Ragnarok: RAndom Graphs Never ARe OK

James A. Jablin
Brown University
Providence, RI 02912
jjablin@cs.brown.edu

Maurice Herlihy
Brown University
Providence, RI 02912
mph@cs.brown.edu

Abstract

Many researchers test graph scheduling algorithms on "random" graphs. We show that many of the random graphs used in the literature are not representative of actual programs by comparing random graphs to graphs derived from the SPECINT2000 benchmarks. We introduce Ragnarok (RAndom Graphs Never ARe OK), a new graph benchmark suite embodying characteristics of SPECINT2000 programs. We hope this benchmark suite will be used instead of random graphs.

1 Introduction

The process of mapping tasks to processors and the determination of start times for each task is called task scheduling. Subtask decomposition, the process of decomposing a program into subtasks connected by precedence constraints, facilitates task scheduling for programs. Precedence constraints define data and control dependences within the program. Subtask decomposition yields a task graph where nodes are tasks and edges are precedence constraints. A scheduler maps tasks to processors and determines start times for each task. Edges may be weighted to represent cost of communication between tasks. The assignment of tasks to processors and allocation of start times is called *scheduling*. Optimal scheduling is NP hard. Therefore heuristics are used to achieve efficient results.

Usually, scheduling is performed on directed acyclic graphs (DAGs). Representing program execution with a DAG misses opportunities for loop optimization. The execution of loops generally consumes the majority of the total execution time. Therefore, it is beneficial to represent loops in the graph and then optimize for them. Thus, prior work has demonstrated results on cyclic and acyclic task graphs.

In the past, no standard existed for either type of graph. Validating techniques required transforming codes into graphs by hand or randomly generating graphs with likely characteristics of real graphs. A wide

array of previous work generates results on random graphs $[1-70]$. Previous researchers assumed random graphs were characteristic of real program graphs. This assumption has never been validated. Without such validation, performance claims based on random graphs may be misleading; they may not translate into improved efficiency in real applications. Additionally, fair comparison between different techniques remains difficult due to the multitude and variety of evaluation methodologies.

We conduct a detailed analysis of random graphs compared to real program graphs. We conclude random graphs are unsuitable inputs for validation. Random graphs are easily constructed but are poor substitutes for real program graphs. Ragnarok (RAndom Graphs Never ARe OK), a new benchmark suite composed of real program graphs, allows researchers to evaluate techniques utilizing identical inputs with the guarantee of real applicable results.

Composed of program graphs from the SPECINT2000 benchmark suite, there are no random graphs in Ragnarok. To compare scheduling algorithms requires head-to-head comparison. When previous studies incorporate random graphs, it is unclear how to perform this comparison fairly. In the past researchers simply generated more random graphs, acquiescing to the fact that they were neither using identical inputs in their comparison nor testing on real inputs. This phenomenon leads to many disparate random graph generation methodologies, an environment not conducive to impartial head-to-head comparison or an intuitive evaluation methodology. Realistically, head-to-head comparison should be performed using identical inputs from related work. Validation on random graphs creates ambiguity as to whether the technique has real merit. Ragnarok allows fair head-to-head comparison with identical inputs by incorporating characteristics of real programs.

The paper outline is as follows. Section 2 provides background. Section 3 provides a detailed evaluation. Section 4 discusses related work. Finally, Section 5 concludes and Section 6 describes future work.

2 Background

The timeline provided in Figure 1 helps motivate the advantages of Ragnarok. Each data point represents a scheduling algorithm evaluated with random graphs. Connected points indicate researchers specifically citing a previous work's random graph generation methodology for their random graphs. As a whole there are few edges in the timeline. There exists a vast number of random graph generation methodologies, but no clear ancestral history tying all methodologies together. A large body of prior work uses unique methodologies, not citing any previous methodology. Low citations per methodology and the large number of single use methodologies is significant. No standard inputs exist for the community to rally behind. A lack of standardization impairs scientific effort. Attempts to compare scheduling algorithms reduce to unraveling the intricacies of experimental methodology for generating random graphs. No authors validate the use

of random graphs for evaluation. Scheduling jobs are not normally random, so it is confusing to test on uncommon random inputs.

