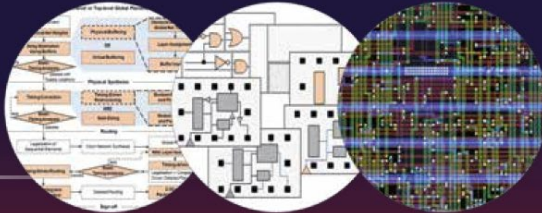


Andrew B. Kahng
Jens Lienig
Igor L. Markov
Jin Hu



VLSI Physical Design: From Graph Partitioning to Timing Closure

Second Edition

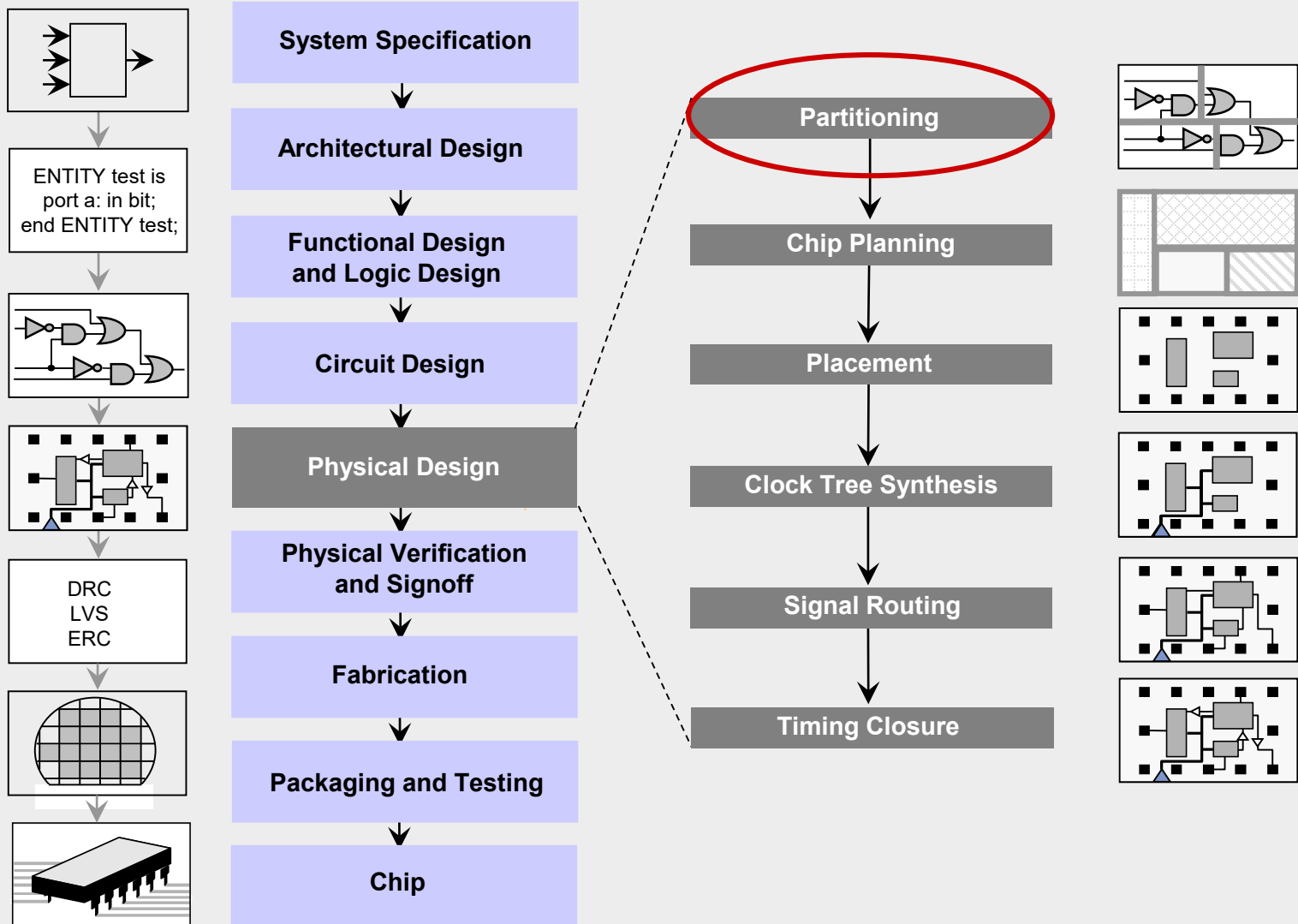
Chapter 2 – Netlist and System Partitioning

 Springer

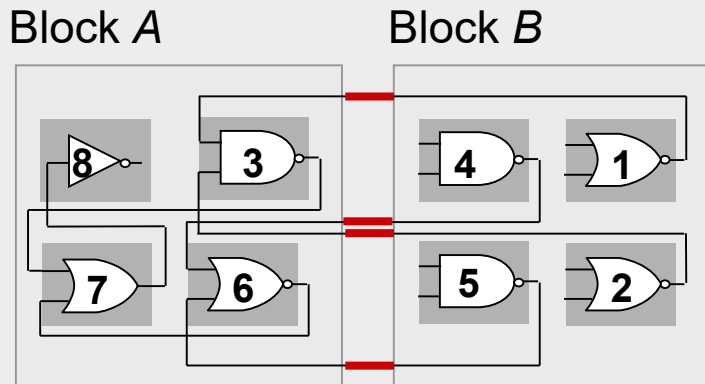
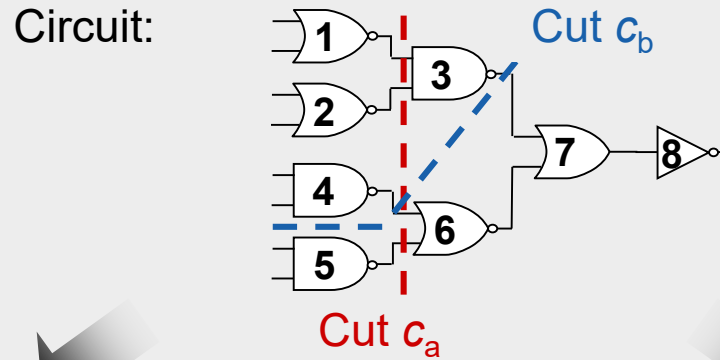
Chapter 2 – Netlist and System Partitioning

- 2.1 Introduction
- 2.2 Terminology
- 2.3 Optimization Goals
- 2.4 Partitioning Algorithms
 - 2.4.1 Kernighan-Lin (KL) Algorithm
 - 2.4.2 Extensions of the Kernighan-Lin Algorithm
 - 2.4.3 Fiduccia-Mattheyses (FM) Algorithm
- 2.5 Framework for Multilevel Partitioning
 - 2.5.1 Clustering
 - 2.5.2 Multilevel Partitioning
- 2.6 System Partitioning onto Multiple FPGAs

