Multi-Criteria Partitioning of Multi-Block Structured Grids

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Outline

Background

Algorithms

Tests and Results

Conclusion

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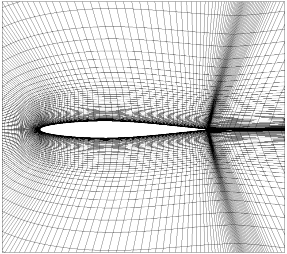
Structured Grid

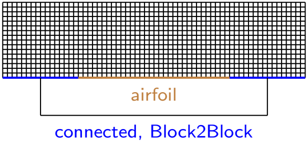
- Structured Grid: Regular connectivity between grid cells.

	i,j+1	
i-1,j	i,j	i+1,j
	i,j-1	

- Block: grid unit equivalent to a single rectangle.



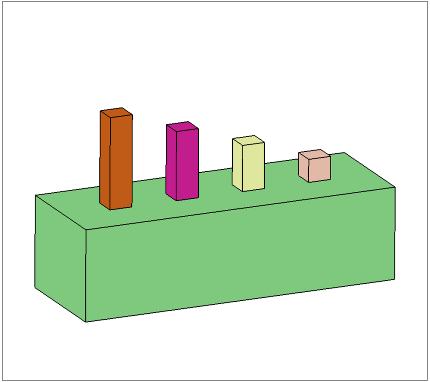
Airfoil Grid



Block

Structured Grid

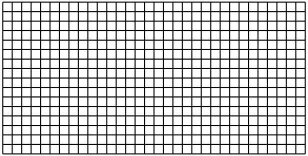
- Multi-Block Structured Grids

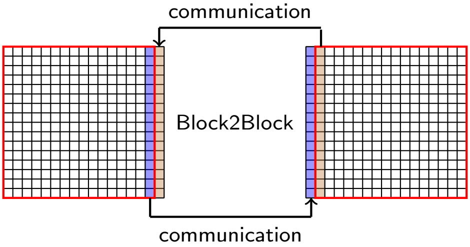


Bump3D, 5 blocks

Halo Exchange

Split a block into 2 partitions and assign each partition to a node:



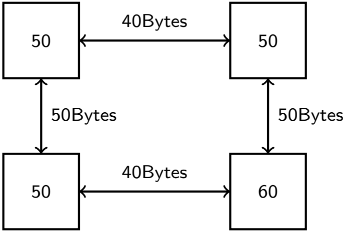


Hybird Programming Model

Hybrid programming model:

- 1 MPI process per node and spawn threads within a node.
- Assume shared memory copy takes no time.

Partition 4 blocks onto 2 nodes:



Average Workload $\overline{W}$ 105

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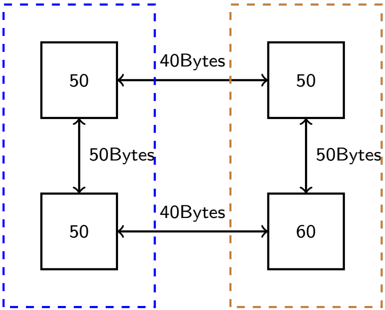

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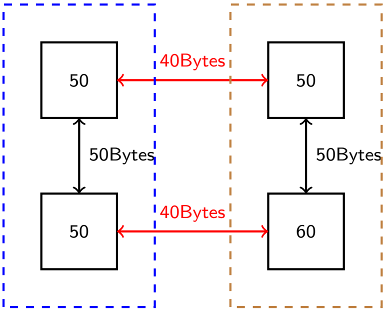

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Communcation Volume	80 Bytes

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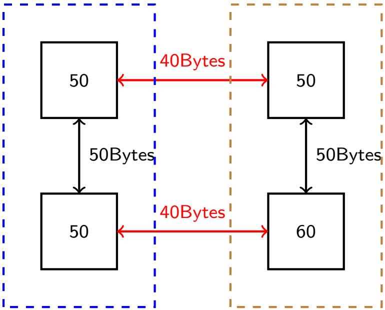

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Objectives

Given the number of partitions n_p, workload per partition $\overline{W}$, the partitioner should:

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- Minimize communication cost
  - Reduce the inter-node communication
  - Convert Block2Block communication to shared memory copy

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State-of-the-art Methods

The state-of-the-art methods can be divided into two strategies:

- Top-down strategy:
  - Cut large blocks and assign sub-blocks to partitions.
  - Group small blocks to fill partitions.

  Examples:
  Greedy [Ytterström 97]
  Recursive Edge Bisection (REB) [Berger 87]
  Integer Factorization (IF)

- Bottom-up strategy:

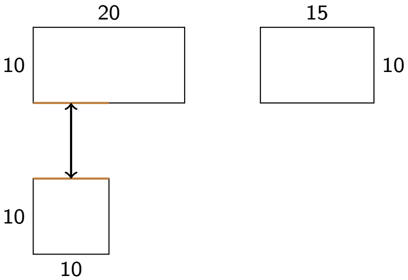
  Transform the problem to graph partitioning and use graph partitioner.

  Examples:
  Metis [Karypis 94], Scotch [Roman 96], Chaco [Leland 95]

Greedy Algorithm

Greedy Algorithm:

- Assign (part of) the largest block to the most underload partition.
- Cut at the longest edge of a block.