All of the works cited use random graphs, not real graphs to evaluate their scheduling algorithms. In this paper, we show that random graphs do not display the same characteristics as real program graphs and are therefore unrepresentative. Using random graphs to evaluate techniques causes confusion and is misleading. These challenges can be overcome by using real program graphs found in Ragnarok.

Section 4 provides a brief survey of random graph generation methodologies in chronological order. To provide a complete survey would be impractical. Many methodologies are unique, never cited subsequently, and provide inadequate detail to reimplement.

Some techniques also supply a means of generating task execution time. Execution time will not be discussed. We concern ourselves with the connectedness or flow of the task graph. As such, all nodes and edges have unit execution time.

3 Results

In this section we introduce Ragnarok, a new standard benchmark suite of cyclic and acyclic task graphs from SPECINT2000 programs. Details of Ragnarok's construction are given. Additionally, we compare Ragnarok to traditional random graphs. Details of the random graph generator used in the evaluation are given as well. Every attempt was made to use a random graph generation methodology with commonalities with a majority of previous work.

3.1 Creating Random Task Graphs

Considering prior work we opt for a simple random graph technique comparable with previous techniques. The random graph generator takes two parameters: the number of nodes in the graph and the density (the number of edges).

Definition 1. *Given the number of vertices* $|V|$ *and density* $\in (0, 1]$*, the number of edges* $|E|$ *is*

$$|E| = density \times (|V|)^2.$$

We use density as the metric for number of edges to maintain parallels with prior work.

For this study, cyclic graphs were generated with between 5–500 nodes in increments of 5 and with density 0.05–0.60 in increments of 0.05. The random graph generator is an accurate reimplementation of

