Optimal Subset Mapping And Convergence Evaluation of Mapping Algorithms for Distributing Task Graphs on Multiprocessor SoC

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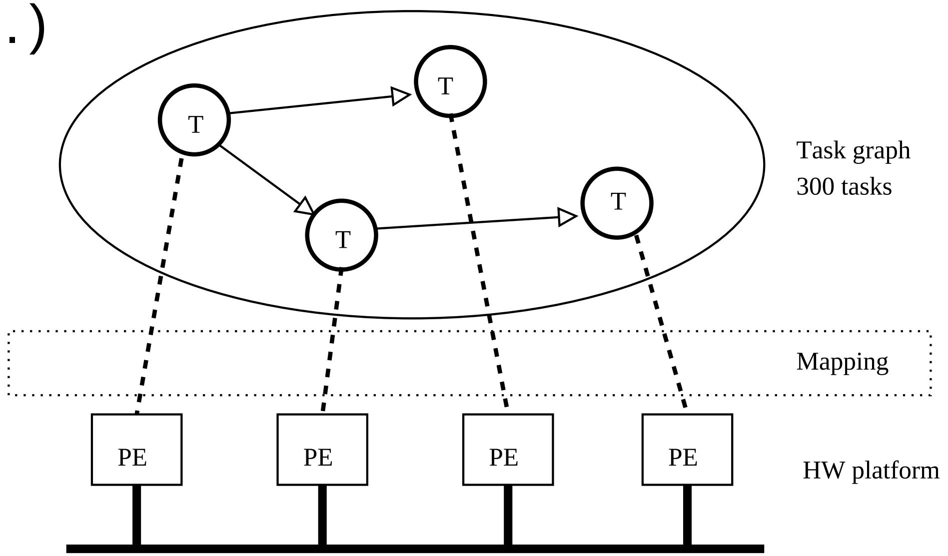
Presentation Outline

- Introduction
- Experiment
- Algorithms
- Comparison of algorithms
- Conclusions
- References

\+ all the algorithms, graphs and pictures in the end

Introduction (1/2)

- Automatic distribution of *process networks* onto a multiprocessor system while satisfying some specific criteria
- Assume N tasks in the process network, and M processing elements (PEs) in the multiprocessor system
- Define *mapping* as one possible placement of N tasks to M processing elements (task i goes to PE x, task j goes to PE y, ...)



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Introduction (2/2)

- The problem is to minimize a cost function
  - Minimizing the cost function often means maximizing performance or optimizing some other property
  - NP problem ⇝ true minimum is not generally achieved or known, but *maybe* the result is *good enough*
- Also, try to minimize optimization time
  - ⇝ trade-off between a good result and short optimization time
  - This is important in exploration of large design space
  - Optimum solution for distribution varies with the architecture

Contributions

- A new mapping algorithm called *Optimal Subset Mapping* (OSM)
  - OSM sacrifices result goodness to decrease optimization time
- Comparison of mapping algorithms with respect to result goodness, optimization time and converge
- Supporting evidence for our simulated annealing parametrization method presented in [2][3]
- These methods are suitable for both shared and distributed memory systems

Experiment

- Compare 6 algorithms
- 10 random graphs, $N = 300$ nodes
- Simulation run 10 times independently, results averaged
- $M = 2$, 4 and 8 processing elements connected with a shared bus
- Measure speedup with respect to a single processor system

Algorithms (1/3)

- Use algorithms that have *reasonable* polynomial optimization time upper-bounds with respect to number of tasks N and processing elements M
- Upper-bounds for mappings tried for algorithms:
  - Optimal subset mapping (OSM): $O(\frac{N^2 M}{\log N + \log M})$
  - Our simulated annealing variant (SA+AT): $O(NM \log \frac{T_0}{T_f})$
  - Group Migration (GM): $O(N^2 M)$
  - Random mapping: fixed number of iterations (only used as a reference)

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Algorithms (2/3)

