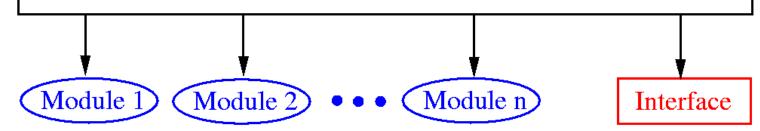
# **Partitioning**

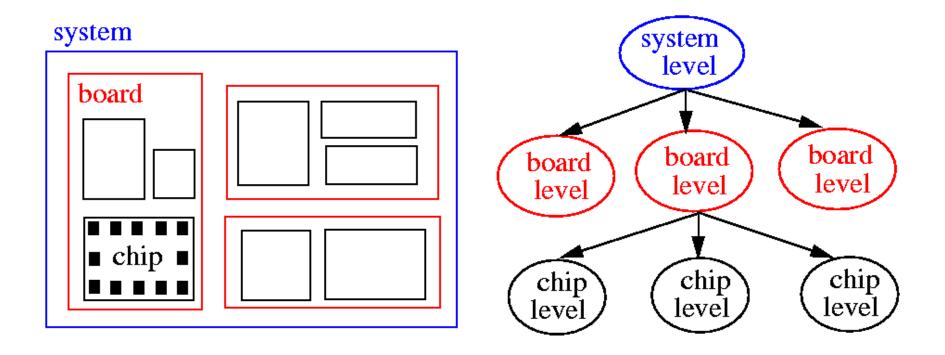
system design

- Decomposition of a complex system into smaller subsystems.
- Each subsystem can be designed independently speeding up the design process.
- Decomposition scheme has to minimize the interconnections among the subsystems.
- Decomposition is carried out hierarchically until each subsystem is of managable size.



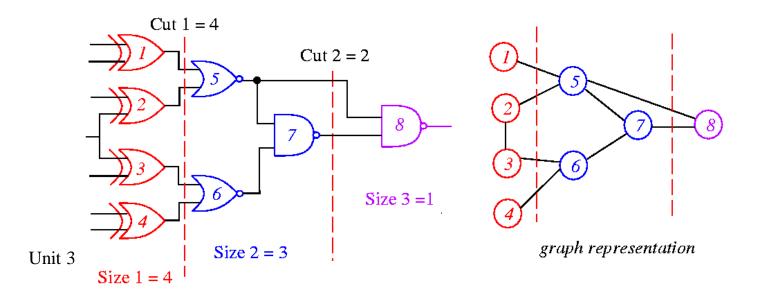
# Levels of Partitioning

• The levels of partitioning: System, Board, Chip.



# Partitioning of a Circuit

- The task of cutting a circuit into smaller parts.
- **Objective:** Partition the circuit into sub-circuits such that every sub-circuit is within a pre-specified size and the # of connections among sub-circuits is minimized.
  - Other possible constraints (e.g., # of pins in a sub-circuit)
  - Other possible objectives (e.g., critical path delay)
- Cutset? Cut size? Size of a sub-circuit?



#### **Problem Definition**

- k-way partitioning: Given a graph G(V,E), where each vertex  $v \in V$  has a size s(v) and each edge  $e \in E$  has a weight w(e), the problem is to divide the set V into k disjoint subsets  $V_1, V_2, \ldots, V_k$ , such that an objective function is optimized, subject to certain constraints.
- **Bounded size constraint:** The size of the *i*-th subset is bounded by  $L_i$  and  $U_i$  (i.e.,  $L_i \leq \sum_{v \in V_i} s(v) \leq U_i$ )
- Min-cut cost between two subsets:  $\sum_{\forall e=(u,v) \land p(u) \neq p(v)} w(e)$  Minimize , where p(u) is the subset where u is.
- The 2-way, size-constrained partitioning problem is NP-hard, even in its simple form with identical vertex sizes and unit edge weights.

# Kernighan-Lin (KL) Algorithm

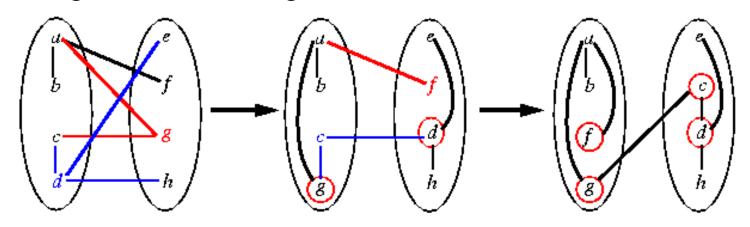
- Kernighan and Lin, "An efficient heuristic procedure for partitioning graphs," *The Bell System Technical Journal*, vol. 49, no. 2, Feb. 1970.
- An **iterative**, **2-way**, **balanced** partitioning (bi-sectioning) heuristic.
- Restrictions:
  - Assume all vertices are of the same size.
  - Work only for 2-terminal nets.

# Key Idea of KL Algorithm

- Start with any initial partitions A and B.
- A pass (exchanging each vertex exactly once) consists of:
  - Exchange a vertex pair which gives the **maximum** gain  $g_i$  (i.e., largest decrease or smallest increase in cut size), and **lock** them (which thus are prohibited from participating in any further exchanges).
  - This process continues until all vertices are locked.
  - Find the largest partial sum G (i.e., find k such that  $g_1+...+g_k$  is maximized).
  - Exchange the first *k* pairs.
- Repeat the pass until there is no improvement (i.e., G=0).

#### **KL Algorithm: A Simple Example**

Each edge has a unit weight.

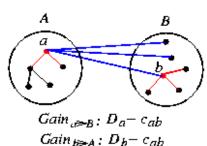


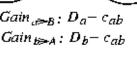
Step #	Vertex pair	Cost reduction	Cut cost
0	-	0	5
1	{d, g}	3	2
2	{c, f}	1	1
3	{b, h}	-2	3
4	{a, e}	-2	5

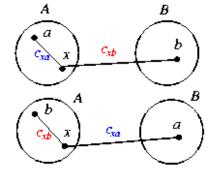
Questions: How to compute cost reduction? What pairs to be swapped?

