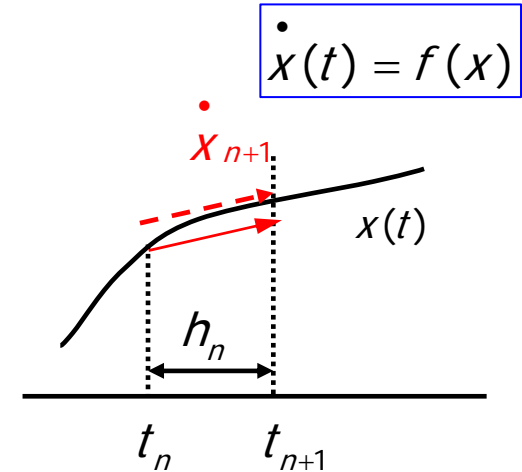


$$x(t_n) + h_n \dot{x}(t_{n+1}) = x_{n+1} \approx x(t_{n+1})$$



The error between x_{n+1} and $x(t_{n+1})$

$$LTE := x(t_{n+1}) - x_{n+1} = ?$$



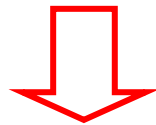
Backward Euler

Taylor expand $x(t)$ at $t = t_{n+1}$

$$x_n = x(t_n)$$

$$\dot{x}_{n+1} = \dot{x}(t_{n+1})$$

$$x(t) = x(t_{n+1}) + \dot{x}(t_{n+1})(t - t_{n+1}) + \frac{\ddot{x}(t_{n+1})}{2}(t - t_{n+1})^2 + O((t - t_{n+1})^3)$$



Evaluate at $t = t_n$:

$$x(t_n) = x(t_{n+1}) - h_n \dot{x}(t_{n+1}) + \frac{h_n^2}{2} \ddot{x}(t_{n+1}) + O(h_n^3)$$

$$\Rightarrow \bullet x(t_{n+1}) = \left[x_n + h_n \dot{x}_{n+1} \right] - \frac{h_n^2}{2} \ddot{x}(t_{n+1}) + O(h_n^3)$$

$$= x_{n+1} - \frac{h_n^2}{2} \ddot{x}(t_{n+1}) + O(h_n^3)$$

$$x_{n+1} = x_n + h_n \dot{x}_{n+1}$$

by B.E.

Backward Euler (cont'd)

$$\begin{aligned}x_n &= x(t_n) \\ \dot{x}_{n+1} &= \dot{x}(t_{n+1})\end{aligned}$$

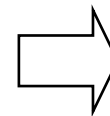
$$\bullet \quad x(t_{n+1}) = \left[x_n + h_n \dot{x}_{n+1} \right] - \frac{h_n^2}{2} \ddot{x}(t_{n+1}) + O(h_n^3)$$

$$\begin{aligned} &\curvearrowright \\ &= x_{n+1} - \frac{h_n^2}{2} \ddot{x}(t_{n+1}) + O(h_n^3)\end{aligned}$$

by B.E.

$$x_{n+1} = x_n + h_n \dot{x}_{n+1}$$

$$\bullet \quad \text{LTE} := x(t_{n+1}) - x_{n+1} = \underbrace{-\frac{h_n^2}{2} \ddot{x}(t_{n+1}) + O(h_n^3)}_{\text{red arrow}}$$

