

Towards Million-Server Network Simulations on Just a Laptop

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ABSTRACT

The growing size of data center and HPC networks pose unprecedented requirements on the scalability of simulation infrastructure. The ability to simulate such large-scale interconnects on a simple PC would facilitate research efforts. Unfortunately, as we first show in this work, existing shared-memory packet-level simulators do not scale to the sizes of the largest networks considered today. We then illustrate a feasibility analysis and a set of enhancements that enable a simple packet-level htsim simulator to scale to the unprecedented simulation sizes on a single PC. Our code is available online and can be used to design novel schemes in the coming era of omnipresent data centers and HPC clusters.

CCS CONCEPTS

• **Networks** → **Network simulations; Network performance evaluation; Network performance analysis; Network experimentation; Data center networks; Packet-switching networks;**

KEYWORDS

Network simulation, scalable simulation, large-scale simulation, packet-level simulation, data center networks, HPC networks, htsim

Implementation:

http://spl.inf.ethz.ch/Research/Scalable_Networking/FatPaths/

1 INTRODUCTION

Interconnection networks play an important role in today’s large-scale computing systems [13, 34, 50, 59]. Large networks with tens of thousands of nodes are deployed in warehouse-sized HPC and data centers [30, 48]. Future exascale supercomputers as well as mega data centers will require even larger scales with hundreds of thousands of servers.

To enable effective design and analysis of such large-scale networks and the associated routing protocols, one must resort to simulation. There exist various simulators that can be largely categorized into flow-level and packet-level. Flow-level simulators enable evaluation of large-scale systems, but their coarse design based on flows hinders realistic insights into performance. Packet-level simulators such as OMNeT++ [61] offer a more detailed packet-based model of the network and routing, but they scale poorly. Usual counts of servers in simulated topologies oscillate between a hundred [52] and ten thousand [42]. Tools that simulate large-scale networks, for example ROSS/CODES [25], use distributed-memory supercomputers and clusters [63] that are unavailable to most researchers. Ideally, we want to be able to simulate largest-scale networks on a simple commodity machine, such as a PC.

We illustrate how to achieve the above goal. In the first contribution, we analyze a broad selection of available simulators and show that none scales to the desired sizes of hundreds of thousands of

servers (§ 2). As the second contribution, we conduct a feasibility analysis in which we argue that million-server packet-level simulators should *in theory be achievable on a simple PC* (§ 3). In the final key contribution, we conduct large-scale simulations using the popular OMNeT++ [61] and htsim [52] simulators (§ 4). We discuss the configuration of such simulations, illustrate the necessary modifications to the simulation infrastructure, and analyze their scalability and bottlenecks. Then, we present results of evaluating networks using htsim, with 10k, 100k, and 1M servers, and we discuss the limitations of OMNeT++ which prevents reaching such large scales beyond 10k servers. To enable testing state-of-the-art designs, we provide the implementations of popular protocols in OMNeT++, including ECN [53], ECMP [39], MPTCP [29], DCTCP [3], and LetFlow [60]. Our codes are available online.

2 BACKGROUND AND RELATED WORK

We first introduce the basic concepts.

2.1 Networks

We model an interconnection network as an undirected graph $G = (V, E)$; V and E are sets of vertices and edges. A vertex models a router¹ ($|V| = N_r$). An edge models a full-duplex inter-router physical link. Servers are modeled implicitly. There are N servers in total. λ and v are the flow arrival rate [flows/s] and the flow volume [bytes] of a used workload.

We consider the following networks, focusing on recent low-diameter designs. Slim Fly [13] is a state-of-the-art cost-effective topology that outperforms virtually all other targets in most metrics by optimizing its structure towards the Moore Bound [38]. HyperX [2] (Hamming graph) generalizes hypercubes [22] and Flattened Butterflies [44]. Dragonfly [45] is an established hierarchical network. Jellyfish [57] is a random regular graph with good expansion properties [22]. Xpander [59] resembles JF but has a deterministic construction variant. Fat tree [47], a widely used interconnect, is similar to the Clos network [24] with disjoint inputs and outputs and unidirectional links. We use three-stage diameter-4 FTs; fewer stages reduce scalability while more stages lead to high diameters. Some works exist into the routing of such networks, with simulation data available [8, 11, 20].

2.2 Simulations

We describe packet-level simulations and comprehensively compare them to flow-level simulations.

2.2.1 Packet-Level Simulations. We simulate a network using packet-level simulation. All actions in the simulation are modeled as *events*, which are scheduled to happen at a given point in time. For

¹We abstract away HW details and use a term “router” for both L2 switches and L3 routers.

