

# BASIC TECHNIQUES FOR COMPUTER SIMULATIONS WPO – 2<sup>ND</sup> SESSION

## LINEAR SYSTEMS

# INTRODUCTION

- In the previous WPO session we determined the value  $x$  that solves a single equation:  $f(x)=0$
- Now, we want to determine the values  $x_1, x_2, \dots, x_n$  that simultaneously satisfy a **set of equations**
- We will deal with **linear algebraic equations** of this general form:

$$\begin{aligned}a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n &= b_1 \\a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n &= b_2 \\&\vdots \\a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n &= b_n\end{aligned}$$

$a$ : constant coefficients,  $b$ : constants,  $x$ : unknowns

# INTRODUCTION

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n &= b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n &= b_2 \\ &\vdots \\ a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n &= b_n \end{aligned}$$

$$[A] = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad (n \times n)$$

$$[x] = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \quad (n \times 1)$$

$$[b] = \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix} \quad (n \times 1)$$

$$Ax = b$$

solve for  $x$

The quick `PYTHON` solution: `x = numpy.linalg.solve(A,b)`

or: `x = numpy.dot(numpy.linalg.inv(A),b)`

time consuming

# GAUSS ELIMINATION

WITHOUT PIVOTING (NAÏVE)

- Example: 3 equations – 3 unknowns

$$\left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ a_{21} & a_{22} & a_{23} & b_2 \\ a_{31} & a_{32} & a_{33} & b_3 \end{array} \right] \downarrow \left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ & a'_{22} & a'_{23} & b'_2 \\ & & a''_{33} & b''_3 \end{array} \right] \quad \left. \vphantom{\begin{array}{c} \left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ a_{21} & a_{22} & a_{23} & b_2 \\ a_{31} & a_{32} & a_{33} & b_3 \end{array} \right] \\ \left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ & a'_{22} & a'_{23} & b'_2 \\ & & a''_{33} & b''_3 \end{array} \right]} \right\} \text{(a) Forward elimination}$$

Step 1: Perform **forward elimination** to reduce the set of equations to an upper triangular system

- a. Eliminate  $a_{21}$  from the 2<sup>nd</sup> row:
- factor =  $a_{21}/a_{11}$
  - Subtract factor\*(1st\_row) from 2<sup>nd</sup> row

- b. Eliminate  $a_{31}$  from the 3<sup>rd</sup> row:
- factor =  $a_{31}/a_{11}$
  - Subtract factor\*(1st\_row) from 3<sup>rd</sup> row

$$(1) \quad a_{11}x_1 + a_{12}x_2 + a_{13}x_3 = b_1$$

$$(2) \quad a'_{22}x_2 + a'_{23}x_3 = b'_2$$

$$(3) \quad a'_{32}x_2 + a'_{33}x_3 = b'_3$$

- c. Eliminate  $a'_{32}$  from the 3<sup>rd</sup> row:
- factor =  $a'_{32}/a'_{22}$
  - Subtract factor\*(2nd\_row) from 3<sup>rd</sup> row

$$a_{11}x_1 + a_{12}x_2 + a_{13}x_3 = b_1$$

$$a'_{22}x_2 + a'_{23}x_3 = b'_2$$

$$a''_{33}x_3 = b''_3$$

source: Chapra SC. Applied numerical methods with MATLAB for engineers and scientific, 2008.

# GAUSS ELIMINATION

WITHOUT PIVOTING (NAÏVE)

## PYTHON

### FORWARD ELIMINATION

$$\left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ a_{21} & a_{22} & a_{23} & b_2 \\ a_{31} & a_{32} & a_{33} & b_3 \end{array} \right] \downarrow \left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ & a'_{22} & a'_{23} & b'_2 \\ & & a''_{33} & b''_3 \end{array} \right] \quad \text{(a) Forward elimination}$$

def main():

- 1) Define arrays A and b, using the numpy module
- 2) Call def forward\_elimination(...)

def forward\_elimination(...):

With 'for' loops eliminate the desired element from  $n^{\text{th}}$  row,  $k^{\text{th}}$  column by:

- 1) Computing the appropriate factor, using two of the elements of the  $k^{\text{th}}$  column
- 2) Multiplying the computed factor with all the elements of the  $k^{\text{th}}$  row and subtracting the resulting elements from the  $n^{\text{th}}$  row.

! Python uses **zero-based indexing**, meaning that the first element of a list has index 0 !

