

# Network Flows

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## Topic 7: Convex Costs Flows

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# 7.- Convex Cost Flows

- Introduction
- Applications
- Transformations to a MCNFP
- Pseudopolynomial Time Algorithms
- Polynomial-Time Algorithm
- Source material:
  - R.K. Ahuja, Th.L. Magnanti, J. Orlin “Network Flows”, chap. 15.
  - R.K. Ahuja “Advanced Network Optimization”  
<http://www.ise.ufl.edu/ANO/>

# Introduction to Convex Cost Flows

- Convex cost flow problems are minimum cost flow problems where the cost of flow is nonlinear.

Minimize  $\sum_{(i,j) \in A} C_{ij}(x_{ij})$

subject to

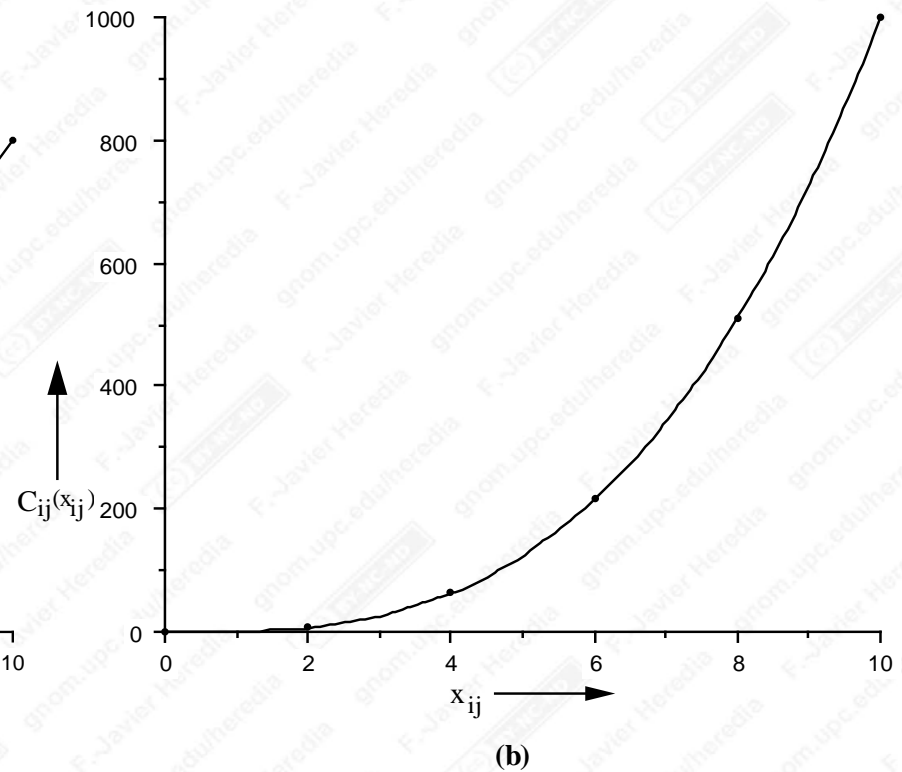
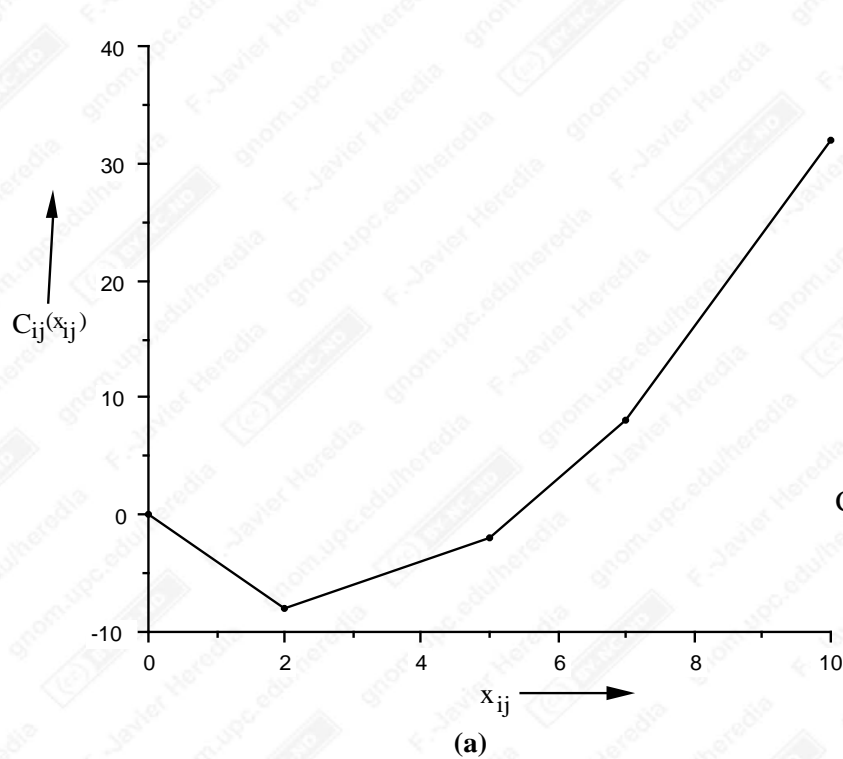
$$\sum_{\{j:(i,j) \in A\}} \mathbf{x}_{ij} - \sum_{\{j:(j,i) \in A\}} \mathbf{x}_{ji} = b(i) \text{ for each node } i \in N$$

$$0 \leq x_{ij} \leq u_{ij} \text{ and integer for each arc } (i, j) \in N$$

- Here we assume that **the total cost is separable**.
- The cost of flow  $C_{ij}(x_{ij})$  is a **convex function** of  $x_{ij}$  instead of a linear function  $c_{ij}x_{ij}$ .

# Introduction to Convex Cost Flows

- Some sample cost functions:

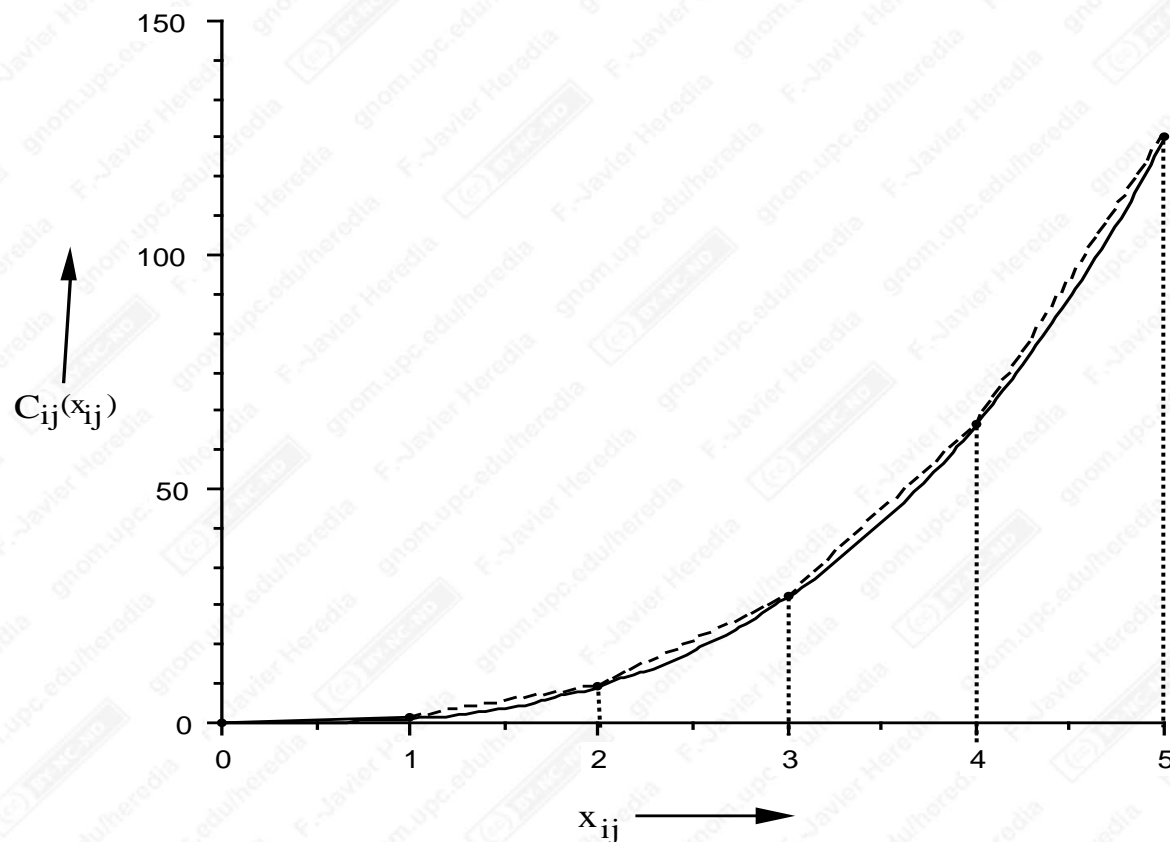


# Applications

- Urban Traffic Flows.
- Area transfer in Communication Networks.
- Matrix Balancing.
- Stick Percolation Problem.

# Piecewise Linear Assumption

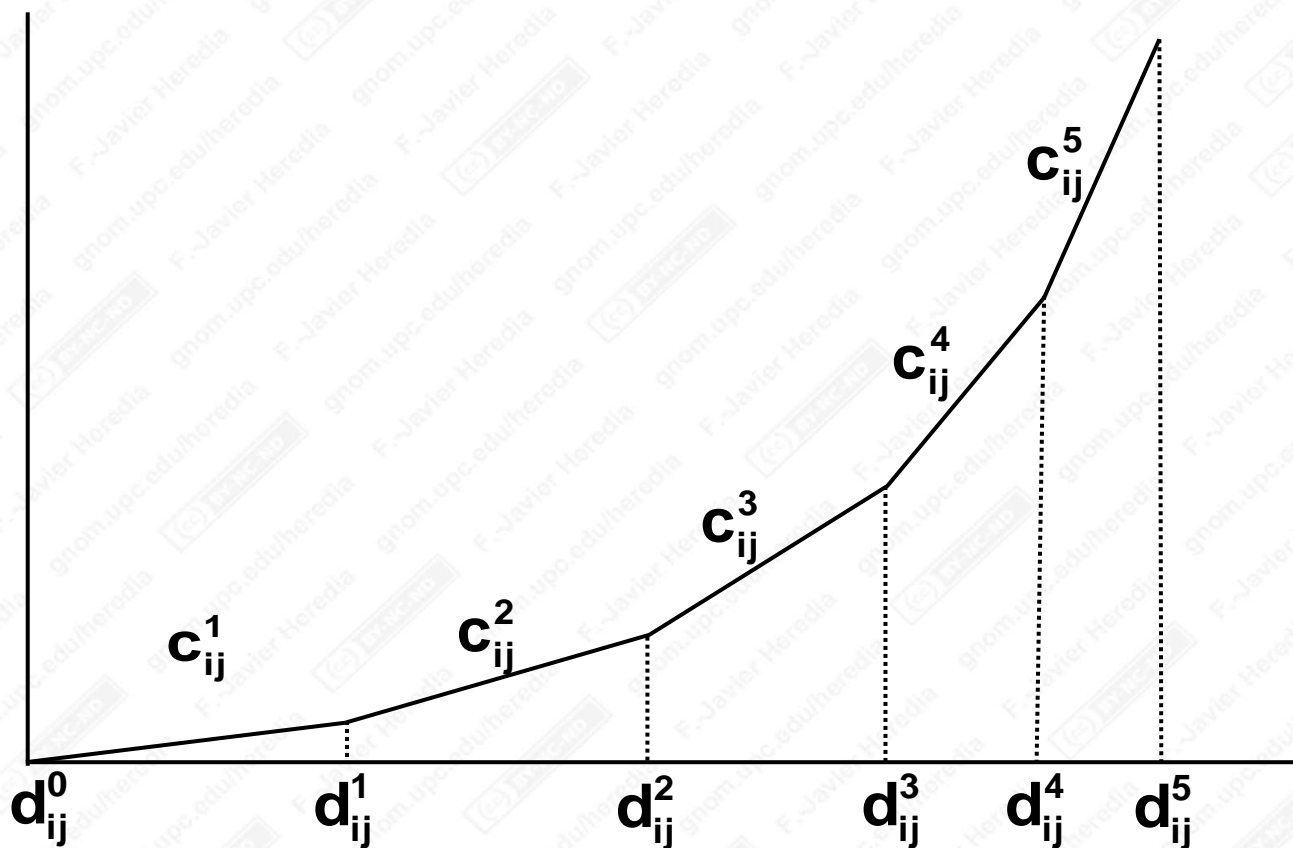
- We will assume that the cost of flow on any arc is a piecewise linear convex function:





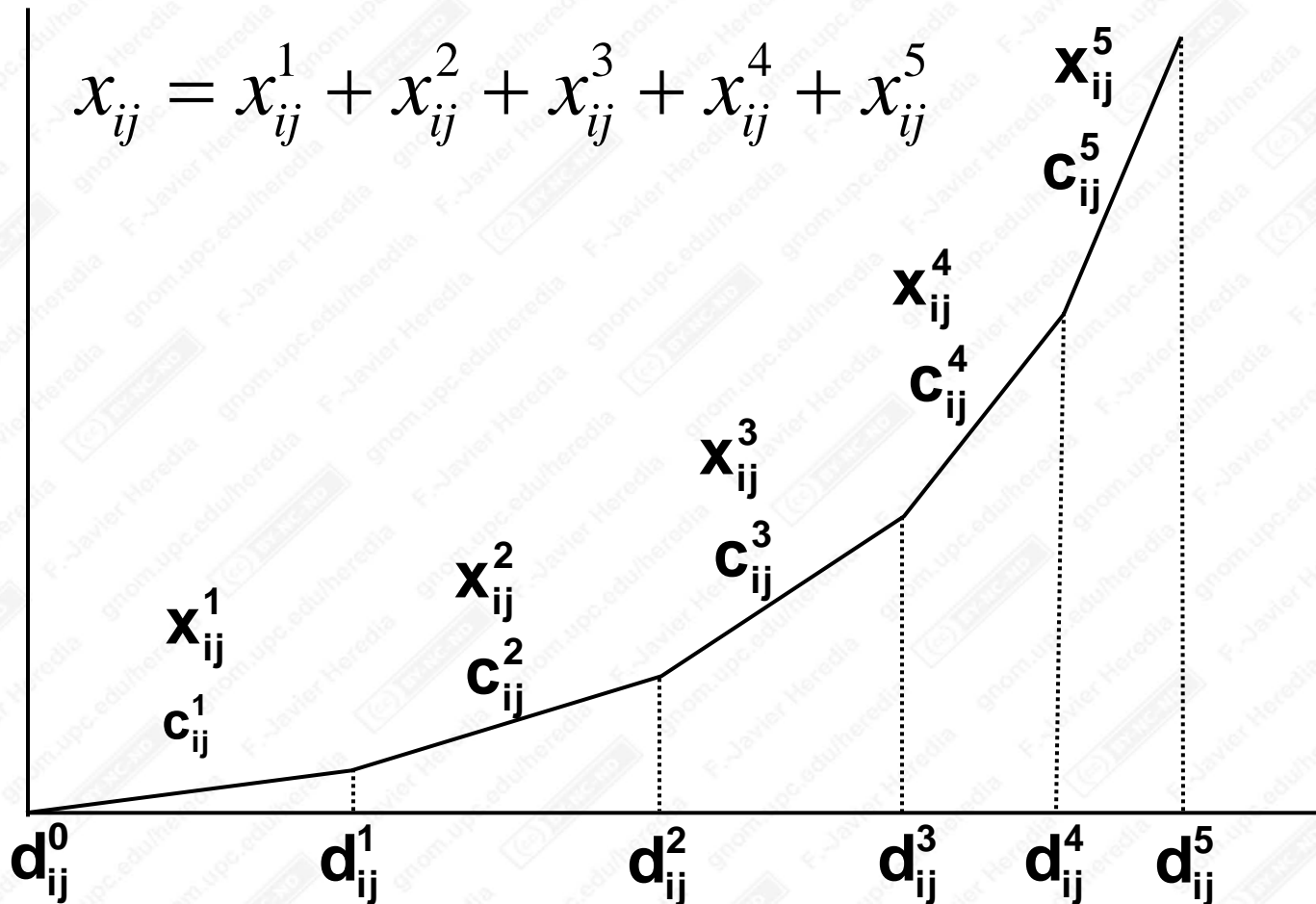
# Nature of the Cost Function

- We will assume that each arc has  $p$  linear segments associated with it. For example, if  $p = 5$ , then the cost function would look like:



# Transformation to Min Cost Flows

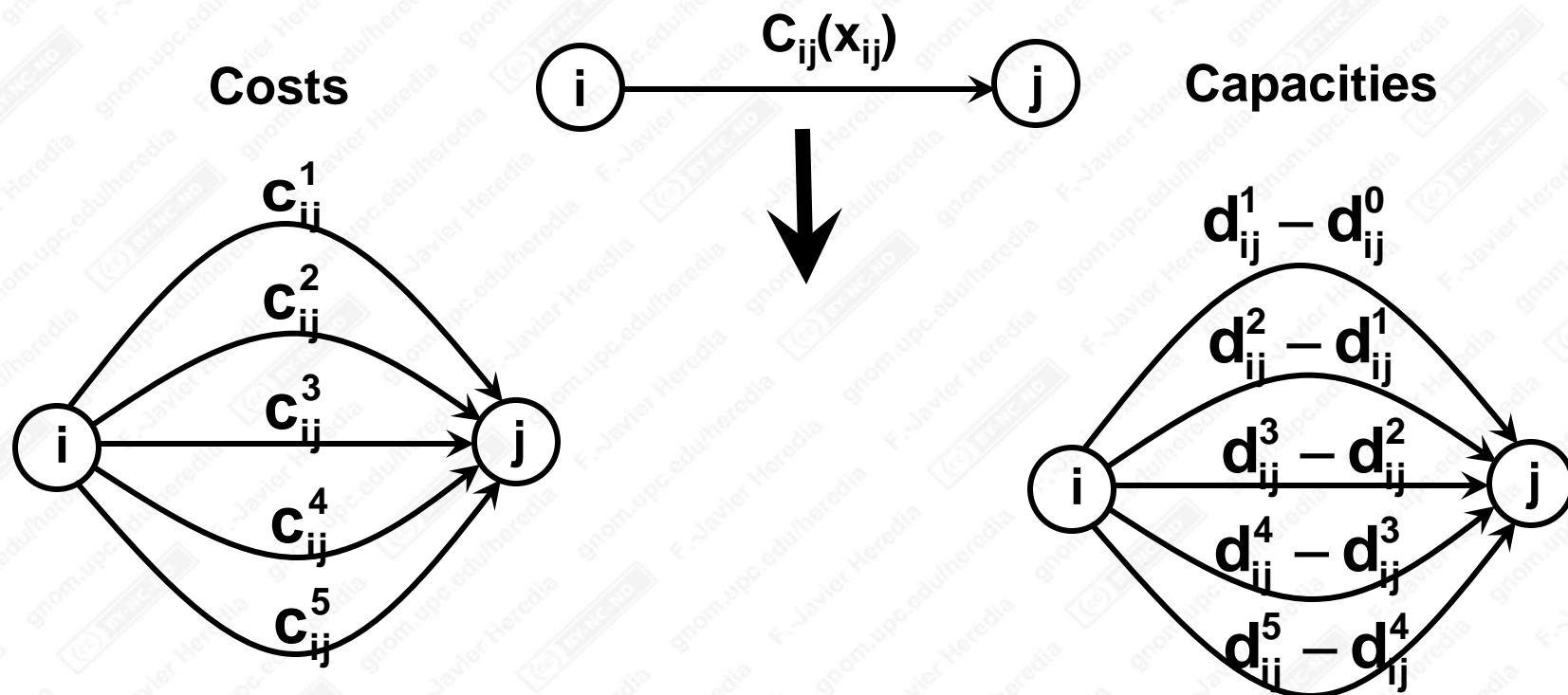
- The convex cost flow problem can be transformed to a minimum cost flow problem by increasing the number of variables:





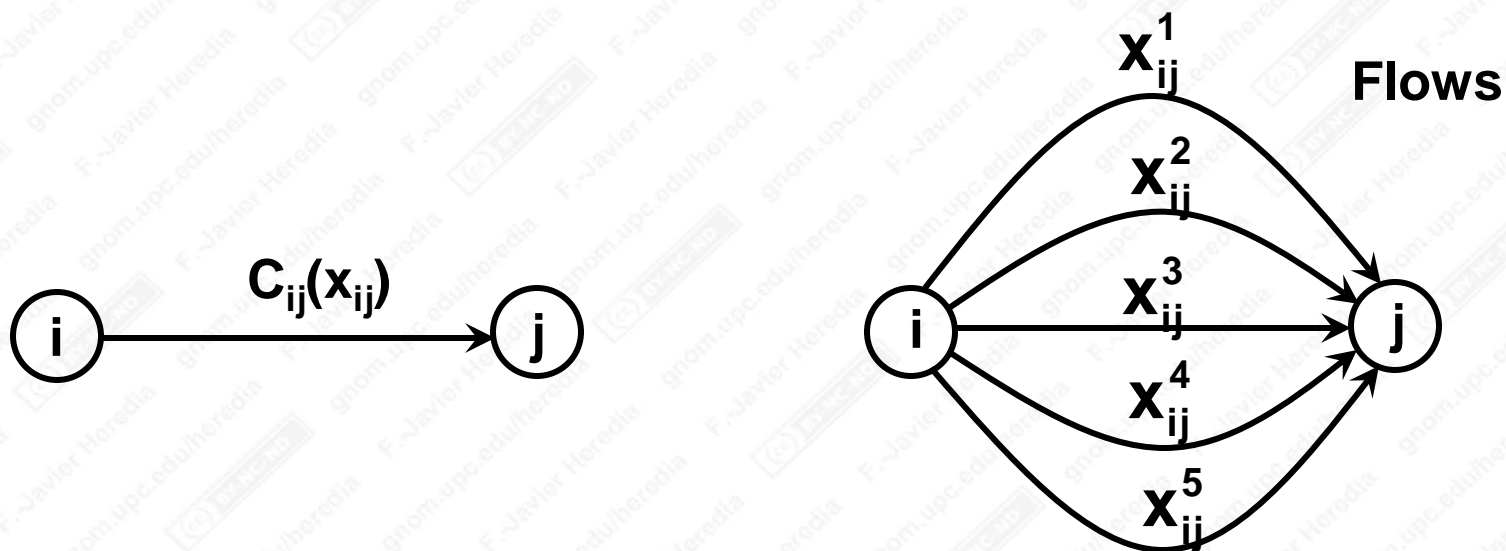
# Transformation to Min Cost Flows (contd.)