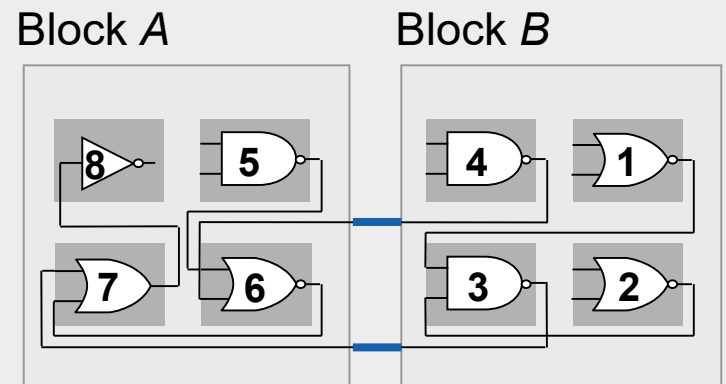
2.1 Introduction



2.1 Introduction

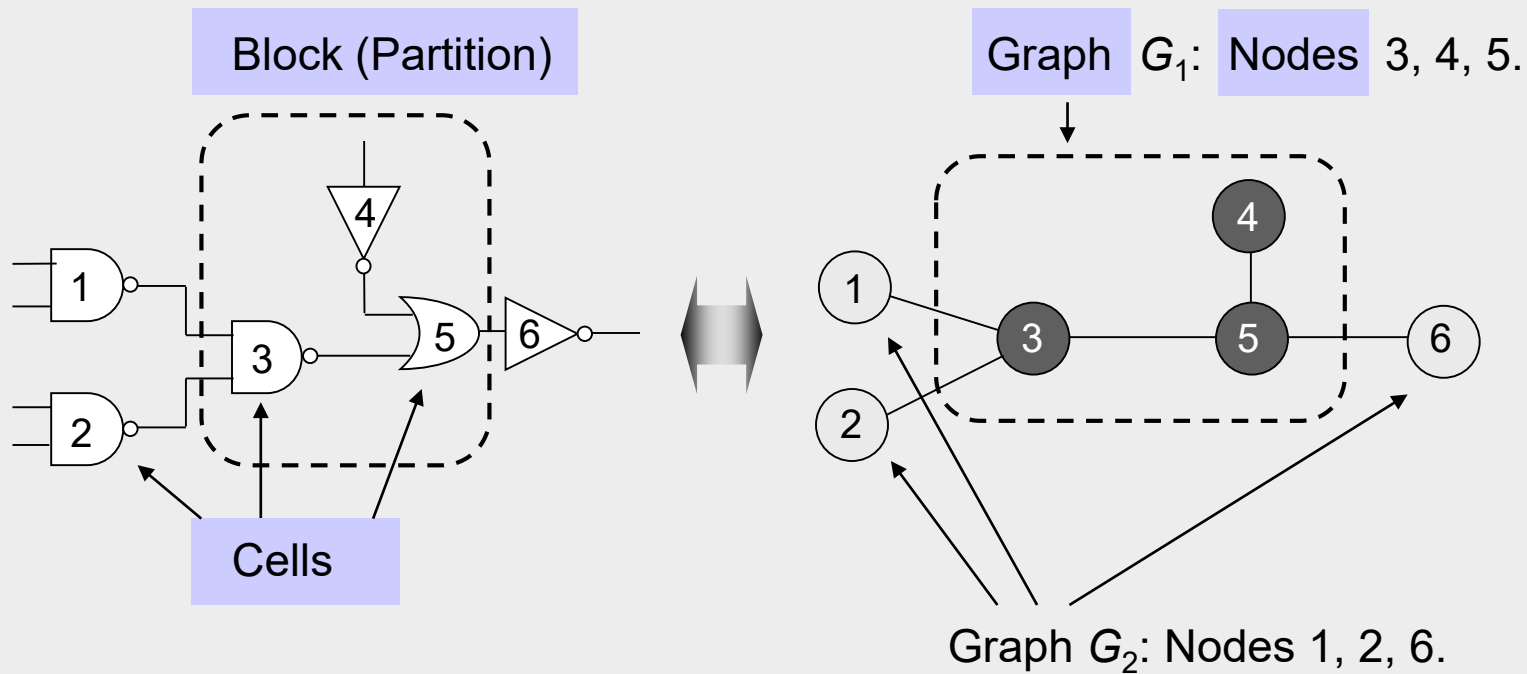


Cut c_a : four external connections



Cut c_b : two external connections

2.2 Terminology



Collection of cut edges

Cut set: (1,3), (2,3), (5,6),

2.3 Optimization Goals

- Given a graph $G(V,E)$ with $|V|$ nodes and $|E|$ edges where each node $v \in V$ and each edge $e \in E$.
- Each node has area $s(v)$ and each edge has cost or weight $w(e)$.
- The objective is to divide the graph G into k disjoint subgraphs such that all optimization goals are achieved and all original edge relations are respected.

2.3 Optimization Goals

- In detail, what are the optimization goals?
 - Number of connections between partitions is minimized
 - Each partition meets all design constraints (size, number of external connections..)
 - Balance every partition as well as possible
- How can we meet these goals?
 - Unfortunately, this problem is NP-hard
 - Efficient heuristics are developed in the 1970s and 1980s. They are high quality and in low-order polynomial time.

Chapter 2 – Netlist and System Partitioning

2.1 Introduction

2.2 Terminology

2.3 Optimization Goals

 2.4 Partitioning Algorithms

2.4.1 Kernighan-Lin (KL) Algorithm

2.4.2 Extensions of the Kernighan-Lin Algorithm

2.4.3 Fiduccia-Mattheyses (FM) Algorithm

2.5 Framework for Multilevel Partitioning

2.5.1 Clustering

2.5.2 Multilevel Partitioning

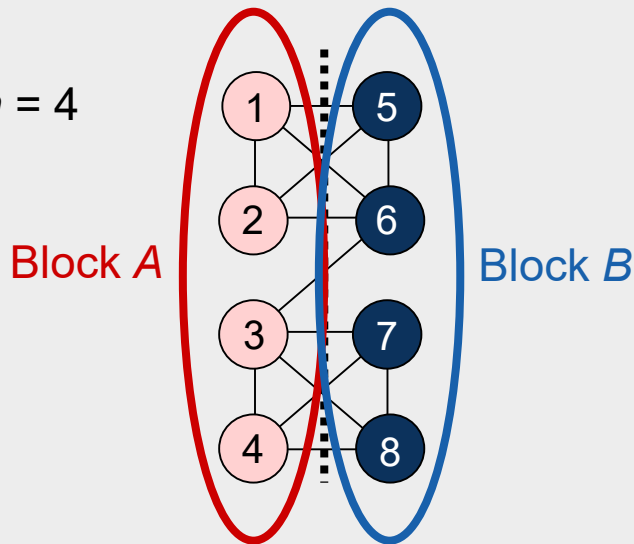
2.6 System Partitioning onto Multiple FPGAs

2.4.1 Kernighan-Lin (KL) Algorithm

Given: A graph with $2n$ nodes where each node has the same weight.

Goal: A partition (division) of the graph into two disjoint subsets A and B with minimum cut cost and $|A| = |B| = n$.

Example: $n = 4$



2.4.1 Kernighan-Lin (KL) Algorithm – Terminology

Cost $D(v)$ of moving a node v

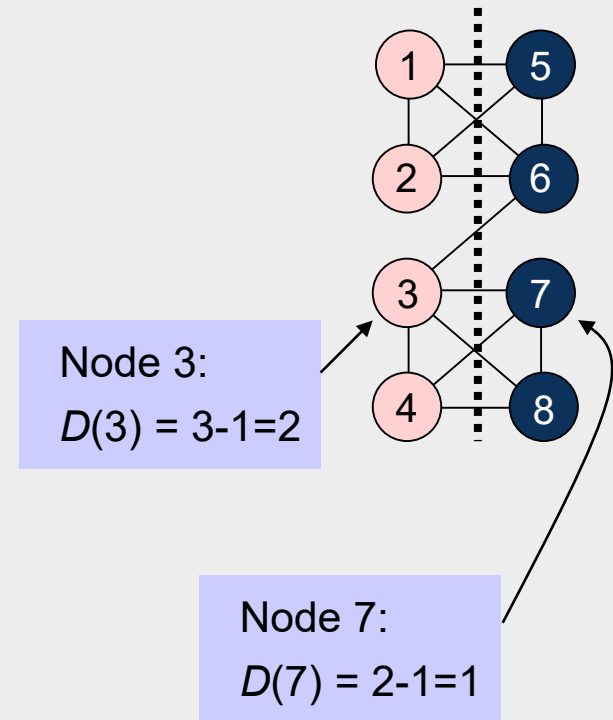
$$D(v) = |E_c(v)| - |E_{nc}(v)|,$$

where

$E_c(v)$ is the set of v 's incident edges that are cut by the cut line, and

$E_{nc}(v)$ is the set of v 's incident edges that are not cut by the cut line.

High costs ($D > 0$) indicate that the node should move, while low costs ($D < 0$) indicate that the node should stay within the same partition.



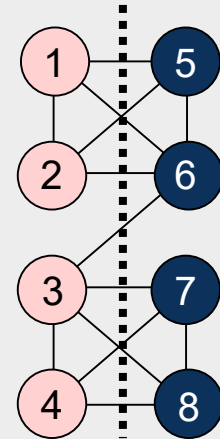
2.4.1 Kernighan-Lin (KL) Algorithm – Terminology

Gain of swapping a pair of nodes a and b

$$\Delta g = D(a) + D(b) - 2 * c(a,b),$$

where

- $D(a)$, $D(b)$ are the respective costs of nodes a , b
- $c(a,b)$ is the connection weight between a and b :
If an edge exists between a and b ,
then $c(a,b) = \text{edge weight (here 1)}$,
otherwise, $c(a,b) = 0$.



The gain Δg indicates how useful the swap between two nodes will be

The larger Δg , the more the total cut cost will be reduced

2.4.1 Kernighan-Lin (KL) Algorithm – Terminology

Gain of swapping a pair of nodes a and b

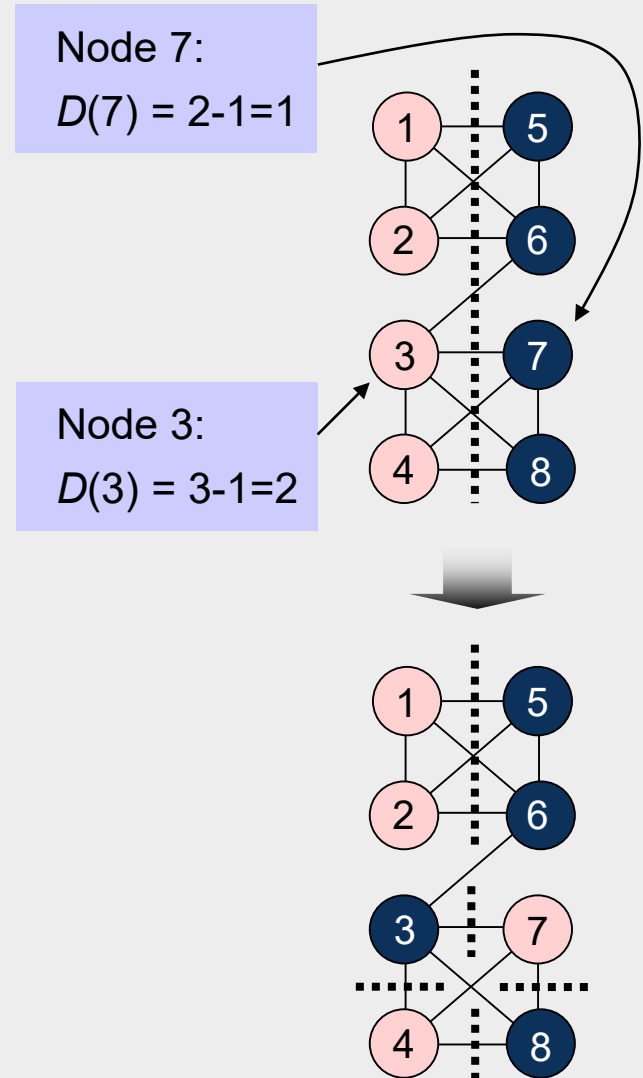
$$\Delta g = D(a) + D(b) - 2 * c(a,b),$$

where

- $D(a)$, $D(b)$ are the respective costs of nodes a , b
- $c(a,b)$ is the connection weight between a and b :
If an edge exists between a and b ,
then $c(a,b) = \text{edge weight (here 1)}$,
otherwise, $c(a,b) = 0$.