$\overline{W} = 300 \quad W_p = 0$

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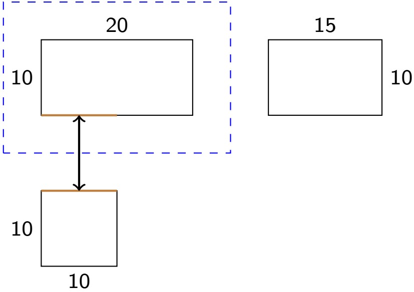

$\overline{W} = 300 \quad W_p = 200$

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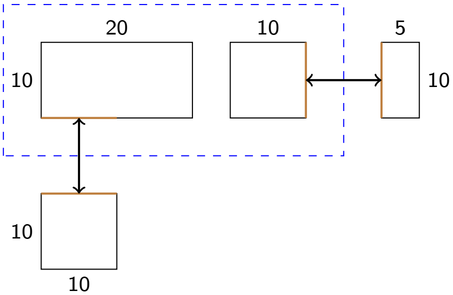

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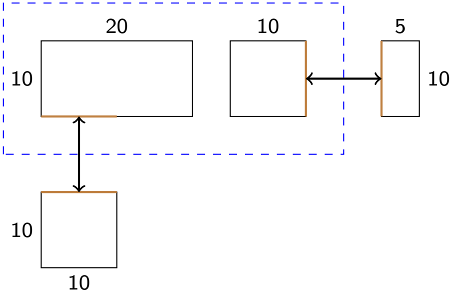
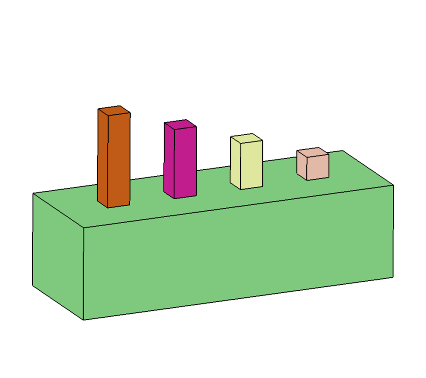


$\overline{W} = 300 \quad W_p = 300$

- ✗ Ignores the connectivity between blocks.
- ✗ Creates excessive small blocks when cutting a large block

Greedy Algorithm

Bump3D grid: 5 blocks, the largest block is 27 times larger than the rest.



Bump3D blocks

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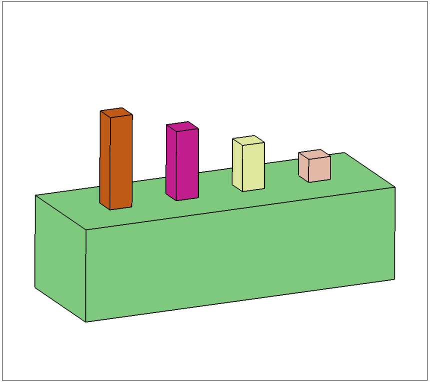

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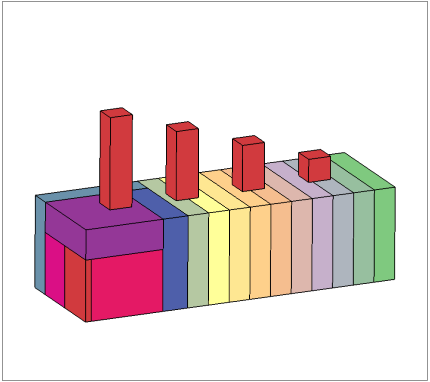


Greedy, 16 partitions

Bottom-up Strategy

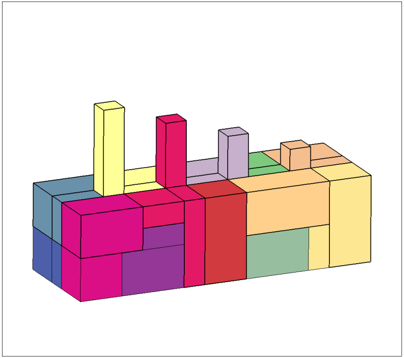
Bottom-up: Convert the structured grid partitioning to general graph partitioning.

For a graph partitioner to work well, it needs **large number of vertices per partition**.

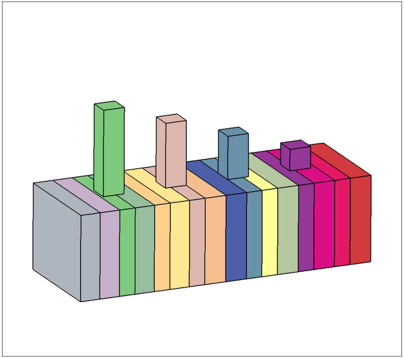
1. **Over-decompose** blocks, construct graph with blocks as vertices
2. Apply graph partitioner: Metis, Scotch, Chaco, etc
3. Merge blocks within one partition

Bottom-up Strategy

Use Metis as the graph partitioner to generate 16 partitions with different over-decomposition method.



Over-Decompose to elementary blocks



Over-Decompose with IF

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Above methods share the limitations:

- Flat MPI, ignore the shared memory on the algorithm level.
- The communication performance does not distinguish the shared memory copy and inter-nodes data transfer.
- Primarily focus on reducing communication volume, ignore the effect of network's latency.

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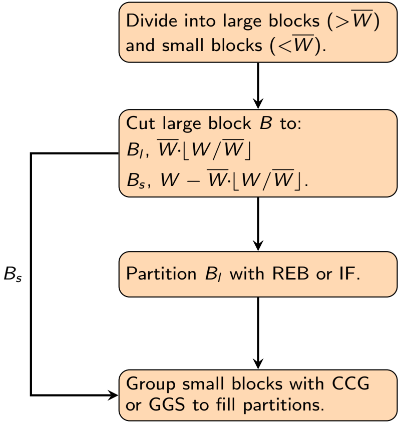
  - Modify Recursive Edge Bisection (REB) and Integer Factorization (IF) for cutting large blocks ($W > \overline{W}$).
  - Propose Cut-Combine-Greedy (CCG) and Graph-Grow-Sweep (GGS) for grouping small blocks.