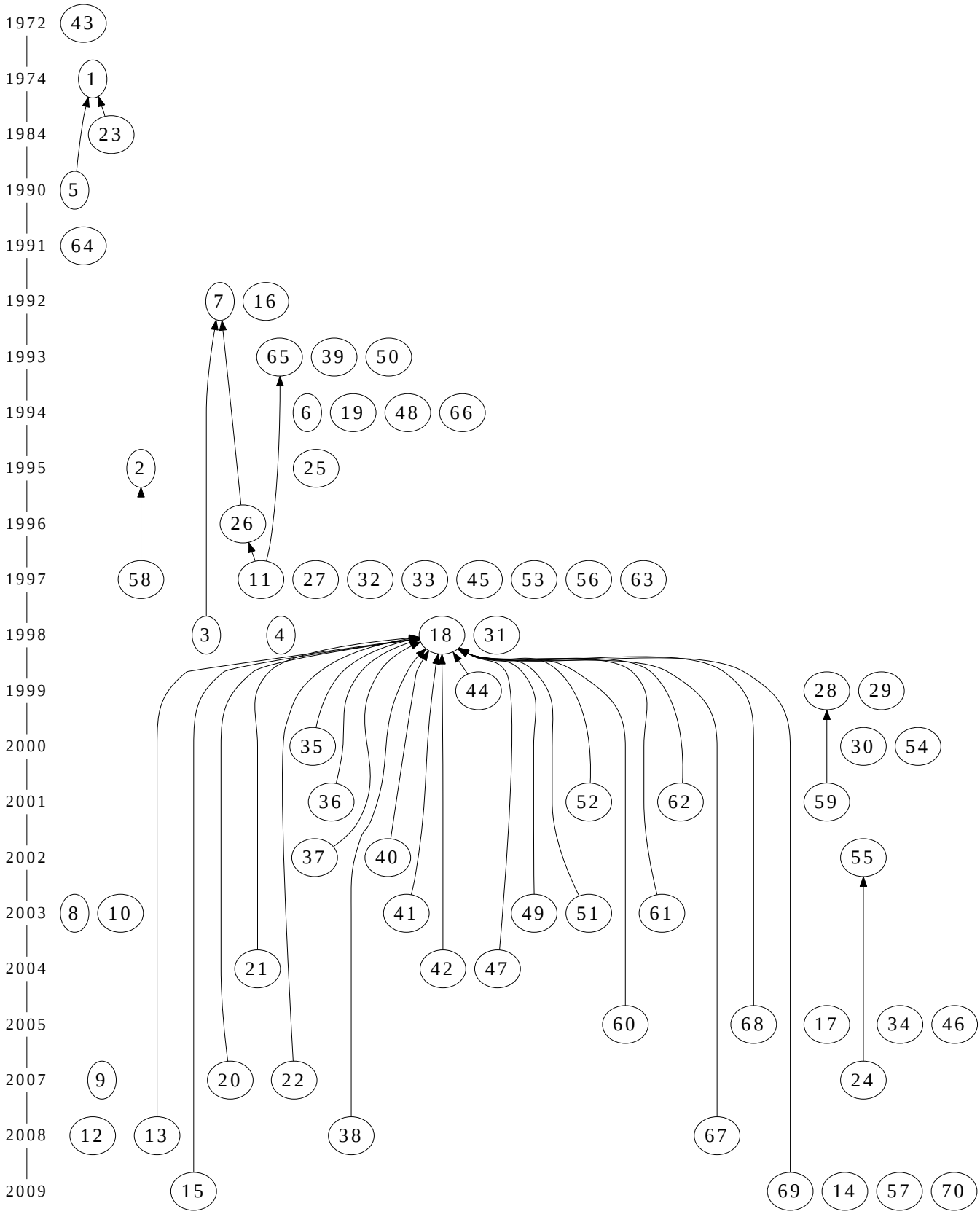


Figure 1: A timeline of random graph methodologies and citations.

```
1)  decyclify(Graph G)
2)      SCCs = strongly_connected_components(G)
3)      DAG_SCC = coalesce_SCCs(G, SCCs)
4)      return DAG_SCC
```

Figure 2: Algorithm to transform a cyclic graph into an acylic graph.

Sandnes and Sinnen's generator [46]. The parameters and the density range are the same. We generate graphs with up to 500 nodes while Sandnes and Sinnen stop at 100. With a density above 0.60, random graphs almost always form a single *strongly connected component* (SCC) composed of nearly all the nodes in the graph. Generating graphs with density beyond 0.60 does not increase the diversity of the data set. These parameters adequately capture the size and degree of random graphs described in prior work.

The generation of acyclic graphs proceeds in a similar fashion to cyclic graph generation with an extra step performed at the end. It is worth noting that DAGs, by definition, cannot have as many edges as a cyclic graph because they do not have back edges.

Definition 2. *Given the number of vertices $|V|$ and density $\in (0, 1]$, the maximum number of edges E in a DAG is*

$$|E| = \frac{|V| \times |V - 1|}{2}.$$

Consequently, choosing a lower upper bound for density has the added benefit of allowing one to use Definition 1 for both cyclic and acyclic graphs.

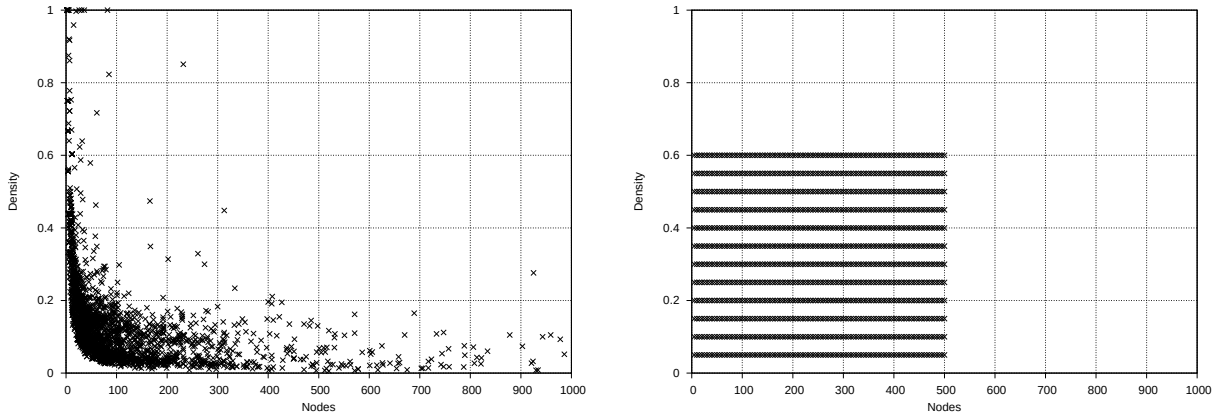
The extra step required for acyclic task graphs handles back edges. First, SCCs in the graph are identified. Then, for each SCC in the graph, we coalesce it into a single node. These steps are simple and solve the problem of cycles. We provide the pseudo-code for `decyclify` in Figure 2.