Simulator	Type*	Scalability [#servers]**	Design***
SimGrid/SMPI [23]	F	3,440 [26]	SM
LogGOPSim [37]	F	1,000,000 [36]	SM
LogGOPSim [35]	P	1024 [35]	SM
hoefer2017spin htsim [52]	P	128 [52]	SM
NS2 [40]	P	< 1,000	SM
booksim [42]	P	10,000 [13]	SM
FOGSim [31]	P	16,512 [7]	SM
NS3 [1]	P	5,000 [51]	DM
NS4 [28]	P	N.A.	DM
BigSim [64]	P	46,656 [41]	DM
SST [54]	P	110,592 [33]	DM
xSim [21]	P	2,097,152 [27]	DM
ROSS/CODES [25]	P	1,000,000 [63] (Slim Fly), 50,000,000 [49] (Dragonfly)	DM
Enhanced OMNet++ [this work]	P	17,000 (full TCP/IP stack)	SM
Enhanced htsim [this work]	P	1,000,000	SM

Table 1: The comparison of available network simulators. *Type is either “P” (packet-level) or “F” (flow-level). **Scalability is the largest size of a topology (simulated with a specific simulator) that we were able to find in the literature. ***Design includes the details of the compute platform used for simulations in the “Scalability” column: “SM” indicates the shared-memory design, “DM” means the distributed-memory design.

each event, some code is executed, which can update the state of the simulation, and produce new events that are scheduled to happen in the future. The main simulation loop keeps the scheduled events in a priority queue and advances the simulation by dequeuing and executing successive events.

2.2.2 Flow-Level Simulations. Flow-level simulations assume a continuous, real-valued flow model. Each flow has a rate $\mu \in \mathbb{R}^+$. The sum of all flows on each link must not exceed the capacity of the cable. Without any additional constraints, this leads to constrained max-flow solutions in the topology graph. Other constraints (e.g., on the routes that can be taken by specific flows) lead to more realistic upper-bounds for performance of various routing schemes on specific topologies. However, since these models do not represent time accurately, they are unable to estimate latency or provide realistic insights into the impact of routing choices on flow control.

2.3 Simulators

We also discuss available network simulators. The overview is in Table 1. In our work, we focus on enhancing two simulators: OMNeT++ [61] and htsim [52].

2.3.1 htsim. The *htsim* simulator [52] provides a lightweight infrastructure that only models the transport layer: there is no model for links or switches. Instead, the route for each packet is pre-computed as a sequence of queues that the packet will pass through. Such a route specification is attached to the packet. Each queue has a finite service rate, which models the link capacity. Due to this design, *htsim* is highly flexible, and new topologies can be added straightforwardly: the topology only affects the route computation, which is explicitly called for every flow during its setup. The disadvantage is that many adaptive routing schemes cannot be modeled, since there is no per-switch state that could affect the routing. Furthermore, all flows are initialized before the first event is processed, and all routes are kept in memory. It may limit the simulation of high path diversity networks like Fat Tree.

We use *htsim* because it supports modern schemes such as NDP [34] and its simple design enables high default scalability.

2.3.2 OMNeT++/INET. OMNeT++ [61] is a discrete-event simulation framework with extensive functionality, including an IDE for development and data analysis, and a visualization tool. OMNeT++ itself does not include network models, and it is not limited to computer network simulations. It needs to be combined with a model library, which provides components that can be used to model the system of interest. One such library is INET [62] which provides models for many internet technologies, including multiple implementations of TCP, various L1 technologies such as Ethernet switches and buses, wireless protocols, and application-level models, for example those of web browsers. INET is not primarily aimed at data center networks, but it includes all the basic technologies, including L2 protocols such as ARP. Modern data center technologies are not present in INET, but could easily be added thanks to the extensible structure of INET. We use OMMeT++ combined with INET [62] because it simulates the full TCP/IP stack and because its code is extensible.

3 FEASIBILITY ANALYSIS

We first analyze the approximate memory and time cost of targeted large-scale simulations. Our goal is to illustrate that large-scale shared-memory packet-level simulations on a commodity PC should in theory be feasible.

3.1 Number of Simulation Elements

We estimate the number of elements of a simulated topology (e.g., servers) and of a simulated workload (e.g., flows which require flow control state). The results of the analysis are in Table 2. The number of network elements does not pose the most serious scalability problems. Instead, *the number and the corresponding size of elements related to workloads dominates the memory usage and the running time.*

3.2 Memory and Time Requirements

The total memory usage and simulation time depend on the simulation software and on *granularity*, i.e., what elements of the simulated workload are explicitly stored and simulated. We estimate these numbers in Table 2.

Table 2 also shows what may *not* be feasible in the largest-scale simulations. Specifically, we cannot simulate large workloads on large networks, and must not store any per-packet state. Another issue can be high path diversity, since the simulator in this example computes and stores all paths ahead of time, leading to a high per-path overhead.

3.2.1 Memory. The lowest required amount of memory is determined by the number of simulated flows. This is because we want to simulate end-to-end flow control for each flow. Thus, the flow control algorithm state for each flow needs to be saved. We also account for the packets in flight on a per-flow basis, since the memory occupied by packets is tightly coupled to the number of concurrent flows. We observe a memory consumption of about 2kB/flow plus 600B/path, which could probably be further reduced, but flow control and packet state put a hard lower bound on the