Our Partition Algorithms

Cut large blocks $\rightarrow$ Group small blocks:



Measure of Communication cost

$\alpha - \beta$ model: α latency (s), β bandwidth (bytes/s)

$$\text{Cost(s)} = \alpha + \frac{\text{sizeof}(message)}{\beta}$$

For Block2Block message:

$$t_{b2b} = \alpha + \frac{\#Halo \cdot FaceArea \cdot \text{sizeof}(cell)}{\beta}$$

Sum over all Block2Block messages:

$$\sum t_{b2b} = \alpha \cdot \sum \text{Edge Cuts} + \frac{\text{Communication Volume}}{\beta}$$

Cut Large Block: find a cut

Input: Block B, workload W_{cut}, tolerance ϵ, partition P (optional)

Output: a cut satisfies:

(1) the cut-off sub-block fits in $[W_{cut}(1-\epsilon),\ W_{cut}(1+\epsilon)]$

(2) introduces minimum communication cost δt

Find a cut

for i = x, y, z **do**
  Get area of i's norm face A_i
  f = floor($W_{cut}(1-\epsilon)/A_i$)
  c = ceil($W_{cut}(1+\epsilon)/A_i$)
  for pos∈[posFloor, posCeil] **do**
    $\delta t_{cut} = \sum_{b2bcut} \alpha + t_{b2b}(A_i) - \sum_{B_j \in p} t_{b2b}(\mathrm{cut}, B_j)$
    if $\delta t_{cut} < \delta t_{min}$ **then**
      $\delta t_{min} = \delta t_{cut}$
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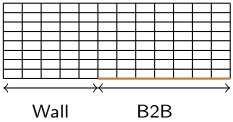

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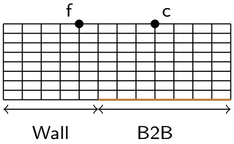

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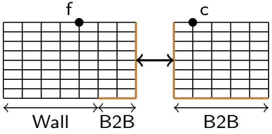

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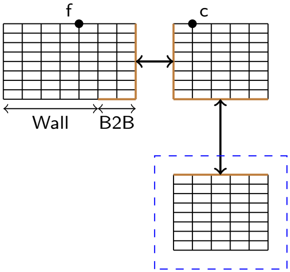

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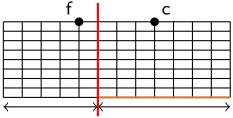

Cut Large Block: REB

Recursive Edge Bisection (REB):