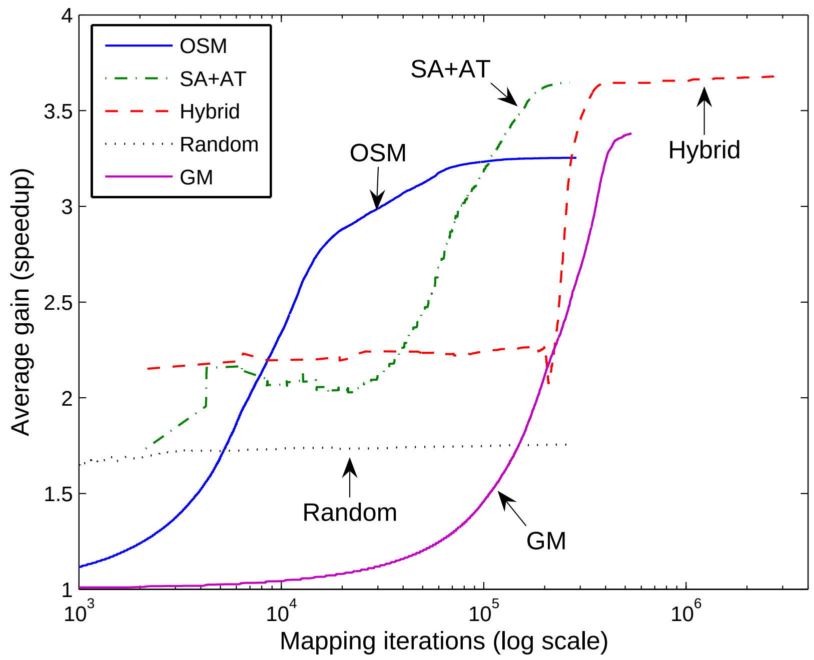
- Group Migration (GM), also known as Kernighan-Lin graph partitioning algorithm
  - deterministic
  - greedy, may get stuck into local minima
- SA+AT is our version of the simulated annealing algorithm [3]
  - Stochastic and non-greedy
  - Automatic temperature (AT) scale is determined from the graph
  - Transition probabilities are normalized for efficient optimization
  - Fully automated parameter selection $\rightsquigarrow$ requires no manual tuning of parameters
- The hybrid algorithm [4] is a combination: result of SA is a starting point for GM

Algorithms (3/3)

- OSM is the Optimal Subset Mapping algorithm
  - A divide and conquer algorithm. Solves a subset of the problem optimally, but does not guarantee global optimum
  - Picks a subset of tasks and brute-forces an optimal mapping for the subset, and then picks another subset and optimizes that
  - The subset size is increased and decreased continuously when and if there is potential for optimization
  - When increasing the subset size does not improve the result anymore, the algorithm terminates
  - Inspired by the *Sequential Minimal Optimization* algorithm [11] invented for optimizing Support Vector Machine neural networks

Comparison of Algorithms (1/3)

The following figure shows convergence for 8 processing elements for each algorithm. The X-axis is the number of mappings tried (logarithmic scale). The Y-axis is the average speedup (1.0 means no speedup) over all graphs.



Comparison of Algorithms (2/3)

Following table shows speedups and convergence rate for each algorithm:

Algorithm	Speedup	Speedup / Iterations	Convergence
Random	1.76	1.0 (reference level)	Too long
OSM	3.25	6.11	Fast
GM	3.38	1.21	Slow
SA+AT	3.65	2.58	Fast
Hybrid	3.69	0.20	Slow

Comparison of Algorithms (3/3)

- Random mapping shows the base-level for optimization
- OSM is most suited for comparing architectures and systems rapidly, but does not yield good speedup
- GM is not suitable for architecture exploration as it is slow and does not yield good speedup
- SA+AT is strong both in convergence speed and speedup $\rightsquigarrow$ this is currently our algorithm of choice
- Hybrid algorithm yields the best speedup, but it is slow

Future directions:

- Combine features of each algorithm. For example, start with OSM, and after rapid initial convergence, switch to SA+AT.
- Try genetic algorithms. Problem: hard to select proper parameters