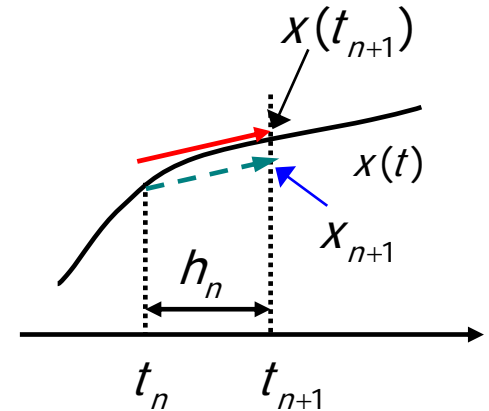


$$\text{LTE}_{BE} = -\frac{h_n^2}{2} \ddot{x}(t_{n+1})$$

Clarification of the Assumption

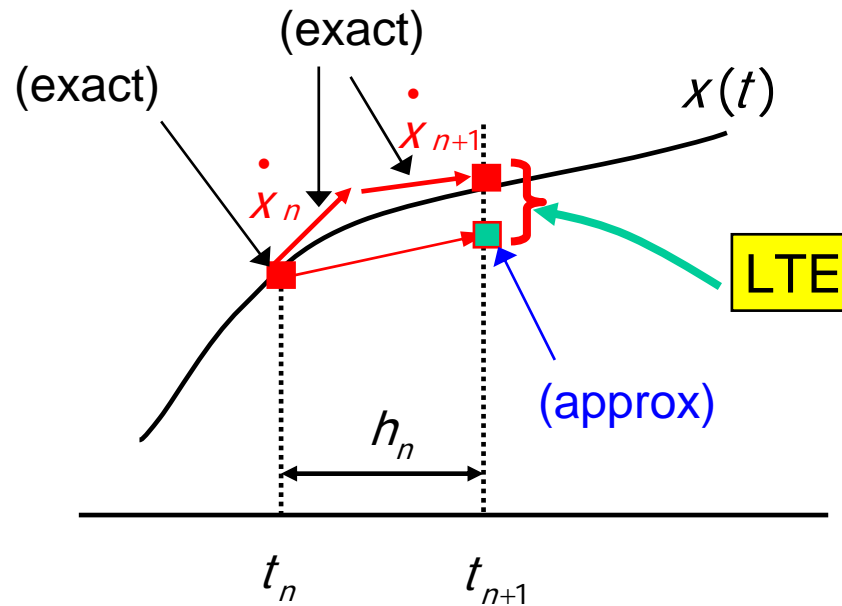
assumed known $\dot{x}(t_{n+1}) = f(x(t_{n+1}))$ **unknown**

$x(t_{n+1})$ will be solved from BE as x_{n+1} .



$$x_{n+1} = x(t_n) + h_n \dot{x}(t_{n+1})$$

Trapezoidal Rule (TR)



x_n, x_n, x_{n+1} are assumed known exactly

LTE of Trapezoidal Rule (TR)

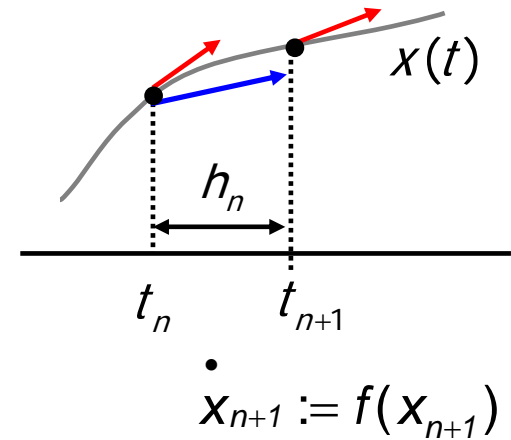
Assume exactly:

$$x_n = x(t_n) \quad \dot{x}_n = \dot{x}(t_n) \quad \dot{x}_{n+1} = \dot{x}(t_{n+1})$$

$$x_{n+1} = x_n + \frac{h_n}{2} (\dot{x}_n + \dot{x}_{n+1})$$

$$x(t_n) + \frac{h_n}{2} (\dot{x}(t_n) + \dot{x}(t_{n+1})) = x_{n+1} \approx x(t_{n+1})$$

↑
↑
error?



The error between x_{n+1} and $x(t_{n+1})$?

$$LTE := x(t_{n+1}) - x_{n+1} = ?$$

LTE of T.R.

Taylor expand $x(t)$ at $t = t_n$ and evaluate at $t = t_{n+1}$:

$$x(t_{n+1}) = x_n + h_n \dot{x}_n + \frac{h_n^2}{2} \ddot{x}_n + \frac{h_n^3}{6} \dddot{x}_n + O(h_n^4)$$

$$h_n = t_{n+1} - t_n$$

(to be cancelled)

Taylor expand $x'(t)$ at $t = t_n$ and evaluate at $t = t_{n+1}$:

$$\dot{x}(t_{n+1}) = \dot{x}_n + h_n \ddot{x}_n + \frac{h_n^2}{2} \dddot{x}_n + O(h_n^3)$$

LTE of Trapezoidal Rule

$$\begin{cases} x(t_{n+1}) = x_n + h_n \dot{x}_n + \frac{h_n^2}{2} \ddot{x}_n + \frac{h_n^3}{6} \dddot{x}_n + O(h_n^4) \\ \dot{x}(t_{n+1}) = \dot{x}_n + h_n \ddot{x}_n + \frac{h_n^2}{2} \dddot{x}_n + O(h_n^3) \end{cases}$$

$$h_n = t_{n+1} - t_n$$

$$\dot{x}(t_{n+1}) = f(x(t_{n+1}), t_{n+1})$$

$$\dot{x}_{n+1} := f(x_{n+1}, t_{n+1})$$

- Eliminate \ddot{x}_n to get

$$\bullet \quad x(t_{n+1}) = x_n + \frac{h_n}{2} \left[\dot{x}_n + \dot{x}(t_{n+1}) \right] - \frac{h_n^3}{12} \dddot{x}_n + O(h_n^4)$$

$$= x_{n+1} - \frac{h_n^3}{12} \dddot{x}_n + O(h_n^4)$$

by T.R.