# GAUSS ELIMINATION

WITHOUT PIVOTING (NAÏVE)

$$\left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ & a'_{22} & a'_{23} & b'_2 \\ & & a''_{33} & b''_3 \end{array} \right]$$

↓

$$\left. \begin{aligned} x_3 &= b''_3 / a''_{33} \\ x_2 &= (b'_2 - a'_{23}x_3) / a'_{22} \\ x_1 &= (b_1 - a_{13}x_3 - a_{12}x_2) / a_{11} \end{aligned} \right\} \text{(b) Back substitution}$$

Step 2: Perform **back substitution** to solve for the unknowns

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + a_{13}x_3 &= b_1 \\ a'_{22}x_2 + a'_{23}x_3 &= b'_2 \\ a''_{33}x_3 &= b''_3 \end{aligned}$$

The third equation is solved for  $x_3$ :

$$x_3 = b''_3 / a''_{33}$$

Back-substitute the result to equation 2 to solve for  $x_2$

Back-substitute both results to equation 1 to solve for  $x_1$

source: Chapra SC. Applied numerical methods with MATLAB for engineers and scientific, 2008.

# GAUSS ELIMINATION

## WITHOUT PIVOTING (NAÏVE)

$$\left[ \begin{array}{ccc|c} a_{11} & a_{12} & a_{13} & b_1 \\ & a'_{22} & a'_{23} & b'_2 \\ & & a''_{33} & b''_3 \end{array} \right]$$

↓

$$\left. \begin{aligned} x_3 &= b''_3 / a''_{33} \\ x_2 &= (b'_2 - a'_{23}x_3) / a'_{22} \\ x_1 &= (b_1 - a_{13}x_3 - a_{12}x_2) / a_{11} \end{aligned} \right\} \text{(b) Back substitution}$$

## PYTHON

### BACK SUBSTITUTION

def main(): 1) Use A (upper diagonal) and b arrays after forward elimination

2) Call def back\_substitution(...)

def back\_substitution(...): For a system of N equations:

- 1) Start from the last row to compute  $x_N$
- 2) Iterate though the equations in reverse order
- 3) At every iteration solve for the corresponding unknown.

! Python uses **zero-based indexing**, meaning that the first element of a list has index 0 !

# LU FACTORIZATION

WITHOUT PIVOTING

LESS TIME CONSUMING FOR A COMPUTER

- Example: 3 equations – 3 unknowns

$$[A] = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad [x] = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad [b] = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

- In order to separate the time-consuming elimination of matrix A from the manipulations of the right-hand side vector b:

A is “factored” or “decomposed” into:

$$[U] = \begin{bmatrix} u_{11} & u_{12} & u_{13} \\ 0 & u_{22} & u_{23} \\ 0 & 0 & u_{33} \end{bmatrix}$$

Upper triangular matrix

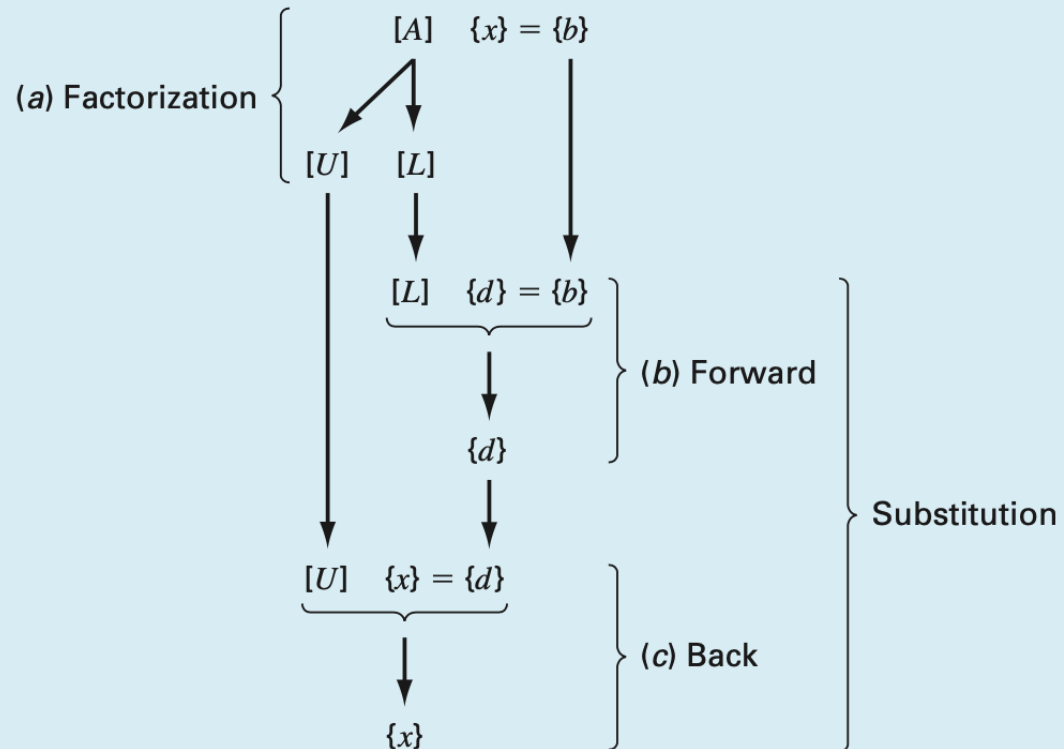
$$[L] = \begin{bmatrix} 1 & 0 & 0 \\ l_{21} & 1 & 0 \\ l_{31} & l_{32} & 1 \end{bmatrix}$$