Discussion

- Almost all papers on task distribution that use Simulated Annealing leave some parameters undocumented
  - Hard to learn about Simulated Annealing even if there are lots of papers that use it
  - We were motivated to document parameters of Simulated Annealing properly [2] [3]
- We use random graphs to avoid application bias in performance
- Static acyclic graphs have very well known scheduling properties, and hence, differences in results are due to mapping algorithms
- Group migration is highly sensitive to initial values, but other algorithms are not

Conclusions

- This paper demonstrates convergence properties of several algorithms
- This paper demonstrates that automatic parameter selection for simulated annealing can be effective
- SA+AT algorithm converges rapidly, but still yields very good results
- The new OSM algorithm converges very rapidly, but does not yield very good results. It is still suitable for comparing architecture and system alternatives in architecture exploration.

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Optimal Subset Mapping Pseudo-code

```
OPTIMAL_SUBSET_MAPPING(S)
S_best ← S
C_best ← COST(S)
X ← 2
for R ← 1 to ∞
do C_old_best ← C_best
    S ← S_best
    Subset ← PICK_RANDOM_SUBSET(S, X)
    for all possible mappings S_sub in Subset
    do S ← APPLY_MAPPING(S, S_sub)
        C ← COST(S)
        if C < C_best
          then S_best ← S
               C_best ← C
    if modulo(R, R_max) = 0
      then if C_best = C_old_best
             then if X = X_max
                    then break
                  X ← X + 1
             else X ← X − 1
           X ← MAX(X_min, X)
           X ← MIN(X_max, X)
return S_best
```

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Application and architecture parameters

	Variable	(note)	Value
Task graphs	# graphs		10
	# tasks per graph (N)		302
	# edges per graph	(1)	1594, 5231, 8703
	comp time per task [us]	(1)	3.2, 5.1, 7.0
	comm vol per task [byte]	(1)	26, 1111, 3679
	comm/comp -ratio [Mbyte/s]	(1)	8, 218, 526
	max theor. parallelism [no unit]	(1)	4.3, 7.9, 12.8
HW Platform	# PEs (M)		2, 4, 8
	PE freq [MHz]		50
	Bus Freq [MHz]	(2)	10, 20, 40
	Bus width [bits]		32
	Bus bandwidth [Mb/s]	(2)	320, 640, 1280
	Bus arb. latency [cycles/send]		8
Algorithms	# runs per graph per alg	(3)	10
	algorithms		6
	determ, non-greedy		1: OSM
	determ, greedy		1: GM
	stoch., non-greedy		4: SA, SA+AT, hybrid, random
	stoch, greedy		-

Notes:

(1) = min, avg, max

(2) = values for 2,4,8 PEs, respectively

(3) = only 1 run for GM

Optimization parameters

Alg.	Variable (note)	Value
SA, SA+AT, Hybrid	# iter per T, $(L = N \cdot (M-1))$ (1)	602, 1208, 2416
	# temperature levels	181
	# temperature scaling	q=0.95
	range of T (SA and hybrid) (2)	T_0= 1.0, T_f=0.0001
	range of T (SA+AT)	T range coefficient k=2
	annealing schedule (T_0, i)	$T_0 \cdot q^{floor(i/L)}$
	move heuristic	move 1 random task
	acceptance function	$(1 + \exp(\Delta C / (0.5\, C_0\, T))^{-1}$
	end condition	$T = T_f$ AND L rejected moves
Rand	# max interations	262 144
GM	no params needed	-
OSM	coefficient c	1.0
	exponent c_N	1.0
	exponent c_M	1.0
	subset size X [#tasks] (1)	9, 5, 3
	# iterations per subset (1)	512, 1024, 512

Notes:

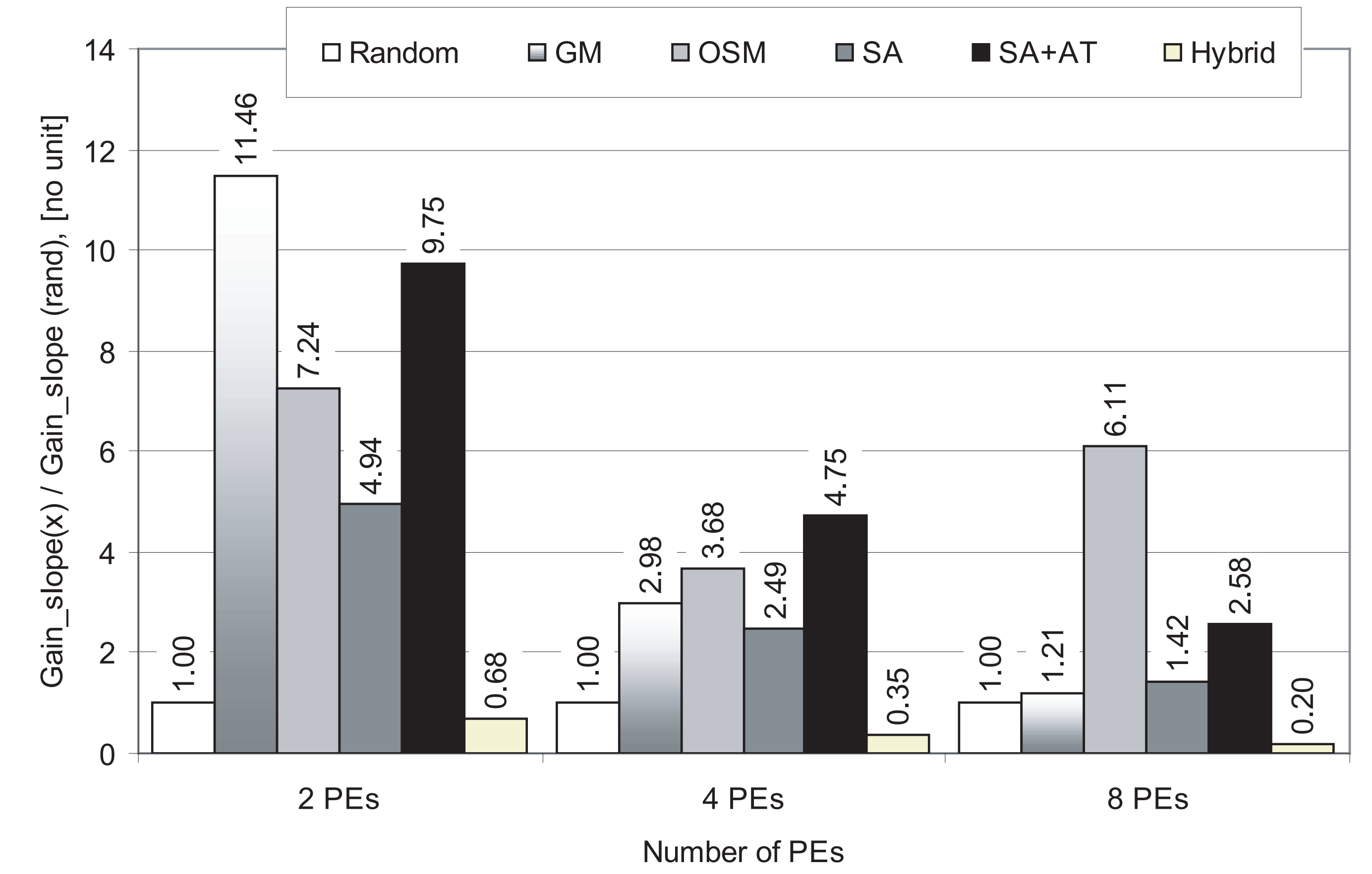
(1) = values for 2,4,8 PEs, respectively

(2) = T_0 and T_f computed automatically in SA+AT

Rounds and mapping iterations for OSM

PEs	rounds (min, avg, max)	Thousands of iterations (min, avg, max)
2	271, 380, 611	34.1, 37.2, 73.6
4	239, 469, 899	80.6, 115.4, 259.1
8	199, 428, 1099	57.1, 88.8, 293.9