$$\Delta g(3,7) = D(3) + D(7) - 2 * c(a,b) = 2 + 1 - 2 = 1$$

=> Swapping nodes 3 and 7 would reduce the cut size by 1



2.4.1 Kernighan-Lin (KL) Algorithm – Terminology

Gain of swapping a pair of nodes a and b

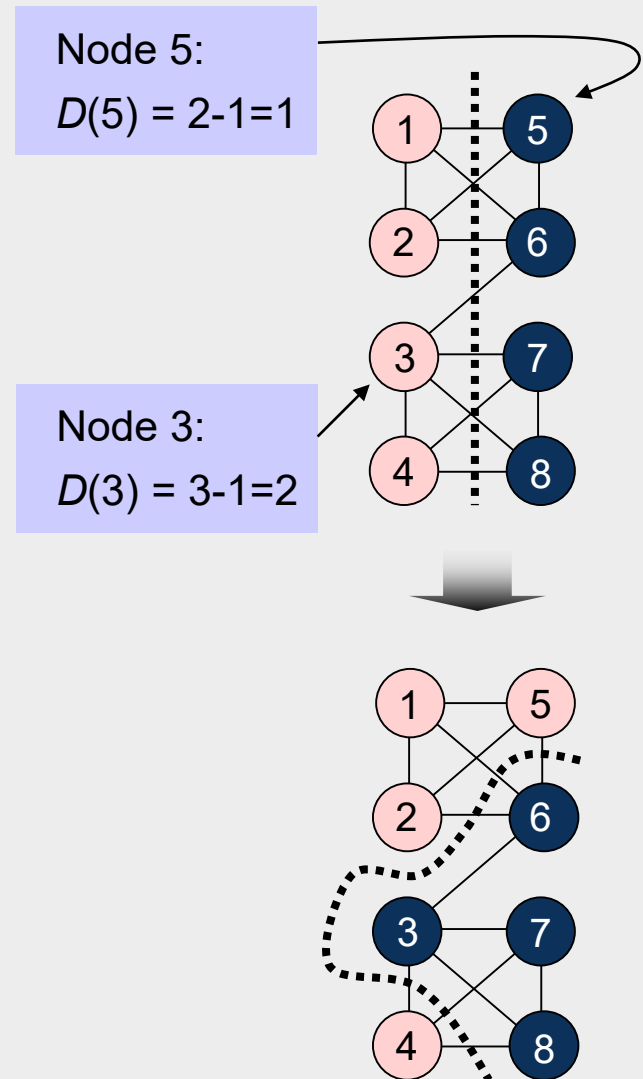
$$\Delta g = D(a) + D(b) - 2 * c(a,b),$$

where

- $D(a)$, $D(b)$ are the respective costs of nodes a , b
- $c(a,b)$ is the connection weight between a and b :
If an edge exists between a and b ,
then $c(a,b) = \text{edge weight (here 1)}$,
otherwise, $c(a,b) = 0$.

$$\Delta g(3,5) = D(3) + D(5) - 2 * c(a,b) = 2 + 1 - 0 = 3$$

=> Swapping nodes 3 and 5 would reduce the cut size by 3



2.4.1 Kernighan-Lin (KL) Algorithm – Terminology

Gain of swapping a pair of nodes a and b

The goal is to find a pair of nodes a and b to exchange such that Δg is maximized and swap them.

2.4.1 Kernighan-Lin (KL) Algorithm – Terminology

Maximum positive gain G_m of a pass

The maximum positive gain G_m corresponds to the best prefix of m swaps within the swap sequence of a given pass.

These m swaps lead to the partition with the minimum cut cost encountered during the pass.

G_m is computed as the sum of Δg values over the first m swaps of the pass, with m chosen such that G_m is maximized.

$$G_m = \sum_{i=1}^m \Delta g_i$$

2.4.1 Kernighan-Lin (KL) Algorithm – One pass

Step 0:

- $V = 2n$ nodes
- $\{A, B\}$ is an initial arbitrary partitioning

Step 1:

- $i = 1$
- Compute $D(v)$ for all nodes $v \in V$

Step 2:

- Choose a_i and b_i such that $\Delta g_i = D(a_i) + D(b_i) - 2 * c(a_i, b_i)$ is maximized
- Swap and fix a_i and b_i

Step 3:

- If all nodes are fixed, go to Step 4. Otherwise
- Compute and update D values for all nodes that are connected to a_i and b_i and are not fixed.
- $i = i + 1$
- Go to Step 2

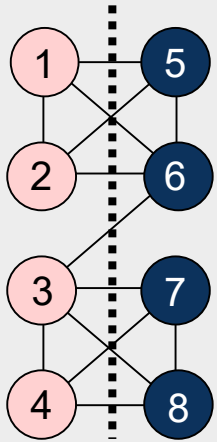
Step 4:

- Find the move sequence $1 \dots m$ ($1 \leq m \leq i$), such that $G_m = \sum_{i=1}^m \Delta g_i$ is maximized
- If $G_m > 0$, go to Step 5. Otherwise, END

Step 5:

- Execute m swaps, reset remaining nodes
- Go to Step 1

2.4.1 Kernighan-Lin (KL) Algorithm – Example

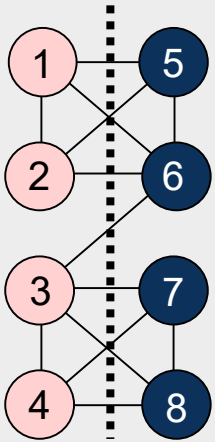


Cut cost: 9

Not fixed:

1,2,3,4,5,6,7,8

2.4.1 Kernighan-Lin (KL) Algorithm – Example



Cut cost: 9

Not fixed:

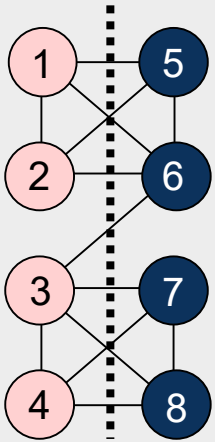
1,2,3,4,5,6,7,8

Costs $D(v)$ of each node:

$D(1) = 1$	$D(5) = 1$
$D(2) = 1$	$D(6) = 2$
$D(3) = 2$	$D(7) = 1$
$D(4) = 1$	$D(8) = 1$

Nodes that lead to maximum gain

2.4.1 Kernighan-Lin (KL) Algorithm – Example



Cut cost: 9

Not fixed:

1,2,3,4,5,6,7,8

Costs $D(v)$ of each node:

$$D(1) = 1 \quad D(5) = 1$$

$$D(2) = 1 \quad D(6) = 2$$

$$D(3) = 2 \quad D(7) = 1$$

$$D(4) = 1 \quad D(8) = 1$$

Nodes that lead to maximum gain

$$\Delta g_1 = 2 + 1 - 0 = 3$$

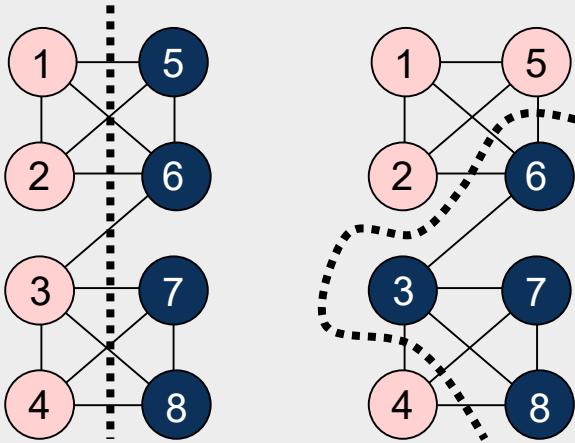
Swap (3,5)

$$G_1 = \Delta g_1 = 3$$

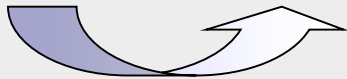
Gain after node swapping

Gain in the current pass

2.4.1 Kernighan-Lin (KL) Algorithm – Example



Cut cost: 9
Not fixed:
1,2,3,4,5,6,7,8



$D(1) = 1$	$D(5) = 1$
$D(2) = 1$	$D(6) = 2$
$D(3) = 2$	$D(7) = 1$
$D(4) = 1$	$D(8) = 1$

Nodes that lead to
maximum gain

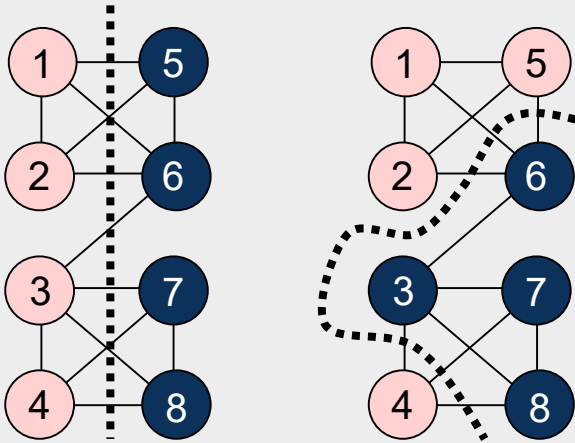
$\Delta g_1 = 2 + 1 - 0 = 3$

Swap (3,5)