Element	Range (lower–upper bounds)			10,000 servers			100,000 servers			1,000,000 servers			
	Count (relative)	Count (total)	Memory (per item)	Count (relative)	Count (total)	Memory (total)	Count (relative)	Count (total)	Memory (total)	Count (relative)	Count (total)	Memory (total)	
Network	switch	1	10^2-10^4	⁽¹⁾	1	242	⁽¹⁾	1	1,058	⁽¹⁾	1	5,618	⁽¹⁾
	cable (per switch)	10–1000	10^4-10^6	⁽¹⁾	⁽⁴⁾ 8.5+40	11,737	⁽¹⁾	⁽⁴⁾ 17.5+90	113,735	⁽¹⁾	⁽⁴⁾ 39.5+200	1,345,511	⁽¹⁾
	server (per switch)	10–1000	10^4-10^6	5kB	40	9,680	47MB	90	95,220	460MB	200	1,123,600	5.4GB
	routing entries	$O(N_r^2)$	10^4-10^8	⁽²⁾ 100B	$O(N_r^2)$	58,564	6MB	$O(N_r^2)$	1,119,364	110MB	$O(N_r^2)$	31,561,924	3GB
Workload	task (per server)	1-10	10^2-10^5	⁽¹⁾	1	968,0	⁽¹⁾	1	95,220	⁽¹⁾	1	1,123,600	⁽¹⁾
	flow (per task)	1-100	10^2-10^7	2kB	100	968,000	1.8GB	10	952,200	1.8GB	1	1,123,600	2.1GB
	path (per flow)	1-10	10^2-10^8	600B	5	4,840,000	2.7GB	5	4,761,000	2.7MB	5	5,618,000	3.2GB
	packet (per flow)	10-1000	10^3-10^{10}	⁽³⁾	⁽⁵⁾ 110	106,480,000	⁽³⁾	⁽⁵⁾ 110	104,742,000	⁽³⁾	⁽⁵⁾ 110	123,596,000	⁽³⁾

Table 2: Estimation of the number of elements of a data center simulation. The numbers and thus required resources vary widely depending on a chosen configuration. “Range” lists parameter bounds considered in this work, in the following columns we show numbers for example configurations. Memory estimates are based on htmsim. The chosen workload parameters keep the simulations feasible on a laptop (configuration details are in § 4).¹ Negligible for relevant configurations.² Data depends on the routing scheme.³ Objects are transient and accounted for in the flow counts.⁴ Inter-router cables + server links.⁵ The average over the flow size distribution, excluding retransmissions.

memory use. To make large simulations feasible, it is crucial to keep the per-flow overhead low. Special attention needs to be paid to monitoring and debugging code, which can easily dominate the per-flow state. For very large networks, the quadratically increasing size of the routing tables starts to dominate, but as Table 2 shows, this was not a problem for our simulations.

3.2.2 Time. The lowest amount of time is determined by the amount of packet forwarding. Each packet forwarding has to be processed as at least one event, and these events constitute the majority of simulation time. In the considered low-diameter networks, each packet has to be forwarded ≈ 4 times to reach its destination, and we observed around 60 events processed for each transmitted packet (this includes entering and leaving queues on the path through the network, for the data packet as well as the ACK packet and potential retransmissions). We observe event rates of around 10^6 per second on one CPU core. Since each event likely causes at least one cache miss, we cannot expect much higher rates without distributed simulation, which is outside the scope of this work.

3.3 Discussion and Takeaway

The scenarios listed in Table 2 can all be simulated within about three hours on a standard laptop with 16GB of memory, while being comparable to the largest available packet-level data center network simulations. On a server, even larger simulations are feasible. Distributed simulation allows even further scaling, but at a considerable cost in software complexity [25]. One important angle of enhancement is to increase the simulation intensity (e.g., count of flows).

4 LARGE-SCALE SIMULATIONS

We now proceed to describe large-scale simulations.

4.1 Simulation Setup

We start with providing the simulation setting.

4.1.1 Machine. All simulations were performed on a laptop with 16GB of memory and a Intel Core i7-8550U CPU. The computation time was between 1h and 3h for each simulation.

4.1.2 Networks. We simulate networks of $\approx 10k$, $\approx 100k$, and $\approx 1M$ servers. The networks are $5\times$ oversubscribed with respect

to a full bandwidth design: This represents networks similar to the ones analyzed by Kassing et al. [43]. The oversubscription also makes the simulation of a 1M server instance feasible on a laptop (cf. Table 2). The used Slim Fly is still larger than the one analyzed (on a supercomputer) by Wolfe et al. [63] with respect to the server count.

4.1.3 Workloads. We use a simple synthetic workload model, where pairs of communicating servers are located at routers chosen uniformly at random. This enables flexibility: we can adapt the workload size for any network topology without changing workload properties, which is important for comparisons across topologies. Such a fixed random permutation pattern (in which all outgoing flows of one host have the same destination), in contrast to a more common random-uniform communication graph (a destination host is picked uniformly at random for each flow) leads to a less uniform load distribution in the network. This puts more pressure on load balancing within the network, a feature that we specifically evaluated. However, for a complete analysis, we also consider skewed non-randomized workloads. Such traffic patterns are to a certain degree a proxy of today’s modern communication-intense irregular workloads such as graph processing [8–10, 14, 19, 55] or .

The ultimately limiting factor for workloads is the high cost of simulating a large network. At the targeted scales, we can only simulate a few milliseconds of operation at a reasonable cost. While it may not suffice to get the network into a state that represents real-world operation well, it is sufficient to obtain the overall impression of network performance,

4.1.4 Flow Arrival Model. The flow model defines the sizes and arrival times of flows on each server. In our simulations, for feasible simulation times, we use a fixed set of flows, but with random arrival times over a fixed range. This means that the number of packets in each simulation run is approximately constant.

