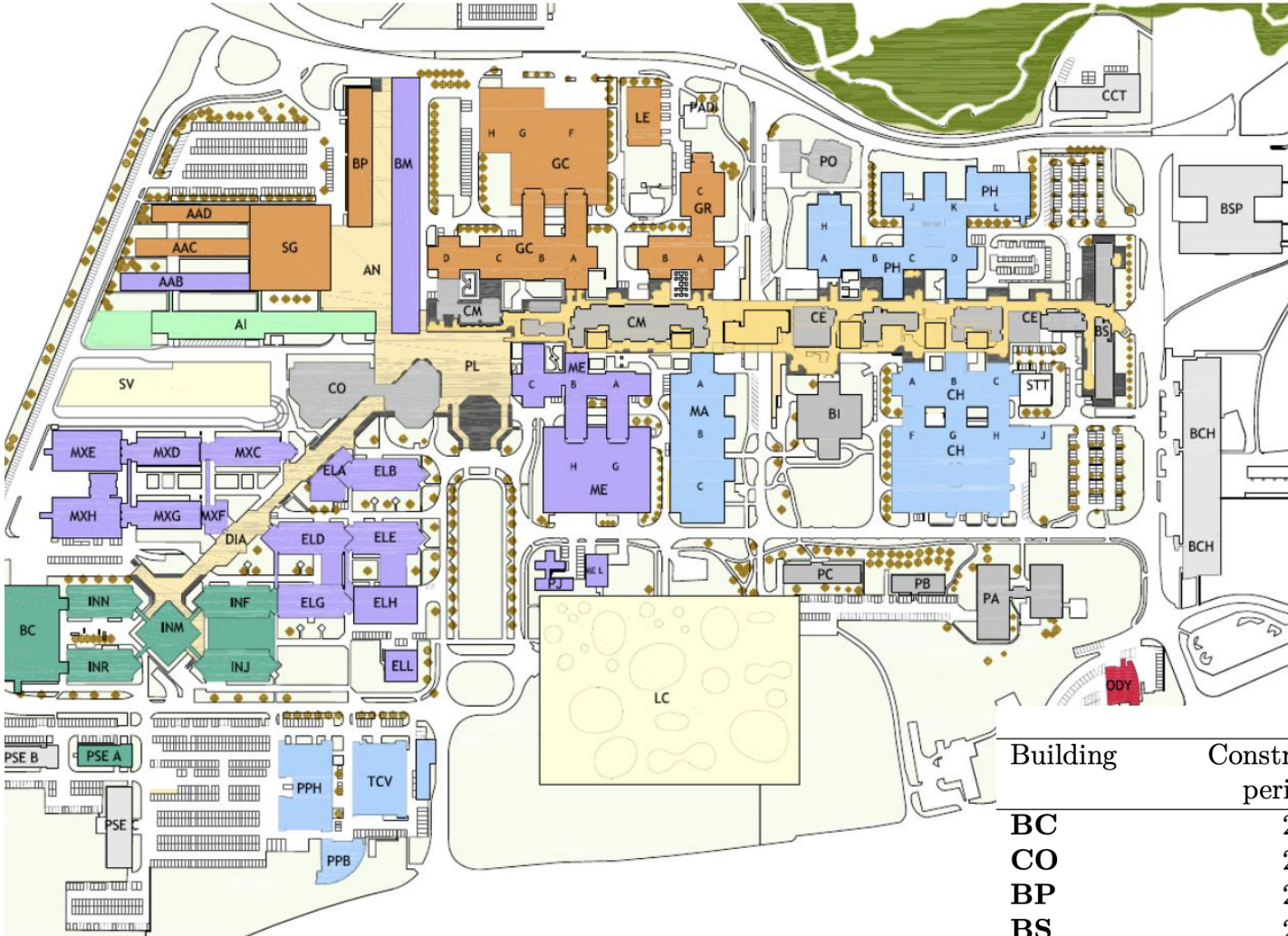


Solving a set of non linear equations

MOES
François Marechal

Buildings stock



Heating needs are defined by :

- $\dot{Q}_{b,t} \quad \forall b \in \{1..n_b\}$ [kW]
heat required by building b
at time t of the year
- $T_{b,t}^{supply} \quad \forall b \in \{1..n_b\}$ [°C]

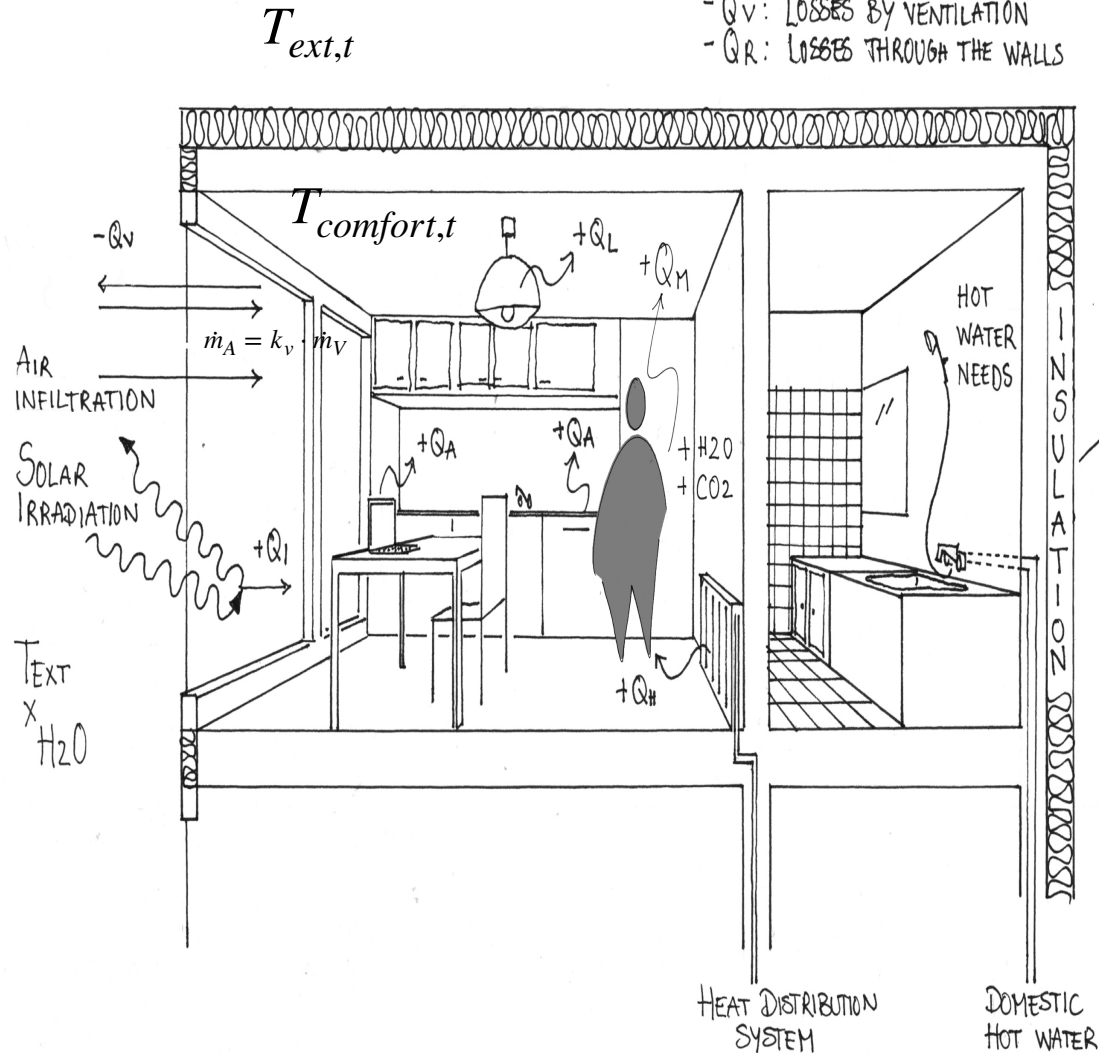
Minimum temperature
of the heat supply of building b
at time t of the year

Available :