$G_1 = \Delta g_1 = 3$

Gain in the current pass

2.4.1 Kernighan-Lin (KL) Algorithm – Example



Cut cost: 9
Not fixed:
1,2,3,4,5,6,7,8

Cut cost: 6
Not fixed:
1,2,4,6,7,8



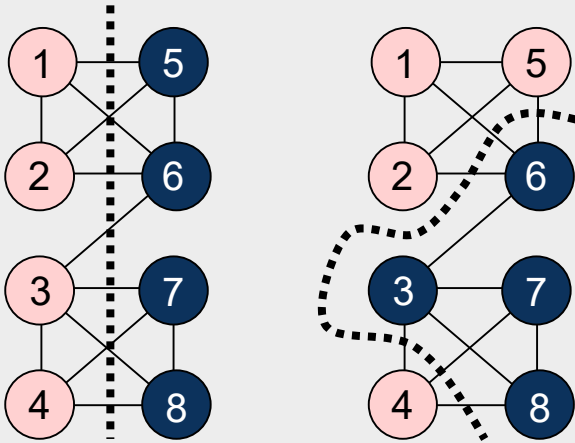
$D(1) = 1$ $D(5) = 1$
 $D(2) = 1$ $D(6) = 2$
 $D(3) = 2$ $D(7) = 1$
 $D(4) = 1$ $D(8) = 1$

$$\Delta g_1 = 2 + 1 - 0 = 3$$

Swap (3,5)

$$G_1 = \Delta g_1 = 3$$

2.4.1 Kernighan-Lin (KL) Algorithm – Example



Cut cost: 9
Not fixed:
1,2,3,4,5,6,7,8

Cut cost: 6
Not fixed:
1,2,4,6,7,8



$D(1) = 1$ $D(5) = 1$
 $D(2) = 1$ $D(6) = 2$
 $D(3) = 2$ $D(7) = 1$
 $D(4) = 1$ $D(8) = 1$

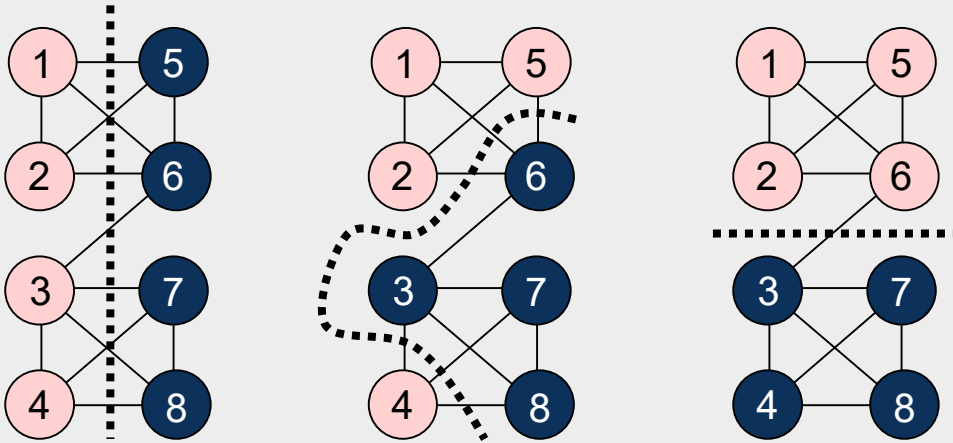
$$\Delta g_1 = 2 + 1 - 0 = 3$$

Swap (3,5)

$$G_1 = \Delta g_1 = 3$$

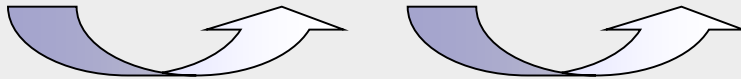
$D(1) = -1$ $D(6) = 2$
 $D(2) = -1$ $D(7) = -1$
 $D(4) = 3$ $D(8) = -1$

2.4.1 Kernighan-Lin (KL) Algorithm – Example



Cut cost: 9
Not fixed:
1,2,3,4,5,6,7,8

Cut cost: 6
Not fixed:
1,2,4,6,7,8



$D(1) = 1$ $D(5) = 1$
 $D(2) = 1$ $D(6) = 2$
 $D(3) = 2$ $D(7) = 1$
 $D(4) = 1$ $D(8) = 1$

$$\Delta g_1 = 2 + 1 - 0 = 3$$

Swap (3,5)

$$G_1 = \Delta g_1 = 3$$

$D(1) = -1$ $D(6) = 2$
 $D(2) = -1$ $D(7) = -1$
 $D(4) = 3$ $D(8) = -1$

Nodes that lead to
maximum gain

$$\Delta g_2 = 3 + 2 - 0 = 5$$

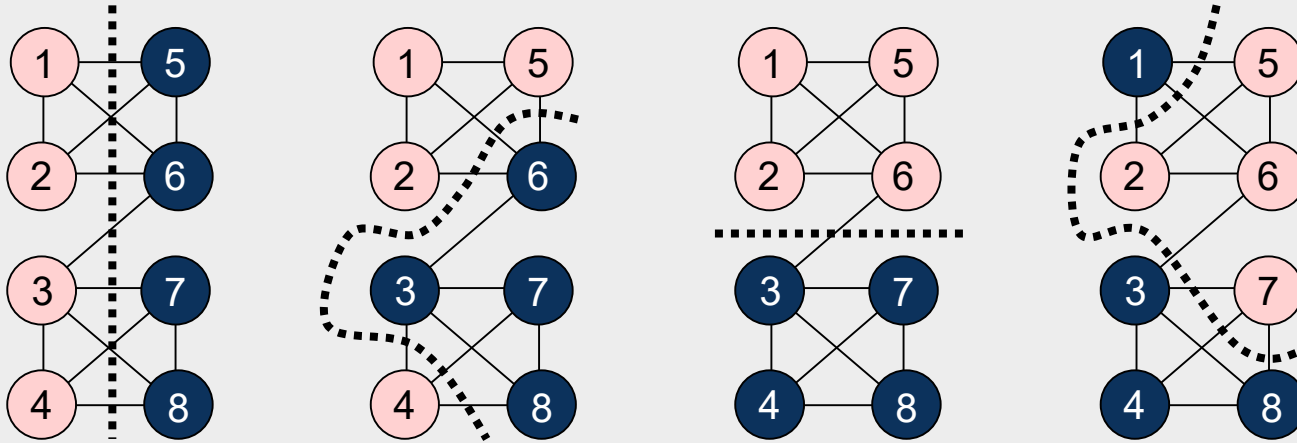
Swap (4,6)

$$G_2 = G_1 + \Delta g_2 = 8$$

Gain after node swapping

Gain in the current pass

2.4.1 Kernighan-Lin (KL) Algorithm – Example

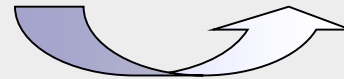
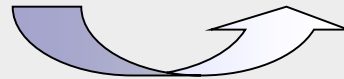