4.1.5 Performance Metrics. A fundamental performance metric is the finishing time of the last flow in a workload. However, this metric is the maximum of a distribution, and therefore most likely an outlier. Thus, we also consider the *distribution of individual flow completion times* (FCT), as a function of flow size. The mean of the FCT distribution is a summary of the overall network performance. The tail towards higher FCT predicts performance for applications

that are sensitive to tail latency. We obtain one FCT distribution per flow size, since the time to complete a flow depends on the transferred data amount. We can normalize this by considering the *flow throughput*, that is the flow size divided by the FCT. Yet, this hides an important detail of network performance: the tradeoff between latency and throughput (FCT is latency-bound for short flows, but throughput-bound for long flows). Thus, we decided to display FCT as a function of flow size. If this is infeasible, we select one specific, representative flow size.

As we simulate flow arrivals only in a fixed time window, but the FCT is flow size dependent, the impact of our approach varies with the flow size. Specifically, short flows might start and finish before any queues are filled and show unrealistically low latency. Next, long flows are unlikely to finish when the flow injection window ends, and observe lower network load. We can avoid the first effect by ignoring the earliest flows, but avoiding the latter effect may be much harder: depending on the network performance, it might be impossible for any long flow to complete during the injection window, and ignoring flows that complete after the flow injections ended would lead to a bias towards the better performing flows. Thus, we accept that the results for long flows can only be considered meaningful in relative comparisons to other simulations with the same workload model.

4.1.6 Parameters. We use the following parameters:

Flow Sizes (v) Flow sizes v are chosen according to the pFabric web search distribution [4], discretized to 20 flow sizes, with the average $v \approx 1\text{MB}$.

Injection Rates (λ) We vary $\lambda \in \{40, 50, 60\}$ [flows/server/s]. For too high injection rates, the network is unable to serve all the flows and throughput collapses, since the arrival process is independent of flow completion. In this case, the simulation may take much longer than expected, since multiple retransmissions for each data packet need to be simulated.

Analysis and Display We measure the completion time for each flow and display it as a function of flow size. Since the flow completion times are a random distribution, we consider their mean, 10% and 99%-iles, and histograms.

Flow and Congestion Control We focus on NDP congestion control [34], but we also evaluated DCTCP [3] and standard TCP in combination with LetFlow [60]. For NDP, we use 9kB jumbo frames, an 8-packet congestion window, and a queue length of 8 full-size packets. We disable NDP fast start by injecting the first packets truncated at the sender, to avoid packet loss due to uncontrolled injections by short flows.

4.1.7 Collecting Statistics. Monitoring and recording data is expensive in large-scale simulations. We found that *storing per-packet (or even smaller granularity) data is infeasible even for smaller ($N < 10,000$) simulations*. Instead, we focus on quantities that can be aggregated per flow, host, link, or switch. Still, there are millions of flows in large simulations, and the resulting output is significant. For visualization, we use aggregates such as mean, maximum, or histograms, grouped by some parameter of interest, such as flow length.

4.2 Scalability of Simulators

We now illustrate several enhancements to the used simulators that enable evaluating larger networks.

4.2.1 OMNeT++/INET. The IP configuration in INET is loaded from an XML file, where we hit various scalability problems. In many places, the translation of rules in the XML file into in-memory data structures shows quadratic $O(N^2)$ behavior due to linear-time searches over the set of configuration rules. Our modifications add faster heuristics for loading the structure of our auto-generated configuration files.

The GUI monitoring tools are not usable for networks of 10,000s of elements, and the output becomes unmanageably large when anything but simple scalar counters are used. Therefore, our monitoring is based on scalar measurements of various quantities on a per-object level, with a custom parser for the OMNeT++ output format to ingest this data into SQLite tables. Even with this limited recording, we hit scalability problems in the OMNeT++ core. Specifically, there was quadratic behavior due to deletions from `std::vector` in the code that manages monitored quantities. We had to patch OMNeT++ to remove the specific feature with the offending code, since it ran even when the feature was not used.

OMNeT++ supports parallel discrete event simulation using its *parsim* mode. However, it turned out that the INET package at version 3.4 does not support *parsim*. We fixed this by providing the required serialization calls and removing some checks within INET, which would fail if only a part of the network is in memory (this is the case with *parsim*, which splits the network into partitions that are each simulated by an independent process, communicating via MPI). The feasibility of parallel or distributed simulations is a topic outside the scope of this work; However, we observed that a parallel simulation with multiple processes on one CPU could provide a $2\times$ speedup when memory consumption would not allow running multiple parallel jobs.

Further, we observed bugs in rare circumstances, where packets would appear with incorrect MAC addresses; we could only work around this by dropping the affected packets. This affected less than one packet in a million.

4.2.2 htsim. As *htsim* is a library of modules to build a network simulator, rather than an integrated network simulation solution, *htsim* is less affected by scalability problems. Yet, existing sample programs were not well suited to our scenario, and we had to add a more efficient, routing table based routing algorithm for arbitrary topologies. We do not use the provided logging solution, which tends to produce too much output at the simulation scales that we consider. Instead, the statistics of each flow are printed in text format to standard output when the flow finishes. Another scalability obstacle was the `net_paths` structure present in the sample programs, a preallocated N^2 size matrix of routes, which would only be sparsely populated for permutation workloads and would dominate memory use for large networks.