Best gain divided by the number of iterations



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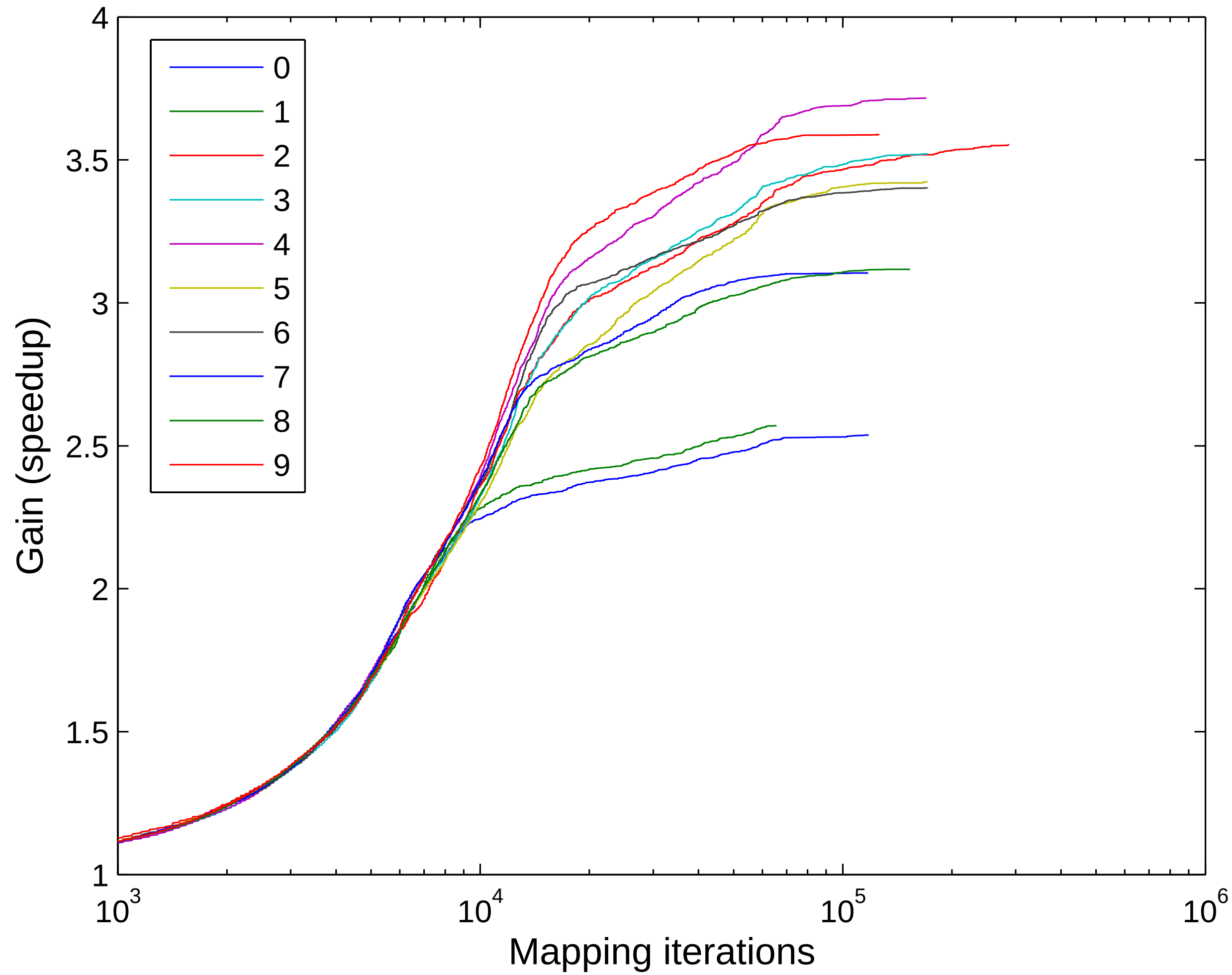
OSM progress plotted for each graph