Lower triangular matrix



# LU FACTORIZATION

## WITHOUT PIVOTING



$$\mathbf{A} = \mathbf{LU},$$

$$\text{So, } \mathbf{Ax} = \mathbf{b} \Leftrightarrow \mathbf{LUx} = \mathbf{b}$$

- $\mathbf{Ld} = \mathbf{b}$ , solve by forward substitution for intermediate vector  $\mathbf{d}$
- $\mathbf{Ux} = \mathbf{d}$ , solve by back substitution for unknown vector  $\mathbf{x}$

source: Chapra SC. Applied numerical methods with MATLAB for engineers and scientific, 2008.

# LU FACTORIZATION

## WITH PIVOTING

- Not all square matrices have a “pure” LU decomposition
- For more reliable results, partial pivoting is employed, so that:

$$\mathbf{PA} = \mathbf{LU} \quad (1),$$

the permutation matrix  $\mathbf{P}$  is employed, to keep track of the row switches

- So,  $\mathbf{Ax} = \mathbf{b} \Leftrightarrow \mathbf{PAx} = \mathbf{Pb}$  (2) which is solved in a similar way as in LU without pivoting:

$$\begin{aligned} \text{(2) using (1): } & \mathbf{LUx} = \mathbf{Pb} \\ & \Leftrightarrow \mathbf{Ld} = \mathbf{Pb} \quad (3), \mathbf{d} = \mathbf{Ux} \quad (4) \end{aligned}$$

- (3) Is solved for  $\mathbf{d}$  and (4) is solved for  $\mathbf{x}$

# LU FACTORIZATION

## WITH PIVOTING

### PYTHON

1) **A** is decomposed to **L** and **U** using **P**, with scipy module:

`scipy.linalg.lu(A, permute_l=False)`

2) Once **L** is known, **Ld = Pb** is solved for **d** with:

forward substitution

`numpy.x = numpy.linalg.solve(A,b)`  
for forward and back substitution`

3) Once **d** is known, **Ux = d** is solved for **x** with:

back substitution

# ITERATIVE METHODS

- Iterative methods provide an alternative to the two elimination methods (Gauss, LU factorization) described so far
- Useful for large, sparse matrices
- Similar logic to the root-finding methods discussed in the 1<sup>st</sup> WPO:
  - An initial guess for all roots of the system
  - Repetitive method to obtain a good approximation of the roots

# GAUSS-SEIDEL

- In our 3x3 example, if the diagonal elements are all non-zero, every equation can be solved for the corresponding unknown:

$$\begin{aligned}a_{11}x_1 + a_{12}x_2 + a_{13}x_3 &= b_1 \\a_{21}x_1 + a_{22}x_2 + a_{23}x_3 &= b_2 \\a_{31}x_1 + a_{32}x_2 + a_{33}x_3 &= b_3\end{aligned}$$

$$\left\{ \begin{aligned}x_{1,\text{new}} &= \frac{b_1 - a_{12}x_2 - a_{13}x_3}{a_{11}} & (A) \\&\downarrow \\x_{2,\text{new}} &= \frac{b_2 - a_{21}x_{1,\text{new}} - a_{23}x_3}{a_{22}} & (B) \\&\downarrow \\x_{3,\text{new}} &= \frac{b_3 - a_{31}x_{1,\text{new}} - a_{32}x_{2,\text{new}}}{a_{33}} & (C)\end{aligned}\right.$$