Table 1.1: EPFL Buildings

Building	Construction period ^a	Heated surface A _{th} [m ²]	Annual heat demand Q _{th} [kWh]	Annual electricity demand Q _{el} [kWh]
BC	2	17480	418,491	1,603,596
CO	2	11901	477,008	943,653
BP	2	10442	457,861	691,031
BS	2	10267	509,183	350,860
TCV	2	6095	318,209	2,067,675

- +Q_A : GAIN BY APPLIANCES
- +Q_H : HEAT TO COMPENSATE LOSSES
- +Q_L : GAIN BY LIGHTING SYSTEM
- +Q_M : GAIN BY HUMAN
- +Q_I : GAIN BY IRRADIATION
- Q_V : LOSSES BY VENTILATION
- Q_R : LOSSES THROUGH THE WALLS



Our knowledge :

The model of the building envelop heat balance

$$\dot{Q}_{A,t}[\text{kW}] = \dot{E}_{A,t}$$

$$\dot{Q}_{L,t}[\text{kW}] = \dot{E}_{L,t}$$

$$\dot{Q}_{M,t}[\text{kW}] = \dot{q}_{cap} \cdot \sum_{cap} cap_t$$

$$\dot{Q}_{I,t}[\text{kW}] = Irr_t \cdot k_{sun}$$

$$\dot{Q}_{V,t}[\text{kW}] = \dot{m}_V \cdot cp_{air} \cdot (T_{comfort,t} - T_{ext,t})$$

$$\dot{Q}_{R,t}[\text{kW}] = \sum_{wall} k_{wall} \cdot S_{wall} \cdot (T_{comfort,t} - T_{ext,t})$$

$$\dot{Q}_{V,t} + \dot{Q}_{R,t} = k_{th}(T_{comfort,t} - T_{ext,t})$$

Gains

Losses

Heat balance :

what is the load to maintain the comfort temperature ?

$$\dot{Q}_{H,t}[\text{kW}] = \max(0, \dot{Q}_{V,t} + \dot{Q}_{R,t} - (\dot{Q}_{A,t} + \dot{Q}_{L,t} + \dot{Q}_{M,t} + \dot{Q}_{I,t}))$$

$$Q_H(t_0, t_{end}) = \int_{t_0}^{t_{end}} \dot{Q}_{H,t} \cdot dt = \int_{t_0}^{t_{end}} \max(0, k_{th} \cdot (T_{comfort,t} - T_{ext,t}) - k_{sun} \cdot Irr_t - \dot{Q}_{gain,t}) \cdot dt$$

Calculate k_{sun} and k_{th} if

$$Q^1 = Q_H(\text{January, December})$$

and

$$Q^2 = Q_H(\text{February, March})$$

$$Q_H(\text{January, December})(k_{sun}, k_{th}) - Q^1 = 0$$

$$Q_H(\text{February, March})(k_{sun}, k_{th}) - Q^2 = 0$$

2 equations and 2 unknowns : k_{sun}, k_{th}

Activate your knowledge :

Solve a set of equations

$$F(X, \pi) = 0$$

When $f(x,\pi)=0$ can not be transformed into $x=\phi(\pi)$ by mathematical manipulation

- Different problem formulations
 - 1 variable & 1 equation
 - $f(x,\pi) = 0$: implicit equation
 - $x=f(x,\pi)$: explicit equation
 - N Equations & N Variables
 - $F(X,\pi) = 0$: implicit equations
 - $X = F(X,\pi)$: explicit equations

find x such that $f(x) = 0$

TAYLOR development to approximate any function :

$$f(x) = f(x^0) + (x - x^0) \cdot f'(x^0) + \frac{(x - x^0)^2}{2!} f''(x^0) + \dots$$

1st order limitation (approximate with a straight line) near x^0

$$f(x^0) + (x^* - x^0) \cdot f'(x^0) \cong f(x^*) = 0$$

$$x^* = x^0 - \frac{f(x^0)}{f'(x^0)}$$

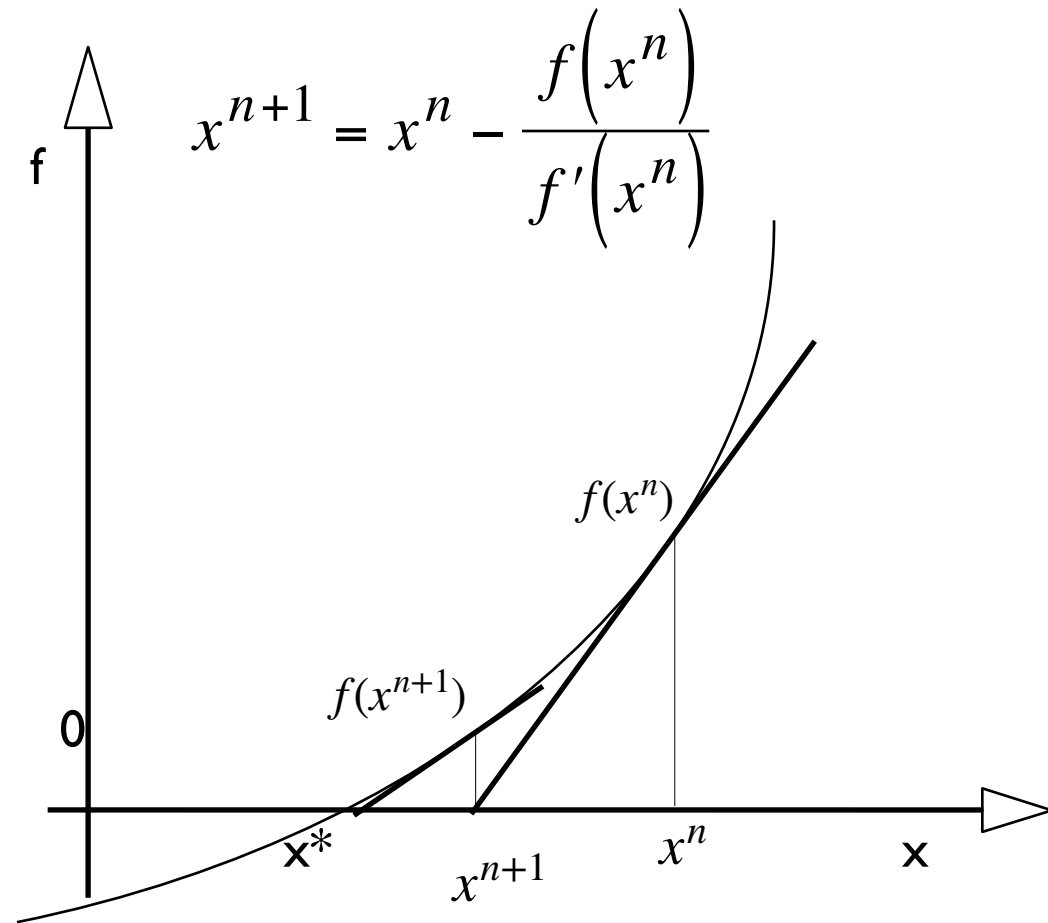
■ Newton Raphson algorithm

- Take $n = 0$ and x^0 = initial guess of x^* .
- Repeat (Iterations) :