Cut cost: 9
Not fixed:
1,2,3,4,5,6,7,8

Cut cost: 6
Not fixed:
1,2,4,6,7,8

Cut cost: 1
Not fixed:
1,2,7,8

Cut cost: 7
Not fixed:
2,8



$D(1) = 1$ $D(5) = 1$
 $D(2) = 1$ $D(6) = 2$
 $D(3) = 2$ $D(7) = 1$
 $D(4) = 1$ $D(8) = 1$

$\Delta g_1 = 2+1-0 = 3$
Swap (3,5)
 $G_1 = \Delta g_1 = 3$

$D(1) = -1$ $D(6) = 2$
 $D(2) = -1$ $D(7) = -1$
 $D(4) = 3$ $D(8) = -1$

$\Delta g_2 = 3+2-0 = 5$
Swap (4,6)
 $G_2 = G_1 + \Delta g_2 = 8$

$D(1) = -3$ $D(7) = -3$
 $D(2) = -3$ $D(8) = -3$

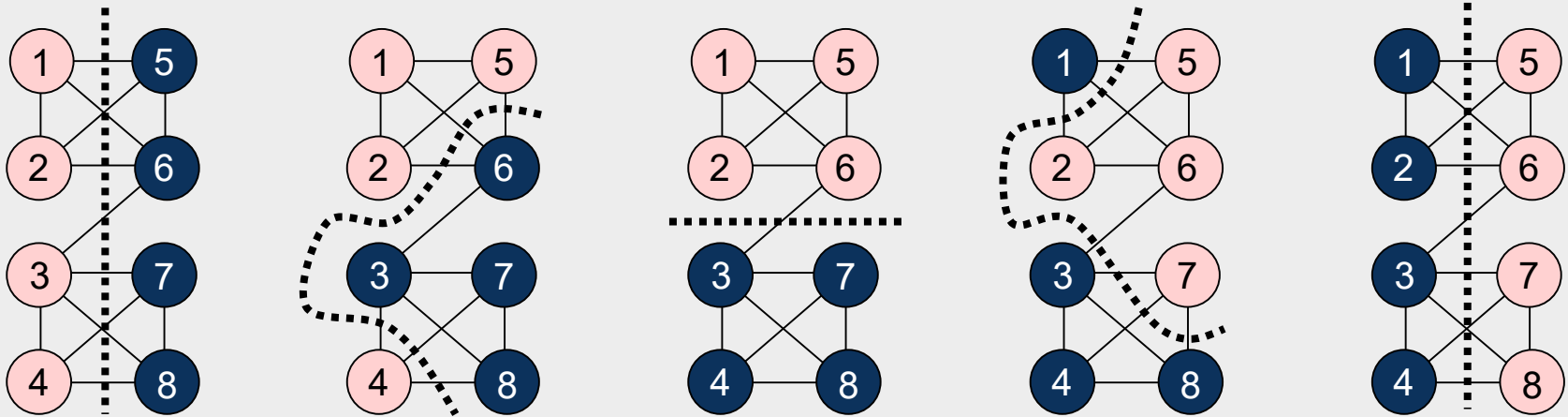
$\Delta g_3 = -3-3-0 = -6$
Swap (1,7)
 $G_3 = G_2 + \Delta g_3 = 2$

Nodes that lead to maximum gain

Gain after node swapping

Gain in the current pass

2.4.1 Kernighan-Lin (KL) Algorithm – Example



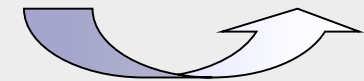
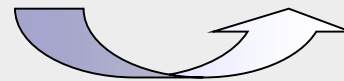
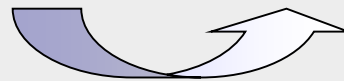
Cut cost: 9
Not fixed:
1,2,3,4,5,6,7,8

Cut cost: 6
Not fixed:
1,2,4,6,7,8

Cut cost: 1
Not fixed:
1,2,7,8

Cut cost: 7
Not fixed:
2,8

Cut cost: 9
Not fixed:
–



$D(1) = 1$ $D(5) = 1$
 $D(2) = 1$ $D(6) = 2$
 $D(3) = 2$ $D(7) = 1$
 $D(4) = 1$ $D(8) = 1$

$\Delta g_1 = 2+1-0 = 3$
Swap (3,5)
 $G_1 = \Delta g_1 = 3$

$D(1) = -1$ $D(6) = 2$
 $D(2) = -1$ $D(7) = -1$
 $D(4) = 3$ $D(8) = -1$

$\Delta g_2 = 3+2-0 = 5$
Swap (4,6)
 $G_2 = G_1 + \Delta g_2 = 8$

$D(1) = -3$ $D(7) = -3$
 $D(2) = -3$ $D(8) = -3$

$\Delta g_3 = -3-3-0 = -6$
Swap (1,7)
 $G_3 = G_2 + \Delta g_3 = 2$

$D(2) = -1$ $D(8) = -1$

$\Delta g_4 = -1-1-0 = -2$
Swap (2,8)
 $G_4 = G_3 + \Delta g_4 = 0$

2.4.1 Kernighan-Lin (KL) Algorithm – Example

$D(1) = 1$ $D(5) = 1$
 $D(2) = 1$ $D(6) = 2$
 $D(3) = 2$ $D(7) = 1$
 $D(4) = 1$ $D(8) = 1$

$$\Delta g_1 = 2+1-0 = 3$$

Swap (3,5)

$$G_1 = \Delta g_1 = 3$$

$D(1) = -1$ $D(6) = 2$
 $D(2) = -1$ $D(7) = -1$
 $D(4) = 3$ $D(8) = -1$

$$\Delta g_2 = 3+2-0 = 5$$

Swap (4,6)

$$G_2 = G_1 + \Delta g_2 = 8$$

$D(1) = -3$ $D(7) = -3$
 $D(2) = -3$ $D(8) = -3$

$$\Delta g_3 = -3-3-0 = -6$$

Swap (1,7)

$$G_3 = G_2 + \Delta g_3 = 2$$

$D(2) = -1$ $D(8) = -1$

$$\Delta g_4 = -1-1-0 = -2$$

Swap (2,8)

$$G_4 = G_3 + \Delta g_4 = 0$$

Maximum positive gain $G_m = 8$ with $m = 2$.

2.4.1 Kernighan-Lin (KL) Algorithm – Example

$D(1) = 1$ $D(5) = 1$
 $D(2) = 1$ $D(6) = 2$
 $D(3) = 2$ $D(7) = 1$
 $D(4) = 1$ $D(8) = 1$

$\Delta g_1 = 2+1-0 = 3$
Swap (3,5)
 $G_1 = \Delta g_1 = 3$

$D(1) = -1$ $D(6) = 2$
 $D(2) = -1$ $D(7) = -1$
 $D(4) = 3$ $D(8) = -1$

$\Delta g_2 = 3+2-0 = 5$
Swap (4,6)
 $G_2 = G_1 + \Delta g_2 = 8$

$D(1) = -3$ $D(7) = -3$
 $D(2) = -3$ $D(8) = -3$

$\Delta g_3 = -3-3-0 = -6$
Swap (1,7)
 $G_3 = G_2 + \Delta g_3 = 2$

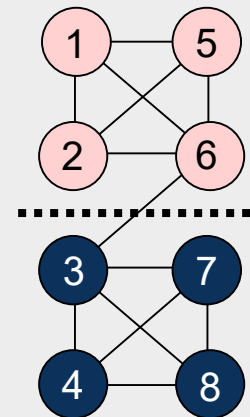
$D(2) = -1$ $D(8) = -1$

$\Delta g_4 = -1-1-0 = -2$
Swap (2,8)
 $G_4 = G_3 + \Delta g_4 = 0$

Maximum positive gain $G_m = 8$ with $m = 2$.

Since $G_m > 0$, the first $m = 2$ swaps (3,5) and (4,6) are executed.

Since $G_m > 0$, more passes are needed until $G_m \leq 0$.



2.4.2 Extensions of the Kernighan-Lin (KL) Algorithm

- Unequal partition sizes
 - Apply the KL algorithm with only $\min(|A|, |B|)$ pairs swapped
- Unequal node weights
 - Try to rescale weights to integers, e.g., as multiples of *the greatest common divisor* of all node weights
 - Maintain area balance or allow a *one-move deviation* from balance
- k -way partitioning (generating k partitions)
 - Apply the KL two-way partitioning algorithm to all possible pairs of partitions
 - Recursive partitioning (convenient when k is a power of two)
 - Direct k -way extensions exist

2.4.3 Fiduccia-Mattheyses (FM) Algorithm

- Single cells are moved independently instead of swapping pairs of cells --- cannot and do not need to maintain exact partition balance
 - The area of each individual cell is taken into account
 - Applicable to partitions of unequal size and in the presence of initially fixed cells
- Cut costs are extended to include hypergraphs
 - nets with 2+ pins
- While the KL algorithm aims to minimize cut costs based on edges, the FM algorithm minimizes cut costs based on nets
- Nodes and subgraphs are referred to as *cells* and *blocks*, respectively

2.4.3 Fiduccia-Mattheyses (FM) Algorithm

Given: a hypergraph $G(V,H)$ with nodes and *weighted* hyperedges
partition size constraints

Goal: to assign all nodes to disjoint partitions,
so as to minimize the total cost (weight) of all cut nets
while satisfying *partition size constraints*

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Terminology

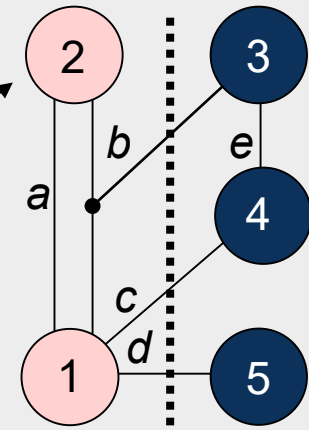
Gain $\Delta g(c)$ for cell c

$$\Delta g(c) = FS(c) - TE(c),$$

where

the “moving force“ $FS(c)$ is the number of nets connected to c but not connected to any other cells within c 's partition, i.e., cut nets that connect only to c , and

the “retention force“ $TE(c)$ is the number of *uncut* nets connected to c .



Cell 2: $FS(2) = 0$ $TE(2) = 1$ $\Delta g(2) = -1$

The higher the gain $\Delta g(c)$, the higher is the priority to move the cell c to the other partition.