Algorithm: REB

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function REB_BLOCK(B, n_p)        ▷ Block B fits in n_p partitions.
    if n_p == 1 then
        return
    W = B's workload
    W_l = W · ⌊n_p/2⌋ / n_p, W_r = W − W_l
    find_min_cut(B, W_l, ε, cut)
    cut B into B_l of W_l and B_r of W_r
    reb_block(B_l, ⌊n_p/2⌋)
    reb_block(B_r, ⌈n_p/2⌉)
```

$n_p = 7$

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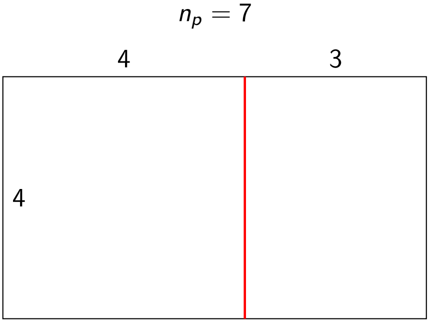

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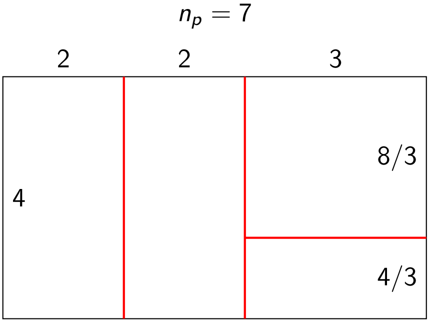

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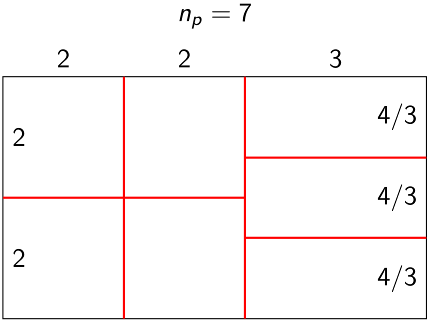
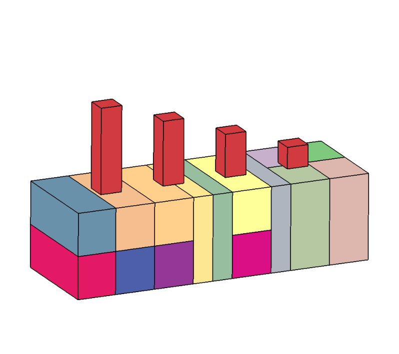
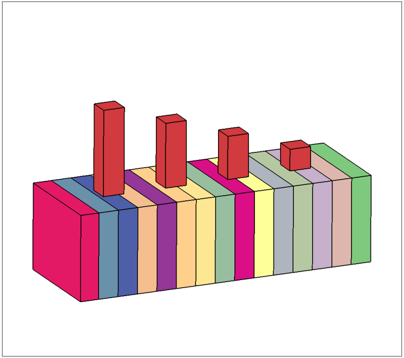


Cut Large Block: REB

Using REB to split Bump3D into 16 partitions with different α, β values:



$\alpha = 10^{-5}$, $\beta = 10^{9}$



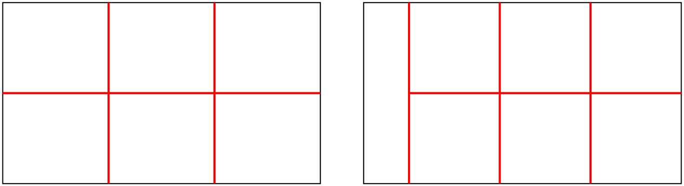
$\alpha = 10^{-4}$, $\beta = 10^{9}$

Cut Large Block: IF

Integer Factorization (IF):

$$n_p = n_x \cdot n_y \cdot n_z, \quad \frac{n_x}{l_x} \approx \frac{n_y}{l_y} \approx \frac{n_z}{l_z}$$

If n_p is prime, cut off one partition and factorize the rest.

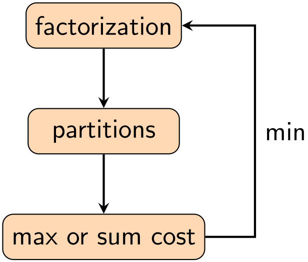


$l_x = 7, l_y = 4, n_p = 6$ $l_x = 7, l_y = 4, n_p = 7$

Cut Large Block: IF

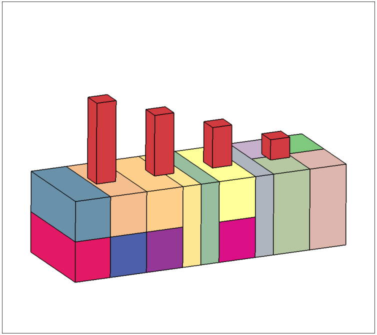
Generalize IF by using $\alpha - \beta$ cost function:

- Compare $n_p = n_x n_y n_z$ and $n_p = 1 + n_x n_y n_z$ for every case.
- Choose the factorization based on max or sum $\alpha - \beta$ cost.

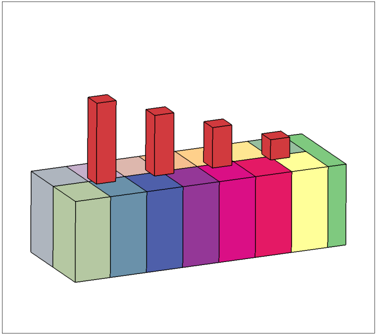


Cut Large Block: Compare REB and IF

Compare REB and IF on Bump3D, $\alpha = 10^{-5}$, $\beta = 10^{9}$, $n_p = 16$.
In general, IF is better at reducing edge cuts and REB better at reducing communication volume.



REB, edge cuts 66, communication volume 1.57×10^{6}

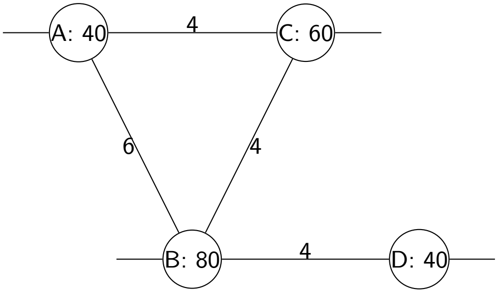


IF, edge cuts 66, communication volume 1.61×10^{6}

Group Small Blocks: CCG