$$x^{n+1} = x^n - \frac{f(x^n)}{f'(x^n)}$$

until $f(x^{n+1})$ sufficiently close to 0

- tangent approximation
- intersection with $f=0$

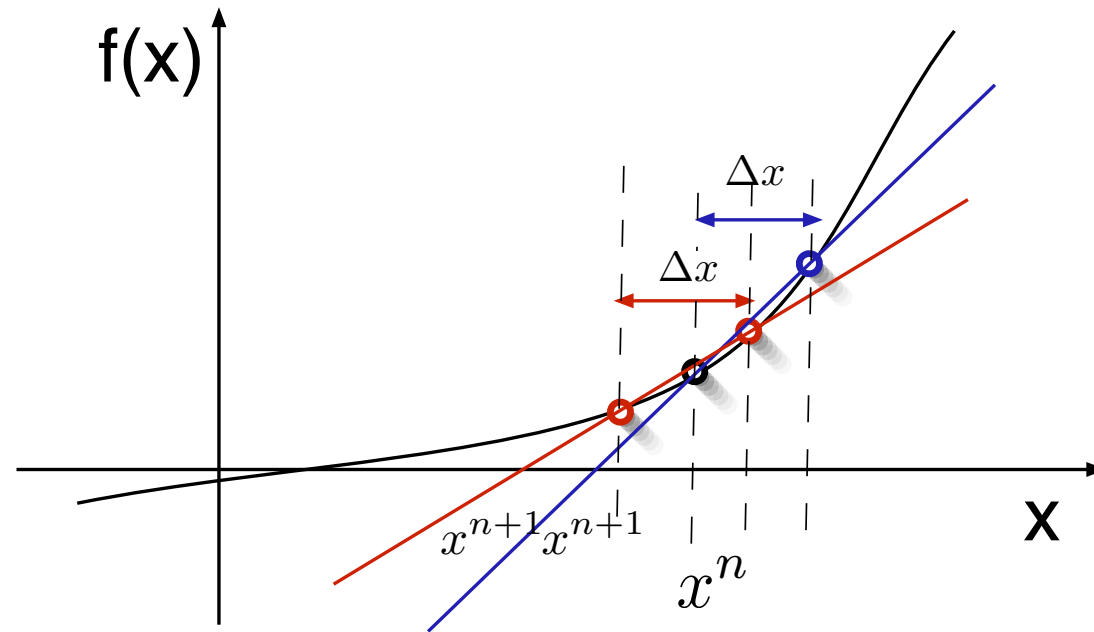


Forward calculation

$$f'(x^n) = \left[\frac{\delta f(x)}{\delta x} \right]_{x^n} = \frac{f(x^n) - f(x^n + \Delta x)}{\Delta x} \quad + 1 \text{ function evaluation}$$

Central value

$$f'(x^n) = \left[\frac{\delta f(x)}{\delta x} \right]_{x^n} = \frac{f(x^n - \frac{\Delta x}{2}) - f(x^n + \frac{\Delta x}{2})}{\Delta x} \quad + 2 \text{ function evaluations}$$



- Choose a small value well chosen value

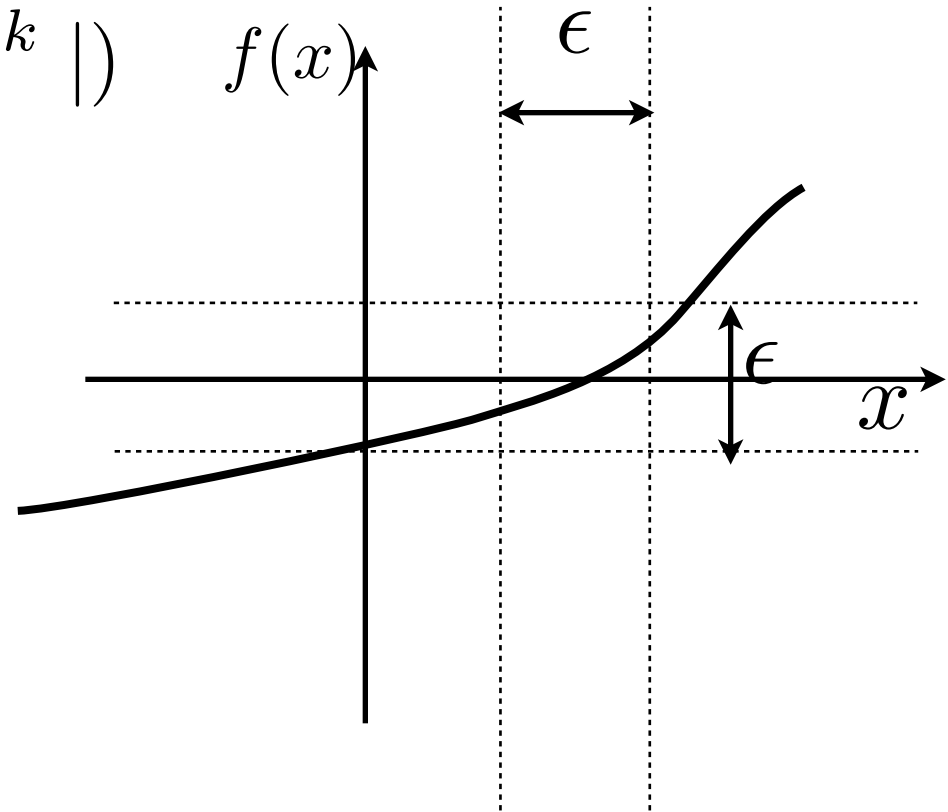
$$\epsilon = 1.0E - 06$$

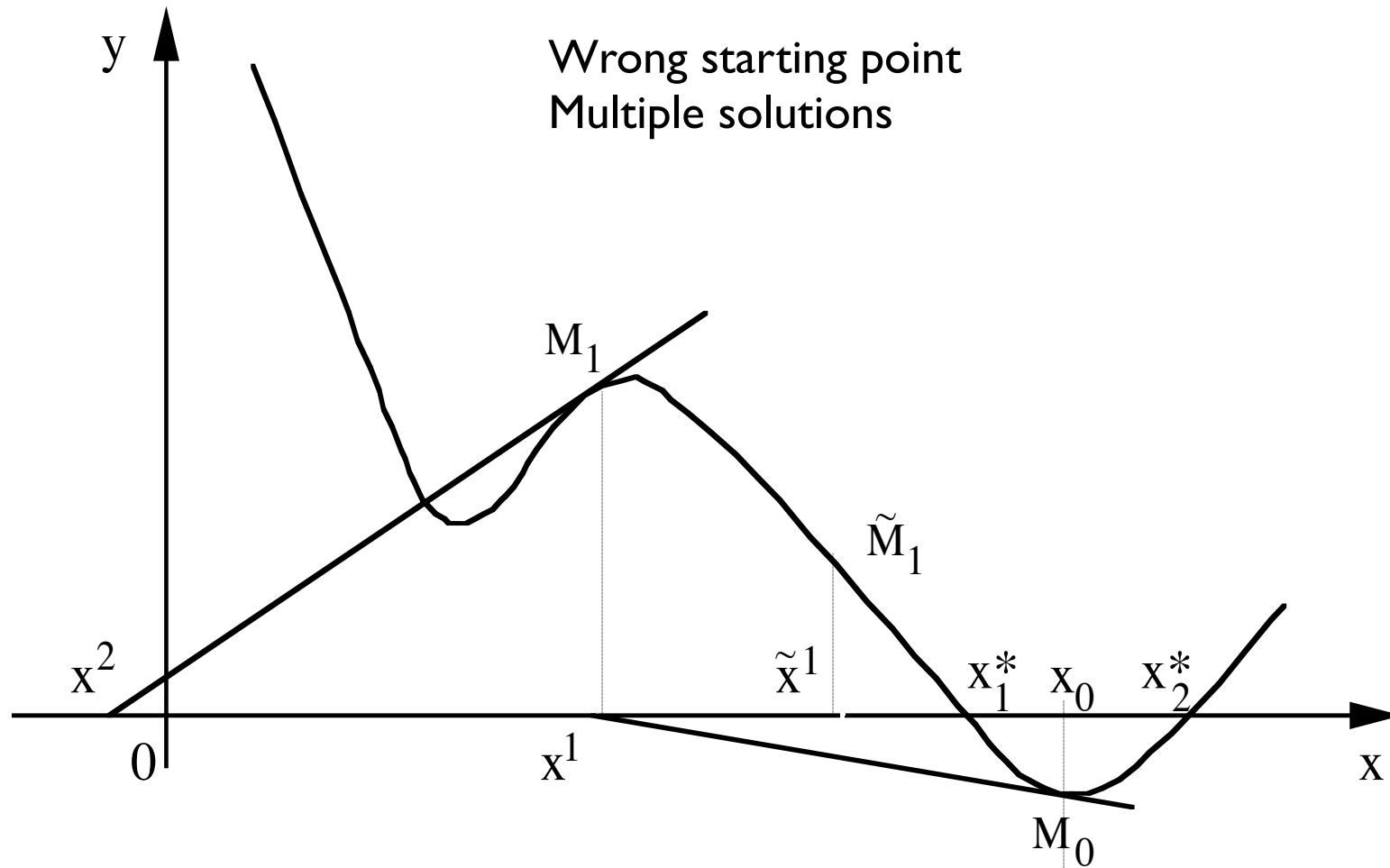
- Test variable variations

$$|x^{k+1} - x^k| \leq \epsilon * (1 + |x^k|)$$

- Test function variation

$$|f(x^k)| \leq \epsilon$$





- When you suspect divergence :
i.e. $|f(x^{n+1})| > |f(x^n)|$ and $\text{sign}(f(x^{n+1})) = \text{sign}(f(x^n))$
- Use relaxation factor $0 < q < 1$
$$x^{n+1} = x^n \cdot q + \left(x^n - \frac{f(x^n)}{f'(x^n)}\right) \cdot (1 - q)$$
 - note : $q=0 \Rightarrow$ full step
- Choice of q is critical ?
 - convergence speed wrt robustness
 - $q \gg$ small steps and lots of iterations
 - $q \ll$ Newton step : direct convergence if linear problem