- We replace each arc with  $p$  linear segments by  $p$  arcs with linear costs.



# Transformation to Min Cost Flows (contd.)

- We call a flow in the transformed network to be a **contiguous flow** if a segment with greater cost is used only if segments of lower costs are saturated.



- There is a one-to-one correspondence between flows in the original network and contiguous flows in the transformed network.

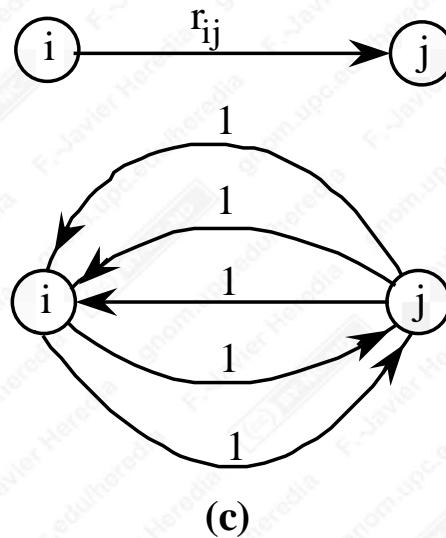
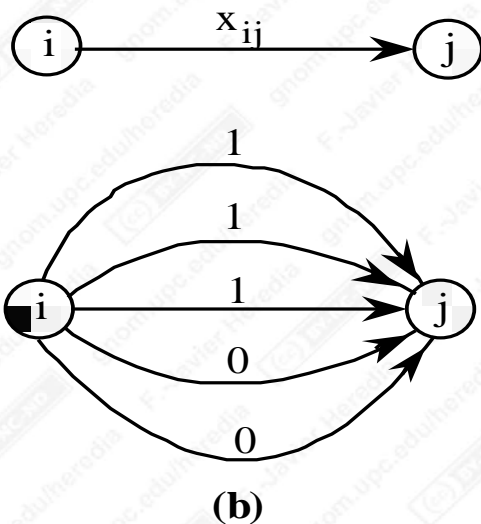
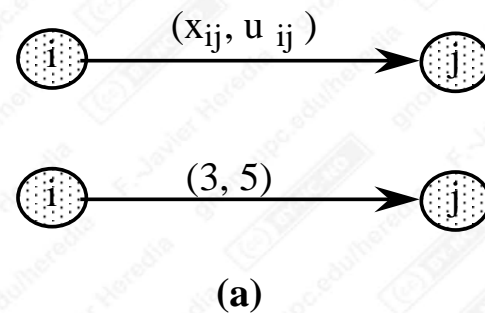
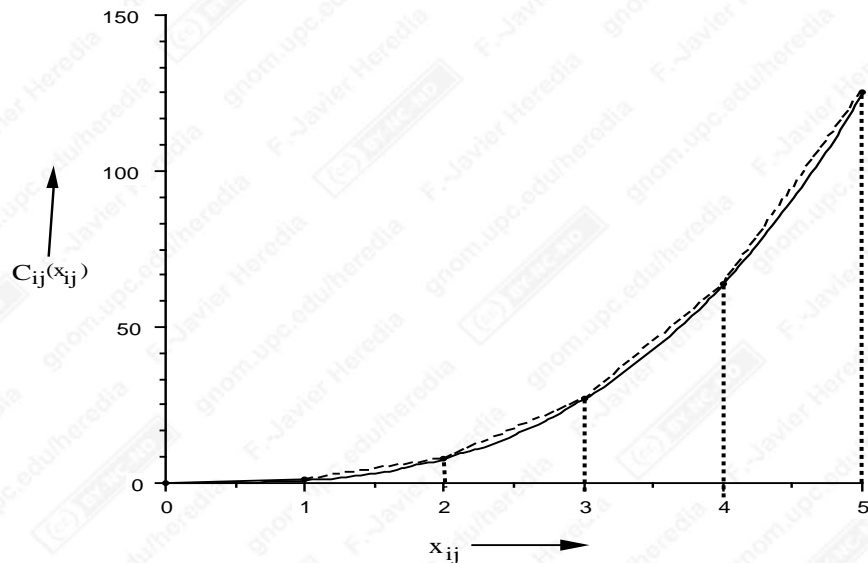
# Transformation to Min Cost Flows (contd.)

- A feasible flow in the transformed network may or may not be contiguous.
- The optimal solution in the transformed network is always a contiguous flow.
- We can solve the convex cost flow problem by solving a minimum cost flow problem.

# Pseudopolynomial-Time algorithms

- We can transform a convex cost flow problem into a minimum cost flow problem and then solve it using any minimum cost flow algorithm.
  - The cycle canceling algorithm
  - The successive shortest path algorithm
- However, the resulting minimum cost flow problem may have too many arcs which might slow down the algorithm.
- We will show that if we define the residual network appropriately, then the network size will not increase at all (that is, extra arcs can be handled implicitly).