Since *htsim* does not use a network model for its simulation, but rather pre-computes the list of queues that a packet will traverse on its way, the memory occupied by these routes becomes a limiting factor, especially for networks with high path diversity. This could

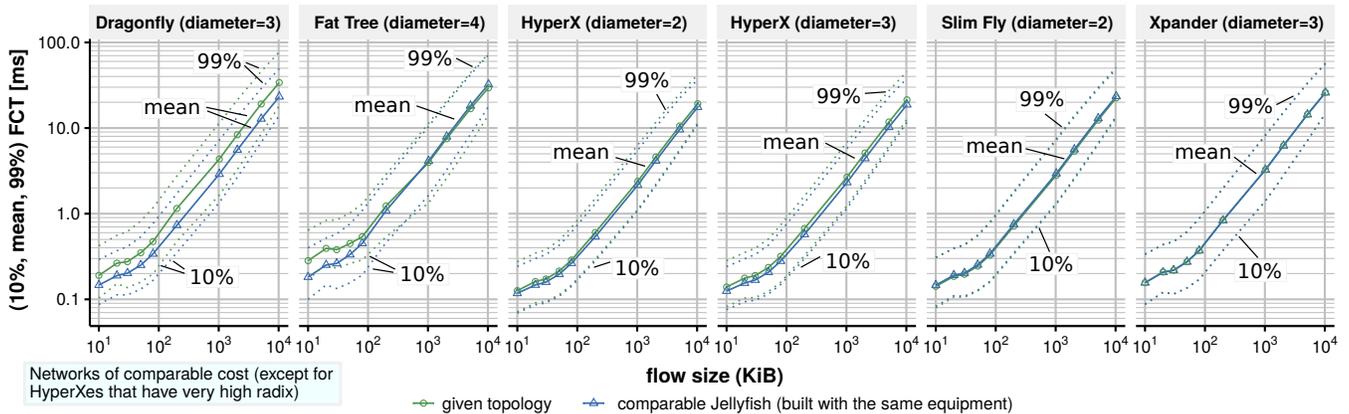


Figure 1: Comparison of topologies on full-bandwidth configurations ($N \approx 10k$ servers).

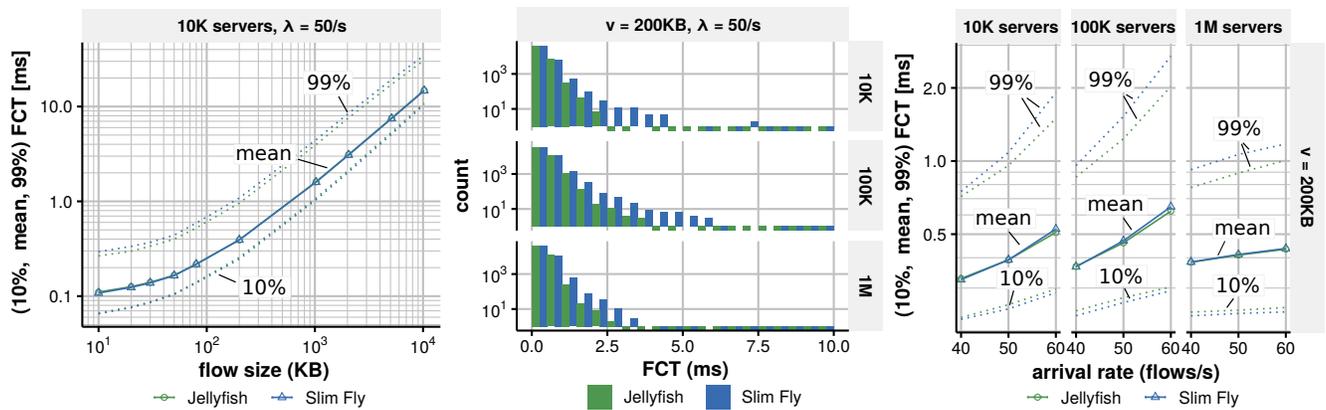


Figure 2: Results of large-scale simulations ($N \approx 1M$ servers).

easily be optimized, but not without significant changes to the htsim codebase.

4.3 Performance Analysis

We now analyze the performance of htsim with the applied modifications. We first analyze performance of different 10k server networks, see Figure 1. For each server, 40 flows are simulated at an arrival rate of 300 per second. Each topology is compared to a Jellyfish network built with the same hardware. Jellyfish outperforms the other topologies with the exception of Slim Fly (similar FCTs to the equivalent Jellyfish) and Xpander (identical FCTs to the equivalent Jellyfish).

Next, we analyze 10k, 100k, and 1M server simulations, see Figure 2. The left plot shows FCT as a function of size. For long flows ($v > 200kB$), FCT is limited by bandwidth, while for shorter flows, latency dominates. The middle plot illustrates the distribution of FCTs for middle-size flows: here, the better tail behavior of the randomized Jellyfish topology is clearly visible. In the right plot, we show the impact of the flow arrival rate λ . Even a small increase in load causes a large degradation in FCT in the considered networks, this is due to the used oversubscription. The 1M server simulation is less affected due to the limited warmup time.