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Terminology

Gain $\Delta g(c)$ for cell c

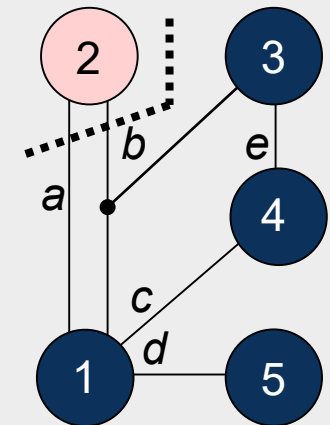
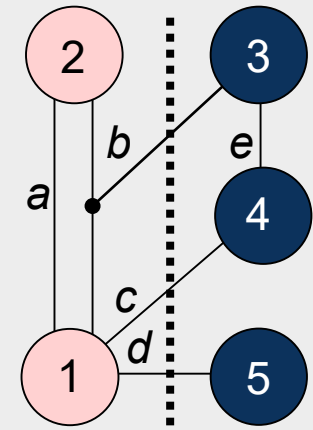
$$\Delta g(c) = FS(c) - TE(c),$$

where

the “moving force“ $FS(c)$ is the number of nets connected to c but not connected to any other cells within c 's partition, i.e., cut nets that connect only to c , and

the “retention force“ $TE(c)$ is the number of *uncut* nets connected to c .

Cell 1:	$FS(1) = 2$	$TE(1) = 1$	$\Delta g(1) = 1$
Cell 2:	$FS(2) = 0$	$TE(2) = 1$	$\Delta g(2) = -1$
Cell 3:	$FS(3) = 1$	$TE(3) = 1$	$\Delta g(3) = 0$
Cell 4:	$FS(4) = 1$	$TE(4) = 1$	$\Delta g(4) = 0$
Cell 5:	$FS(5) = 1$	$TE(5) = 0$	$\Delta g(5) = 1$



Maximum positive gain G_m of a pass

The maximum positive gain G_m is the cumulative cell gain of m moves that produce a minimum cut cost.

G_m is determined by the maximum sum of cell gains Δg over a prefix of m moves in a pass

$$G_m = \sum_{i=1}^m \Delta g_i$$

Ratio factor

The *ratio factor* is the relative balance between the two partitions with respect to cell area

It is used to prevent all cells from clustering into one partition.

The ratio factor r is defined as

$$r = \frac{\mathit{area}(A)}{\mathit{area}(A) + \mathit{area}(B)}$$

where $\mathit{area}(A)$ and $\mathit{area}(B)$ are the total respective areas of partitions A and B

Balance criterion

The balance criterion enforces the ratio factor.

To ensure feasibility, the maximum cell area $area_{max}(V)$ must be taken into account.

A partitioning of V into two partitions A and B is said to be balanced if

$$[r \cdot area(V) - area_{max}(V)] \leq area(A) \leq [r \cdot area(V) + area_{max}(V)]$$

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Terminology

Base cell

A base cell is a cell c that has the greatest cell gain $\Delta g(c)$ among all free cells, and whose move does not violate the balance criterion.

Base cell



Cell 1:	$FS(1) = 2$	$TE(1) = 1$	$\Delta g(1) = 1$
Cell 2:	$FS(2) = 0$	$TE(2) = 1$	$\Delta g(2) = -1$
Cell 3:	$FS(3) = 1$	$TE(3) = 1$	$\Delta g(3) = 0$
Cell 4:	$FS(4) = 1$	$TE(4) = 1$	$\Delta g(4) = 0$

2.4.3 Fiduccia-Mattheyses (FM) Algorithm - One pass

Step 0: Compute the balance criterion

Step 1: Compute the cell gain Δg_1 of each cell

Step 2: $i = 1$

– Choose base cell c_1 that has maximal gain Δg_1 , move this cell

Step 3:

– Fix the base cell c_i

– Update all cells' gains that are connected to critical nets via the base cell c_i

Step 4:

– If all cells are fixed, go to Step 5. If not:

– Choose next base cell c_i with maximal gain Δg_i and move this cell

– $i = i + 1$, go to Step 3

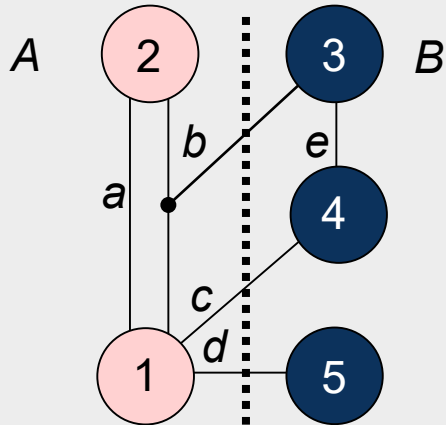
Step 5:

– Determine the best move sequence c_1, c_2, \dots, c_m ($1 \leq m \leq i$), so that $G_m = \sum_{i=1}^m \Delta g_i$ is maximized

– If $G_m > 0$, go to Step 6. Otherwise, END

Step 6:

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example



Given:

Ratio factor $r = 0,375$

$area(\text{Cell}_1) = 2$

$area(\text{Cell}_2) = 4$

$area(\text{Cell}_3) = 1$

$area(\text{Cell}_4) = 4$

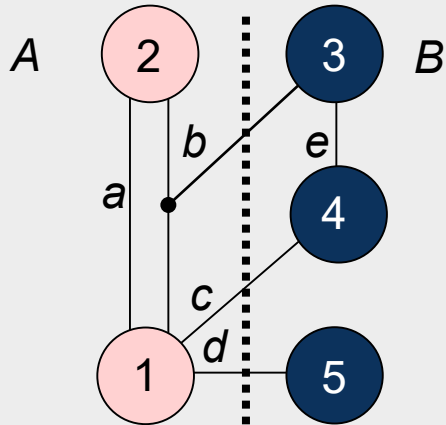
$area(\text{Cell}_5) = 5.$

Step 0: Compute the balance criterion

$$[r \cdot area(V) - area_{max}(V)] \leq area(A) \leq [r \cdot area(V) + area_{max}(V)]$$

$$0,375 * 16 - 5 = 1 \leq area(A) \leq 11 = 0,375 * 16 + 5.$$

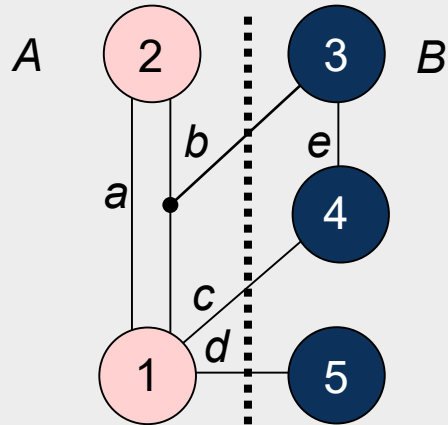
2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example



Step 1: Compute the gains of each cell

Cell 1:	$FS(\text{Cell}_1) = 2$	$TE(\text{Cell}_1) = 1$	$\Delta g(\text{Cell}_1) = 1$
Cell 2:	$FS(\text{Cell}_2) = 0$	$TE(\text{Cell}_2) = 1$	$\Delta g(\text{Cell}_2) = -1$
Cell 3:	$FS(\text{Cell}_3) = 1$	$TE(\text{Cell}_3) = 1$	$\Delta g(\text{Cell}_3) = 0$
Cell 4:	$FS(\text{Cell}_4) = 1$	$TE(\text{Cell}_4) = 1$	$\Delta g(\text{Cell}_4) = 0$
Cell 5:	$FS(\text{Cell}_5) = 1$	$TE(\text{Cell}_5) = 0$	$\Delta g(\text{Cell}_5) = 1$

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example



Cell 1:	$FS(\text{Cell}_1) = 2$	$TE(\text{Cell}_1) = 1$	$\Delta g(\text{Cell}_1) = 1$
Cell 2:	$FS(\text{Cell}_2) = 0$	$TE(\text{Cell}_2) = 1$	$\Delta g(\text{Cell}_2) = -1$
Cell 3:	$FS(\text{Cell}_3) = 1$	$TE(\text{Cell}_3) = 1$	$\Delta g(\text{Cell}_3) = 0$
Cell 4:	$FS(\text{Cell}_4) = 1$	$TE(\text{Cell}_4) = 1$	$\Delta g(\text{Cell}_4) = 0$
Cell 5:	$FS(\text{Cell}_5) = 1$	$TE(\text{Cell}_5) = 0$	$\Delta g(\text{Cell}_5) = 1$

Step 2: Select the base cell

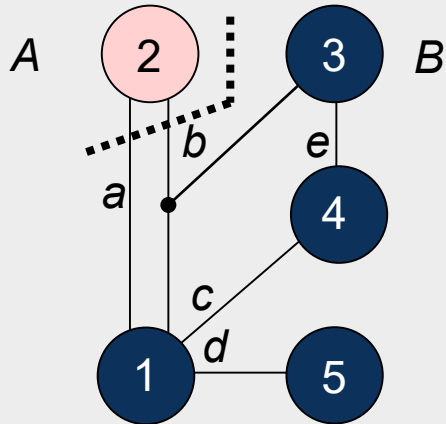
Possible base cells are Cell 1 and Cell 5

Balance criterion after moving Cell 1: $area(A) = area(\text{Cell}_2) = 4$

Balance criterion after moving Cell 5: $area(A) = area(\text{Cell}_1) + area(\text{Cell}_2) + area(\text{Cell}_5) = 11$

Both moves respect the balance criterion, but Cell 1 is selected, moved, and fixed as a result of the tie-breaking criterion.