3.2 Ragnarok Benchmark

To create a new set of standard graphs that embody real characteristics of programs, we start with real programs rather than a random graph generator. We exploit a widely-used benchmark suite, the SPECINT2000 benchmark suite. Because it is tedious and error prone to transform programs into task graphs by hand, we use the LLVM compiler with the Clang front-end for translation. We translate with full alias analysis. Alias analysis more accurately characterizes program dependences.

These steps are all that is necessary for generating accurate cyclic task graphs from SPECINT2000 programs. To represent acyclic task graphs, we apply the `decyclify` algorithm. Other techniques to remove cycles by arbitrarily cutting edges is unsound.

3.3 Results for Acyclic Task Graphs



(a) Acyclic Ragnarok task graphs.

(b) Acyclic random task graphs.

Figure 3: Comparison of cyclic Ragnarok task graphs and random task graphs

Figure 3 contrasts acyclic random graphs and acyclic Ragnarok graphs. The random graphs were generated using the methodology similar to Yang and Gerasoulis [66]. Acyclic random graphs are characterized by a higher mode for the number of out edges. A higher modal score corresponds to a more strongly connected graph, reducing opportunities for parallelism, adversely affecting performance. Global connectedness throughout the program serializes execution. Acyclic random graphs are homogeneous in structure.

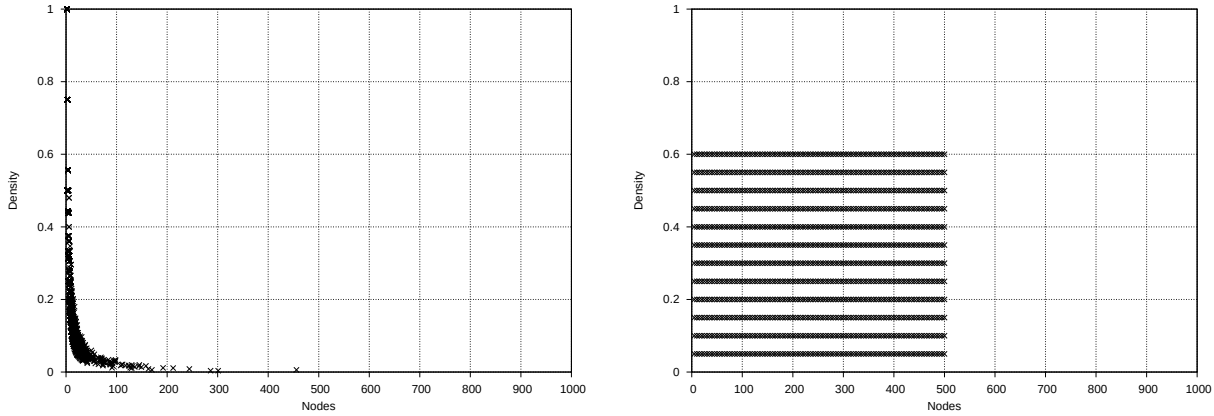
In contrast, real program graphs tend to have a lower mode, and therefore have a small number of nodes with very high and very low out degree. The variable density of different subgraphs within real graphs is not a normal distribution and defies random graph generation.

If acyclic random graphs are homogeneous, then real program graphs are heterogeneous. In practice, many real programs are known to contain parallelizable sections. Density in real program graphs is a local phenomenon, lowering the modal score. A lower modal score enables optimization opportunities. Real program graphs contain local diversity. Optimization leverages these natural opportunities for performance benefits.

3.4 Results for Cyclic Task Graphs

Results of comparing number of nodes and edges for cyclic graphs are shown in Figure 4. The generation methodology for cyclic random graphs parallels the technique in Sandnes and Sinnen [46]. The results are quite similar to the previous section. Considering the number of edges found in real programs, size of graph does not correlate to the number of edges. To the contrary, program graphs exhibit low density compared to random graphs. In real program graphs, larger graphs tend to have lower densities. Intuitively, programs

do not have large areas of task-parallelism, rather parallelism is locked inside SCCs. The SCCs represent loops and loop nests in the program.



(a) Cyclic Ragnarok task graphs.