Various scalability issues in OMNeT++ prevented us from reaching the desired scale of 1M servers. However, we were still able to

extensively simulate all the considered topologies of sizes around 10,000 endpoints, with the full TCP/IP stack. Extensive results are elsewhere [20].

4.4 Discussion and Takeaway

Our analysis illustrates that million-server packet-level simulations on a simple commodity laptop are feasible. However, they require some compromises on the quality of simulation, most importantly on the number of allowed flows and on the methodology (i.e., simulating a fixed amount of flows instead of a fixed time window after reaching a steady-state).

An important direction of future work is also considering more realistic large-scale distributed workloads (e.g., using traces), such as different Remote Direct Memory Access based applications [12, 15, 32, 56], deep learning training and inference [5, 6], communication-intensive linear algebra kernels [46], or irregular processing [16–18, 58].

5 CONCLUSION

The growing network sizes go in tandem with the increasing size and complexity of distributed workloads and underlying routing and switching schemes. The effective design and analysis of such networks and protocols requires simulation. Unfortunately, today's

simulators do not scale to the sizes of interconnects in large data centers and HPC clusters.

In this work, we investigate how to run packet-level simulators of such largest networks on a simple commodity PC laptop. For this, we analyze the scalability of existing simulators, investigate the feasibility of our goal, introduce modifications to the popular OMNeT++ and htsim tools, discuss methodological tradeoffs that must be taken, and illustrate example simulations of 10k, 100k, and 1M servers on htsim, focusing on the popular topologies such as fat trees and modern designs such as Slim Fly. Our work will facilitate research into modern networking.