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example

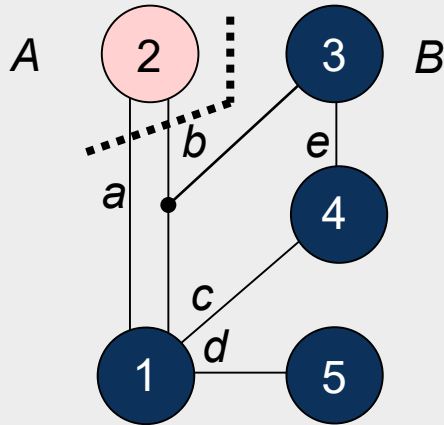


Step 3: Fix base cell, update Δg values

Cell 2:	$FS(\text{Cell}_2) = 2$	$TE(\text{Cell}_2) = 0$	$\Delta g(\text{Cell}_2) = 2$
Cell 3:	$FS(\text{Cell}_3) = 0$	$TE(\text{Cell}_3) = 1$	$\Delta g(\text{Cell}_3) = -1$
Cell 4:	$FS(\text{Cell}_4) = 0$	$TE(\text{Cell}_4) = 2$	$\Delta g(\text{Cell}_4) = -2$
Cell 5:	$FS(\text{Cell}_5) = 0$	$TE(\text{Cell}_5) = 1$	$\Delta g(\text{Cell}_5) = -1$

After Iteration $i = 1$: Partition $A_1 = \{2\}$, Partition $B_1 = \{1,3,4,5\}$, with fixed cell $\{1\}$.

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example



Iteration $i = 1$

Cell 2:	$FS(\text{Cell}_2) = 2$	$TE(\text{Cell}_2) = 0$	$\Delta g(\text{Cell}_2) = 2$
Cell 3:	$FS(\text{Cell}_3) = 0$	$TE(\text{Cell}_3) = 1$	$\Delta g(\text{Cell}_3) = -1$
Cell 4:	$FS(\text{Cell}_4) = 0$	$TE(\text{Cell}_4) = 2$	$\Delta g(\text{Cell}_4) = -2$
Cell 5:	$FS(\text{Cell}_5) = 0$	$TE(\text{Cell}_5) = 1$	$\Delta g(\text{Cell}_5) = -1$

Iteration $i = 2$

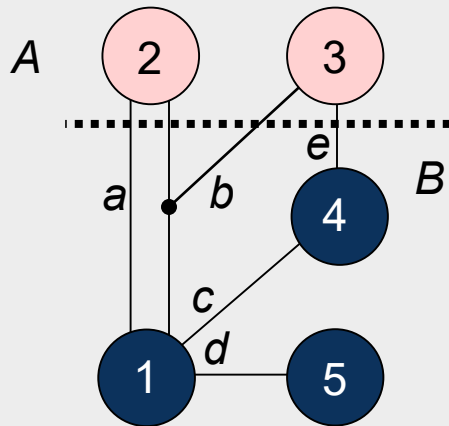
Cell 2 has maximum gain $\Delta g_2 = 2$, $area(A) = 0$, balance criterion is violated.

Cell 3 has next maximum gain $\Delta g_2 = -1$, $area(A) = 5$, balance criterion is met.

Cell 5 has next maximum gain $\Delta g_2 = -1$, $area(A) = 9$, balance criterion is met.

Move cell 3, updated partitions: $A_2 = \{2,3\}$, $B_2 = \{1,4,5\}$, with fixed cells $\{1,3\}$

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example



Iteration $i = 2$

Cell 2: $\Delta g(\text{Cell}_2) = 1$

Cell 4: $\Delta g(\text{Cell}_4) = 0$

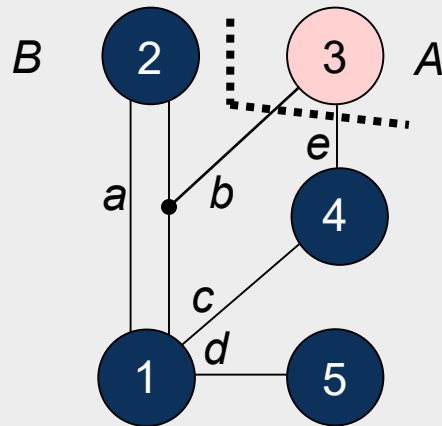
Cell 5: $\Delta g(\text{Cell}_5) = -1$

Iteration $i = 3$

Cell 2 has maximum gain $\Delta g_3 = 1$, $area(A) = 1$, balance criterion is met.

Move cell 2, updated partitions: $A_3 = \{3\}$, $B_3 = \{1,2,4,5\}$, with fixed cells $\{1,2,3\}$

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example



Iteration $i = 3$

Cell 4: $\Delta g(\text{Cell}_4) = 0$

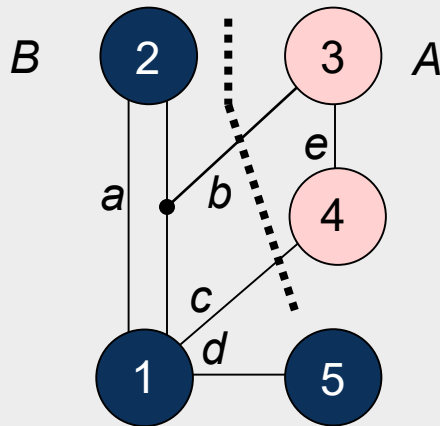
Cell 5: $\Delta g(\text{Cell}_5) = -1$

Iteration $i = 4$

Cell 4 has maximum gain $\Delta g_4 = 0$, $area(A) = 5$, balance criterion is met.

Move cell 4, updated partitions: $A_4 = \{3,4\}$, $B_3 = \{1,2,5\}$, with fixed cells $\{1,2,3,4\}$

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example



Iteration $i = 4$

Cell 5: $\Delta g(\text{Cell}_5) = -1$

Iteration $i = 5$

Cell 5 has maximum gain $\Delta g_5 = -1$, $area(A) = 10$, balance criterion is met.

Move cell 5, updated partitions: $A_4 = \{3,4,5\}$, $B_3 = \{1,2\}$, all cells $\{1,2,3,4,5\}$ fixed.

2.4.3 Fiduccia-Mattheyses (FM) Algorithm – Example

Step 5: Find best move sequence $c_1 \dots c_m$

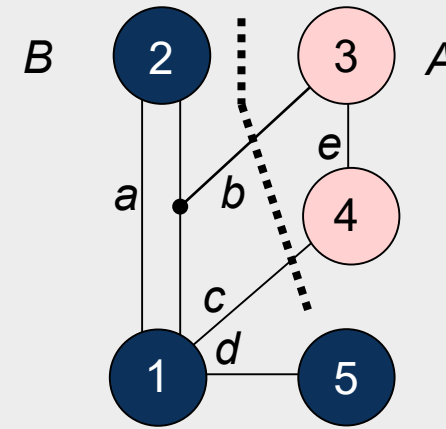
$$G_1 = \Delta g_1 = 1$$

$$G_2 = \Delta g_1 + \Delta g_2 = 0$$

$$G_3 = \Delta g_1 + \Delta g_2 + \Delta g_3 = 1$$

$$G_4 = \Delta g_1 + \Delta g_2 + \Delta g_3 + \Delta g_4 = 1$$

$$G_5 = \Delta g_1 + \Delta g_2 + \Delta g_3 + \Delta g_4 + \Delta g_5 = 0.$$



Maximum positive cumulative gain $G_m = \sum_{i=1}^m \Delta g_i = 1$


found in iterations 1, 3 and 4.

The move prefix $m = 4$ is selected due to the better balance ratio ($area(A) = 5$); the four cells 1, 2, 3 and 4 are then moved.

Result of Pass 1: Current partitions: $A = \{3,4\}$, $B = \{1,2,5\}$, cut cost reduced from 3 to 2.