- Initial guess: vector  $\mathbf{x}$  ( $x_1, x_2, x_3$ )
- Substitute  $x_2, x_3$  guesses to Eq. (A) and solve for new  $x_1$
- Substitute the new  $x_1$  along with the initial guess for  $x_3$  to Eq. (B) and get new  $x_2$ ...
- Continue the process till convergence criterion is met for every element of vector  $\mathbf{x}$ :

$$\left| \frac{x_{i,\text{new}} - x_{i,\text{old}}}{x_{i,\text{new}}} \right| \leq \text{chosen\_tolerance}, i = 1, 2, 3$$

$$x_{1,\text{new}} = \frac{b_1 - a_{12}x_2 - a_{13}x_3}{a_{11}}$$



$$x_{2,\text{new}} = \frac{b_2 - a_{21}x_{1,\text{new}} - a_{23}x_3}{a_{22}}$$



$$x_{3,\text{new}} = \frac{b_3 - a_{31}x_{1,\text{new}} - a_{32}x_{2,\text{new}}}{a_{33}}$$

def main():

- 1) Define arrays **A** and **b**, using the numpy module
- 2) Make initial guess for solution vector **x**
- 3) Call def gauss\_seidel(...)

def gauss\_seidel(...):

- 1) For every element *i* of vector **x**, update values **x**[*i*] one at a time, using equations on the left
- 2) Compare **updated x** vector with **x** of previous iteration

Repeat until convergence criterion is met

# JACOBI

$$\begin{aligned}a_{11}x_1 + a_{12}x_2 + a_{13}x_3 &= b_1 \\a_{21}x_1 + a_{22}x_2 + a_{23}x_3 &= b_2 \\a_{31}x_1 + a_{32}x_2 + a_{33}x_3 &= b_3\end{aligned}$$



$$\begin{aligned}x_{1,\text{new}} &= \frac{b_1 - a_{12}x_2 - a_{13}x_3}{a_{11}} & (1) \\x_{2,\text{new}} &= \frac{b_2 - a_{21}x_1 - a_{23}x_3}{a_{22}} & (2) \\x_{3,\text{new}} &= \frac{b_3 - a_{31}x_1 - a_{32}x_2}{a_{33}} & (3)\end{aligned}$$

- While Gauss-Seidel method always applies the latest updated values of the elements during the iterations, Jacobi method uses the set of values ( $x_{1,\text{new}}, x_{2,\text{new}}, x_{3,\text{new}}$ ) obtained from the previous step
- Solution vector  $\mathbf{x}$  is updated as a whole in every iteration and not element by element
- Continue iterations till convergence criterion is met for all elements of solution vector  $\mathbf{x}$ :

$$\left| \frac{x_{i,\text{new}} - x_{i,\text{old}}}{x_{i,\text{new}}} \right| \leq \text{chosen\_tolerance}, i = 1, 2, 3$$

# JACOBI

# PYTHON

- Eq. (1-3) in the form of matrices:

$$\begin{aligned}
 x_1^{\text{new}} &= \frac{b_1}{a_{11}} - \frac{a_{12}}{a_{11}}x_2 - \frac{a_{13}}{a_{11}}x_3 \\
 x_2^{\text{new}} &= \frac{b_2}{a_{22}} - \frac{a_{21}}{a_{22}}x_1 - \frac{a_{23}}{a_{22}}x_3 \\
 x_3^{\text{new}} &= \frac{b_3}{a_{33}} - \frac{a_{31}}{a_{33}}x_1 - \frac{a_{32}}{a_{33}}x_2
 \end{aligned}$$

$$[d] = \begin{bmatrix} \frac{b_1}{a_{11}} \\ \frac{b_2}{a_{22}} \\ \frac{b_3}{a_{33}} \end{bmatrix} \quad [C] = \begin{bmatrix} 0 & \frac{a_{12}}{a_{11}} & \frac{a_{13}}{a_{11}} \\ \frac{a_{21}}{a_{22}} & 0 & \frac{a_{23}}{a_{22}} \\ \frac{a_{31}}{a_{33}} & \frac{a_{32}}{a_{33}} & 0 \end{bmatrix} \quad [x] = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

def main():

- 1) Define arrays **A** and **b**, using the numpy module
- 2) Make initial guess for solution vector **x**
- 3) Call def jacobi(...)

def jacobi(...):

- 1) Compute **d** and **C**
- 2) **x\_new** = **d** - np.dot(**C**,**x**)
- 3) Compare **x\_new** with **x** of previous iteration  
Repeat until convergence criterion is met

! Make sure that all vectors are vertical during computations !