- Requires initial point
- Requires derivatives calculation
- divergence possible
- no step if tangent = 0

- 2nd order development (quadratic) to accelerate convergence

$$-f(x) = 0 \approx c + b(x - x^0) + a(x - x^0)^2$$

$$-x - x_0 = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

- a, b, c obtained if we know 3 values of f(x)

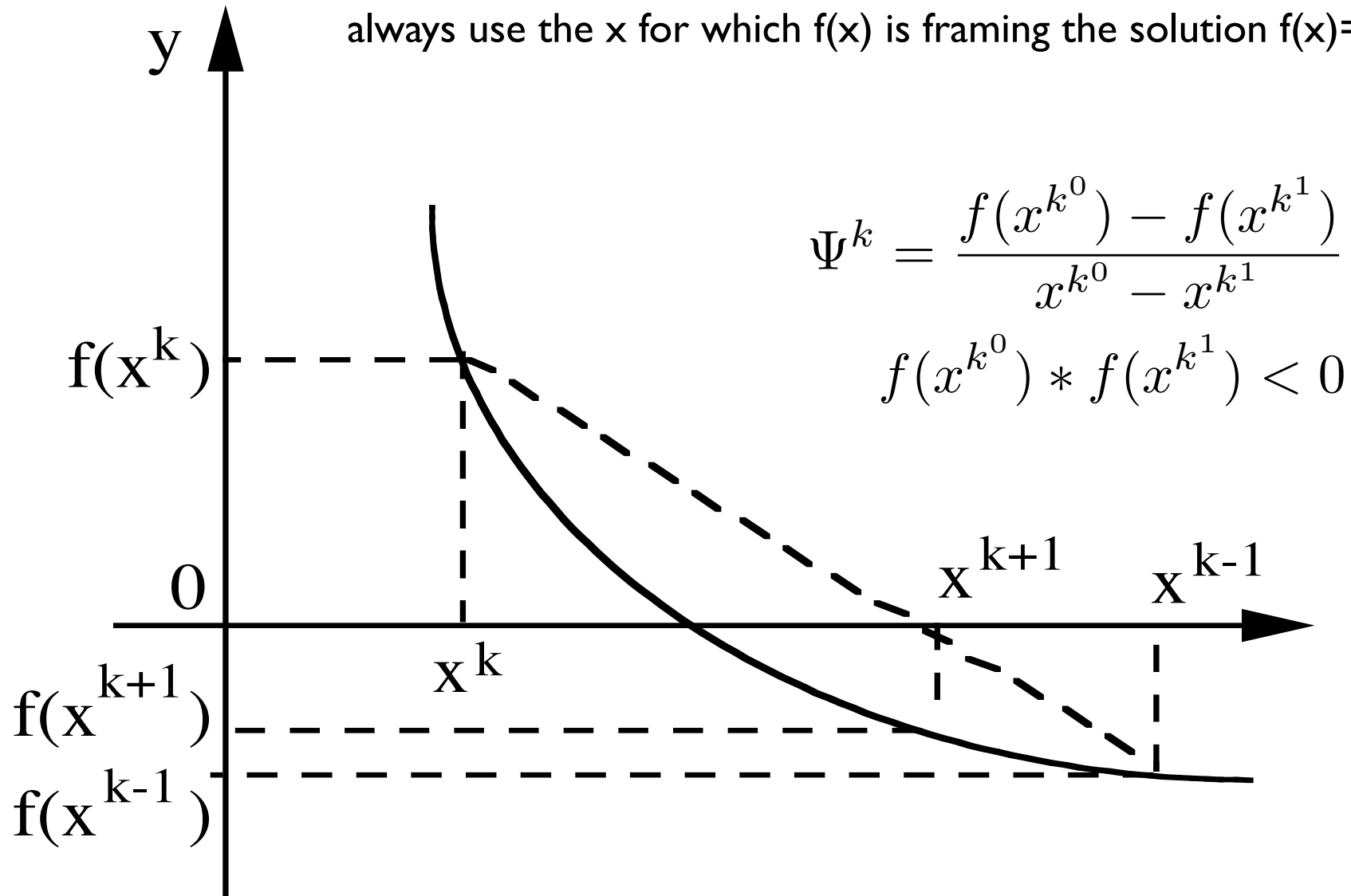
$$f(x) - f(x^k) = \frac{f(x^k) - f(x^{k-1})}{x^k - x^{k-1}} \cdot (x - x^k)$$

$$x^{k+1} = x^k - \psi^{-1} \cdot f(x^k)$$

$$\psi = \frac{f(x^k) - f(x^{k-1})}{x^k - x^{k-1}}$$

approximation of the
derivative by the
iteration step

always use the x for which $f(x)$ is framing the solution $f(x)=0$,



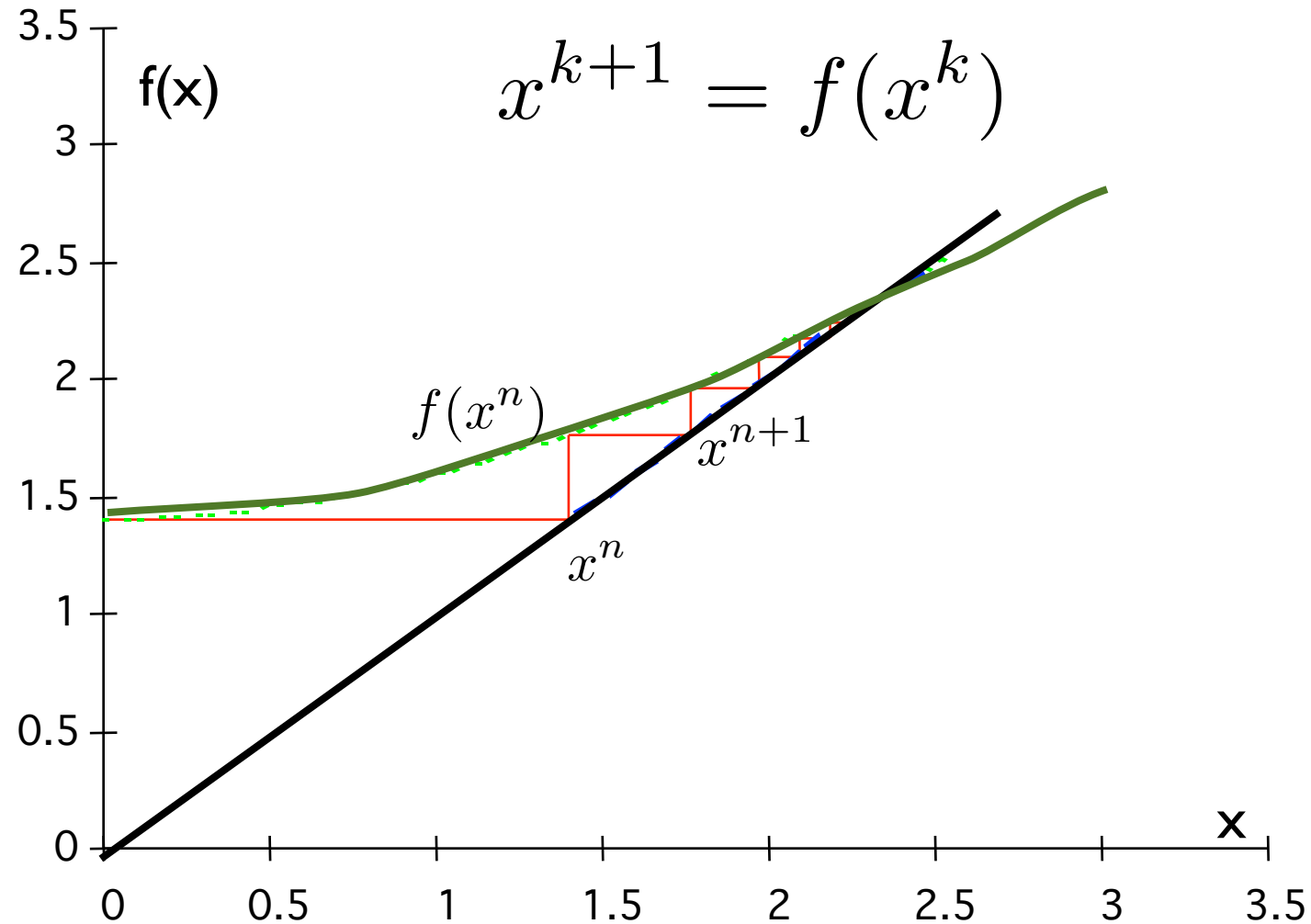
- Pro :
 - No derivative needed
 - Similar speed as Newton-Raphson.
- Cons :
 - Slow near the solution
 - Initial point like in newton method