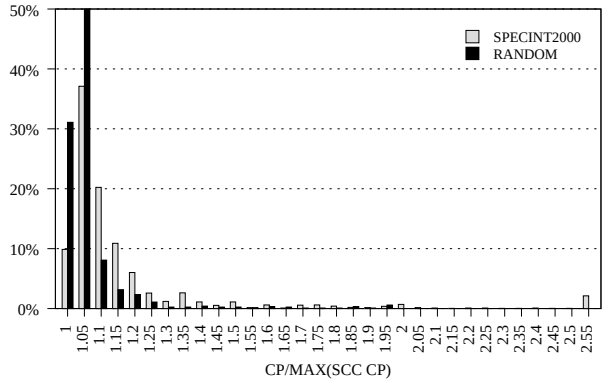
(b) Cyclic random task graphs.

Figure 4: Comparison of cyclic Ragnarok task graphs and random task graphs.

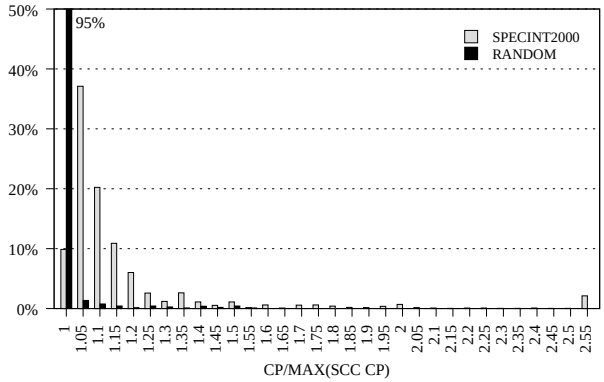
In order to diagnose whether cyclic random graphs are representative of real program graphs, we attempt to software pipeline both cyclic random graphs and cyclic Ragnarok graphs. Software pipelining is a graph-based compiler optimization that has demonstrated performance on program graphs. Software pipelining partitions a graph into subgraphs. Each subgraph becomes a stage in a pipeline, executing separately on its own processor and communicating its results to neighboring stages via a queue. Pipelining is most effective when stages are balanced. Pipelining achieves high performance because it maximizes throughput. Figure 5(a) shows the relationship between the size of the critical path for the largest SCC and the critical path for the whole program. A high ratio of $\frac{CP}{MAX(SCC\ CP)}$ strongly indicates increasing performance using software pipelining. Graphs with ratios close to 1.0 execute sequentially. The ratio therefore displays the raw ability of the graph to attain speedups using pipelining. Ragnarok is composed of many programs that can take advantage of software pipelining. On the other hand, random graphs show very little capability for software pipelining. Notice how the number of graphs with higher speedups abruptly stops after 1.05. Contrarily, Ragnarok graphs have a slow decrease in the number of graphs in each step to 2.0.

As indicated by Figure 4(a), random graphs are unrepresentative of real program structure. Thus, techniques utilizing real program structure fail on random graphs. An example of this fallacy is shown in Figure 5(a). Software pipelining shows potential performance benefits with Ragnarok graphs, but little to no speedup on random graphs. Consequently, techniques validated on random graphs may not show similar results on real program graphs.

Changing the parameters to the random graph generator does not help generate more "real" graphs. In Figure 5(b) the number of nodes and density for each cyclic Ragnarok graph was used to generate a

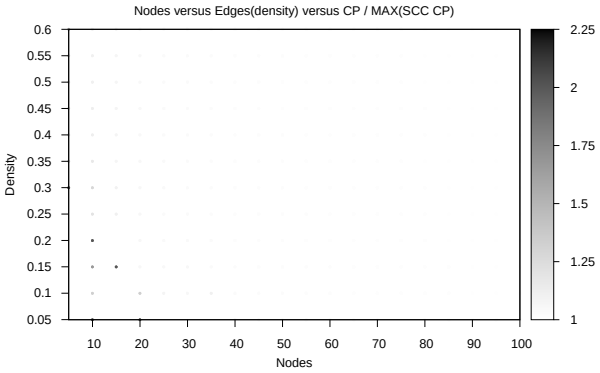


(a) Speedup with pipeline parallelism for cyclic task graphs.