# **Properties**

- Two sets A and B such that |A|=n=|B| and  $A\cap B=\emptyset$ .
- External cost of  $a \in A$ :  $E_a = \sum_{n \in B} c_{an}$ .
- Internal cost of  $a \in A$ :  $I_a = \sum_{n \in A} c_{an}$ .
- D-value of a vertex a:  $D_a = E_a I_a$  (cost reduction for moving a).
- Cost reduction (gain) for swapping a and b:  $g_{ab} = D_a + D_b 2c_{ab}$ .
- If  $a \in A$  and  $b \in B$  are interchanged, then the new D-values, D', are given by  $D'_x = D_x + 2c_{xa} - 2c_{xb}, \forall x \in A - \{a\}$   $D'_y = D_y + 2c_{yb} - 2c_{ya}, \forall y \in B - \{b\}.$





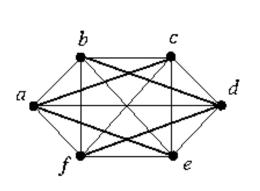


before swap	after swap	$\triangle C$
$-c_{xu}$	$+c_{xa}$	$+2c_{xa}$
$+c_{xb}$	$-c_{xb}$	$-2c_{xb}$

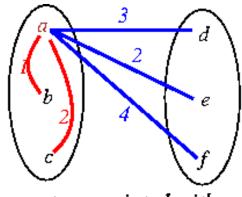
Internal cost vs. External cost

updating D-values

#### KL Algorithm: A Weighted Example



					е		
$ \begin{array}{c} a \\ b \\ c \\ d \\ e \\ f \end{array} $	0 1 2 3 2 4	I 0 I 4 2 I	2 I 0 3 2 I	3 4 3 0 4 3	2 2 2 4 0 2	4 I I 3 2 0	



costs associated with a

Initial cut 
$$cost = (3+2+4)+(4+2+1)+(3+2+1) = 22$$

#### • Iteration 1:

$$I_a=1+2=3$$
;  $E_a=3+2+4=9$ ;  $D_a=E_a-I_a=9-3=6$ 

$$I_b=1+1=2;$$
  $E_b=4+2+1=7;$   $D_b=E_b-I_b=7-2=5$ 

$$I_c=2+1=3;$$
  $E_c=3+2+1=6;$   $D_c=E_c-I_c=6-3=3$ 

$$I_d=4+3=7$$
;  $E_d=3+4+3=10$ ;  $D_d=E_d-I_d=10-7=3$ 

$$I_e$$
=4+2=6;  $E_e$ =2+2+2=6;  $D_e$ = $E_e$ - $I_e$ =6-6=0

Unit 3 
$$I_f$$
=3+2=5;  $E_f$ =4+1+1=6;  $D_f$ = $E_f$ - $I_f$ =6-5=1

• Iteration 1:

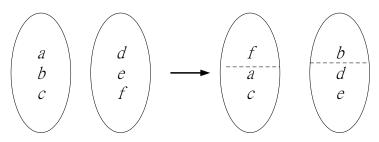
$$\begin{split} I_a &= 1 + 2 = 3; & E_a = 3 + 2 + 4 = 9; & D_a = E_a - I_a = 9 - 3 = 6 \\ I_b &= 1 + 1 = 2; & E_b = 4 + 2 + 1 = 7; & D_b = E_b - I_b = 7 - 2 = 5 \\ I_c &= 2 + 1 = 3; & E_c = 3 + 2 + 1 = 6; & D_c = E_c - I_c = 6 - 3 = 3 \\ I_d &= 4 + 3 = 7; & E_d = 3 + 4 + 3 = 10; & D_d = E_d - I_d = 10 - 7 = 3 \\ I_e &= 4 + 2 = 6; & E_e = 2 + 2 + 2 = 6; & D_e = E_e - I_e = 6 - 6 = 0 \\ I_f &= 3 + 2 = 5; & E_f = 4 + 1 + 1 = 6; & D_f = E_f - I_f = 6 - 5 = 1 \end{split}$$

•  $g_{xy} = D_x + D_y - 2c_{xy}$ .  $g_{ad} = D_a + D_d - 2c_{ad} = 6 + 3 - 2 * 3 = 3$   $g_{ae} = 6 + 0 - 2 * 2 = 2$   $g_{af} = 6 + 1 - 2 * 4 = -1$   $g_{bd} = 5 + 3 - 2 * 4 = 0$   $g_{be} = 5 + 0 - 2 * 2 = 1$   $g_{bf} = 5 + 1 - 2 * 1 = 4$  (maximum)  $g_{cd} = 3 + 3 - 2 * 3 = 0$ 

 $\underset{\text{Unit }3}{\bullet}$  Swap b and f! ( $\bar{g_1}$ =4)

 $g_{ce} = 3 + 0 - 2 * 2 = -1$ 

 $g_{cf} = 3 + 1 - 2 * 1 = 2$ 



• 
$$D_x' = D_x + 2c_{xp} - 2c_{xq}, \forall x \in A - \{p\}$$
 (swap  $p$  and  $q, p \in A, q \in B$ )
$$D_a' = D_a + 2c_{ab} - 2c_{af} = 6 + 2*1 - 2*4 = 0$$

$$D_c' = D_c + 2c_{cb} - 2c_{cf} = 3 + 2*1 - 2*1 = 3$$

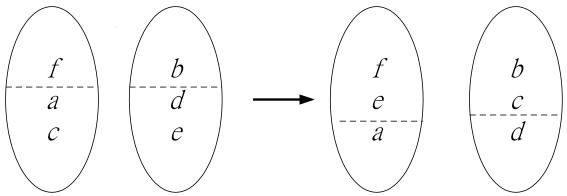
$$D_d' = D_d + 2c_{df} - 2c_{db} = 3 + 2*3 - 2*4 = 1$$

$$D_e' = D_e + 2c_{ef} - 2c_{eb} = 0 + 2*2 - 2*2 = 0$$
•  $g_{xy} = D_x' + D_y' - 2c_{xy}$ .
$$g_{ad} = D_a' + D_d' - 2c_{ad} = 0 + 1 - 2*3 = -5$$

$$g_{ae} = D_a' + D_e' - 2c_{ae} = 0 + 0 - 2*2 = -4$$

$$g_{cd} = D_c' + D_d' - 2c_{cd} = 3 + 1 - 2*3 = -2$$

$$g_{ce} = D_c' + D_e' - 2c_{ce} = 3 + 0 - 2*2 = -1 \text{ (maximum )}$$
• Swap  $c$  and  $e!$  ( $q_2' = -1$ )