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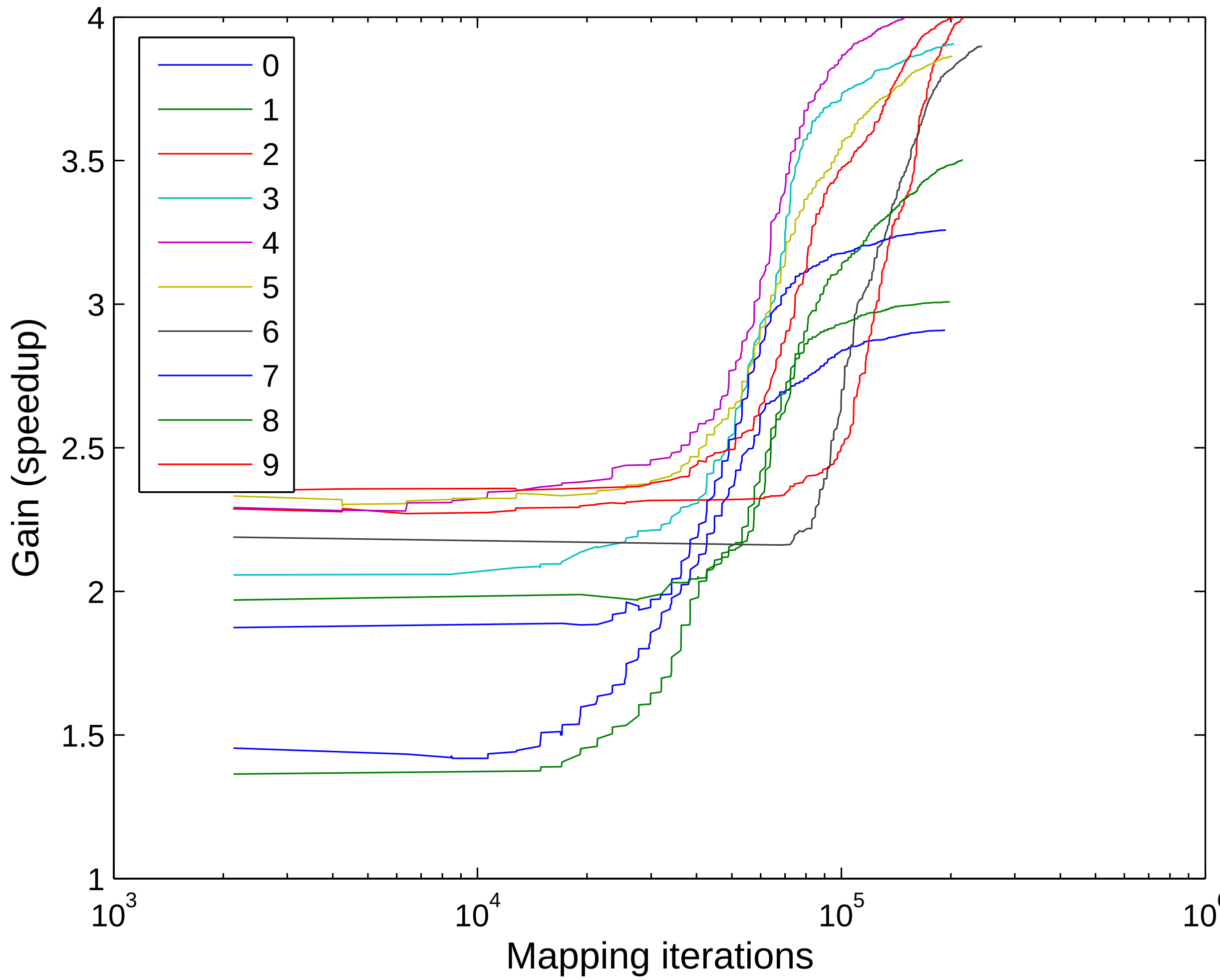
SA+AT progress plotted for each graph