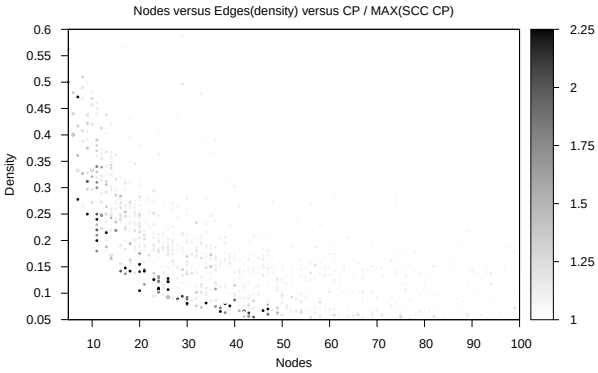


(b) Speedup with pipelin parallelism for cyclic task graphs: random graphs parameterized with Ragnarok values.

Figure 5: Parallelism exhibited by SCCs within cyclic task graphs and random task graphs.



(a) Cyclic random graphs.



(b) Cyclic Ragnarok graphs.

Figure 6: The effect of the number of nodes and density of cyclic graphs on pipeline parallelism.

corresponding cyclic random graph. The results in Figure 5(b) for random graphs are strictly worse than the results in Figure 5(a).

Complementing the results from Figure 5(a), Figure 6 helps characterize the types of graphs amenable to pipelining. As shown in Figure 6(a), only a sub-class of random graphs display the characteristics necessary for effective software pipelining. This sub-class includes random graphs with a very small number of nodes between 5 and 20 and densities of 0.05–0.30. As the number of edges grows quadratically with the number of nodes, large random graphs are characterized by a single SCC composed of a majority of the nodes. Real graphs, depicted in Figure 6(b), do not have these problems. Larger, more dense real graphs are amenable to pipelining. Random graphs are not representative of real graphs. Random graphs are unsuitable for validating scheduling algorithms.

Ragnarok enables easy validation of techniques for real inputs. Random graphs only guarantee demon-

strable performance benefits for random inputs. Ragnarok achieves the standardization and fair comparison required.

4 Related Work

Task graphs are most often modeled as DAGs. Previous work on scheduling assumes this acyclic representation of tasks and communication for scheduling purposes. Many languages provide some form of looping construct for iterative computation. Consequently, DAGs cannot accurately represent program structure. We first explore random acyclic task graph generation and subsequently move on to cyclic task graphs.

4.1 Random Acyclic Task Graphs

Adam et al. [1] generate random task graphs using four characteristics: (a) number of nodes, (b) height of the graph, (c) number of nodes at each level, and (d) average number of successors per node. Edges are randomly connected vertices from higher to lower levels. Edges must not violate this "high-to-lower" property lest the acyclic property be violated.

Almeida et al.'s technique favors a more probabilistic approach [7]. Random graphs have parameter π, representing the probability that two nodes are connected by an edge. Given an incidence matrix A with elements $a(i,j)$ representing a task graph with N nodes:

$$\begin{array}{lll} P[a(i,j)=0] = 1-\pi & \textbf{for} & 1 \leq i < j \leq N \\ P[a(i,j)=0] = 1 & \textbf{if} & i \geq j. \end{array} \quad (1)$$

Consequently, π serves a metric for the number of edges to insert into the graph. Task graphs exhibiting high parallelism will have π close to 1.0, while sequential task graphs will have π close to 0.0. Equation (1) prevents the formation of cycles.

Yang and Gerasoulis's approach to generating random task graphs compares favorably to Adam et al.'s [66]. Again Yang and Gerasoulis parameterize on number of nodes and number of levels. Instead of first choosing the number of nodes, the algorithm starts by randomly generating the number of levels. Then the number of nodes per level is chosen. Finally, nodes from disparate levels are connected by edges. It is assumed that some means of preventing cycles is imposed when inserting edges.

The methodology used in Ahmad and Kwok is very tersely described and thus the most mysterious. The authors control the number of nodes. No other details are given. With only this information, it would be hard to recreate this implementation. Wu and Shu [58] state they were provided the original implementation

of the random graph generator for their use.