• 
$$D_{x}^{"} = D_{x}^{'} + 2c_{xp} - 2c_{xq}, \forall x \in A - \{p\}$$

$$D_{a}^{"} = D_{a}^{'} + 2c_{ac} - 2c_{ae} = 0 + 2*2 - 2*2 = 0$$

$$D_{d}^{"} = D_{d}^{'} + 2c_{de} - 2c_{de} = 1 + 2*4 - 2*3 = 3$$

- $g_{xy} = D_x'' + D_y'' 2x_{xy}.$   $g_{ad} = D_a'' + D_d'' 2c_{ad} = 0 + 3 2 \cdot 3 = -3 \quad (\hat{g_3} = -3)$
- Note that this step is redundant  $\left(\sum_{i=1}^{n} \bar{g}_{i} = 0\right)$
- Summary:  $\hat{g}_1 = g_{bf} = 4$ ,  $\hat{g}_2 = g_{ce} = -1$ ,  $\hat{g}_3 = g_{ad} = -3$ .
- Largest partial sum max  $\sum_{i=1}^{k} \hat{g_i} = 4 \ (k = 1) \Rightarrow \text{Swap } b \text{ and } f$ .

	abcde	f	(f	<u>1</u>
a b c d e f	0 1 2 3 2 1 0 1 4 2 2 1 0 3 2 3 4 3 0 4 2 2 2 4 0 4 1 1 3 2	1 1 3 2		$\frac{3}{2}$ $d$

Initial cut cost = (1+3+2)+(1+3+2)+(1+3+2) = 18(22-4)

- Iteration 2: Repeat what we did at Iteration 1 (Initial cost=22-4=18)
- Summary:  $\hat{g}_1 = g_{ce} = -1$ ,  $\hat{g}_2 = g_{ab} = -3$ ,  $\hat{g}_3 = g_{fd} = 4$ .
- Largest partial sum=  $\max \sum_{i=1}^{k} \hat{g}_i = 0 \ (k = 3) \Rightarrow \text{Stop!}$

#### **Algorithm:** Kernighan-Lin(*G*)

**Input:** G=(V,E), |V|=2n.

**Output:** Balanced bi-partition A and B with "small" cut cost.

#### 1 begin

- 2 Bi-partition G into A and B such that  $|V_A|=|V_B|$ ,  $|V_A \cap V_B|=\emptyset$ , and  $|V_A \cup V_B|=V$ .
- 3 repeat
- 4 Compute  $D_{\nu}$ ,  $\forall \nu \in V$ .
- 5 for i=1 to n do
- Find a pair of unlocked vertices  $v_{ai} \in V_A$  and  $v_{bi} \in V_B$  whose exchange makes the largest decrease or smallest increase in cut cost;
- Mark  $v_{ai}$  and  $v_{bi}$  as locked, store the gain  $\hat{g}_i$ , and compute the new  $D_v$ , for all unlocked  $v \in V$ ;
- 8 Find k, such that  $G_k = \sum_{i=1}^k \hat{g_i}$  is maximized;
- 9 **if**  $G_k > 0$  **then**
- Move  $v_{ai},...,v_{ak}$  from  $V_A$  to  $V_B$  and  $v_{bi},...,v_{bk}$  from  $V_B$  to  $V_A$ ;
- 11 Unlock  $v, \forall v \in V$ .
- 12 until  $G_k \leq 0$ ;
- 13 **end**

# **Time Complexity**

- Line 4: Initial computation of D:  $O(n^2)$
- Line 5: The **for**-loop: O(n)
- The body of the loop:  $O(n^2)$ 
  - Lines 6-7: Step i takes  $O(n-i+1)^2$  time.
- Lines 4-11: Each pass of the repeat loop:  $O(n^3)$ .
- Suppose the repeat loop terminates after r passes.
- The total running time:  $O(rn^3)$ .

# **Extension of KL Algorithm**

- *k*-way partitioning
  - 1. Partition the graph into *k* equal-sized sets. Apply the KL algorithm for each pair of subsets.
  - 2. Apply the KL algorithm recursively.

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#### **Drawbacks of KL Algorithm**

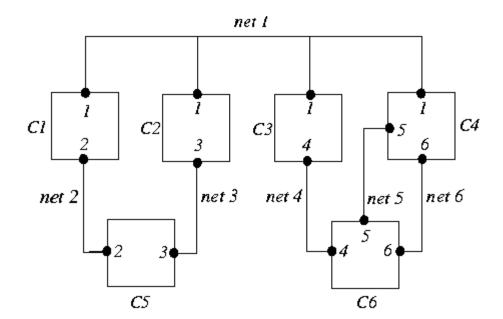
- KL handles only unit vertex weights.
  - Vertex weights might represent block sizes, different from blocks to blocks.
  - Reducing a vertex with weight w(v) into a clique with w(v) vertices and edges with a high cost increases the size of the graph substantially.
- KL handles only exact bisections.
  - Need dummy vertices to handle the unbalanced problem.
- KL cannot handle hypergraphs.
  - A hypergraph consists of a set of vertices and a set of hyperedges, where each hyperedge  $e_i$  corresponds to a subset  $N_i$  of distinct vertices with  $|N_i| \ge 2$
- The time complexity of a pass is high,  $O(n^3)$ .

#### Fiduccia-Mattheyses (FM) Algorithm

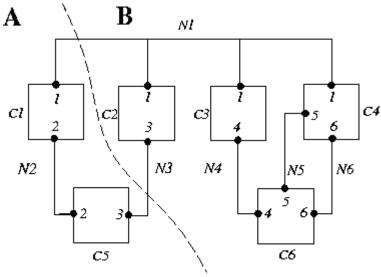
- Fiduccia and Mattheyses. "A linear time heuristic for improving network partitions," 19th Design Automation Conf.,1982.
- Same as KL:
  - Work in passes.
  - Lock vertices after moved.
  - Actually, only move those vertices up to the maximum partial sum of gain.
- Different from KL:
  - Aim at reducing net-cut costs; the concept of cut size is extended to hypergraphs.
  - Only a single vertex is moved across the cut in a move.
  - Vertices are weighted.
  - Can handle "unbalanced" partitions; a balance factor is introduced.
  - A special data structure is used to select vertices to be moved across the cut to improve running time.
  - **Time complexity of a pass is** O(P), where P is the total # of pins.