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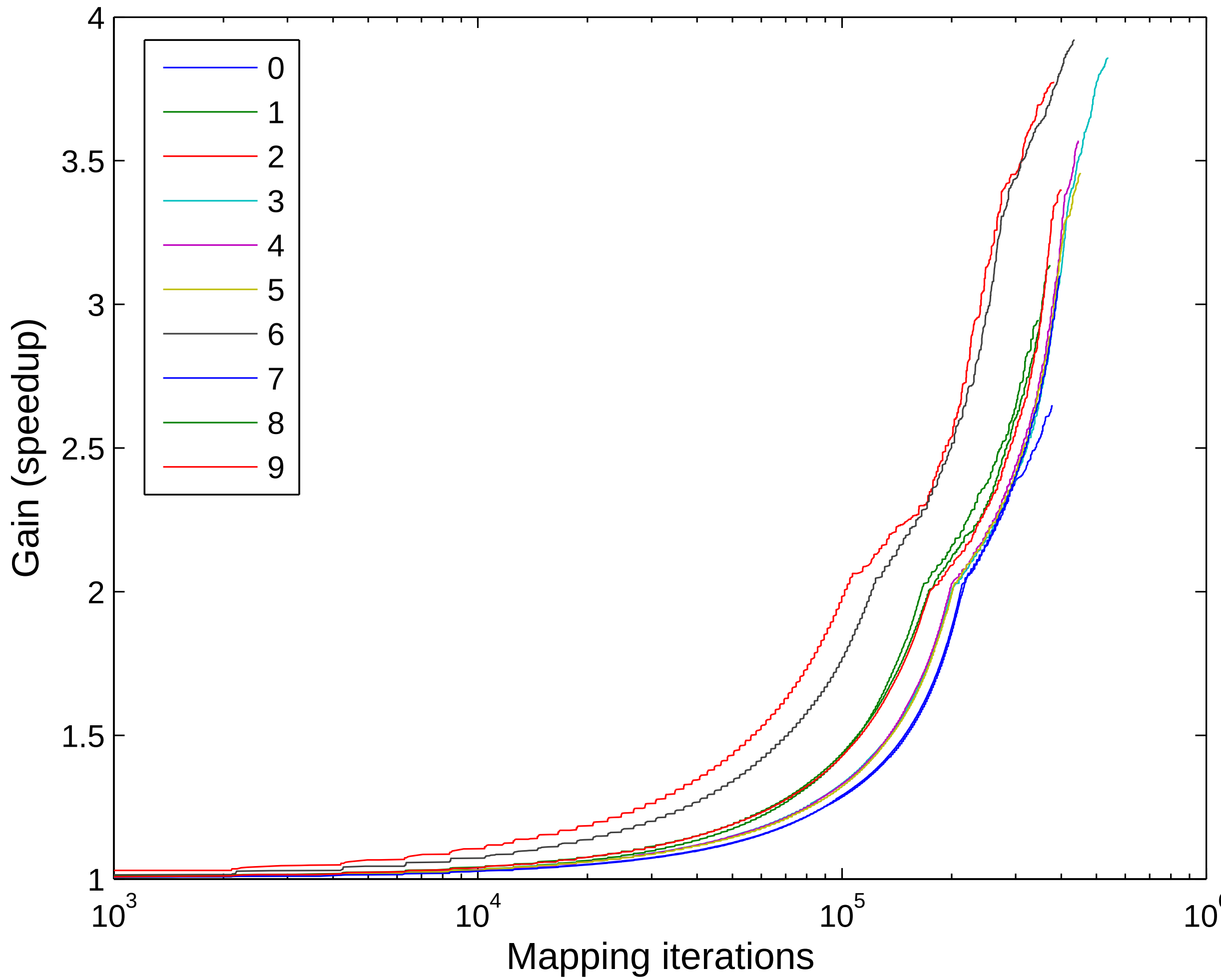
GM progress plotted for each graph



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