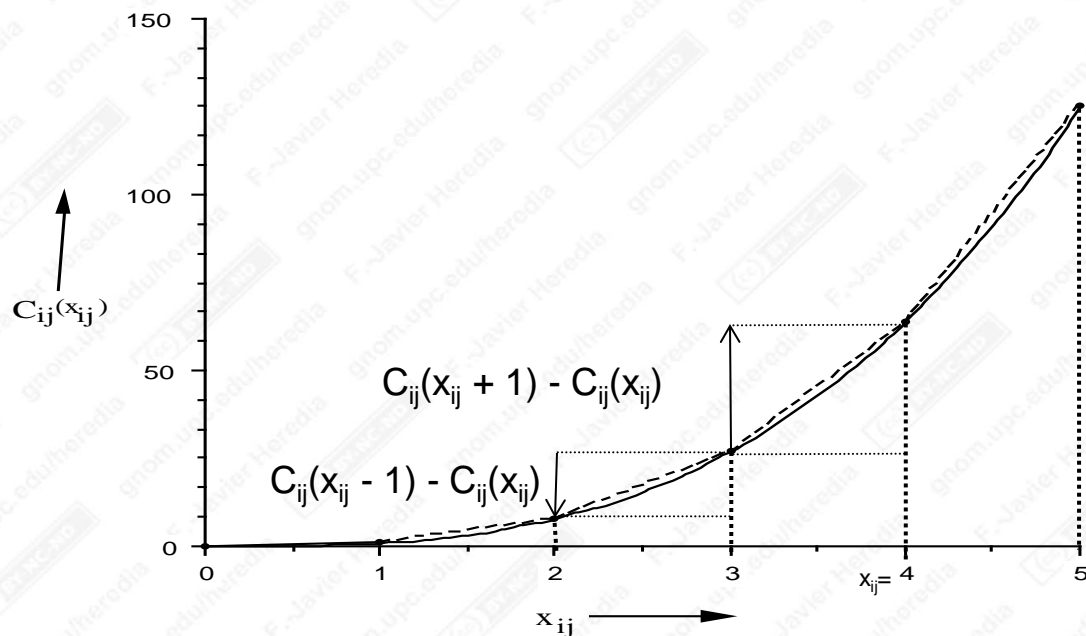
# Constructing the Residual Network





# Constructing the Residual Network (contd.)

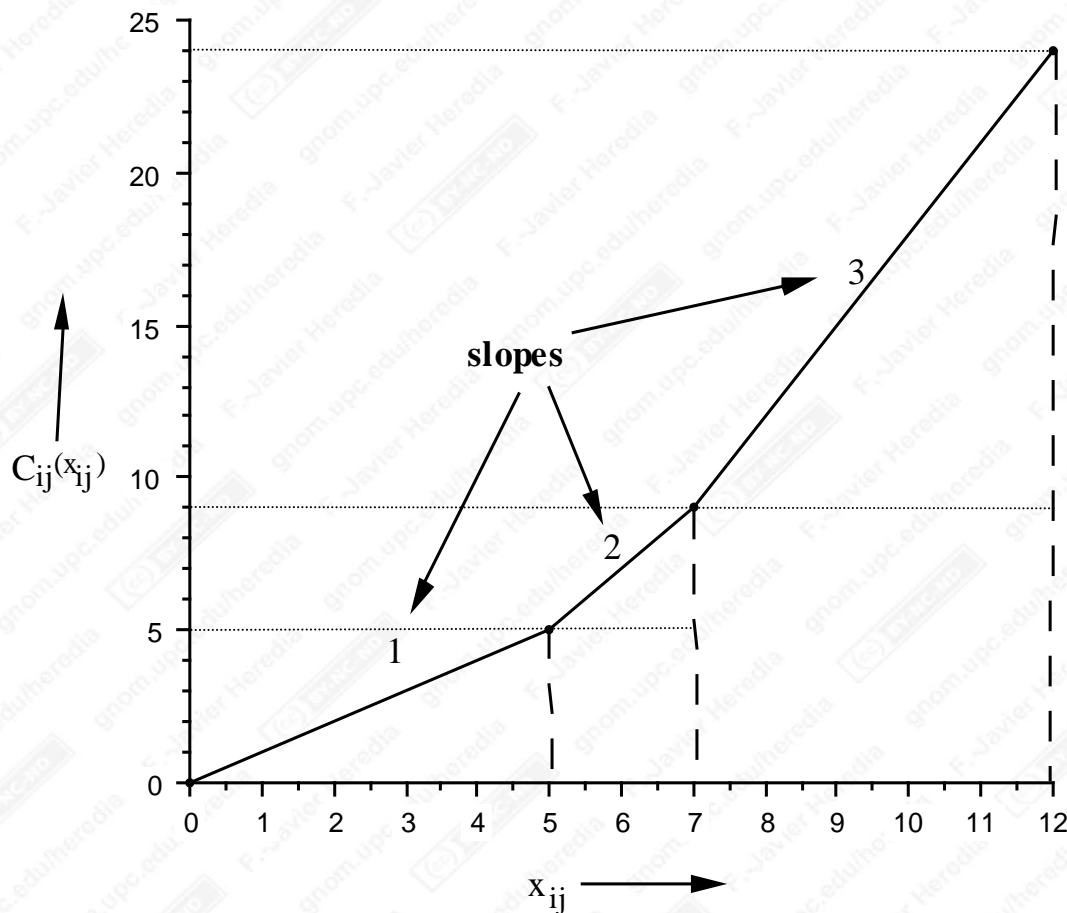
- We need to maintain only two arcs for any arc (i, j): one from node i to node j and another from node j to node i.
- For the exemple:
  - Cost of the arc (i, j):  $C_{ij}(x_{ij} + 1) - C_{ij}(x_{ij})$
  - Cost of the arc (j, i):  $C_{ij}(x_{ij} - 1) - C_{ij}(x_{ij})$





# Constructing the Residual Network (contd.)

- What will be the costs and residual capacity of arcs in the residual networks if  $x_{ij} = 5, 6, 10$ .