#### **FM: Notation**

- n(i): # of cells in Net i; e.g., n(1)=4.
- s(i): size of Cell i.
- p(i): # of pins in Cell i; e.g., p(6)=3.
- *C*: total # of cells; e.g., *C*=6.
- *N*: total # of nets; e.g., *N*=6.
- P: total # of pins; P = p(1) + ... + p(C) = n(1) + ... + n(N).



### Cut



- **Cutstate** of a net:
  - Net 1 and Net 3 are cut.
  - Net 2, Net 4, Net 5, and Net 6 are uncut.
- **Cutset**= {Net 1, Net 3}.
- |A|=size of A = s(1)+s(5); |B|=s(2)+s(3)+s(4)+s(6).
- Balanced 2-way partitioning: Given a fraction r, 0 < r < 1, partition a graph into two sets A and B such that

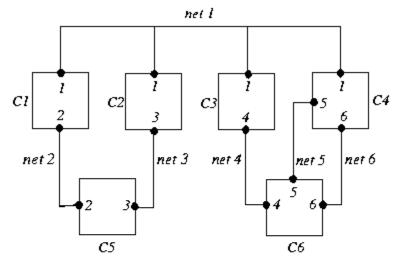
$$-\frac{|A|}{|A|+|B|} \approx r$$

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Size of the cutset is minimized.

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# Input Data Structures



	Cell array	Net array			
C1	Nets 1, 2	Net 1	C1, C2, C3, C4		
C2	Nets 1, 3	Net 2	C1, C5		
C3	Nets 1, 4	Net 3	C2, C5		
C4	Nets 1, 5, 6	Net 4	C3, C6		
C5	Nets 2, 3	Net 5	C4, C6		
C6	Nets 4, 5, 6	Net 6	C4, C6		

- Size of the circuit:  $P = \sum_{i=1}^{6} n(i) = 14$
- Construction of the two arrays takes O(P) time.

#### **Basic Ideas: Balance and Movement**

• Only move a cell at a time, preserving "balance."

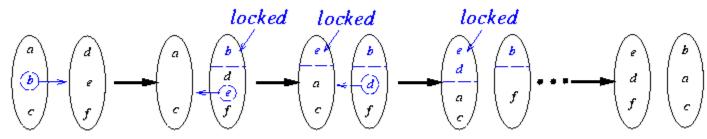
$$\frac{|A|}{|A|+|B|} \approx r$$

$$rW - S_{\text{max}} \le |A| \le rW + S_{\text{max}},$$

$$|A|+|B|: S = -\text{max } s(i)$$

when W=|A|+|B|;  $S_{\text{max}}=\max_{i}s(i)$ .

• g(i): gain in moving cell i to the other set, i.e., size of **old** cutset - size of **new** cutset.



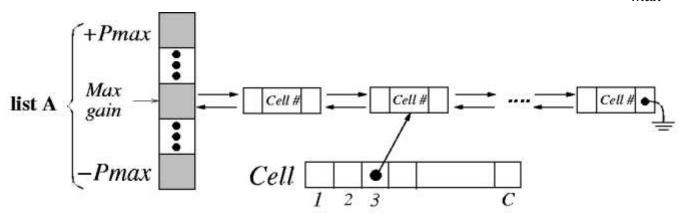
g(b) is the largest

balanced condition holds

• Suppose  $\widehat{g}_i$ 's: g(b), g(e), g(d), g(a), g(f), g(c) and the largest partial sum is g(b)+g(e)+g(d). Then we should move  $b,e,d \rightarrow$  resulting two sets:  $\{a,c,e,d\},\{b,f\}$ 

#### Cell Gains and Data Structure Manipulation

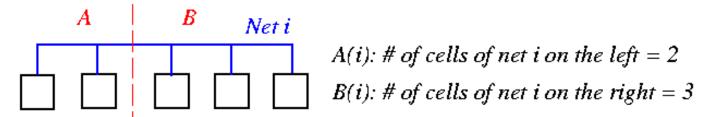
• Two "bucket list" structures, one for set A and one for set  $B(P_{max}=\max_{i} p(i))$ .



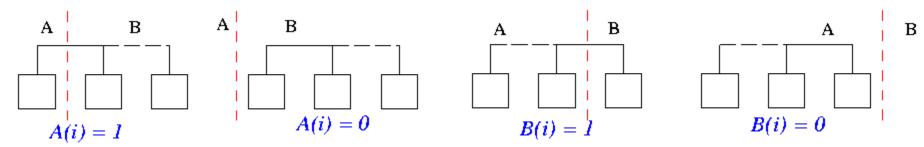
• O(1)-time operations: find a cell with Max Gain, remove Cell i from the structure, insert Cell i into the structure, update g(i) to  $g(i) + \Delta$ , update the Max Gain pointer.

#### **Net Distribution and Critical Nets**

- Distribution of Net i: (A(i), B(i)) = (2, 3).
  - (A(i), B(i)) for all i can be computed in O(P) time.



- Critical Nets: A net is critical if it has a cell which if moved will change its cutstate.
  - 4 cases: A(i) = 0 or 1, B(i) = 0 or 1.



• Gain of a cell depends only on its critical nets.

# **Computing Cell Gains**

Initialization of all cell gains requires O(P) time:

translation of all cell gains requires 
$$O(P)$$
 time  $g(i) \leftarrow 0$ ;  $F \leftarrow$  the "from block" of cell  $i$ ;  $T \leftarrow$  the "to block" of cell  $i$ ; for each net  $n$  on Cell  $i$  do

if  $F(n) = 1$  then  $g(i) \leftarrow g(i) + 1$ ;

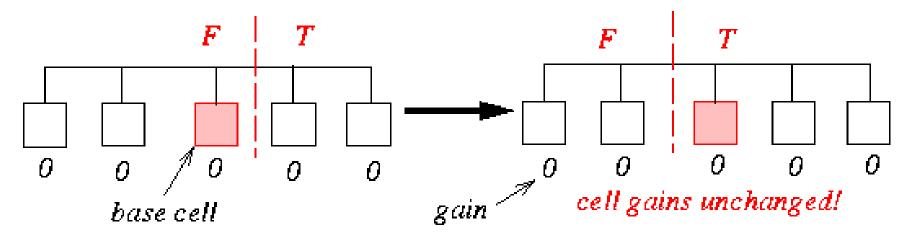
if  $T(n) = 0$  then  $g(i) \leftarrow g(i) - 1$ ;

Only need O(P) time to maintain all cell gains in one pass.