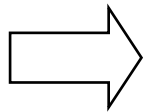
Assuming

$$\dot{x}_{n+1} = \dot{x}(t_{n+1})$$

$$\bullet \quad x_{n+1} = x_n + \frac{h_n}{2} \left(\dot{x}_n + \dot{x}_{n+1} \right)$$

TR LTE (cont'd)

- $$\begin{aligned}x(t_{n+1}) &= x_n + \frac{h_n}{2} \left[\dot{x}_n + \dot{x}(t_{n+1}) \right] - \frac{h_n^3}{12} \ddot{x}_n + O(h_n^4) \\ &= x_{n+1} - \frac{h_n^3}{12} \ddot{x}_n + O(h_n^4)\end{aligned}$$



$$x(t_{n+1}) - x_{n+1} = \underbrace{-\frac{h_n^3}{12} \ddot{x}_n + O(h_n^4)}_{\text{LTE}}$$

LTE



$$LTE_{TR} = -\frac{h_n^3}{12} \ddot{x}_n$$

LMS Error Analysis

Local error of LMS methods
Error expression of pth order LMS

Error Analysis of LMS Methods

- We shall compare “local error” and “local truncation error”:
 - **Local Error** – also known as the **Error of the formula** (or called “**residue**”)
 - **LTE** – One-step Error of the solution

General LMS formula:

$$\sum_{i=0}^k \alpha_i y_{n-i} + h_n \sum_{j=0}^m \beta_j \dot{y}_{n-j} = 0, \quad (\alpha_0 = 1)$$

LMS Error

General LMS :

$$\sum_{i=0}^k \alpha_i y_{n-i} + h_n \sum_{j=0}^m \beta_j \dot{y}_{n-j} = 0, \quad (\alpha_0 = 1)$$

simulated values

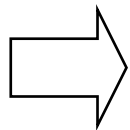
(simulated)

$$y_{n-i} \leftrightarrow y(t_{n-i})$$

$$\dot{y}_{n-j} \leftrightarrow \dot{y}(t_{n-j})$$

(exact)

If the **simulated** values are replaced by the **exact** values, the LMS formula might result in “errors”, **because the exact solution might not satisfy the LMS formula.**



$$\sum_{i=0}^k \alpha_i y(t_{n-i}) + h_n \sum_{j=0}^m \beta_j \dot{y}(t_{n-j}) \neq 0$$

Error

LMS Local Error

$$\sum_{i=0}^k \alpha_i y(t_{n-i}) + h_n \sum_{j=0}^m \beta_j \dot{y}(t_{n-j}) \neq 0$$

called “Local Error”

Local Error (LE) is defined as the residue of the LMS formula with all y_i and y'_i substituted by their *exact* values, i.e.

$$y_i = y(t_i), \quad y'_i = f(y(t_i))$$

Define:

$$LE \triangleq \sum_{i=0}^k \alpha_i y(t_{n-i}) + h_n \sum_{j=0}^m \beta_j \dot{y}(t_{n-j})$$

Local Error (LE) Analysis

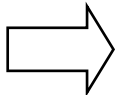
Assuming **perfect** past data:

$$y(t_{n-i}) = y_{n-i} \quad \text{for } i = 1, 2, \dots, k$$

Solve the current solution y_n :

$$y_n \approx y(t_n)$$

In general, y_n is only an **approximation** of $y(t_n)$.



$$LTE_n := y(t_n) - y_n$$

Question: What is the relation between LE and LTE?

Local Error (LE) Analysis

$$LE_n = \sum_{i=0}^k \alpha_i y(t_{n-i}) + h_n \sum_{j=0}^m \beta_j \dot{y}(t_{n-j})$$

$$= y(t_n) + h_n \beta_0 \dot{y}(t_n) + \sum_{i=1}^k \alpha_i y(t_{n-i}) + h_n \sum_{j=1}^m \beta_j \dot{y}(t_{n-j})$$

$$= y(t_n) + h_n \beta_0 \dot{y}(t_n) + \sum_{i=1}^k \alpha_i y_{n-i} + h_n \sum_{j=1}^m \beta_j \dot{y}_{n-j}$$

by
assumption

$$LE_n = [y(t_n) - y_n] + h_n \beta_0 [\dot{y}(t_n) - \dot{y}_n] + \sum_{i=0}^k \alpha_i y_{n-i} + h_n \sum_{j=0}^m \beta_j \dot{y}_{n-j}$$

Note the index change !

Local Error (LE)

$$LE_n = [y(t_n) - y_n] + h_n \beta_0 \left[\dot{y}(t_n) - \dot{y}_n \right] + \sum_{i=0}^k \alpha_i y_{n-i} + h_n \sum_{j=0}^m \beta_j \dot{y}_{n-j}$$

$$\begin{aligned} \Rightarrow LE &= [y(t_n) - y_n] + h_n \beta_0 \left[\dot{y}(t_n) - \dot{y}_n \right] \\ &= [y(t_n) - y_n] + h_n \beta_0 \left[f(y(t_n)) - \dot{y}_n \right] \\ &= \text{LTE} \end{aligned}$$

= 0 by LMS definition

LTE = 0 → LE = 0 (easy to see)

$$LTE = y(t_n) - y_n = 0 \quad \Rightarrow \quad f(y(t_n)) - \dot{y}_n = f(y(t_n)) - \dot{y}(t_n) = 0$$

What about the converse: LE = 0 → LTE = 0 ?