REFERENCES

- [1] Network Simulator 3. 2018.
- [2] J. H. Ahn, N. Binkert, A. Davis, M. McLaren, and R. S. Schreiber. HyperX: topology, routing, and packaging of efficient large-scale networks. In *SC*, 2009.
- [3] M. Alizadeh, A. Greenberg, D. A. Maltz, J. Padhye, P. Patel, B. Prabhakar, S. Sengupta, and M. Sridharan. Data center TCP (DCTCP). *SIGCOMM CCR*, 2011.
- [4] M. Alizadeh, S. Yang, M. Sharif, S. Katti, N. McKeown, B. Prabhakar, and S. Shenker. pFabric: Minimal near-optimal datacenter transport. *SIGCOMM CCR*, 2013.
- [5] T. Ben-Nun, M. Besta, S. Huber, A. N. Ziogas, D. Peter, and T. Hoefler. A modular benchmarking infrastructure for high-performance and reproducible deep learning. *arXiv preprint arXiv:1901.10183*, pages 66–77, 2019.
- [6] T. Ben-Nun and T. Hoefler. Demystifying parallel and distributed deep learning: An in-depth concurrency analysis. *ACM Computing Surveys (CSUR)*, 52(4):1–43, 2019.
- [7] M. Benito, E. Vallejo, and R. Beivide. On the use of commodity ethernet technology in exascale HPC systems. In *HiPC*, 2015.
- [8] M. Besta, A. Carigiet, Z. Vonarburg-Shmaria, K. Janda, L. Gianinazzi, and T. Hoefler. High-performance parallel graph coloring with strong guarantees on work, depth, and quality. In *ACM/IEEE Supercomputing*, pages 1–17, 2020.
- [9] M. Besta et al. Graph-minesuite: Enabling high-performance and programmable graph mining algorithms with set algebra. Unpublished report, 2021.
- [10] M. Besta, M. Fischer, V. Kalavri, M. Kapralov, and T. Hoefler. Practice of streaming processing of dynamic graphs: Concepts, models, and systems. *arXiv preprint arXiv:1912.12740*, 2019.
- [11] M. Besta, S. M. Hassan, S. Yalamanchili, R. Ausavarungnirun, O. Mutlu, and T. Hoefler. Slim noc: A low-diameter on-chip network topology for high energy efficiency and scalability. *ACM SIGPLAN Notices*, 53(2):43–55, 2018.
- [12] M. Besta and T. Hoefler. Fault tolerance for remote memory access programming models. In *Proceedings of the 23rd international symposium on High-performance parallel and distributed computing*, pages 37–48. ACM, 2014.
- [13] M. Besta and T. Hoefler. Slim fly: A cost effective low-diameter network topology. In *SC’14: Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, pages 348–359. IEEE, Nov. 2014. ACM/IEEE Supercomputing.
- [14] M. Besta and T. Hoefler. Accelerating irregular computations with hardware transactional memory and active messages. In *Proceedings of the 24th International Symposium on High-Performance Parallel and Distributed Computing*, pages 161–172. ACM, 2015.
- [15] M. Besta and T. Hoefler. Active access: A mechanism for high-performance distributed data-centric computations. In *Proceedings of the 29th ACM on International Conference on Supercomputing*, pages 155–164. ACM, 2015.
- [16] M. Besta, R. Kanakagiri, H. Mustafa, M. Karasikov, G. Rättsch, T. Hoefler, and E. Solomonik. Communication-efficient jaccard similarity for high-performance distributed genome comparisons. In *2020 IEEE International Parallel and Distributed Processing Symposium (IPDPS)*, pages 1122–1132. IEEE, 2020.
- [17] M. Besta, F. Marending, E. Solomonik, and T. Hoefler. Slimsell: A vectorizable graph representation for breadth-first search. In *Proc. IEEE IPDPS*, volume 17, pages 32–41. IEEE, 2017.
- [18] M. Besta, E. Peter, R. Gerstenberger, M. Fischer, M. Podstawski, C. Barthels, G. Alonso, and T. Hoefler. Demystifying graph databases: Analysis and taxonomy of data organization, system designs, and graph queries. *arXiv preprint arXiv:1910.09017*, 2019.
- [19] M. Besta, M. Podstawski, L. Groner, E. Solomonik, and T. Hoefler. To push or to pull: On reducing communication and synchronization in graph computations. In *Proceedings of the 26th International Symposium on High-Performance Parallel and Distributed Computing*, pages 93–104. ACM, 2017.
- [20] M. Besta, M. Schneider, M. Konieczny, K. Cynk, E. Henriksson, S. Di Girolamo, A. Singla, and T. Hoefler. Fatpaths: Routing in supercomputers and data centers when shortest paths fall short. In *SC20: International Conference for High Performance Computing, Networking, Storage and Analysis*, pages 1–18. IEEE, 2020.
- [21] S. Böhm and C. Engelmann. xsim: The extreme-scale simulator. In *High Performance Computing and Simulation (HPCS), 2011 International Conference on*, pages 280–286. IEEE, 2011.
- [22] J. A. Bondy and U. S. R. Murty. *Graph theory with applications*. Macmillan London, 1976.
- [23] P.-N. Clausm, M. Stillwell, S. Genaud, F. Suter, H. Casanova, and M. Quinson. Single node on-line simulation of mpi applications with smpi. In *Parallel & Distributed Processing Symposium (IPDPS), 2011 IEEE International*, pages 664–675. IEEE, 2011.
- [24] C. Clos. A study of non-blocking switching networks. *Bell Labs Technical Journal*, 1953.
- [25] J. Cope, N. Liu, S. Lang, P. Carns, C. Carothers, and R. Ross. Codes: Enabling co-design of multilayer exascale storage architectures. In *WEST*, 2011.
- [26] F. Desprez, G. S. Markomanolis, and F. Suter. Improving the accuracy and efficiency of time-independent trace replay. In *High Performance Computing, Networking, Storage and Analysis (SCC), 2012 SC Companion.*, pages 446–455. IEEE, 2012.
- [27] C. Engelmann. Scaling to a million cores and beyond: Using light-weight simulation to understand the challenges ahead on the road to exascale. *Future Generation Computer Systems*, 30:59–65, 2014.
- [28] C. Fan, J. Bi, Y. Zhou, C. Zhang, and H. Yu. NS4: A P4-driven Network Simulator. In *SIGCOMM Posters and Demos*, 2017.
- [29] A. Ford, C. Raiciu, M. Handley, and O. Bonaventure. RFC 6824, TCP extensions for multipath operation with multiple addresses. 2013.
- [30] H. Fu, J. Liao, J. Yang, L. Wang, Z. Song, X. Huang, C. Yang, W. Xue, F. Liu, F. Qiao, et al. The Sunway TaihuLight supercomputer: system and applications. *Science China Information Sciences*, 2016.
- [31] M. Garcia, P. Fuentes, M. Odrizola, E. Vallejo, and R. Beivide. FOGSim interconnection network simulator, 2014.
- [32] R. Gerstenberger, M. Besta, and T. Hoefler. Enabling highly-scalable remote memory access programming with mpi-3 one sided. *Scientific Programming*, 22(2):75–91, 2014.
- [33] T. Groves, R. E. Grant, S. Hemmer, S. Hammond, M. Levenhagen, and D. C. Arnold. (sai) stalled, active and idle: Characterizing power and performance of large-scale dragonfly networks. In *Cluster Computing (CLUSTER), 2016 IEEE International Conference on*, pages 50–59. IEEE, 2016.
- [34] M. Handley, C. Raiciu, A. Agache, A. Voinescu, A. W. Moore, G. Antichi, and M. Wójcik. Re-architecting datacenter networks and stacks for low latency and high performance. In *SIGCOMM Conference*, 2017.
- [35] T. Hoefler, S. Di Girolamo, K. Taranov, R. E. Grant, and R. Brightwell. sPIN: High-performance streaming Processing in the Network. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, page 59. ACM, 2017.
- [36] T. Hoefler, T. Schneider, and A. Lumsdaine. Characterizing the influence of system noise on large-scale applications by simulation. In *SC*, 2010.
- [37] T. Hoefler, T. Schneider, and A. Lumsdaine. LogGOPSim: simulating large-scale applications in the LogGOPS model. In *HPDC*, 2010.
- [38] A. J. Hoffman and R. R. Singleton. On Moore graphs with diameters 2 and 3. In *Selected Papers Of Alan J Hoffman: With Commentary*. 2003.
- [39] C. Hopps. RFC 2992: Analysis of an Equal-Cost Multi-Path Algorithm, 2000.
- [40] T. Issariyakul and E. Hossain. Introduction to Network Simulator 2 (NS2). 2012.
- [41] N. Jain, A. Bhatle, S. White, T. Gambin, and L. V. Kale. Evaluating hpc networks via simulation of parallel workloads. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, page 14. IEEE Press, 2016.
- [42] N. Jiang, G. Michelogiannakis, D. Becker, B. Towles, and W. Dally. Booksim interconnection network simulator. 2016.
- [43] S. Kassing, A. Valadarsky, G. Shahaf, M. Schapira, and A. Singla. Beyond fat-trees without antennae, mirrors, and disco-balls. In *Proceedings of the Conference of the ACM Special Interest Group on Data Communication, SIGCOMM 2017, Los Angeles, CA, USA, August 21–25, 2017*, pages 281–294, 2017.
- [44] J. Kim, W. J. Dally, and D. Abts. Flattened butterfly: a cost-efficient topology for high-radix networks. In *SIGARCH CAN*, 2007.
- [45] J. Kim, W. J. Dally, S. Scott, and D. Abts. Technology-Driven, Highly-Scalable Dragonfly Topology. In *ISCA*, 2008.
- [46] G. Kwasniewski, M. Kabić, M. Besta, J. VandeVondele, R. Solcà, and T. Hoefler. Red-blue pebbling revisited: near optimal parallel matrix-matrix multiplication. In *ACM/IEEE Supercomputing*, page 24. ACM, 2019.
- [47] C. E. Leiserson, Z. S. Abuhameed, D. C. Douglas, C. R. Feynman, M. N. Ganmukhi, J. V. Hill, W. D. Hillis, B. C. Kuszmaul, M. A. S. Pierre, D. S. Wells, M. C. Wong-Chan, S. Yang, and R. Zak. The Network Architecture of the Connection Machine CM-5. *JPDC*, 1996.
- [48] X. Liao, L. Xiao, C. Yang, and Y. Lu. MilkyWay-2 supercomputer: system and application. *Frontiers of Computer Science*, 2014.
- [49] M. Mubarak, C. D. Carothers, R. B. Ross, and P. H. Carns. Modeling a Million-Node Dragonfly Network Using Massively Parallel Discrete-Event Simulation. In *SC Companion*, 2012.