F(n) = 1

# **Updating Cell Gains**

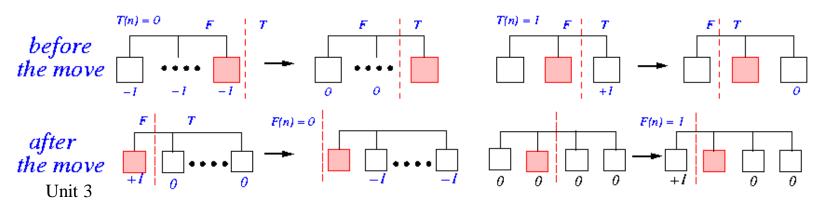
- To update the gains, we only need to look at those nets, connected to the base cell, which are critical before or after the move.
- **Base cell**: The cell selected for movement from one set to the other.



#### Algorithm for Updating Cell Gains

#### Algorithm: Update\_Gain

- 1 **begin** /\* move base cell and update neighbors' gains \*/
- $2 F \leftarrow$  the *Front Block* of the base cell;
- $3 T \leftarrow \text{the } To Block \text{ of the base cell;}$
- 4 Lock the base cell and complement its block;
- 5 **for** each net *n* on the base cell **do** 
  - /\* check critical nets before the move \*/
- 6 **if** T(n) = 0 then increment gains of all free cells on n **elseif** T(n) = 1 **then** decrement gain of the only T cell on n, if it is free /\* change F(n) and T(n) to reflect the move \*/
- 7  $F(n) \leftarrow F(n) 1$ ;  $T(n) \leftarrow T(n) + 1$ ; /\* check for critical nets after the move \*/
- 8 **if** F(n) = 0 **then** decrement gains of all free cells on n **elseif** F(n) = 1 **then** increment gain of the only F cell on n, if it is free
- 9 end

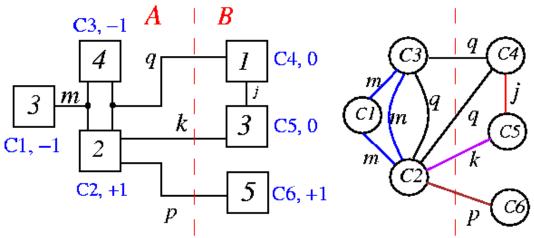


# **Complexity of Updating Cell Gains**

- Once a net has "locked" cells at both sides, the net will remain cut from now on.
- To update the cell gains, it takes O(n(i)) work for Net i.
- Total time = n(1) + n(2) + ... + n(N) = O(P)

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### FM: An Example

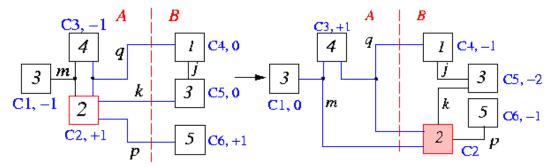


• Computing cell gains:  $F(n) = 1 \Rightarrow g(i) + 1$ ;  $T(n) = 0 \Rightarrow g(i) - 1$ 

		m	q		k		p			$\overline{j}$	
Cell	F	T	F	T	F	T	F	T	F	T	g(i)
c1	0	-1									-1
c2	0	-1	0	0	+1	0	<b>+</b> 1	0			+1
с3	0	-1	0	0							-1
с4			+1	0					0	-1	0
c4 c5					+1	0			0	-1	0
с6							+1	0			+1

- Balanced criterion: r|V|  $S_{max} \le |A| \le r|V| + S_{max}$ . Let  $r = 0.4 \Rightarrow |A| = 9$ , |V| = 18,  $S_{max} = 5$ ,  $r|V| = 7.2 \Rightarrow$  Balanced:  $2.2 \le 9 \le 12.2!$
- Maximum gain:  $c_2$  and balanced:  $2.2 \le 9-2 \le 12.2 =>$  Move  $c_2$  from A to B (use size criterion if there is a tie).

## FM: An Example (Cont'd)



• Changes in net distribution:

	Be	fore move	After move			
Net	F	T	F'	T'		
k	1	1	0	2		
m	3	0	2	1		
q	2	1	1	2		
p	1	1	0	2		

• Updating cell gains on critical nets (run Algorithm Update\_Gain):

	Gains due to $T(n)$ Gain due to $F(n)$				Gain	changes				
Cells	k	m	q	p	k	m	q	p	Old	New
$c_1$		+1							-1	0
<b>c</b> 3		+1					+1		-1	+1
<b>c</b> 4			-1						0	-1
$c_5$	-1				-1				0	-2
$c_6$				-1				-1	<b>+</b> 1	-1

• Maximum gain:  $c_3$  and balanced!  $(2.2 \le 7-4 \le 12.2)$ 

Unit  $\equiv$  > Move  $c_3$  from A to B (use size criterion if there is a tie).

### Summary of the Example

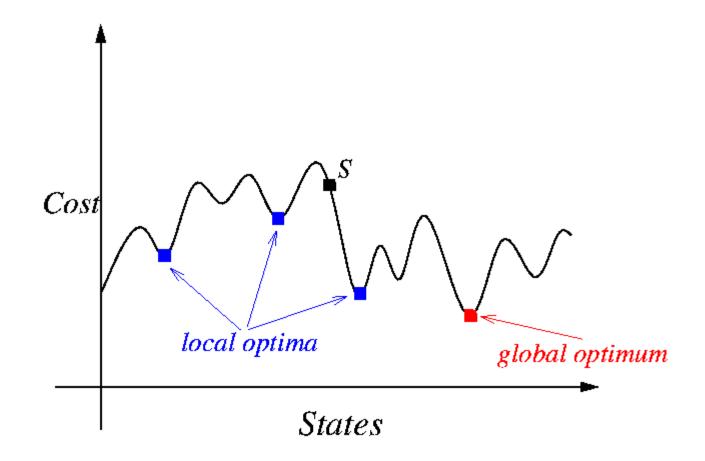
Step	Cell	Max gain		Balanced?	Locked cell	A	В
0	-	-	9	_	Ø	1, 2, 3	4, 5, 6
1	$c_2$	+1	7	yes	$c_2$	1, 3	2, 4, 5, 6
2	<i>c</i> 3	+1	3	yes	$c_2, c_3$	1	2, 3, 4, 5, 6
3	$c_1$	+1	0	no	-	-	-
3′	c <sub>6</sub>	-1	8	yes	$c_2, c_3, c_6$	1, 6	2, 3, 4, 5
4	$c_1$	<b>+</b> 1	5	yes	$c_1, c_2, c_3, c_6$	6	1, 2, 3, 4, 5
5	$c_5$	-2	8	yes	$c_1, c_2, c_3, c_5, c_6$	5, 6	1, 2, 3, 4
6	<b>C</b> 4	0	9	yes	all cells	4, 5, 6	1, 2, 3