LTE versus LE

$$\boxed{LTE \triangleq y(t_n) - y_n}$$

$$LE = [y(t_n) - y_n] + h_n \beta_0 [\dot{y}(t_n) - f(y_n)]$$

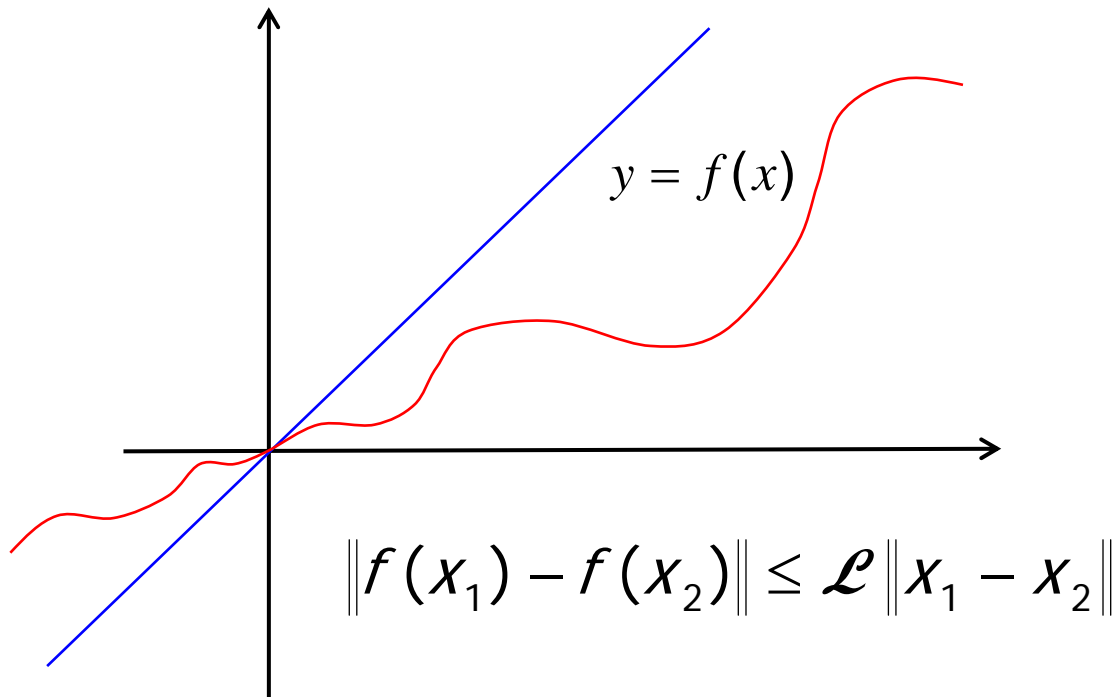


$$\begin{aligned} LTE &= -h_n \beta_0 [\dot{y}(t_n) - f(y_n)] + LE \\ &= -h_n \beta_0 [f(y(t_n)) - f(y_n)] + LE \end{aligned}$$

We have to assume that $f(\cdot)$ is “**Lipschitz**” in order to derive a bound for the “LTE” in terms of “LE”.

Lipschitz Condition

- A function $y = f(x)$ is Lipschitz if the variation of y can be “**linearly bounded**” by the variation of x .



\mathcal{L} is called a **Lipshitz constant**.

LTE Bound by LE

$$\begin{aligned}\|LTE\| &= \|y(t_n) - y_n\| \\ &\leq |h_n \beta_0| \|f(y(t_n)) - f(y_n)\| + \|LE\| \\ &\leq |h_n \beta_0| \mathcal{L} \|y(t_n) - y_n\| + \|LE\| \\ &\leq |h_n \beta_0| \mathcal{L} \|LTE\| + \|LE\|\end{aligned}$$

\mathcal{L} is the Lipschitz constant for $f(x)$

for $h_n = h$



$$\|f(x_1) - f(x_2)\| \leq \mathcal{L} \|x_1 - x_2\|$$

$$\|LTE\| \leq \frac{\|LE\|}{1 - |h\beta_0| \mathcal{L}}$$

If \mathcal{L} is large, choose h small to get a valid bound.