EPFL Solving explicit equations : $x=f(x)$

- may be transformed into implicit form
 - $x = f(x) \Rightarrow \varphi(x) = x - f(x) = 0$

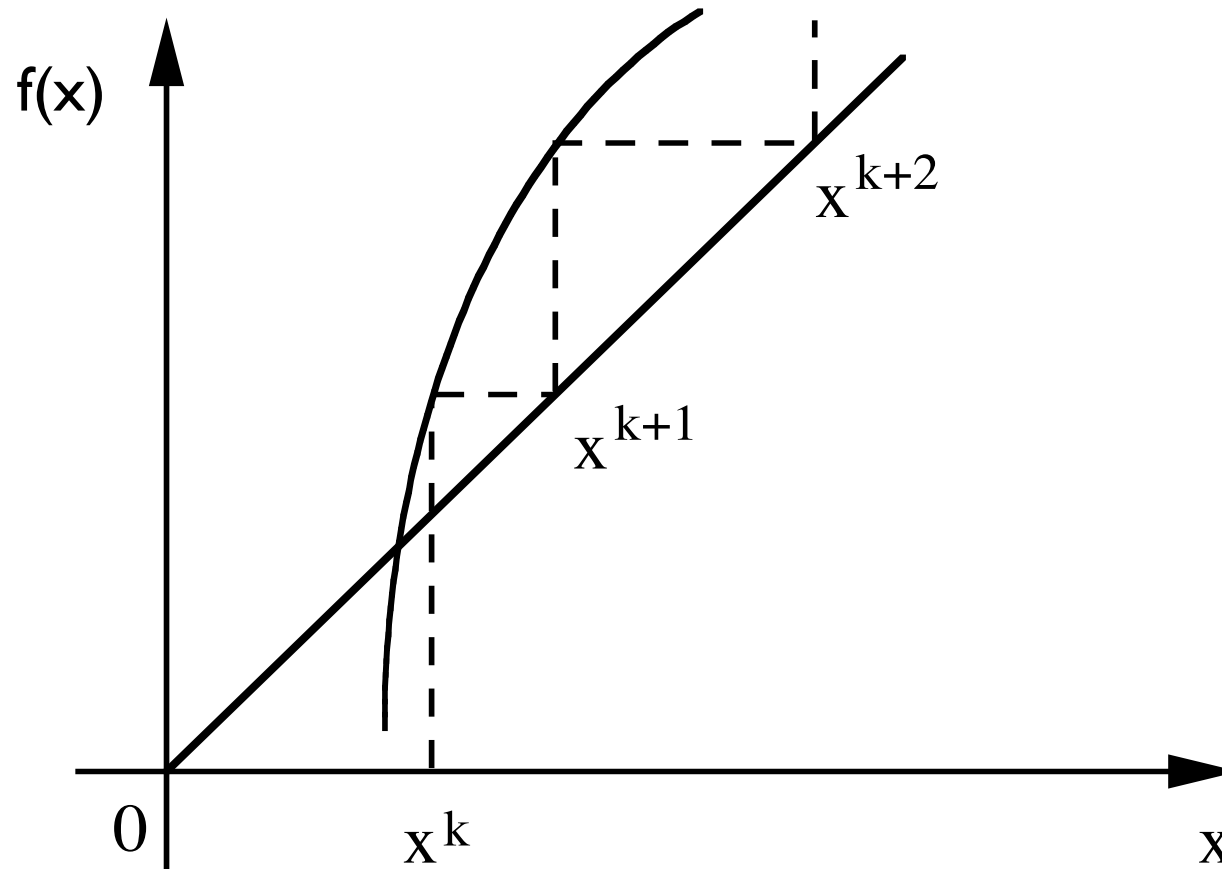
- Substitution method

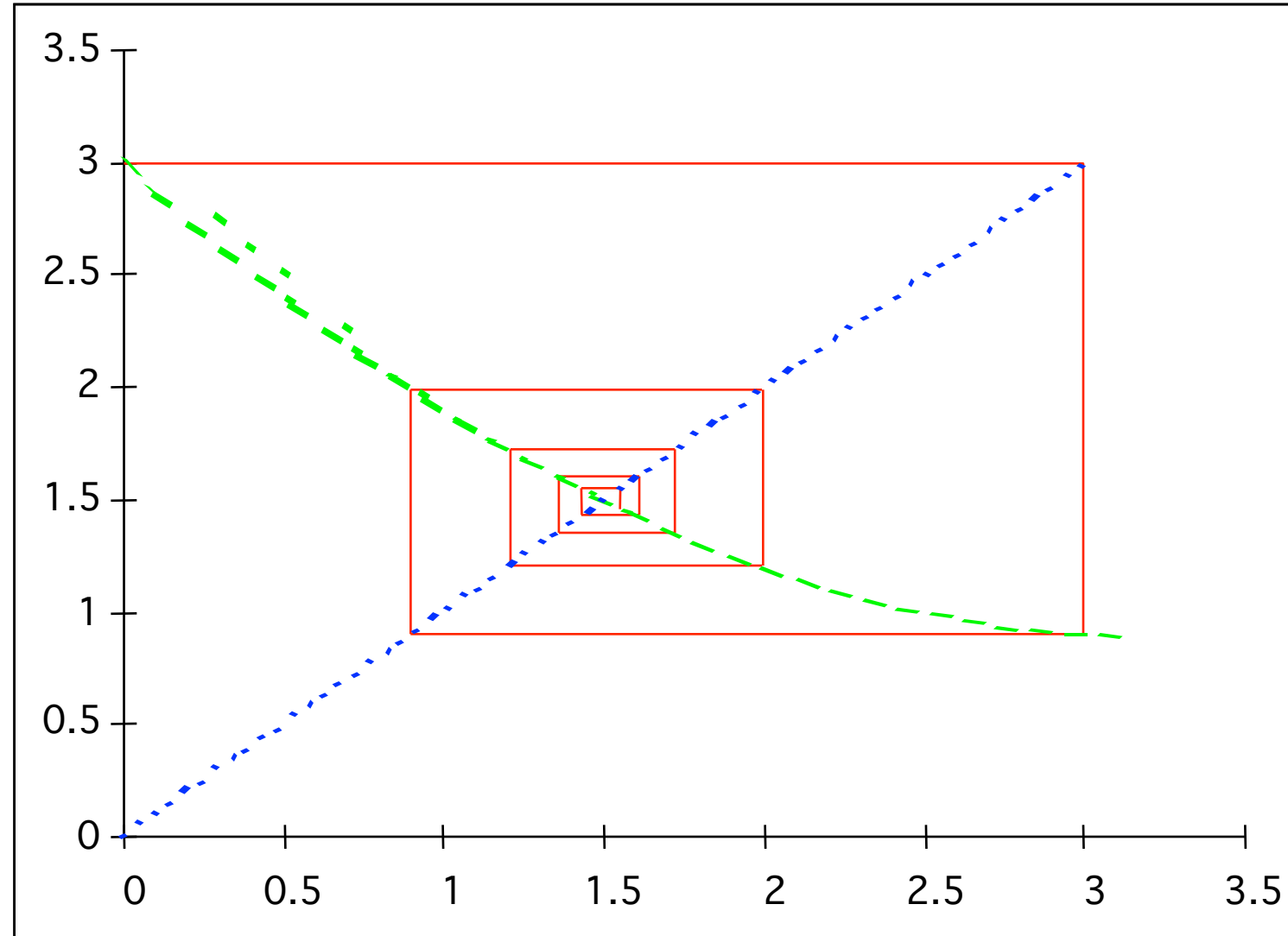
Solving $x=f(x)$: Explicit Equation

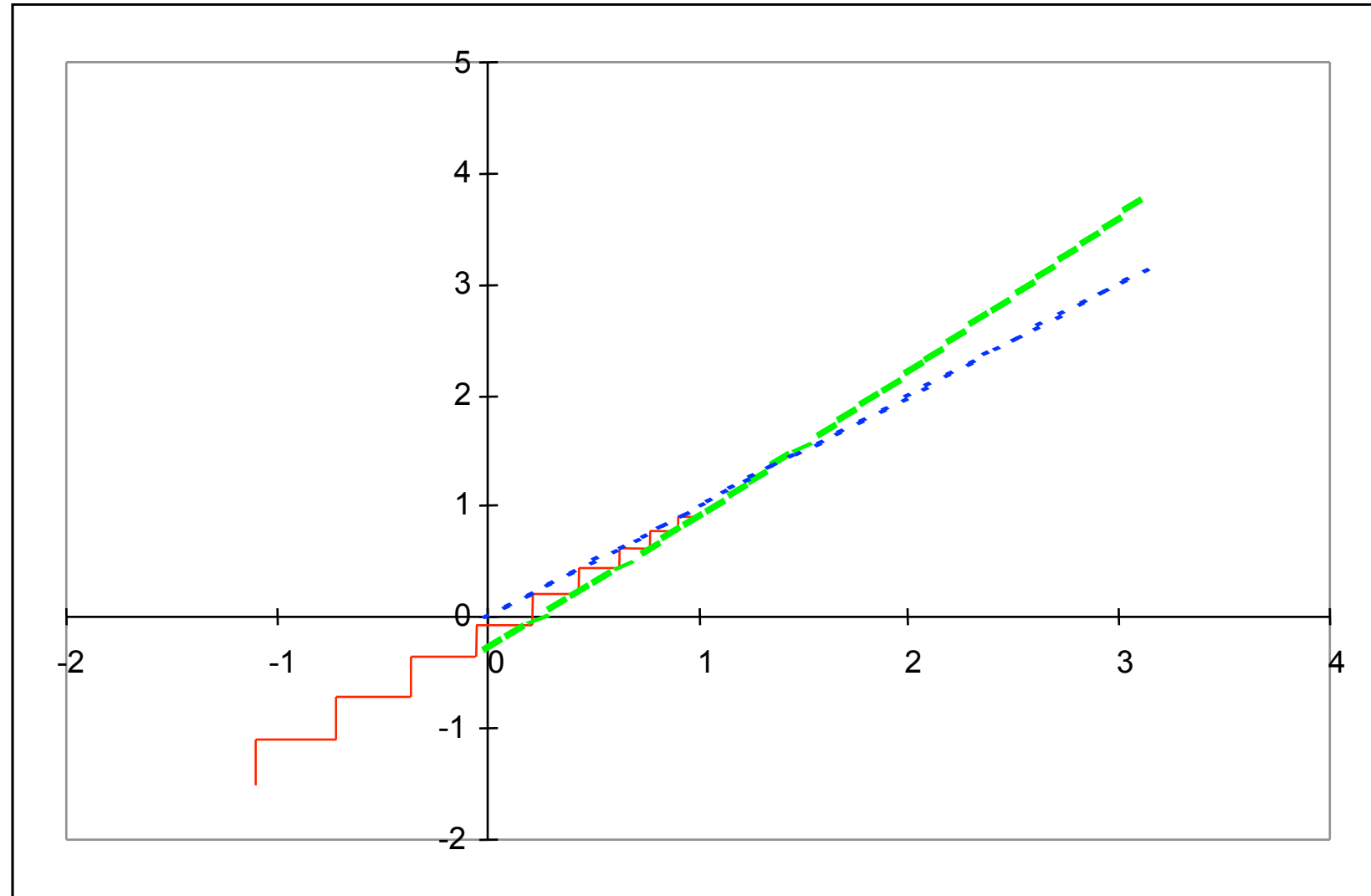


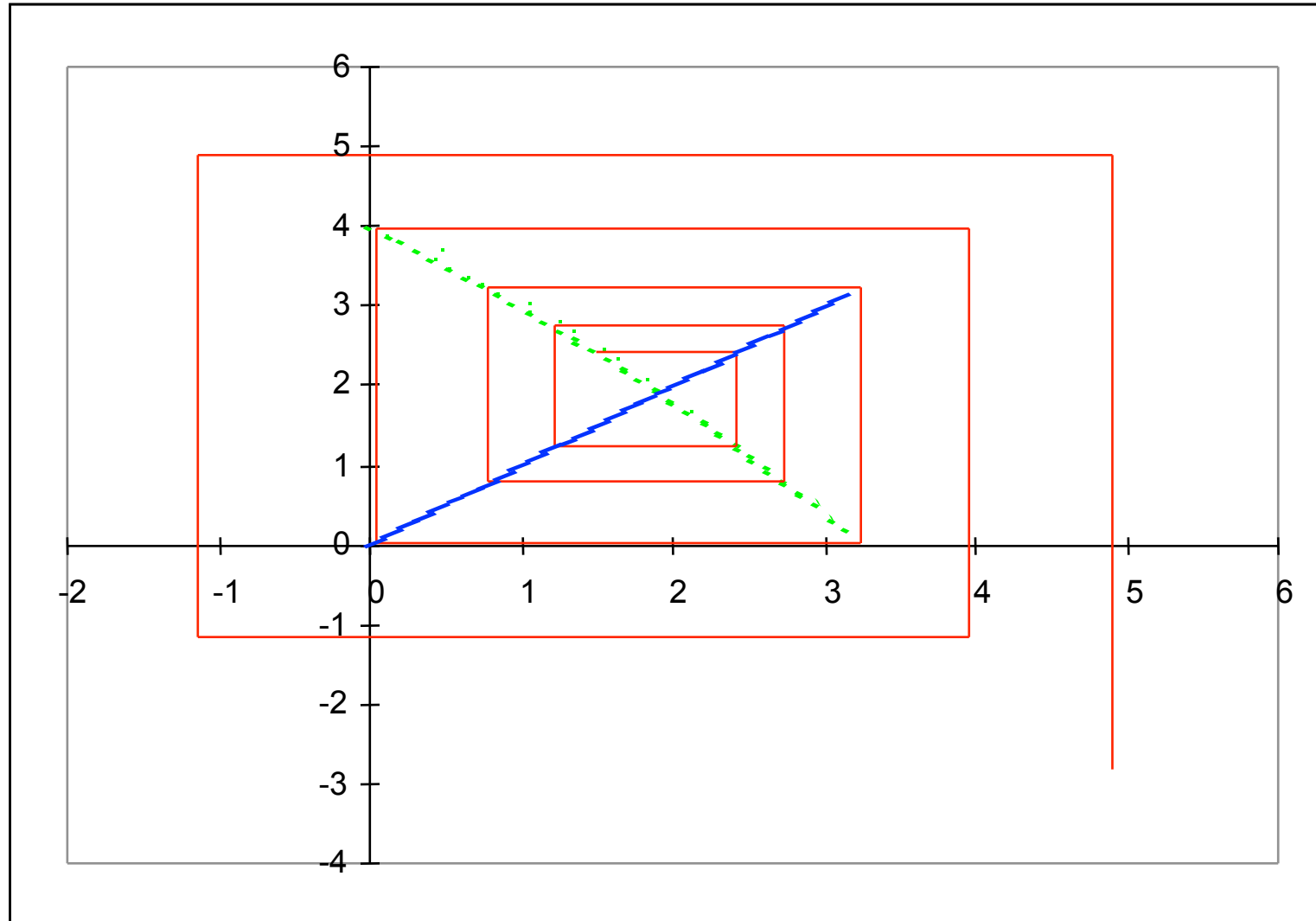
EPFL $x=f(x)$: Substitution may diverge

- Substitution : $x = f(x)$ May diverge



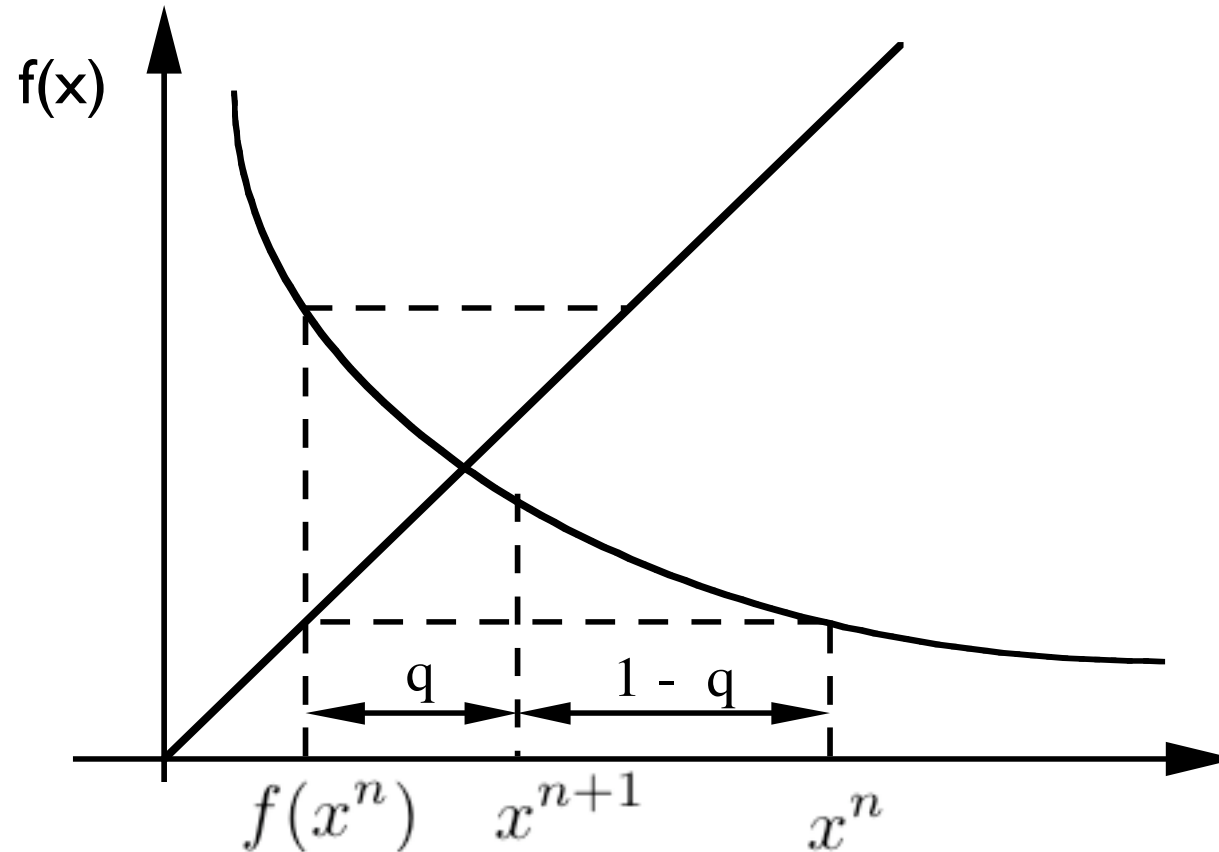






$$x^{n+1} = x^n \cdot q + f(x^n) \cdot (1 - q)$$

Full substitution if $q = 0$



- System to be solved : intersection of two curves

$$y - y^k = \frac{y^{k+1} - y^k}{x^{k+1} - \tilde{x}^k} (x - \tilde{x}^k) = \psi (x - \tilde{x}^k)$$

$$y = x$$

- ψ = Chord slope

- Therefore

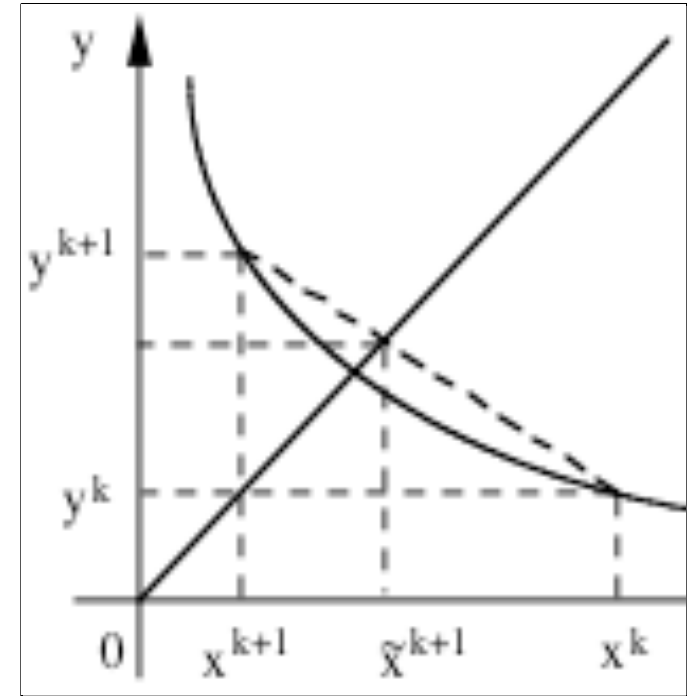
$$\tilde{x}^{k+1} = \frac{1}{1 - \psi} (x^{k+1} - \psi \tilde{x}^k)$$

- relaxation of substitution