- $g_1=1$ ,  $g_2=1$ ,  $g_3=-1$ ,  $g_4=1$ ,  $g_5=-2$ ,  $g_6=0 =>$  Maximum partial sum  $G_k=+2$ , k=2 or 4.
- Since k = 4 results in a better balanced => Move  $c_1$ ,  $c_2$ ,  $c_3$ ,  $c_6$  =>  $A = \{6\}$ ,  $B = \{1,2,3,4,5\}$ .
- Repeat the whole process until new  $G_k \le 0$ .

# Simulated Annealing Revisited

• Kirkpatrick, Gelatt, and Vecchi, "Optimization by simulated annealing," *Science*, May 1983.

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## **Simulated Annealing Basics**

- Non-zero probability for "up-hill" moves.
- Probability depends on
  - 1. magnitude of the "up-hill" movement
  - 2. total search time

$$Prob(S \rightarrow S') = \left\{ \begin{array}{ll} 1 & \text{if } \Delta C \leq \texttt{0} & /* \text{``down} - hill'' \text{ moves * /} \\ e^{-\frac{\Delta C}{T}} & \text{if } \Delta C > \texttt{0} & /* \text{``up} - hill'' \text{ moves * /} \end{array} \right.$$

- $\triangle C = cost(S') cost(S)$
- T: Control parameter (temperature)
- Annealing schedule:  $T = T_0, T_1, T_2, ...$ , where  $T_i = r^i T_0, r < 1$ .