TGFF provides a standard method for generating random task graphs [18]. It has fine-grained control of all conceivable attributes for composing nodes and edges. Publicly available, TGFF solves the problem of fair comparison between scheduling techniques. While exact recreation of a previous work's method for task graph generation may be impossible due to lack of details, TGFF supplies a shareable and reproducible set of tasks. Looking at the timeline in Figure 1, TGFF is the de facto standard tool for random graph generation. It is clearly the most cited. On the other hand, contemporaneous work exists that does not not cite it. Moreover, TGFF makes no effort to observe characteristics of real programs in its generated graphs. Not specifically created for validation purposes, TGFF only generates random graphs. The usefulness of these graphs is left open.

Strangely, we encounter a second random graph generator by Kwok and Ahmad [28]. This generator takes as input the number of nodes. The number of edges for each node is chosen from a uniform distribution with mean equal to $\frac{|V|}{10}$. Consequently, larger graphs have higher connectivity. Why this behavior is beneficial or valid is not discussed.

Similar to Adam et al.'s methodology, Topcuouglu et al. [55] generate task graphs using three parameters: (a) number of nodes N, (b) shape of the graph α, and (c) out degree of a node. The height of a graph is calculated from a uniform distribution with mean value equal to $\frac{\sqrt{N}}{\alpha}$. The width of each level is chosen from a uniform distribution with mean value equal to $\alpha(\sqrt{N})$. A short dense graph with high parallelism has α close to 1.0, whereas α close to 0 generates a long graph with low parallelism.

All the methodologies work similarly, but none use the same implementation. All the descriptions fail as adequate specifications for exact reimplementation; separate is inherently unequal. Fair comparison of scheduling algorithms cannot be made when no definitive standard exists.

Ragnarok alleviates the problem of standard inputs. The reimplementation of random graph methodologies becomes necessary. In addition, fair comparison can be performed easily. Ragnarok solves the problems in prior work.

4.2 Random Cyclic Task Graphs

Few previous works attempt to expose higher performance by utilizing a cyclic task graph representation. To statically schedule a cyclic graph, a "decyclifying" process must remove the cycles. Sandnes and Sinnen [46] implement a decyclification process to transform a cyclic task graph into a DAG. Their process is presented in two stages. In stage one, for each start node in a cyclic graph, construct a new acyclic graph by removing back edges. The *decyclify* algorithm behaves similarly to depth-first search. In stage two, search the constructed

DAGs for the graph with the shortest critical path.

Definition 3. *The length of a path p in $G = (\boldsymbol{V}, \boldsymbol{E}, w, c)$ is the sum of its nodes and edges:*

$$len(p) = \sum_{n \in p, \boldsymbol{V}} w(n) + \sum_{e \in p, \boldsymbol{E}} c(e).$$

Definition 4. *A critical path CP of a graph $G = (\boldsymbol{V}, \boldsymbol{E}, w, c)$ is a longest path in G.*

$$len(cp) = \max_{p \in G} \{len(p)\}.$$

Sandnes and Sinnen evaluate their *decyclify* algorithm on random cyclic task graphs. The two tunable parameters are the number of nodes and the graph density. Cyclic task graphs more successfully capture the flow of computation and communication inherent in the program.

Ragnarok's simple and straightforward methodology releases the researcher from the burden of fair comparison, few suitable inputs, and random graphs. Ragnarok contains program graphs from the SPECINT2000 benchmark. These programs provide a wide variety of characteristics found in other programs. Ragnarok enables fair comparison and a multitude of different inputs to facilitate standardization. Using random graphs for testing, it is both unclear and unlikely that results are applicable to real programs. Ragnarok fills the gap of uncertainty by providing real world inputs.

5 Conclusion

Random Task Graph generation is simple and creates a large set of inputs to test against. However, rather than preventing bias toward a particular scheduling algorithm, we conclude that the use of random graph generation creates an unrealistic experiment environment and a barrier for fair comparison between scheduling algorithms. Ragnarok incorporates characteristics of programs from SPECINT2000 benchmarks. Ragnarok achieves the necessary standardization to facilitate realistic and therefore useful comparison between disparate scheduling algorithms, while still incorporating a wide diversity of real program graph structure.

6 Future Work

In the near future, the Ragnarok Benchmark Suite of program graphs will be made publicly accessible via web site. We hope that Ragnarok will be used instead of random graphs for validating future work. A standardized benchmark would also facilitate comparison of related work. We also plan to reevaluate prior

work using Ragnarok. Certainly random graphs are a poor choice for validation, but most of the scheduling algorithms have merit, albeit less than initially advertised.

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