$$\tilde{x}^{k+1} = q \tilde{x}^k + (1 - q) x^{k+1}$$

$$q = \frac{-\psi}{1 - \psi} \quad \text{et} \quad 1 - q = \frac{1}{1 - \psi}$$

- Increased speed of convergence
- More robust



- **Newton-Raphson n dimensions**

- Solve $F(X) = 0$ (Array)

$$f_1(x) = f_1(x_1, x_2, \dots, x_n) = 0$$

$$f_2(x) = f_2(x_1, x_2, \dots, x_n) = 0$$

.....

$$f_n(x) = f_n(x_1, x_2, \dots, x_n) = 0$$

- Initial guess is given

- $X_0 = [x_1 \dots x_n]$

- Taylor development

-

$$f_i(x) \approx f_i(x^0) + \left(\frac{\delta f(x)}{\delta x}\right)_{x^0} \cdot (x - x^0) = 0 \quad i = 1, n$$

Jacobian matrix
matrix of derivatives

function evaluated for x_0

$$\begin{vmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_j} & \dots & \frac{\partial f_1}{\partial x_n} \\ \vdots & & \vdots & & \vdots \\ \frac{\partial f_i}{\partial x_1} & \dots & \frac{\partial f_i}{\partial x_j} & \dots & \frac{\partial f_i}{\partial x_n} \\ \vdots & & \vdots & & \vdots \\ \frac{\partial f_n}{\partial x_1} & \dots & \frac{\partial f_n}{\partial x_j} & \dots & \frac{\partial f_n}{\partial x_n} \end{vmatrix} \cdot \begin{vmatrix} \Delta x_1 \\ \vdots \\ \Delta x_j \\ \vdots \\ \Delta x_n \end{vmatrix} + \begin{vmatrix} f_1(x^0) \\ \vdots \\ f_i(x^0) \\ \vdots \\ f_n(x^0) \end{vmatrix} = \begin{vmatrix} f_1(x) \\ \vdots \\ f_i(x) \\ \vdots \\ f_n(x) \end{vmatrix}$$

$${}^t \underline{\underline{J}} \underline{\underline{\Delta x}} + \underline{\underline{F}}(x^0) = \underline{\underline{F}}(x)$$



$${}^t \underline{J} \underline{\Delta x} + \underline{F}(\underline{x}^0) = \underline{F}(\underline{x})$$

$$\underline{F}(\underline{X}) = 0$$

$$\underline{x}^1 = \underline{x}^0 - {}^t \underline{J}_{\underline{x}^0}^{-1} \underline{F}(\underline{x}^0)$$

Iteration n :

$$\underline{x}^{n+1} = \underline{x}^n - {}^t \underline{J}_{\underline{x}^n}^{-1} \underline{F}(\underline{x}^n)$$