# Generic Simulated Annealing Algorithm

#### **Algorithm: Simulated\_Annealing**

```
1 begin
2 Get an initial solution S;
3 Get an initial temperature T > 0;
4 while not yet "frozen" do
     for 1 \le i \le P do
        Pick a random neighbor S' of S;
        \triangle \leftarrow cost(S') - cost(S);
         /* down hill move */
        if \triangle < 0 then S \leftarrow S'
         /* uphill move */
        if \triangle > 0 then S \leftarrow S' with probability e^{-\frac{\Delta}{T}};
9
      T \leftarrow rT; /* reduce temperature */
11 return S
12 end
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```

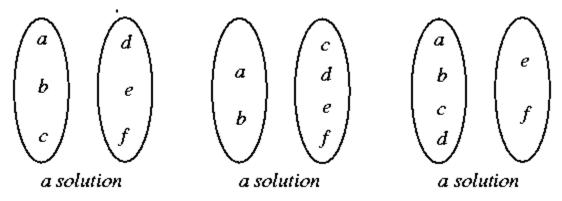
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### **Basic Ingredients for Simulated Annealing**

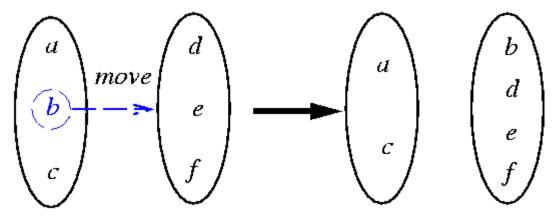
- Solution space
- Neighborhood structure
- Cost function
- Annealing schedule

### Partitioning by Simulated Annealing

- Kirkpatrick, Gelatt, and Vecchi, "Optimization by simulated annealing," *Science*, May 1983.
- Solution space: set of all partitioning solutions

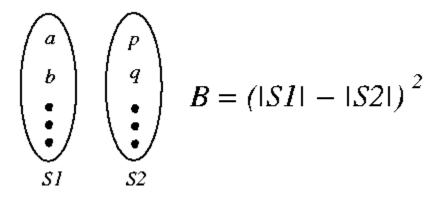


Neighborhood structure:



#### Partitioning by Simulated Annealing (cont'd)

- Cost function:  $f = C + \lambda B$ 
  - C: the solution cost as used before.
  - B: a measure of how balance the solution is
  - $\lambda$ : a constant



#### • Annealing schedule:

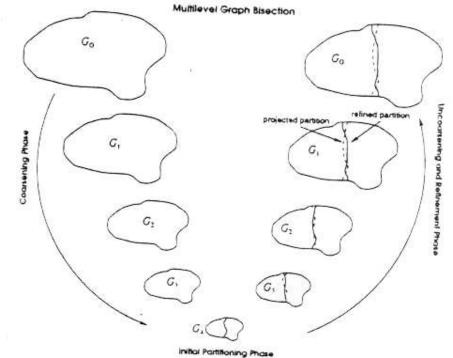
- $T_n = r^n T_0$ , r = 0.9.
- At each temperature, either
  - 1. There are 10 accepted moves/cell on the average, or
  - 2. # of attempts  $\geq 100 * total # of cells$ .
- The system is "frozen" if very low acceptances at 3 consecutive temperatures.

# **Multilevel Partitioning**

• Three phases (for bipartitioning)

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- Coarsening: construct a sequence of smaller (coarser) graphs.
- Initial partitioning: construct a bipartitioning solution for the coarsest graph.
- Uncoarsening & refinement: the bipartitioning solution is successively projected to the next-level finer graph, and at each level an iterative refinement algorithm (such as KL or FM) is used to further improve the solution.

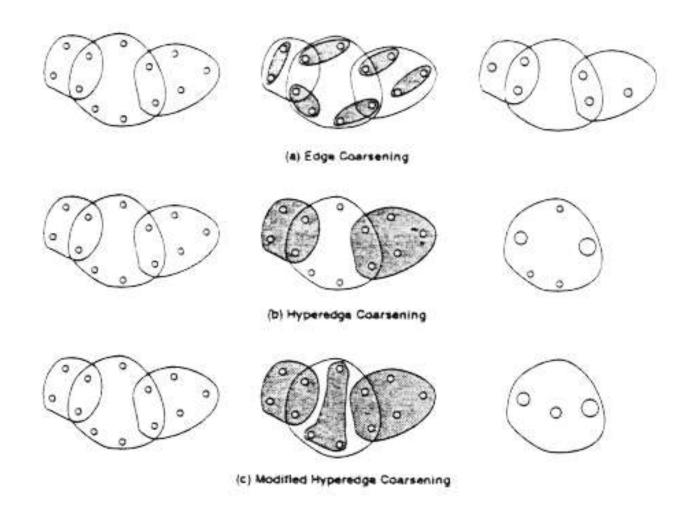


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#### **hMETIS**

- Kayrpis, Aggarwal, Kumar and Shekhar, "Multilevel hypergraph partitioning: application in VLSI domain," DAC, 1997.
- Three coarsening algorithms:
  - Edge coarsening: A maximal matching of the vertices.
  - **Hyperedge coarsening**: a set of hyperedges is selected, and the vertices belonging to a selected hyperedge are merged into a cluster. (Preference: hyperedges with large weights and hyperedges of small size.)
  - Modified hyperedge coarsening: hyperedge coarsening + merging the remaining vertices of each hyperedge into a cluster.

# hMETIS (Cont'd)



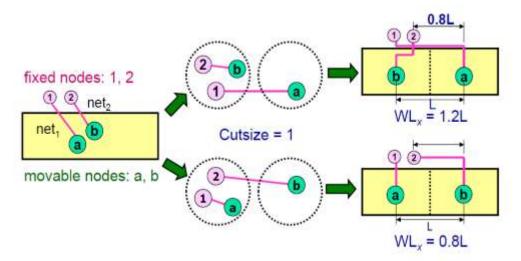
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### hMETIS (Cont'd)

- Two uncoarsening & refinement algorithms:
  - FM algorithm with modifications:
    - \* Restrict the maximum number of passes to 2.
    - \* Stop each pass when no improvement is made from the first *k* moves.
  - Hyperedge refinement: move groups of vertices between subsets so that an entire hyperedge is removed from the cut set.

### Partitioning for Wirelength Minimization

- Chen, Chang, Lin, "IMF: Interconnection-driven floorplanning for large-scale building-module designs," ICCAD-05
- Minimizing cut size is *not* equivalent to minimizing wirelength (WL)



- Problem: hyperedge weight is a constant value!
  - Shall map the min-cut cost to wirelength (WL) change
  - Shall assign the hyperedge weight as the value of wirelength contribution if the hyperedge is cut

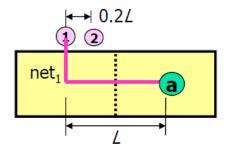
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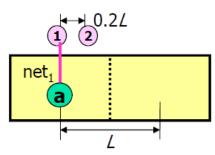
# Net Weight Assignment

• net<sub>1</sub> connects a movable node *a* and a fixed node 1.

Weight(
$$net_1$$
) = WL( $net_1$  is  $cut$ ) – WL( $net_1$  is not  $cut$ )

$$=L-0L=L$$

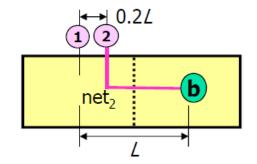


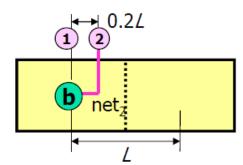


• net<sub>2</sub> connects a movable node *b* and a fixed node 2.

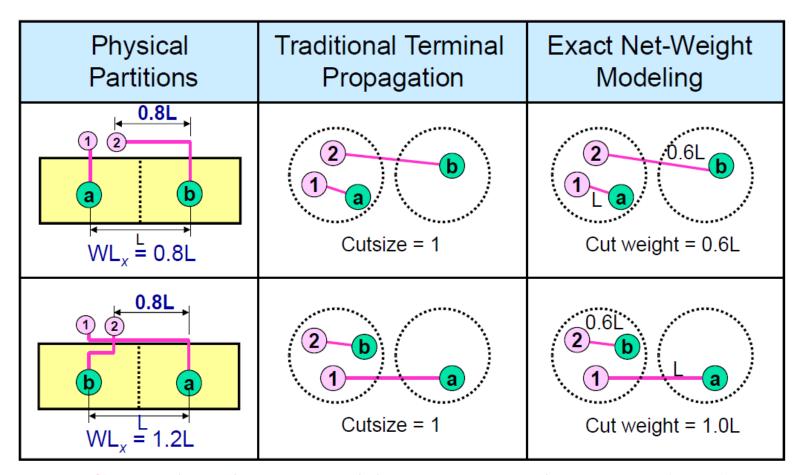
Weight(
$$net_2$$
) = WL( $net_2$  is  $cut$ ) – WL( $net_2$  is not  $cut$ )

$$= 0.8L - 0.2L = 0.6L$$





### **Examples**



Cut weight is proportitional to the wirelength (WL)  $WL = Cut \ weight + 0.2L$ 

(0.2L is the WL lower bound: placing a & b in the left side)

#### Relationship Between WL and Cut Weight

- Theorem:  $WL_i = W_{1,i} + n_{cut,i}$ 
  - n<sub>cut.i</sub>: cut weight for net i
  - $w_{1,i}$ : the wirelength lower bound for net i
- Then, we have  $\min(\sum WL_i) = \min(\sum (w_{1,i} + n_{cut,i})) = \sum w_{1,i} + \min(\sum n_{cut,i})$

Finding the minimum wirelength is equivalent to finding the cut weight

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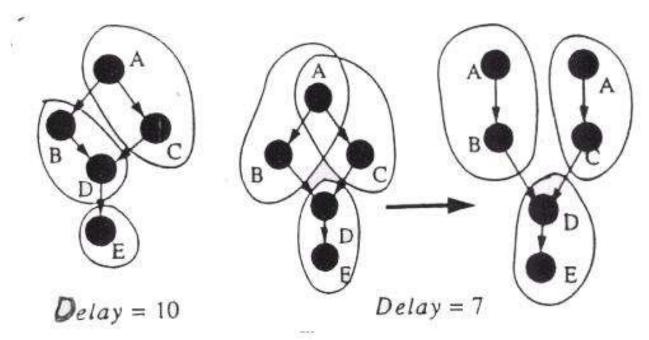
### Clustering for Delay Minimization

- Allow gate duplication.
- Gate duplication may help reduce delay.

 $D=3; M=2; \delta(v)=1, w(v)=1, \text{ for each } v.$ 

Without gate duplication

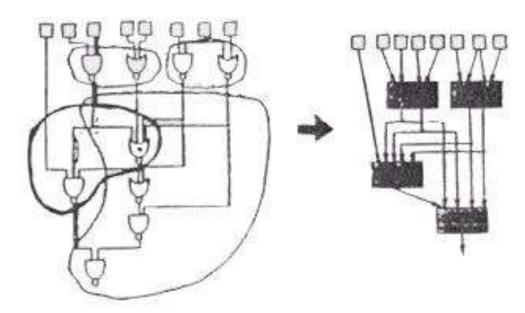
With gate duplication



## **Unit Delay Model**

- No gate delay.
- No interconnection delay within a cluster.
- Delay of 1 unit for an interconnection between 2 clusters.
- An optimal algorithm for area constraint only (Lawler, Levitt and Turner, IEEE TC, 1966).
- An optimal algorithm for pin constraint only (Cong and Ding, ICCAD, 1992).

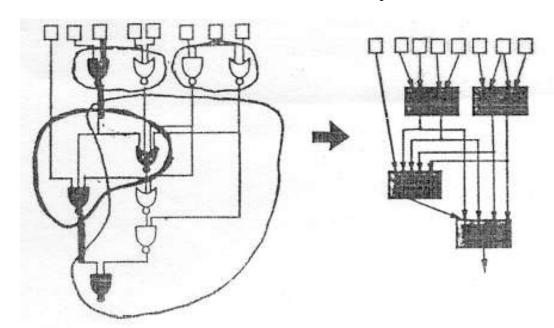
Circuit delay = 3.



# General Delay Model

- Each gate has a delay.
- No interconnection delay within a cluster.
- Delay of *D* units for an interconnection between 2 clusters.
- A heuristic algorithm for area constraint only (Murgai, Brayton and Sangivanni-Vincentelli, ICCAD, 1991).

$$D = 2$$
,  $\delta(v) = 1$ , circuit delay = 6+4 = 10.



- Rajaraman and Wong, "Optimal clustering for delay minimization," DAC, 1993.
- Optimal algorithm:  $O(n^2 \log n + nm)$ , where n is # of gates, m is # of interconnections.
- Definitions:
  - M: the area constraint on a cluster.
  - W(C): the total area of the gates in cluster C.
  - *N*: a given combinational circuit.
  - $N_v$ : v and all its *predecessors* in N.
  - $\delta(v)$ : the delay of v.
  - $\Delta(u,v)$ : maximum delay along any path from the output of u to the output of v, ignoring delays on interconnections.
  - w(v): the area of v.
  - l(v): the delay at v in an optimal clustering of  $N_v$ . For each *primary input* v,  $l(v) = \delta(v)$ .
  - $-l'(u)=l(u)+\Delta(u,v), \text{ for each } u \text{ in } N_v-\{v\}.$

- Algorithm: labeling phase + clustering phase.
- Labeling phase: compute l(v) for each v in a topological order.
  - P: the set of nodes in  $N_v$ -{v} sorted in non-increasing order in the value of l'.

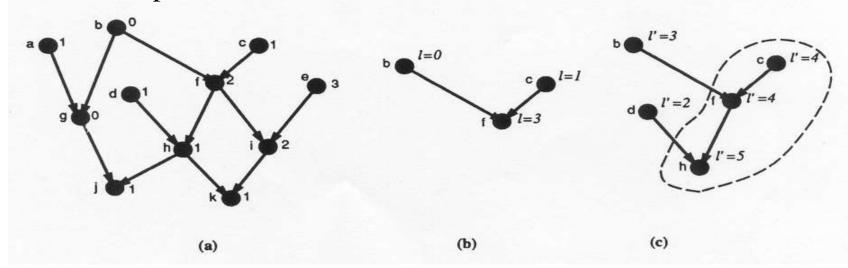
```
Algorithm Labeling(v);
begin
done \leftarrow false;
cluster(v) \leftarrow \{v\};
while (not done)
       Remove the first node u in P;
       if (W(cluster(v)) + w(u)) \leq M
                cluster(v) \leftarrow cluster(v) \cup \{u\};
                 if P is empty
                         done ← true;
                endif
       else
                 done ← true;
       endif
endwhile
l_1(v) \leftarrow max\{l'(x) \mid x \in cluster(v) \cap PI\};