Cut-Combine-Greedy (CCG): cut and combine small blocks in a greedy fashion.

- Include (part of) the block reducing max communication cost to the partition.
- Convert Block2Block communication to shared memory copy.

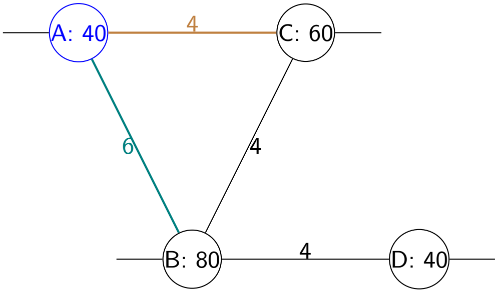


$\overline{W} = 160 \quad W_p = 0$

Group Small Blocks: CCG

Cut-Combine-Greedy (CCG): cut and combine small blocks in a greedy fashion.

- Include (part of) the block reducing max communication cost to the partition.
- Convert Block2Block communication to shared memory copy.



$\overline{W} = 160 \quad W_p = 40$

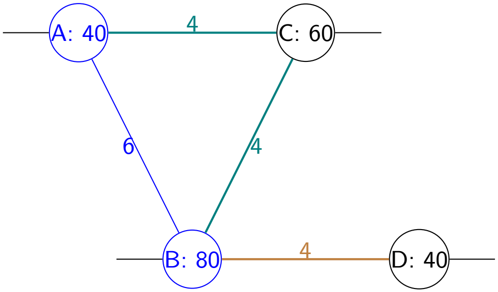
B cost: -6

C cost: -4

Group Small Blocks: CCG

Cut-Combine-Greedy (CCG): cut and combine small blocks in a greedy fashion.

- Include (part of) the block reducing max communication cost to the partition.
- Convert Block2Block communication to shared memory copy.



$\overline{W} = 160 \quad W_p = 120$

C overload

D cost: -4

Group Small Blocks: CCG

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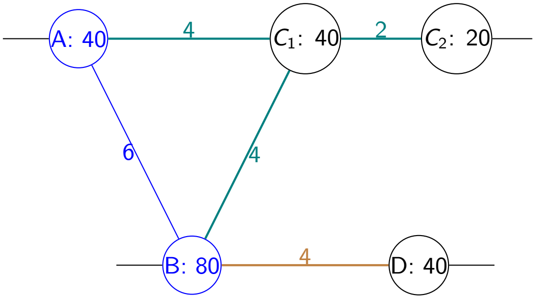
- Convert Block2Block communication to shared memory copy.



$\overline{W} = 160 \quad W_p = 120$

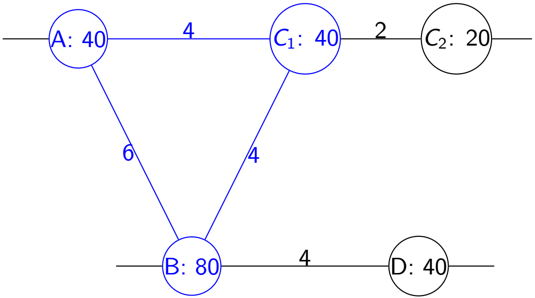
C_1 cost: -4-4+2 = -6

D cost: -4

Group Small Blocks: CCG

Cut-Combine-Greedy (CCG): cut and combine small blocks in a greedy fashion.

- Include (part of) the block reducing max communication cost to the partition.
- Convert Block2Block communication to shared memory copy.



$\overline{W} = 160 \quad W_p = 160$

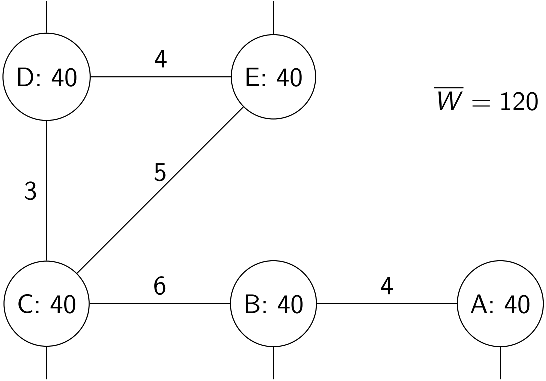
Convert cost: 14

Introduce new cost: 2

Group Small Blocks: GGS

Graph-Growth-Sweep (GGS): Repeatedly use graph growing to group small blocks.

- Convert Block2Block communication to shared memory copy.
- Avoid cutting blocks.



$\overline{W} = 120 \quad W_1 = 0 \quad W_2 = 0$

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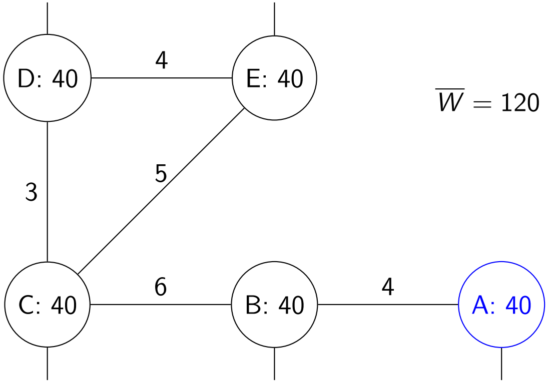

$\overline{W} = 120 \quad W_1 = 40 \quad W_2 = 0$