- At iteration k
 - Variables variations

$$| x^{k+1} - x^k | \leq \epsilon * (1 + | x^k |)$$

- Functions variation

$$| f(x^k) | \leq \epsilon$$

Variables

Original problem

$$\begin{aligned} |f^{k+1}| &\leq \epsilon \\ |x^{k+1} - x^k| &\leq \epsilon * (1 + |x^k|) \end{aligned}$$

Scaling $F(X) = 0 \rightarrow \Phi(\Xi) = 0$

$$\Xi = Scale_x \cdot X$$

$$\Phi = Scale_f \cdot F(X)$$

All equations and variables are compared with the same reference value

New problem

$$\begin{aligned} |\chi_j^{k+1} - \chi_j^k| &\leq \epsilon * (1 + |\chi_j^k|) \quad \forall j \\ |\phi_j^{k+1}(\chi) - \phi_j^k(\chi)| &\leq \epsilon \quad \forall j \end{aligned}$$

- Initial guess
- Matrix inversion + derivatives
- Matrix inversion at each iteration n*n derivatives,
- Relaxation may be applied :

$$\underline{\tilde{x}}^{n+1} = \underline{\tilde{x}}^n - {}^t \underline{L}_{\underline{x}^n}^{-1} \underline{F}(\underline{\tilde{x}}^n) \cdot (1 - q)$$

- Forward numerical estimation

$$\frac{\partial f}{\partial x_i} = \frac{f(X + \Delta x_i) - f(X)}{\Delta x_i} \quad \forall i = 1, \dots, n_X + 1$$

- Computation time cost !
 - central derivatives avoided
- Numerical noise (is the derivative a derivative ?)

$$\Delta f(X) = |F(X)_0 - F(X)_{n_X + 1}|$$

- $f(x) = x - \psi(x) = 0$
- Newton?
 - $x^{k+1} = x^k - \{tJ [f(x^k)]\}^{-1} f(x^k)$
- How to estimate the Jacobian matrix ?
 - $x^{k+1} = x^k - \{E - tJ [\psi(x^k)]\}^{-1} [x^k - \psi(x^k)]$

■

- Taylor development

$$\psi_1(\underline{x}) = \psi_1(\underline{x}^k) + \left(\frac{\delta \psi_1}{\delta x_1} \right)^k \cdot (x_1 - x_1^k) + \dots + \left(\frac{\delta \psi_1}{\delta x_n} \right)^k \cdot (x_n - x_n^k)$$

...

$$\psi_j(\underline{x}) = \psi_j(\underline{x}^k) + \left(\frac{\delta \psi_j}{\delta x_1} \right)^k \cdot (x_1 - x_1^k) + \dots + \left(\frac{\delta \psi_j}{\delta x_n} \right)^k \cdot (x_n - x_n^k)$$

...

$$\psi_n(\underline{x}) = \psi_n(\underline{x}^k) + \left(\frac{\delta \psi_n}{\delta x_1} \right)^k \cdot (x_1 - x_1^k) + \dots + \left(\frac{\delta \psi_n}{\delta x_n} \right)^k \cdot (x_n - x_n^k)$$

- select $n+1$ initial points (by substitution for example)

$x_0, x_1, x_2, \dots, x_k,$

- For each iteration store x and $\psi(x)$

Soit les matrices $\underline{\underline{C}}$ et $\underline{\underline{D}}$ ($n+1$ lignes et n colonnes)

$$\underline{\underline{C}} = \begin{matrix} & x_1^0 & \dots & x_j^0 & \dots & x_n^0 \\ & x_1^1 & \dots & x_j^1 & \dots & x_n^1 \\ & \dots & & \dots & & \dots \\ & x_1^k & \dots & x_j^k & \dots & x_n^k \\ & \dots & & \dots & & \dots \\ & x_1^n & \dots & x_j^n & \dots & x_n^n \end{matrix}$$

$$\underline{\underline{D}} = \begin{matrix} & \psi_1(\underline{x}^0) & \dots & \psi_j(\underline{x}^0) & \dots & \psi_n(\underline{x}^0) \\ & \psi_1(\underline{x}^1) & \dots & \psi_j(\underline{x}^1) & \dots & \psi_n(\underline{x}^1) \\ & \dots & & \dots & & \dots \\ & \psi_1(\underline{x}^k) & \dots & \psi_j(\underline{x}^k) & \dots & \psi_n(\underline{x}^k) \\ & \dots & & \dots & & \dots \\ & \psi_1(\underline{x}^n) & \dots & \psi_j(\underline{x}^n) & \dots & \psi_n(\underline{x}^n) \end{matrix}$$

After n iterations
we have n equations
 $\Rightarrow J$ is estimated

- From C and D,

$$\underline{\underline{A}} = \begin{bmatrix} x_1^1 - x_1^0 & \cdots & x_j^1 - x_j^0 & \cdots & x_n^1 - x_n^0 \\ \vdots & \ddots & \vdots & & \vdots \\ x_1^k - x_1^0 & \cdots & x_j^k - x_j^0 & \cdots & x_n^k - x_n^0 \\ \vdots & & \vdots & \ddots & \vdots \\ x_1^n - x_1^0 & \cdots & x_j^n - x_j^0 & \cdots & x_n^n - x_n^0 \end{bmatrix}$$

$$\underline{\underline{B}} = \begin{bmatrix} \psi_1(\underline{x}^1) - \psi_1(\underline{x}^0) & \cdots & \psi_j(\underline{x}^1) - \psi_j(\underline{x}^0) & \cdots & \psi_n(\underline{x}^1) - \psi_n(\underline{x}^0) \\ \vdots & \ddots & \vdots & & \vdots \\ \psi_1(\underline{x}^k) - \psi_1(\underline{x}^0) & \cdots & \psi_j(\underline{x}^k) - \psi_j(\underline{x}^0) & \cdots & \psi_n(\underline{x}^k) - \psi_n(\underline{x}^0) \\ \vdots & & \vdots & \ddots & \vdots \\ \psi_1(\underline{x}^n) - \psi_1(\underline{x}^0) & \cdots & \psi_j(\underline{x}^n) - \psi_j(\underline{x}^0) & \cdots & \psi_n(\underline{x}^n) - \psi_n(\underline{x}^0) \end{bmatrix}$$

System to be solved

$$\underline{\psi}(\underline{x}) - \underline{\psi}(\underline{x}^k) = \left\{ {}^t \underline{J} [\underline{\psi}(\underline{x}^k)] \right\} \underline{\Delta x}^k$$

$${}^t \underline{B} = {}^t \underline{J} {}^t \underline{A}$$

ou ${}^t \underline{B} {}^t \underline{A}^{-1} = {}^t \underline{J}$

and

d'où $\underline{J} = \underline{A}^{-1} \underline{B}$

After n iterations J can be evaluated and Newton-Raphson can be applied to calculate the new point.

$$\tilde{\underline{x}}^{n+1} = \underline{x}^n - \left\{ \underline{E} - {}^t (\underline{A}^{-1} \underline{B}) \right\}^{-1} \left[\underline{x}^n - \underline{\psi}(\underline{x}^n) \right]$$

From this point the **J** matrix can be updated at each step.
eliminate the worst point in the list and then reevaluate **J**

- As calculating Jacobian matrix is expensive, the idea is to preserve the validity of the inverted matrix for several steps : i.e.

$$\underline{\tilde{x}}^{n+1} = \underline{x}^n - \{ \underline{E} - (\underline{A}^{k_n})^{-1} \underline{B}^{k_n} \}^{-1} (\underline{x}^n - \psi(\underline{x}^n))$$

- k_n is the evaluation k of the Jacobian matrix used at iteration n
- the validity of the step is obtained by comparing the x obtained and the expected value (is the difference decreasing ?)

- Iterative procedure when no mathematical formulation is found
 - Does not always converge !
 - Bounds on variables + safe guards
- Initialisation point : use ranges of x
 - bad initialisation point means long calculations
- Direction (derivative) + Step length (relaxation)
 - Derivatives : defines direction
 - Numerical calculations $\Rightarrow$ length of Δx
 - Numerical calculation cost + noise
 - Matrix inversion : defines the direction
 - Try to reuse direction for several steps
 - Relaxation : if divergence observed
- Test of convergence
 - on both equations and variables
 - one criteria for several equations+ variables $\Rightarrow$ scaling