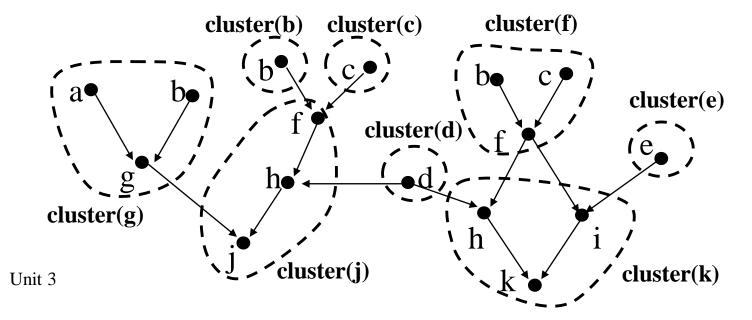
l_2(v) \leftarrow l(u) + D; max\{l'(u) + P \mid u \in N_u - cluster(v)\}
l(v) \leftarrow max\{l_1(v), l_2(v)\};
end
```

- Clustering phase: generate the clusters based on the information obtained in the labeling phase.
- Overall algorithm:

```
begin
Compute the maximum delay matrix \Delta. \Delta(i, j) is the
maximum delay along any path from the output of i
to the output of j;
for each PI i, do l(i) \leftarrow \delta(i);
Sort the non-PI nodes of N in topological order
to obtain list T;
while T is non-empty
      Remove the first node v from T;
      Compute N_v;
      for each node u \in N_v \setminus \{v\} do
               l'(u) \leftarrow l(u) + \Delta(u, v);
       Sort the nodes in N_v \setminus \{v\} in order of
       decreasing value of l' to form list P;
       Call Labeling(v);
endwhile
L \leftarrow \mathcal{PO};
S \leftarrow \phi;
while L is not empty
       Remove a node v from L; N-cluster(v) S \leftarrow S \cup \{cluster(v)\};
       for all nodes x in (N), such that x is adjacent
       to y, for some y \in cluster(v), L \leftarrow L \cup \{x\};
 endwhile
 end
```

• An example: M=3, D=3





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