Taylor Analysis of Local Error

$$LE = \mathcal{E}[y(t), h] := \sum_{i=0}^k \alpha_i y(t_{n-i}) + h \sum_{i=0}^m \beta_i \dot{y}(t_{n-i})$$

Suppose $y(t)$ is smooth. Its Taylor expansion at $t = t_n$

$$y(t) = y(t_n) + y^{(1)}(t_n)(t - t_n) + \dots + \frac{y^{(p+1)}(t_n)}{(p+1)!} (t - t_n)^{p+1} + \dots$$

$$= q_p(t) + r_p(t)$$

remainder

$$q_p(t) = \sum_{i=0}^p \frac{y^{(i)}(t_n)}{i!} (t - t_n)^i$$

(polynomial part)

$$r_p(t) = \frac{y^{(p+1)}(t_n)}{(p+1)!} (t - t_n)^{p+1} + \dots$$
$$= O((t - t_n)^{p+1})$$

for the remainder

Analytical Expression for LE

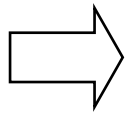
$$LE = \mathcal{E}[y(t), h] := \sum_{i=0}^k \alpha_i y(t_{n-i}) + h \sum_{i=0}^m \beta_i \dot{y}(t_{n-i})$$

linear

plug in

$$y(t) = q_p(t) + r_p(t)$$

pth order polynomial: $q_p(t) = \sum_{i=0}^p \frac{y^{(i)}(t_n)}{i!} (t - t_n)^i$



remainder: $r_p(t) = \frac{y^{(\rho+1)}(t_n)}{(\rho+1)!} (t - t_n)^{\rho+1} + O((t - t_n)^{\rho+2})$

Analytical Expression for LE

Assume the LMS is a ρ th order method; namely, it is exact for any ρ th order polynomials.

$$\begin{aligned}
 LE &= \mathcal{E} [q_\rho(t), h] + \mathcal{E} [r_\rho(t), h] \\
 &= \sum_{i=0}^k \left[\alpha_i \frac{y^{(\rho+1)}(t_n)}{(\rho+1)!} (t_{n-i} - t_n)^{\rho+1} \right] + h \sum_{i=1}^m \beta_i \frac{y^{(\rho+1)}(t_n)}{\rho!} (t_{n-i} - t_n)^\rho \\
 &\quad + O(h^{\rho+2})
 \end{aligned}$$

Terms from the remainder of $y(t)$

$$y(t) = y(t_n) + y^{(1)}(t_n)(t - t_n) + \dots + \left[\frac{y^{(\rho+1)}(t_n)}{(\rho+1)!} (t - t_n)^{\rho+1} \right] + \dots$$

Analytical Expression for Local Error

$$\begin{aligned}
 LE &= \mathcal{E}[r_p(t), h] \\
 &= \sum_{i=0}^k \left[\frac{\alpha_i y^{(\rho+1)}(t_n)}{(\rho+1)!} (t_{n-i} - t_n)^{\rho+1} \right] + \sum_{i=1}^m \left(\frac{h \beta_i y^{(\rho+1)}(t_n)}{\rho!} (t_{n-i} - t_n)^\rho \right) + O(h^{\rho+2}) \\
 &= \sum_{i=0}^k \left[\alpha_i \left(\frac{t_{n-i} - t_n}{h} \right)^{\rho+1} \right] + (\rho+1) \sum_{i=1}^m \left[\beta_i \left(\frac{t_{n-i} - t_n}{h} \right)^\rho \right] \frac{y^{(\rho+1)}(t_n)}{(\rho+1)!} h^{\rho+1} + O(h^{\rho+2}) \\
 &= \varepsilon_{\rho+1} y^{(\rho+1)}(t_n) h^{\rho+1} + \dots
 \end{aligned}$$

High Order Terms

$O(h^{\rho+1})$

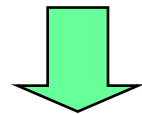
coefficient

$$\varepsilon_{\rho+1} \triangleq \sum_{i=0}^k \left[\alpha_i \left(\frac{t_{n-i} - t_n}{h} \right)^{\rho+1} + (\rho+1) \beta_i \left(\frac{t_{n-i} - t_n}{h} \right)^\rho \right] \frac{1}{(\rho+1)!}$$

for any method of order p

Expression for Local Error

$$\varepsilon_{p+1} \triangleq \frac{1}{(\rho+1)!} \left\{ \sum_{i=1}^k \alpha_i \left(\frac{t_{n-i} - t_n}{h} \right)^{\rho+1} + (\rho+1) \sum_{i=1}^m \beta_i \left(\frac{t_{n-i} - t_n}{h} \right)^{\rho} \right\}$$



$$h = t_n - t_{n-1}$$

time stepsize

$$\varepsilon_{p+1} \triangleq \frac{1}{(\rho+1)!} \sum_{i=1}^k (-i)^{\rho+1} \alpha_i + \frac{1}{\rho!} \sum_{i=1}^m (-i)^{\rho} \beta_i$$

Coefficient of the local error (LE)

$$LE = \mathcal{E} [r_{\rho}(t), h] = \varepsilon_{p+1} y^{(\rho+1)}(t_n) h^{\rho+1} + \dots$$

(for a pth order LMS)

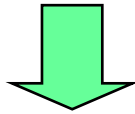
LE Examples

Applying the analytical LE expression to some basic integration methods:

- **Forward Euler**
- **Backward Euler**
- **Trapezoidal Rule**
- **Gear Integration Formulas**

LE of Forward Euler

$$\varepsilon_{p+1} \triangleq \frac{1}{(p+1)!} \sum_{i=1}^k (-i)^{p+1} \alpha_i + \frac{1}{p!} \sum_{i=1}^m (-i)^p \beta_i$$



F.E. : $\alpha_0 = 1, \alpha_1 = -1, \beta_0 = 0, \beta_1 = -1 \rightarrow$ Order of method $p = 1$

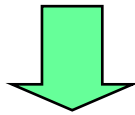
$$\varepsilon_2 = [(-1)(-1)^2 - 2(-1)] / 2 = \mathbf{1/2} \leftarrow \mathbf{Coefficient\ of\ LE}$$

$$LE = \mathcal{E}[r_1(t), h] = \varepsilon_2 \ddot{y}(t_n) h^2 = \frac{1}{2} \ddot{y}(t_n) h^2$$

(Same result as the LTE analysis)

LE of Backward Euler

$$\varepsilon_{p+1} \triangleq \frac{1}{(p+1)!} \sum_{i=1}^k (-i)^{p+1} \alpha_i + \frac{1}{p!} \sum_{i=1}^m (-i)^p \beta_i$$

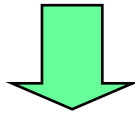


B.E. : $\alpha_0=1, \alpha_1=-1, \beta_0=-1, \beta_1=0 \rightarrow$ Order of method $p = 1$

$\varepsilon_2 = [(-1)(-1)^2] / 2 = -1/2 \leftarrow$ **Coefficient of LE**

LE of Trapezoidal Rule

$$\varepsilon_{p+1} \triangleq \frac{1}{(p+1)!} \sum_{i=1}^k (-i)^{p+1} \alpha_i + \frac{1}{p!} \sum_{i=1}^m (-i)^p \beta_i$$



T.R. : $\alpha_0=1, \alpha_1=-1, \beta_0=-1/2, \beta_1=-1/2 \rightarrow$ Order of method $p = 2$

$$\varepsilon_3 = [(-1)(-1)^3 - (3/2) (-1)^2] / 3! = -1/12 \leftarrow \text{Coefficient of LE}$$

LE of Gear's Formula

Gear's formula (kth order):

$$\dot{y}_n = -\frac{1}{\beta_0 h} \sum_{i=0}^k \alpha_i y_{n-i}$$

The coefficient equations:

$$\sum_{i=0}^k (i^q) \alpha_i - (q \cdot 0^{q-1}) \beta_0 = 0; \quad q = 0, 1, \dots, k$$

Truncation error coefficient:

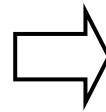
$$\mathcal{E}_{k+1} \triangleq \frac{1}{(k+1)!} \sum_{i=1}^k (-i)^{k+1} \alpha_i$$

Examples (Gear Coefficients)

1st order Gear (Backward Euler)

$k = 1$

$$\alpha_0 = 1 \quad \begin{cases} \alpha_0 + \alpha_1 = 0 \\ \alpha_1 = \beta_0 \end{cases}$$



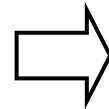
$$\alpha_1 = -1, \beta_0 = -1,$$

$$\varepsilon_2 = \frac{\alpha_1}{2!} = -\frac{1}{2}$$

2nd order Gear

$k = 2$

$$\alpha_0 = 1 \quad \begin{cases} \alpha_0 + \alpha_1 + \alpha_2 = 0, \\ \alpha_1 + 2\alpha_2 = \beta_0, \\ \alpha_1 + 4\alpha_2 = 0. \end{cases}$$



$$\alpha_1 = -\frac{4}{3}, \alpha_2 = \frac{1}{3}, \beta_0 = -\frac{2}{3},$$

$$\varepsilon_3 = \frac{\alpha_1 + 2^3 \alpha_2}{3!} = \frac{2}{9} = 0.222222$$

Gear Coefficients

3rd order Gear

k = 3

$$\sum_{i=0}^3 \alpha_i y_{n-i} + h \beta_0 \dot{y}_n = 0$$

Coef. eqn.:

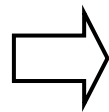
$$\alpha_0 = 1$$

$$\begin{cases} \alpha_1 + \alpha_2 + \alpha_3 = -1, \\ \alpha_1 + 2\alpha_2 + 2\alpha_3 = \beta_0, \\ \alpha_1 + 4\alpha_2 + 9\alpha_3 = 0, \\ \alpha_1 + 8\alpha_2 + 27\alpha_3 = 0. \end{cases}$$



$$\alpha_1 = -\frac{18}{11}, \alpha_2 = \frac{9}{11}, \alpha_3 = -\frac{2}{11}, \\ \beta_0 = -\frac{6}{11}$$

$$\varepsilon_{k+1} \triangleq \frac{1}{(k+1)!} \sum_{i=1}^k (-i)^{k+1} \alpha_i$$



$$\varepsilon_4 = \frac{\alpha_1 + 2^4 \alpha_2 + 3^4 \alpha_3}{4!} = -\frac{3}{22} = -0.1363636$$