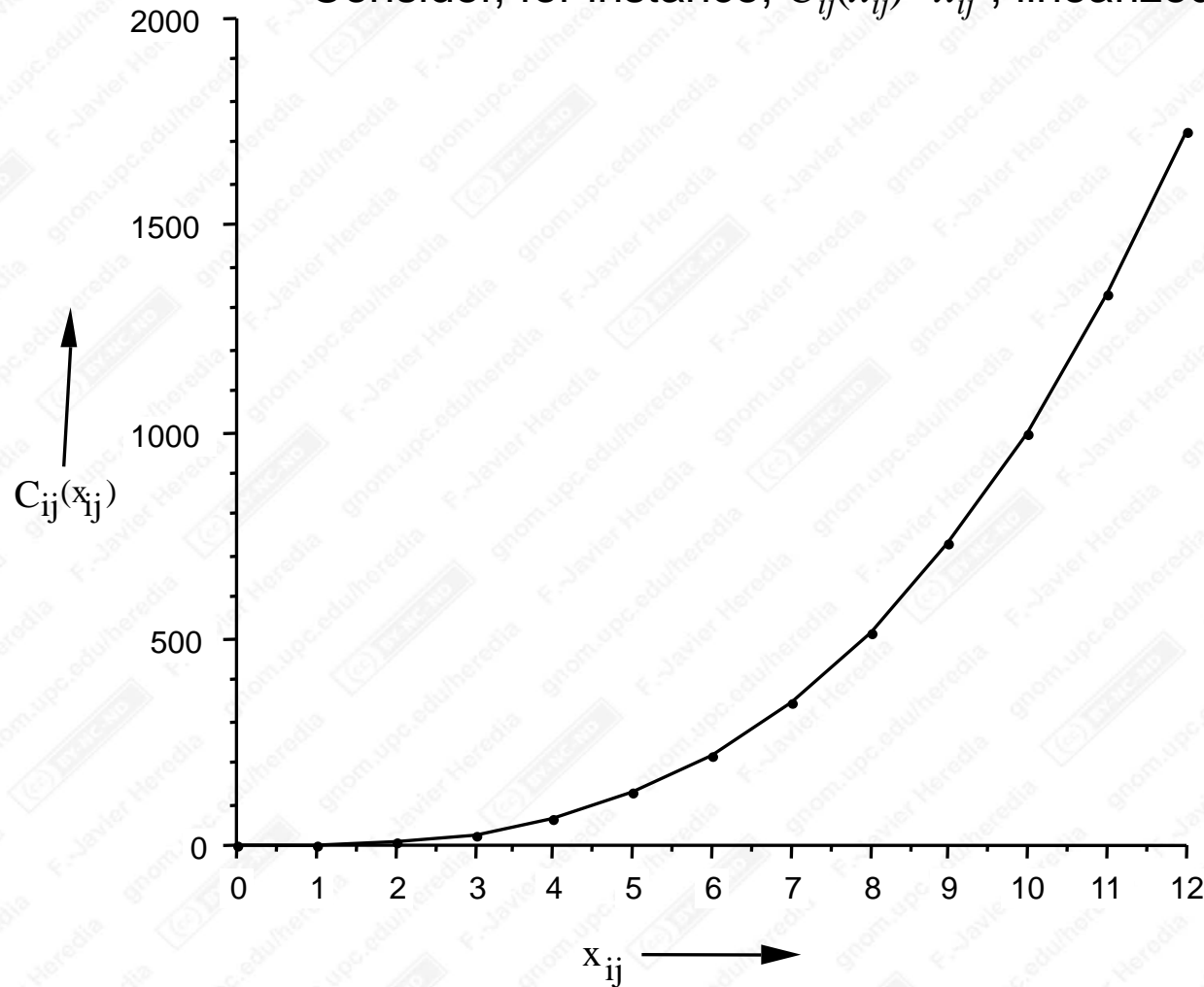


# Polynomial Time Capacity Scaling Algorithm

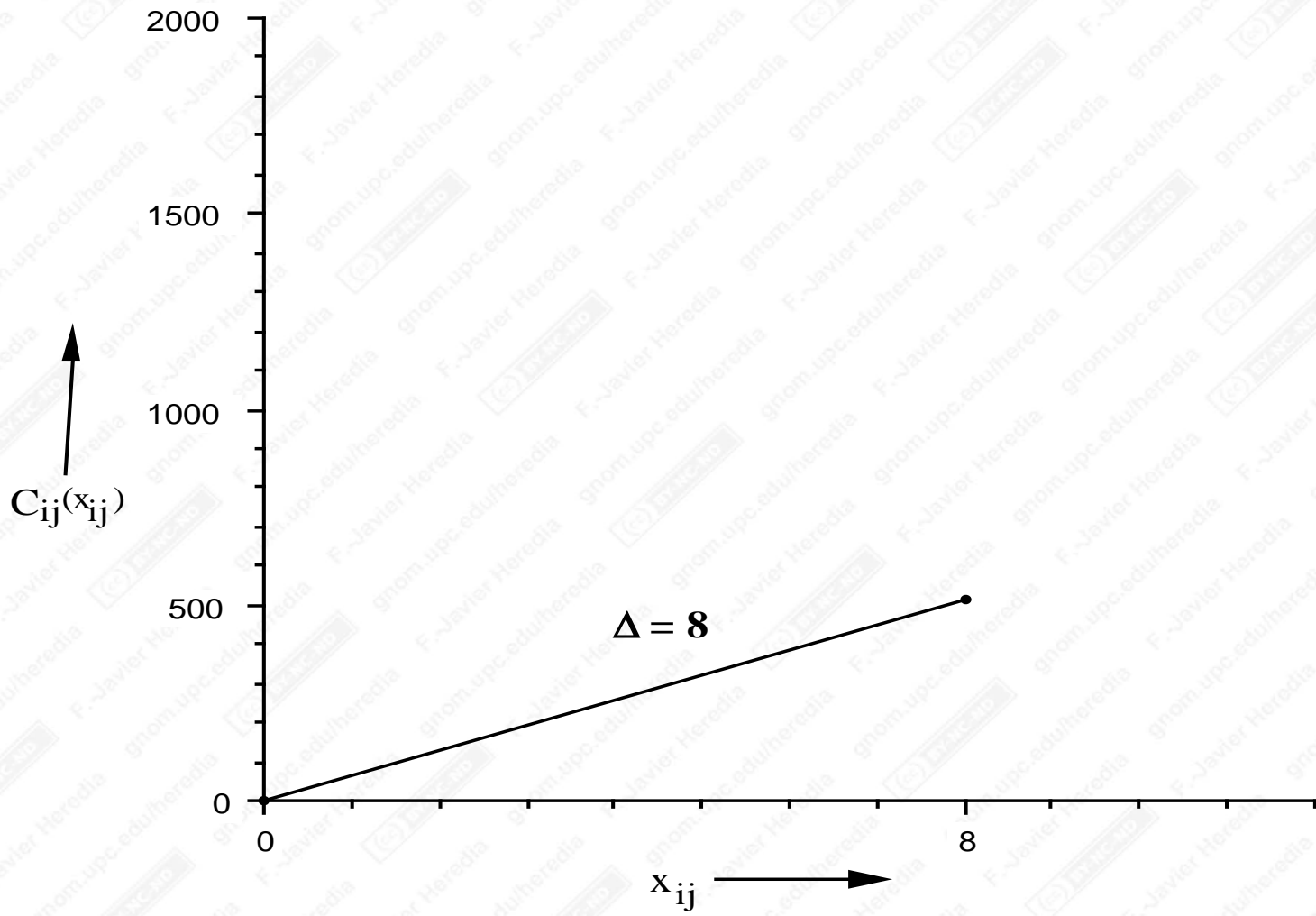
- The capacity scaling algorithm approximates the convex cost function with greater refinements (in terms of a parameter  $\Delta$ ).
- This algorithm is a modification of the capacity scaling algorithm for the minimum cost flow problem and has the same running time.