Group Small Blocks: GGS

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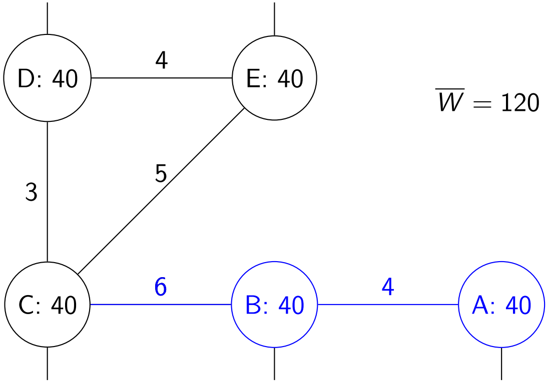

$$\overline{W} = 120 \quad W_1 = 80 \quad W_2 = 0$$

Group Small Blocks: GGS

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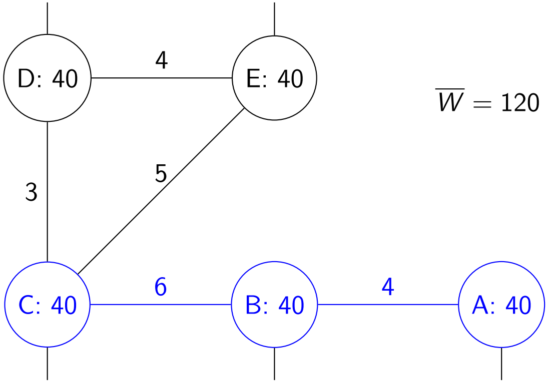

$\overline{W} = 120 \quad W_1 = 120 \quad W_2 = 0$

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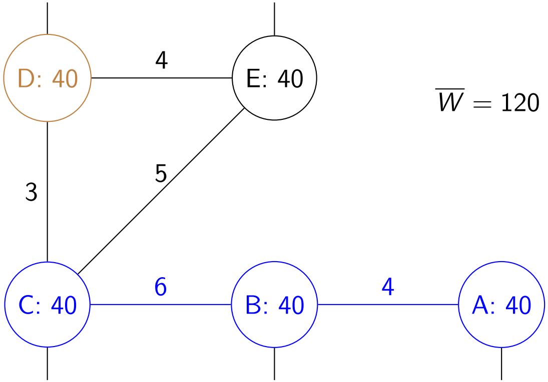

$\overline{W} = 120 \quad W_1 = 120 \quad W_2 = 40$

Group Small Blocks: GGS

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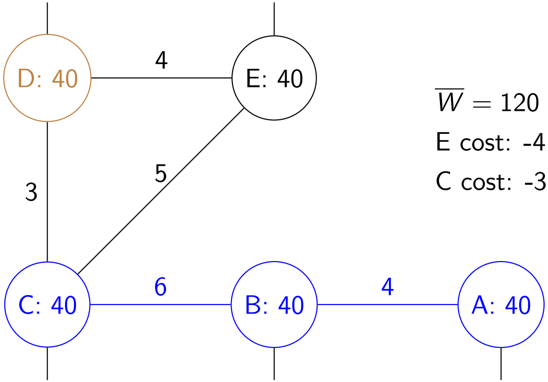

$\overline{W} = 120 \quad W_1 = 120 \quad W_2 = 40$

E cost: -4

C cost: -3 + 6 = 3

Group Small Blocks: GGS

Graph-Growth-Sweep (GGS): Repeatedly use graph growing to group small blocks.

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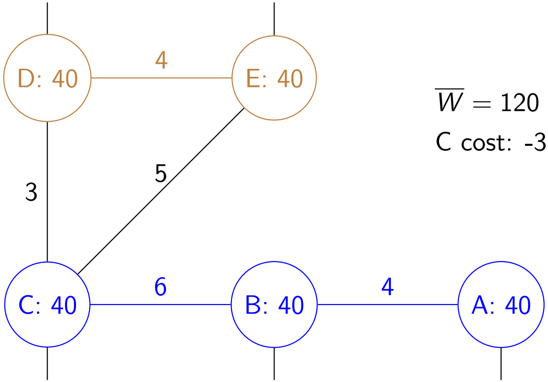


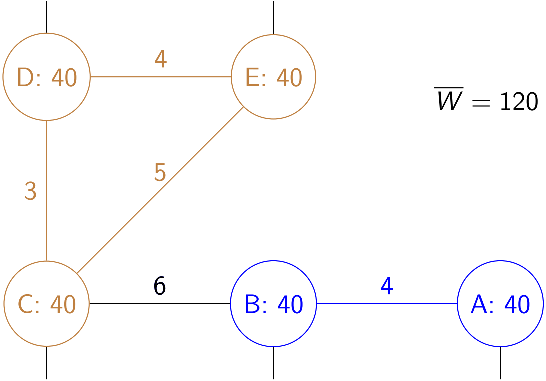
$\overline{W} = 120 \quad W_1 = 120 \quad W_2 = 80$

C cost: -3 - 5 + 6 = -2

Group Small Blocks: GGS

Graph-Growth-Sweep (GGS): Repeatedly use graph growing to group small blocks.

- Convert Block2Block communication to shared memory copy.
- Avoid cutting blocks.



$\overline{W} = 120 \quad W_1 = 80 \quad W_2 = 120$

Group Small Blocks: Compare CCG and GGS

To compare CCG and GGS:

When the #blocks is large, CCG

- ✔ converts more communication to shared memory copy.
- ✘ creates more cuts and new Block2Block communications.

GGS

- ✘ converts less communication to shared memory copy.
- ✔ avoids cutting blocks and introduces less new Block2Block communications.

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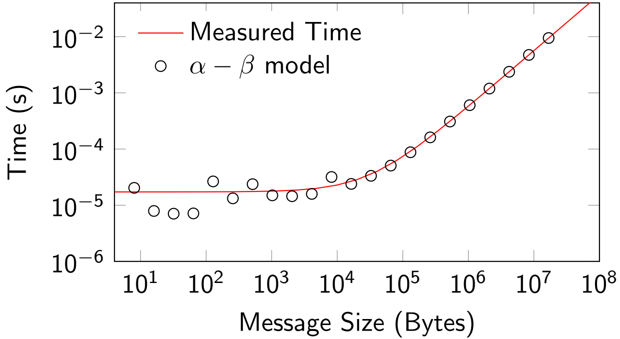
Hardware and Network Specs

- Our experiments are performed on Mira.

  IBM BlueGene/Q cluster, 16 cores per node
- The latency $\alpha = 1.73 \times 10^{-5}s$ and bandwidth $\beta = 1.77 \times 10^{9}$ bytes/s are measured by a pingpong test.