PRINCIPLES OF CIRCUIT SIMULATION

Time Step Control

Calculation of Finite Difference

Time Step Control

- Let E be the allowed LTE bound at any time point.

$$|LTE(t_n)| \leq E$$

- Then the time step bound for the TR is calculated as

$$\left| \frac{h_n^3}{12} \ddot{x}_n \right| \leq E \quad \Rightarrow \quad h_n \leq \left(\frac{12E}{|\ddot{x}_n|} \right)^{1/3}$$

$$LTE_{TR}(t_n) = -\frac{h_n^3}{12} \ddot{x}_n$$

We need to calculate the high-order derivative approximately by finite differences.

Finite Difference Calculation

- Let $\Delta^k(t_n)$ be the **kth order finite difference (FD)** at t_n .
- It can be calculated by recursive formulas using the past data.

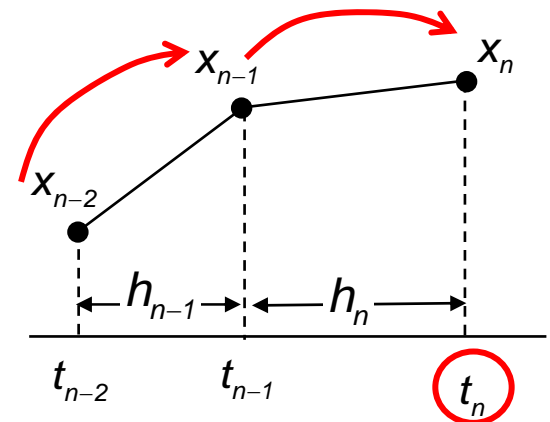
1st order FD:

$$\Delta x(t_n) = \frac{x_n - x_{n-1}}{h_n}$$

$$h_n = t_n - t_{n-1}$$

2nd order FD:

$$\Delta^2 x(t_n) \approx \frac{\Delta x(t_n) - \Delta x(t_{n-1})}{h_n}$$



Higher-order FD computation will have to use polynomial interpolation.

FD Calculation (cont'd)

High-order finite-differences with varying time-steps:

$$\Delta^p x(t_n) = \frac{\Delta^{p-1} x(t_n) - \Delta^{p-1} x(t_{n-1})}{(t_n - t_{n-p})(p-1)/p}$$

$$p \geq 2$$

Derived from Lagrange interpolation (details omitted).



(approximated by)

$$\Delta^p x(t_n) \approx \frac{\Delta^{p-1} x(t_n) - \Delta^{p-1} x(t_{n-1})}{(h_n + h_{n-1} + \dots + h_{n-p-2})}$$

OR

$$\Delta^p x(t_n) \approx \frac{\Delta^{p-1} x(t_n) - \Delta^{p-1} x(t_{n-1})}{(p-1)h_n}$$



Implemented in Spice3f5.

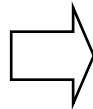
* These formulas are equivalent for the case of uniform time step.

LTE for C with B.E.

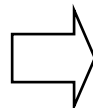
- With Backward Euler, the LTE's for capacitances (C) is given by

$$i = \mathbf{C} \frac{dv}{dt} \quad \rightarrow \quad \frac{d^2 v}{dt^2} = \frac{1}{\mathbf{C}} \frac{di}{dt} \quad \rightarrow \quad \ddot{v}(t_n) = \frac{1}{\mathbf{C}} \frac{i(t_{n+1}) - i(t_n)}{h_n}$$

$$LTE_{BE} = -\frac{h_n^2}{2} \ddot{x}_n$$



$$|LTE_{BE}| = \frac{h_n^2}{2} \ddot{v}_n = \frac{h_n}{2C} |i(t_{n+1}) - i(t_n)| \leq E_C$$



$$\Delta t_n \leq \frac{2C}{|i_C(t_{n+1}) - i_C(t_n)|} E_C$$

E_C is the LTE bound for C

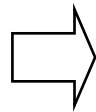
$$\Delta t_n = t_{n+1} - t_n = h_n$$

LTE for L with B.E.