# The Original Cost Function

Consider, for instance,  $C_{ij}(x_{ij})=x_{ij}^4$ , linearized with step length

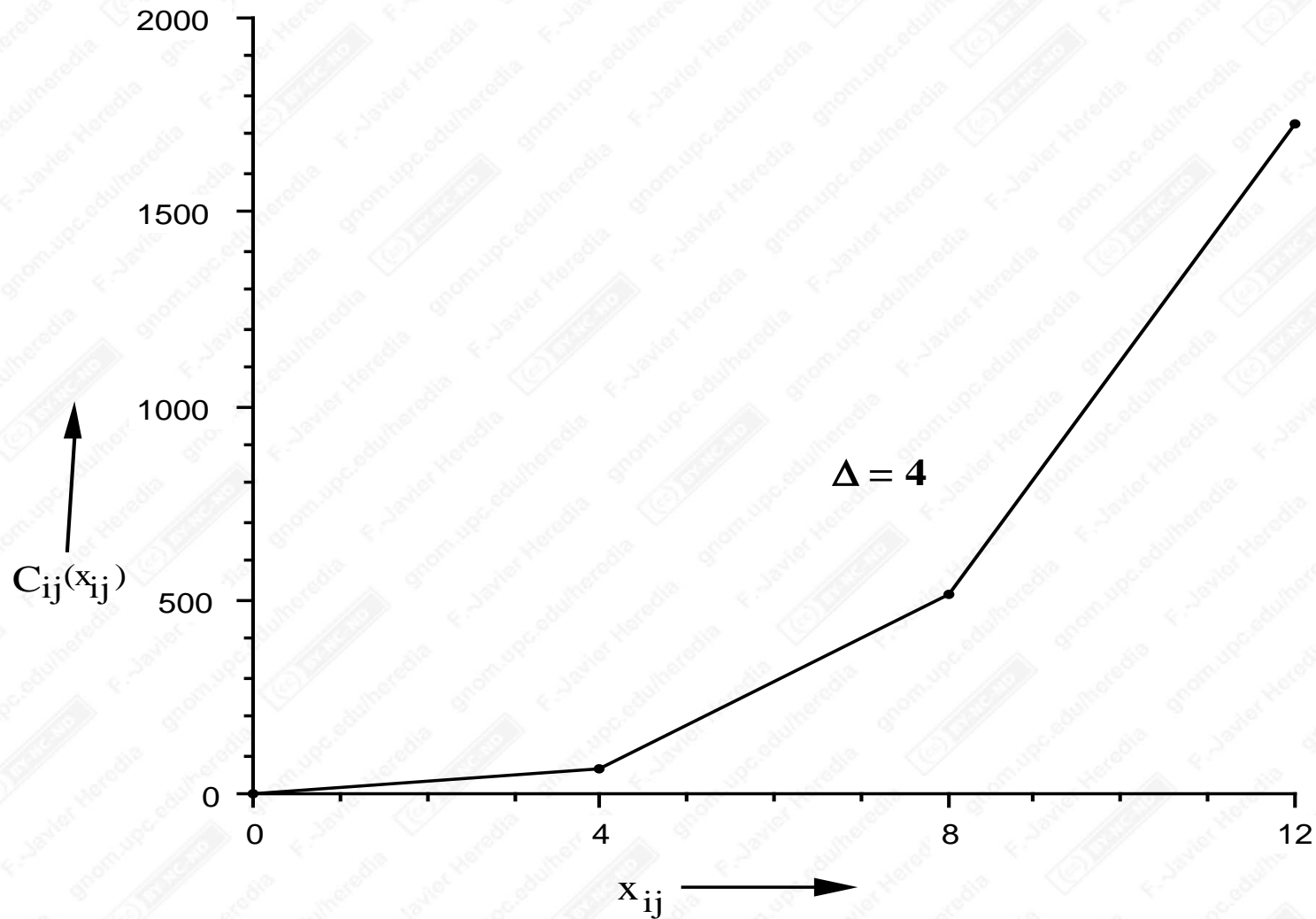


# The Approximate Cost Function ( $\Delta = 8$ )



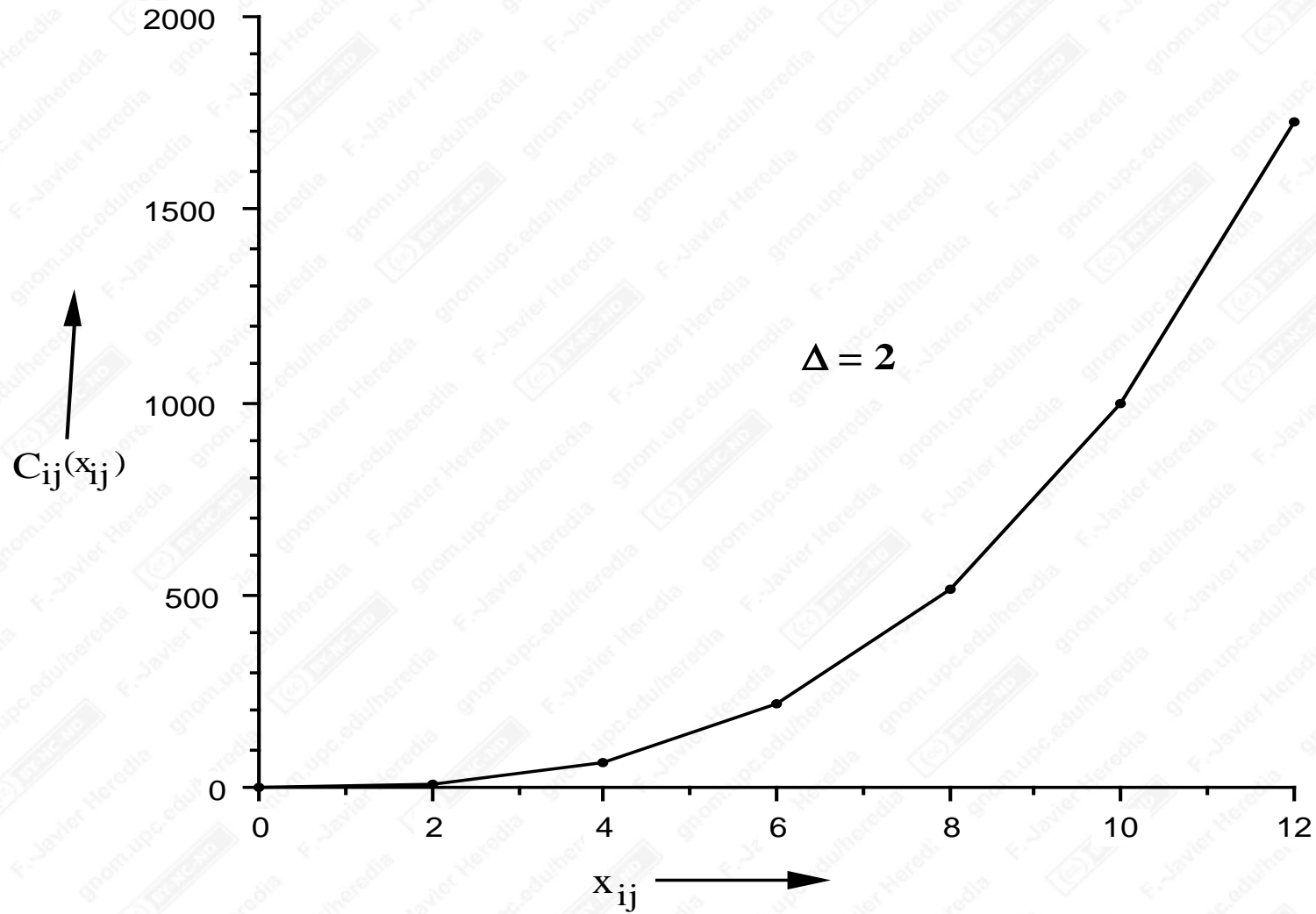
(a)

# The Approximate Cost Function ( $\Delta = 4$ )



(b)

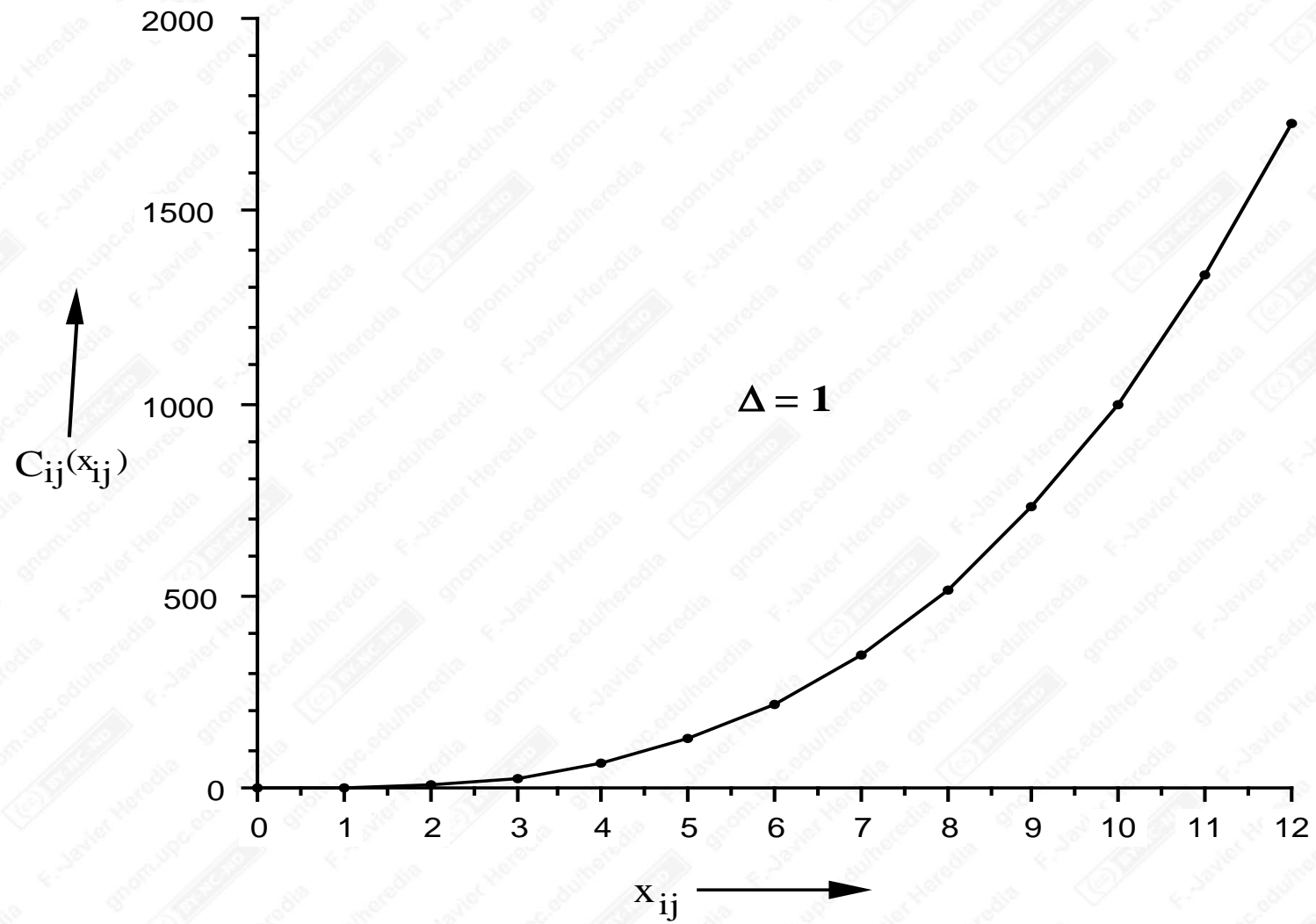
# The Approximate Cost Function ( $\Delta = 2$ )