Numerical Experiment

Implement a Jacobi type solver with MPI and OpenMP.

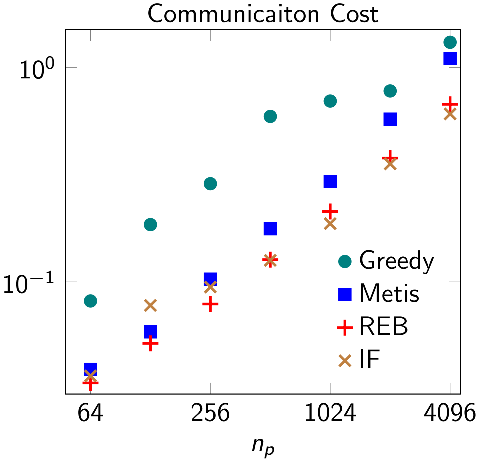
- Assign each MPI process to a node and spawn one OpenMP thread per core.
- Master thread calls MPI non-blocking routines which overlaps with shared memory copy.

Experimental Jacobi Solver

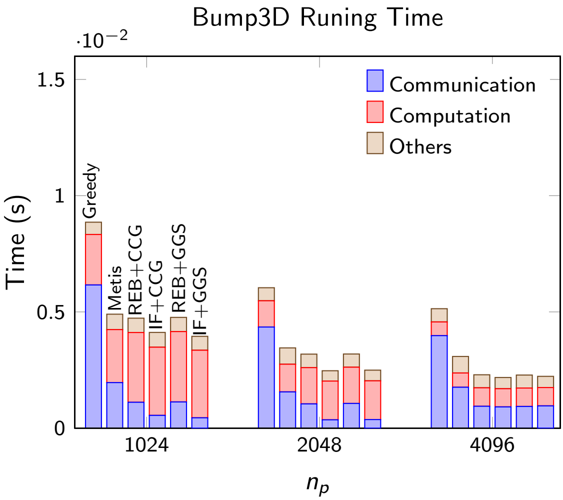
```
for i = 1 → NSTEP do
  ▷ #pragma omp for
    Copy halo data to sending buffer
  ▷ #pragma omp barrier
  ▷ #pragma omp master
    Update halo using non-blocking p2p communication
  ▷ #pragma omp for
    Copy halo data via shared memory within node
  ▷ #pragma omp barrier
  ▷ #pragma omp for
    Copy data from receiving buffer to halo region
  ▷ #pragma omp barrier
  ▷ split blocks evenly among threads
    Computation
  ▷ #pragma omp barrier
```

Bump3D Metrics: Communication Cost

Refine Bump3D 4 times in each direciton, 8.3×10^7 cells in total.
Beyond 512 partitions: Greedy $>$ Metis $>$ REB $>\approx$ IF

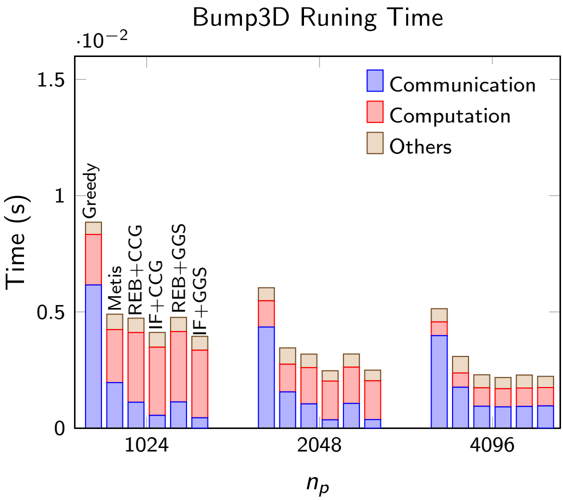


Bump3D Running Time



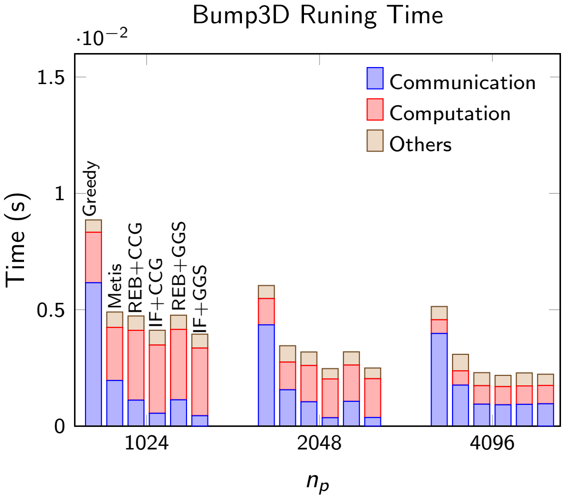
- Consistent with $\alpha - \beta$ cost.

Bump3D Running Time



- Consistent with $\alpha - \beta$ cost.
- Latency has more effect.

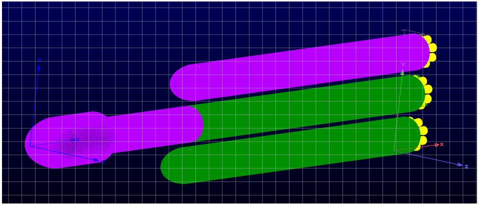
Bump3D Running Time

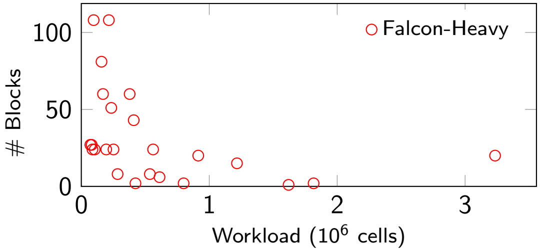


- Consistent with $\alpha - \beta$ cost.
- Latency has more effect.
- At 4096 partitions, IF achieves 5.80x over Greedy and 2.56x over Metis in communication.

Space X's Falcon-Heavy Grid

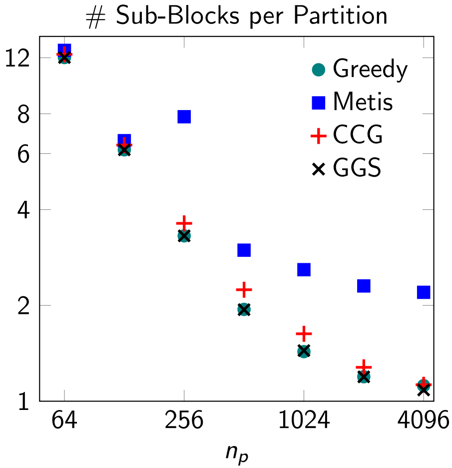
The Space X's Falcon-Heavy grid and its blocks' distribution:





Falcon-Heavy Metrics: # Sub-Blocks

Choose REB+GGS and IF+CCG to present GGS and CCG respectively.



Sub-Blocks:

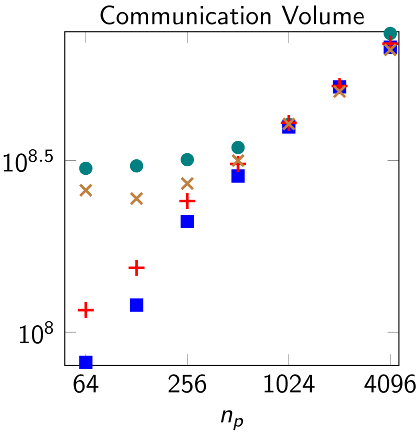
Metis > CCG > Greedy ≥ GGS

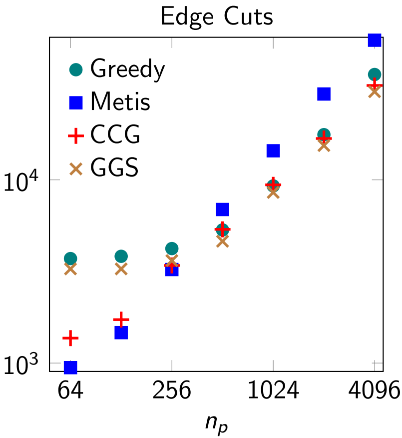
Dominating Pattern:

- 64-256 partitions group small blocks
- 1024-4096 partitions both

Falcon-Heavy Metrics: Volume and Edge Cuts