- [50] R. Niranjana Mysore, A. Pamboris, N. Farrington, N. Huang, P. Miri, S. Radhakrishnan, V. Subramanya, and A. Vahdat. Portland: a scalable fault-tolerant layer 2 data center network fabric. *ACM SIGCOMM Computer Communication Review*, 39(4):39–50, 2009.
- [51] J. Pelkey and G. Riley. Distributed simulation with MPI in *ns-3*. In *SIMUtools*, 2011.
- [52] C. Raiciu, C. Pluntke, S. Barre, A. Greenhalgh, D. Wischik, and M. Handley. Data center networking with multipath TCP. In *HotNets*, 2010.
- [53] K. Ramakrishnan, S. Floyd, and D. Black. RFC 3168, The addition of Explicit Congestion Notification (ECN) to IP. 2001.
- [54] A. F. Rodrigues, G. R. Voskuilen, S. D. Hammond, and K. S. Hemmert. Structural Simulation Toolkit (SST). Technical report, 2016.
- [55] S. Sakr, A. Bonifati, H. Voigt, A. Iosup, K. Ammar, R. Angles, W. Aref, M. Arenas, M. Besta, P. A. Boncz, et al. The future is big graphs! a community view on graph processing systems. *arXiv preprint arXiv:2012.06171*, 2020.
- [56] P. Schmid, M. Besta, and T. Hoefler. High-performance distributed RMA locks. In *ACM HPDC*, pages 19–30. ACM, 2016.
- [57] A. Singla, C.-Y. Hong, L. Popa, and P. B. Godfrey. Jellyfish: Networking data centers randomly. *NSDI*, 2012.
- [58] E. Solomonik, M. Besta, F. Vella, and T. Hoefler. Scaling betweenness centrality using communication-efficient sparse matrix multiplication. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, page 47. ACM, 2017.
- [59] A. Valadarsky, M. Dinitz, and M. Schapira. Xpander: Unveiling the Secrets of High-Performance Datacenters. In *HotNets*, 2015.
- [60] E. Vanini, R. Pan, M. Alizadeh, P. Taheri, and T. Edsall. Let It Flow: Resilient Asymmetric Load Balancing with Flowlet Switching. In *NSDI*, 2017.
- [61] A. Varga and R. Hornig. An overview of the OMNeT++ simulation environment. In *SIMUtools*, 2008.
- [62] A. Varga and R. Hornig. INET Framework for OMNeT++. Technical report, 2012.
- [63] N. Wolfe, C. D. Carothers, M. Mubarak, R. B. Ross, and P. H. Carns. Modeling a Million-Node Slim Fly Network Using Parallel Discrete-Event Simulation. In *SIGSIM-PADS*, 2016.
- [64] G. Zheng, G. Kakulapati, and L. V. Kalé. Bigsim: A parallel simulator for performance prediction of extremely large parallel machines. In *Parallel and Distributed Processing Symposium, 2004. Proceedings. 18th International*, page 78. IEEE, 2004.