(c)



# The Approximate Cost Function ( $\Delta = 1$ )



(d)

# The $\Delta$ -Residual Network

- For any arc  $(i, j) \in A$  with  $x_{ij} + \Delta \leq u_{ij}$ , the  $\Delta$ -residual network contains the arc  $(i, j)$  with residual capacity  $\Delta$  and cost equal to

$$(C_{ij}(x_{ij} + \Delta) - C_{ij}(x_{ij}))/\Delta$$

- For any arc  $(i, j) \in A$  with  $x_{ij} \geq \Delta$ , the  $\Delta$ -residual network contains the arc  $(j, i)$  with residual capacity  $\Delta$  and cost equal to

$$(C_{ij}(x_{ij} - \Delta) - C_{ij}(x_{ij}))/\Delta$$

# The Capacity Scaling Algorithm

*algorithm* capacity scaling;

*begin*

$x := 0, \pi := 0;$

$\Delta := 2^{\lfloor \log U \rfloor};$

*while*  $\Delta \geq 1$

*begin* { $\Delta$ -scaling phase}

preprocessing;

$S(\Delta) := \{i \in N : e(i) \geq \Delta\};$

$T(\Delta) := \{i \in N : e(i) \leq -\Delta\};$

*while*  $S(\Delta) \neq \Phi$  and  $T(\Delta) \neq \Phi$  *do*

*begin*

select a node  $k \in S(\Delta)$  and a node  $l \in T(\Delta);$

determine shortest path distances  $d(\cdot)$  from node  $k$  to all other nodes in the  $\Delta$ -residual network  $G(x, \Delta)$  with respect to the reduced costs;

let  $P$  denote a shortest path from node  $k$  to node  $l$  in  $G(x, \Delta);$

update  $\pi := \pi - d;$

augment  $\Delta$  units of flow along the path  $P;$

update  $x, S(\Delta), T(\Delta)$  and  $G(x, \Delta);$

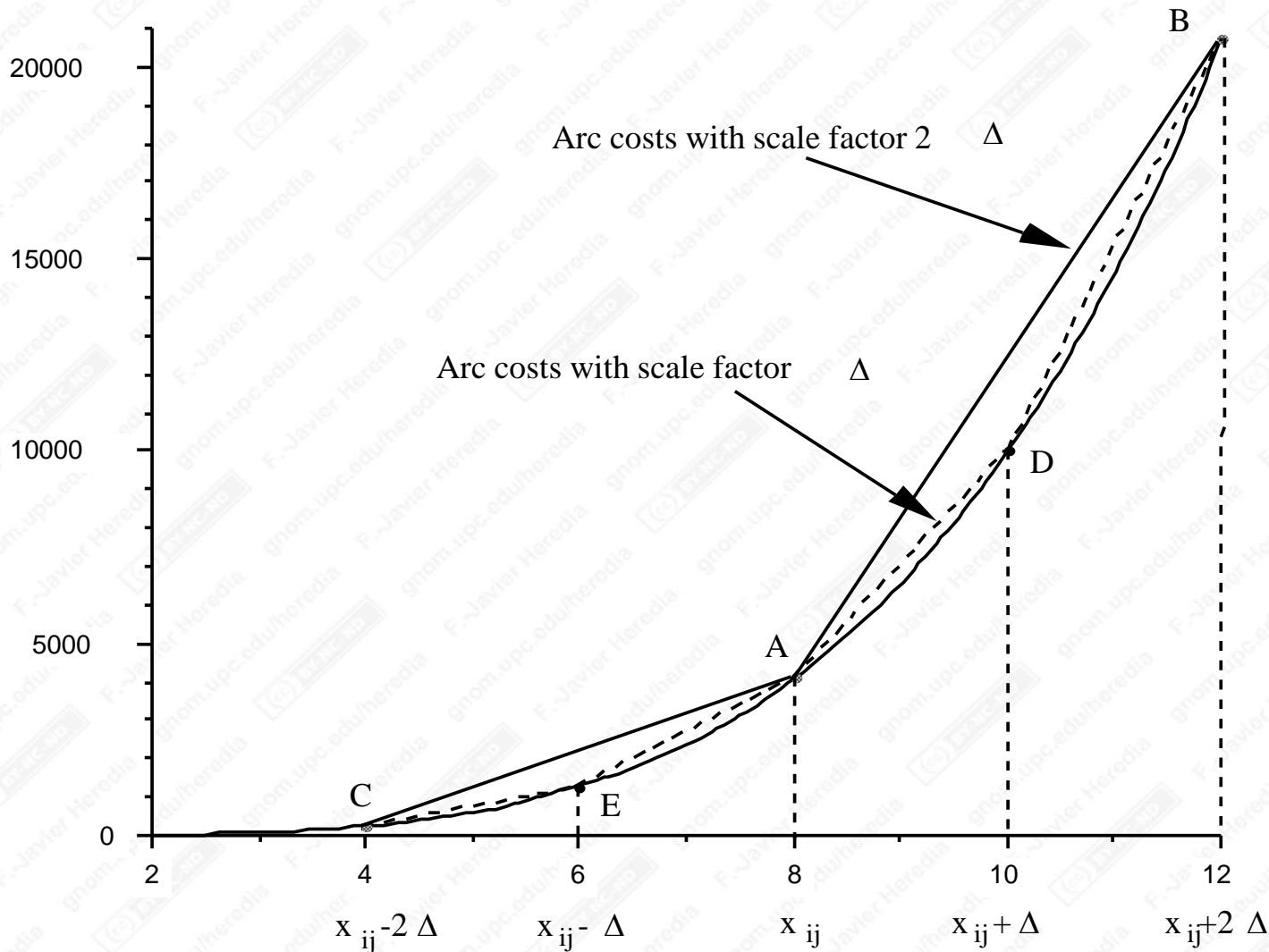
*end;*

$\Delta := \Delta/2;$

*end;*

*end;*

# Going from One Scaling Phase to Another



# Preprocessing

- As we go from  $2\Delta$ -scaling phase to  $\Delta$ -scaling phase, the costs of the arc  $(i, j)$  and  $(j, i)$  change and so their reduced costs.
- There are four possibilities to consider after the reduced costs are changed:

(1)	$c_{ij}^{\pi} \geq 0$ and $c_{ji}^{\pi} \geq 0$	Nothing needs to be done.
(2)	$c_{ij}^{\pi} \geq 0$ and $c_{ji}^{\pi} < 0$	Decrease $x_{ij}$ by $\Delta$ units
(3)	$c_{ij}^{\pi} < 0$ and $c_{ji}^{\pi} \geq 0$	Increase $x_{ij}$ by $\Delta$ units.
(4)	$c_{ij}^{\pi} < 0$ and $c_{ji}^{\pi} < 0$	This case cannot occur.

It can be show that the actions in (2) and (3) conserve the RCOC.



# Running Time Analysis

**Theorem:** *In a scaling phase, the algorithm performs at most  $m$  augmentations. Overall, the algorithm performs  $O(m \log U)$  augmentations, and its running time equals solving  $O(m \log U)$  shortest path problems.*