- Runtime of partitioning algorithms
 - KL is sensitive to the number of nodes and edges
 - FM is sensitive to the number of nodes and nets (hyperedges)
- Asymptotic complexity of partitioning algorithms
 - KL has cubic time complexity *per pass*
 - FM has linear time complexity *per pass*

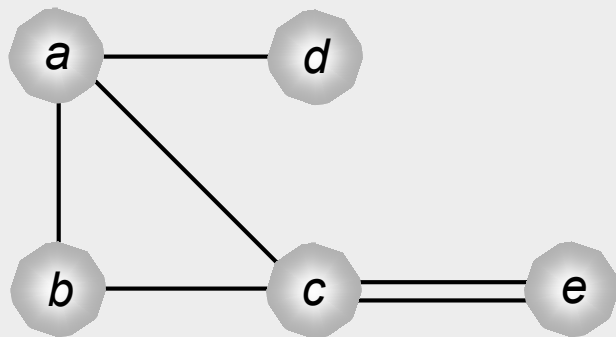
Chapter 2 – Netlist and System Partitioning

- 2.1 Introduction
- 2.2 Terminology
- 2.3 Optimization Goals
- 2.4 Partitioning Algorithms
 - 2.4.1 Kernighan-Lin (KL) Algorithm
 - 2.4.2 Extensions of the Kernighan-Lin Algorithm
 - 2.4.3 Fiduccia-Mattheyses (FM) Algorithm
-  **2.5 Framework for Multilevel Partitioning**
 - 2.5.1 Clustering
 - 2.5.2 Multilevel Partitioning
- 2.6 System Partitioning onto Multiple FPGAs

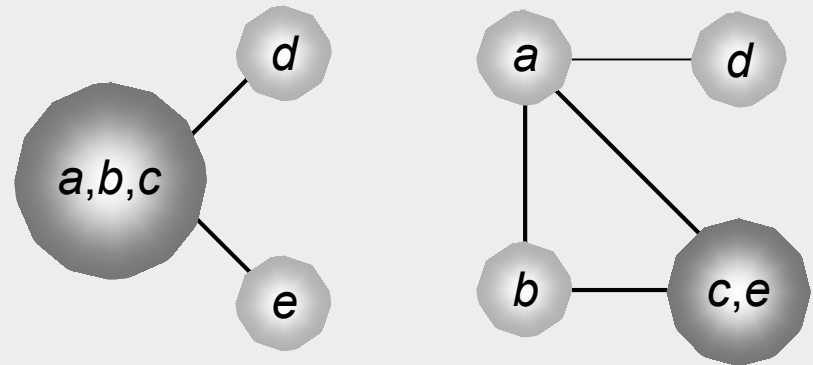
2.5.1 Clustering

- To simplify the problem, groups of tightly-connected nodes can be clustered, absorbing connections between these nodes
- Size of each cluster is often limited so as to prevent degenerate clustering, i.e. a single large cluster dominates other clusters
- Refinement should satisfy balance criteria

2.5.1 Clustering

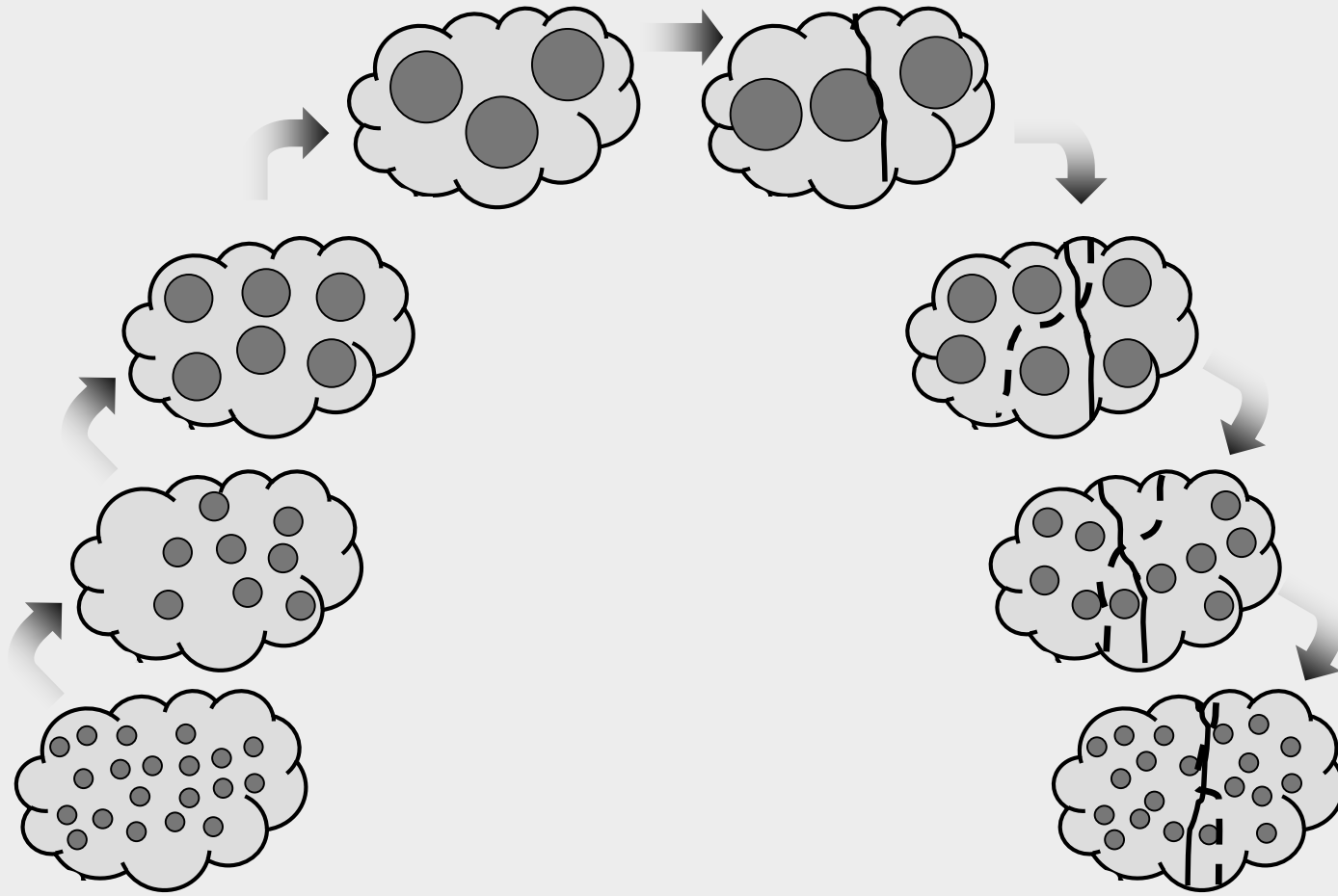


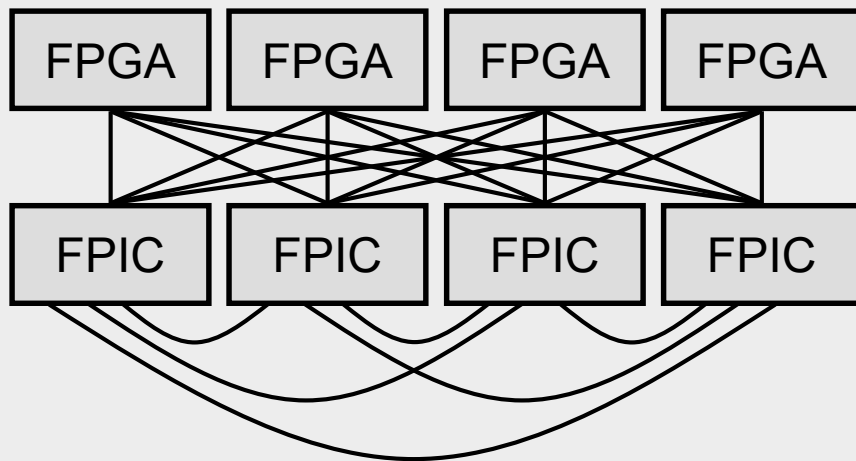
Initial graph



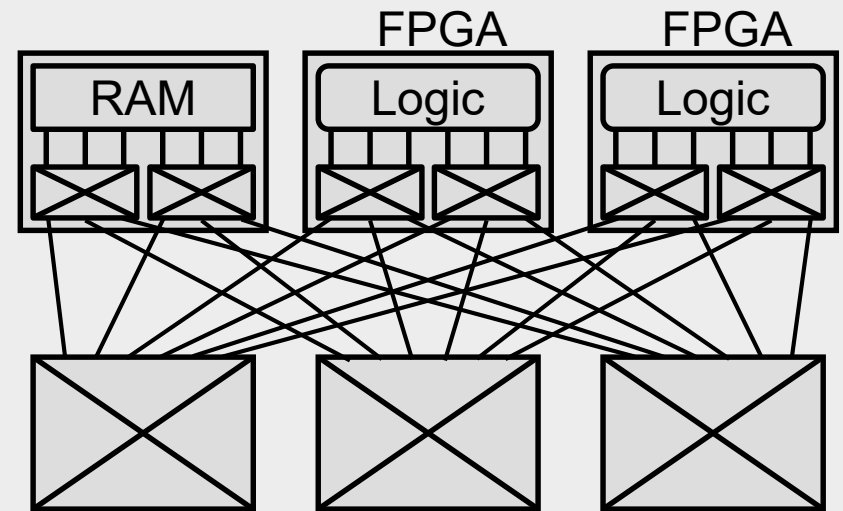
Possible clustering hierarchies of the graph

2.5.2 Multilevel Partitioning





Reconfigurable system with multiple FPGA and FPIC devices



Mapping of a typical system architecture onto multiple FPGAs

Summary of Chapter 2

- Circuit netlists can be represented by graphs
- Partitioning a graph means assigning nodes to disjoint partitions
 - Total size of each partition (number/area of nodes) is limited
 - Objective: minimize the number connections between partitions
- Basic partitioning algorithms
 - Move-based, moves are organized into passes
 - KL swaps pairs of nodes from different partitions
 - FM re-assigns one node at a time
 - FM is faster, usually more successful
- Multilevel partitioning
 - Clustering
 - FM partitioning
 - Refinement (also uses FM partitioning)
- Application: system partitioning into FPGAs
 - Each FPGA is represented by a partition