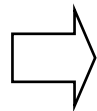
- By Backward Euler, the LTE for inductances (L) is given by

$$v = L \frac{di}{dt} \quad \rightarrow \quad \frac{d^2 i}{dt^2} = \frac{1}{L} \frac{dv}{dt} \quad \rightarrow \quad \ddot{i}(t_n) = \frac{1}{L} \frac{v(t_{n+1}) - v(t_n)}{h_n}$$

$$LTE_{BE} = -\frac{h_n^2}{2} \ddot{x}_n$$



$$|LTE_{BE}| = \frac{h_n^2}{2} \ddot{i}_n = \frac{h_n}{2L} |v(t_{n+1}) - v(t_n)| \leq E_L$$

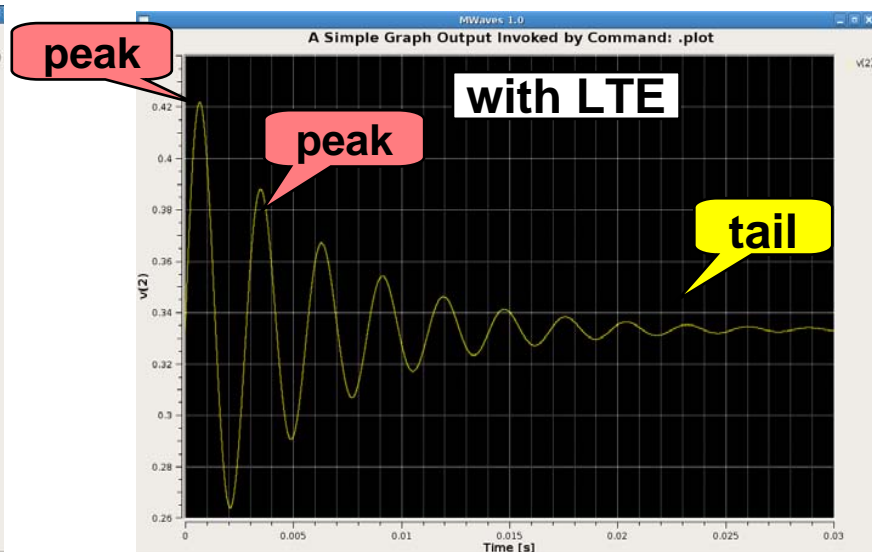
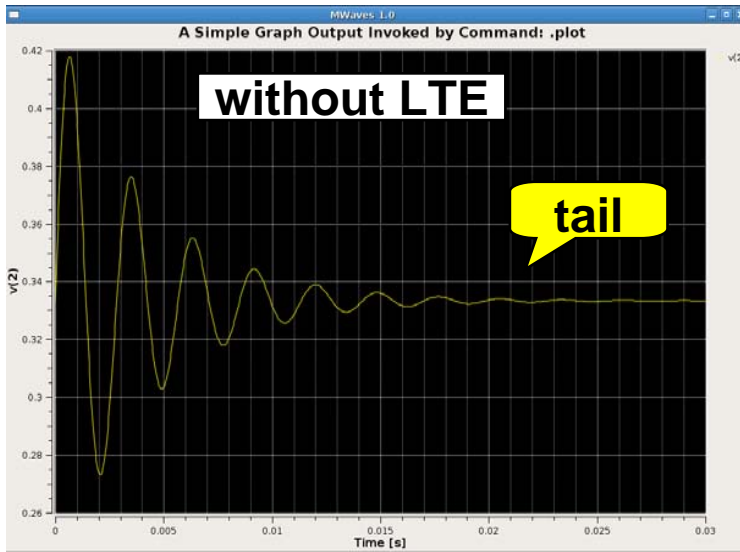


$$\Delta t_n \leq \frac{2L}{|v_L(t_{n+1}) - v_L(t_n)|} E_L$$

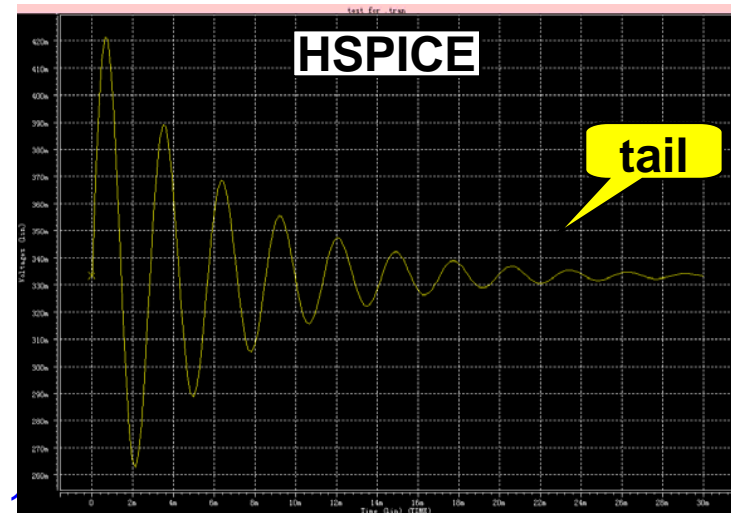
E_L is the LTE bound

$$\Delta t_n = t_{n+1} - t_n = h_n$$

Student Implementations



Implementation by XU Hui
(class 2008)



Acknowledgement

- **Some slides are adapted from**
 - **Prof. Albert Sangiovanni-Vincentelli's lecture at University of California, Berkeley (instructor Alessandra Nardi)**
 - **Prof. C.-K. Cheng's lecture at University of California at San Diego**