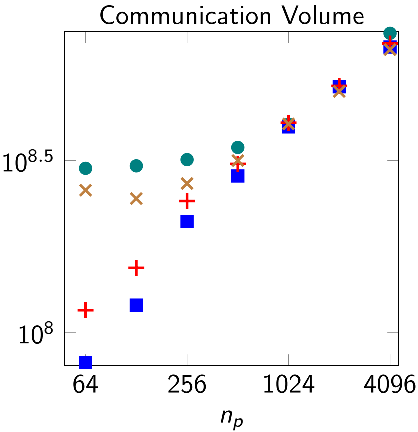
- Greedy produces the max communication volume and edge cuts for 64-256 partitions

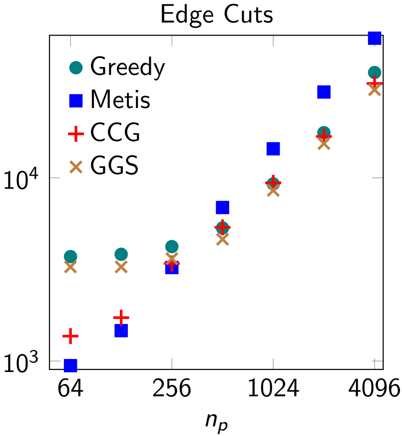




Falcon-Heavy Metrics: Volume and Edge Cuts

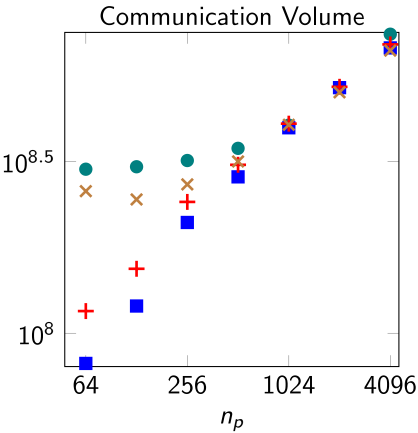
- Metis produces the min communication volume and edge cuts for 64-256 partitions, CCG 2nd.

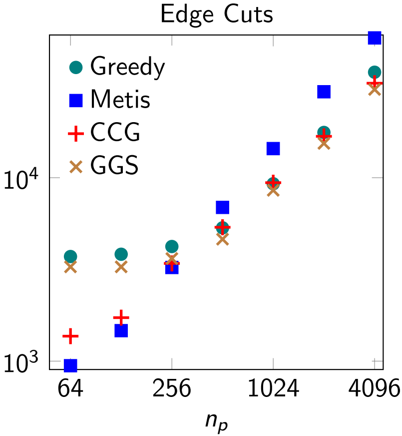




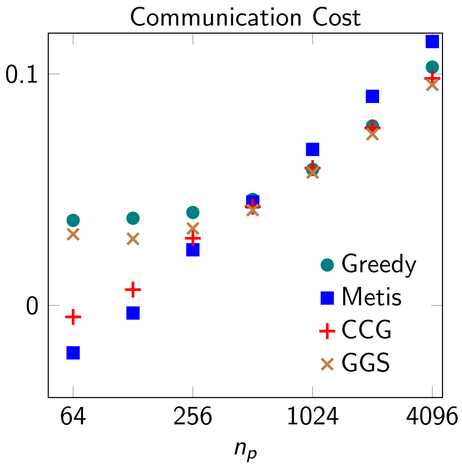
Falcon-Heavy Metrics: Volume and Edge Cuts

- Greedy, CCG, GGS produce close results for 1024–4096 partitions; GGS min.





Falcon-Heavy Metrics: Communication Cost



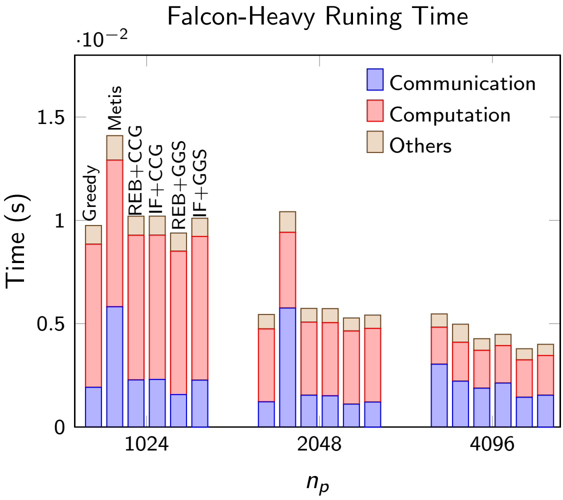
Consistent Pattern with metrics:

- 64-256 partitions

  Metis best, CCG 2nd
- 1024-4096 partitions

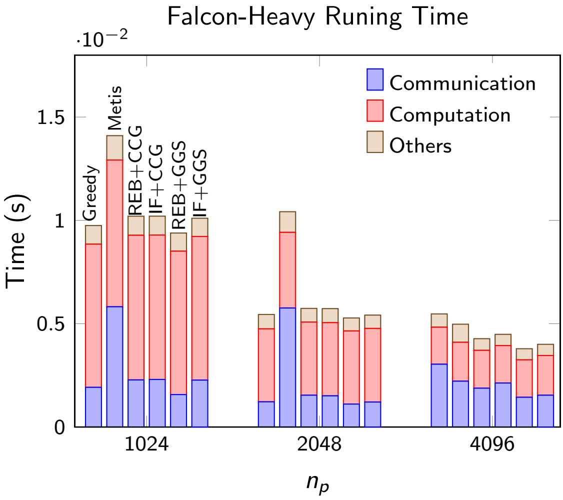
  Metis worst, GGS best

Falcon-Heavy Running Time



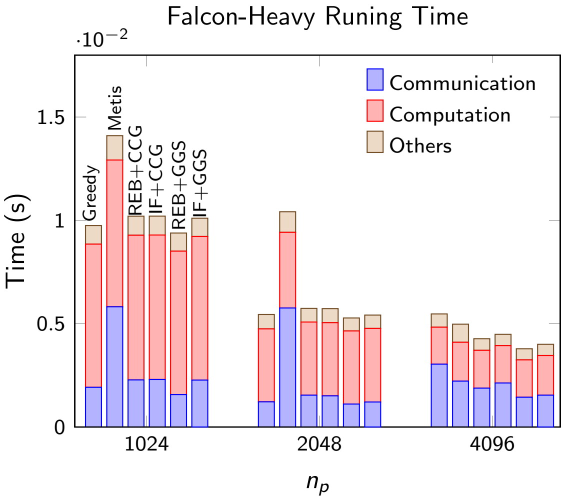
- Metis produces good result at 4096 partitions

Falcon-Heavy Running Time



- Metis produces good result at 4096 partitions
- Greedy creates good result at 1024, 2048 partitions

Falcon-Heavy Running Time



- Metis produces good result at 4096 partitions
- Greedy creates good result at 1024, 2048 partitions
- At 4096 partitions, REB+GGS achieves 2.11x over Greedy and 1.54x over Metis in communication.

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- Propose modified REB, IF for cutting large blocks and CCG, GGS for grouping small blocks.

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- Test our partitioner with a hybrid MPI+OpenMP based Jacobi solver on up to 4096 nodes.

Conclusion

- Use the $\alpha - \beta$ model to construct a cost function incorporating the edge cuts, communication volume and network specifics.
- Propose modified REB, IF for cutting large blocks and CCG, GGS for grouping small blocks.
- Test our partitioner with a hybrid MPI+OpenMP based Jacobi solver on up to 4096 nodes.
- Achieve significant speedup in communication on both Bump3D and Falcon-Heavy.