Making congestion control robust to per-packet load balancing in datacenters

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***Abstract*—Per-packet load-balancing approaches are increasingly deployed in datacenter networks. However, their combination with existing congestion control algorithms (CCAs) may lead to poor performance, and even state-of-the-art CCAs can collapse due to duplicate ACKs. A typical approach to handle this collapse is to make CCAs resilient to duplicate ACKs.**

In this paper, we first model the throughput collapse of a wide array of CCAs when some of the paths are congested. We show that addressing duplicate ACKs is insufficient. Instead, we explain that since CCAs are typically designed for single-path routing, their estimation function focuses on the latest feedback and mishandles feedback that reflects multiple paths. We propose to use a median feedback that is more robust to the varying signals that come with multiple paths. We introduce MSwift, which applies this principle to make Google's Swift robust to multi-path routing while keeping its incast tolerance and single-path performance. Finally, we demonstrate that MSwift improves the 99th-percentile FCT by up to 25%, both with random packet spraying and adaptive routing.

I. Introduction

Motivation. In recent years, datacenter networks have faced a dual challenge: a dramatic increase in traffic volumes alongside client demands for shorter job completion times. This combination has sparked widespread calls for better utilization of existing infrastructure. A prominent approach involves *per-packet load balancing*, including *adaptive routing (AR)* [1]–[3], e.g., in NVIDIA's Spectrum-X [4], [5]; *random packet spraying (RPS)* [6]–[8]; and adaptive packet spraying algorithms [9], [10], e.g., in the Ultra Ethernet Consortium specification [11].

However, these per-packet load-balancing approaches are particularly challenging for state-of-the-art datacenter congestion control algorithms (CCAs) that operate with single-path assumptions, such as DCTCP, which is deployed in Meta's production datacenters [12]–[14], and Swift, which is deployed in Google's [15]. The throughput of these CCAs simply collapses when using such per-packet load balancing. Long-term congestion on one of the paths due to single-path background elephant flows or asymmetric topologies only worsens this collapse.

To handle this mismatch, (1) one alternative solution in the literature is to limit the per-packet load balancing policy. For example, Hermes [16] reduces path changes to avoid getting congestion signals from multiple routes. (2) Another approach is to focus only on the *packet reordering* problem, especially with TCP [6], [7], [17]–[24]. When a packet traverses a high-latency path and arrives later than its predecessors, it can trigger duplicate ACKs and cause unnecessarily aggressive multiplicative decreases in the congestion window. Similarly, since many datacenter CCAs like DCTCP and Swift also rely on packet reordering as a congestion signal, having a reordering buffer to solve the reordering problem can help them as well.

Unfortunately, per-packet load balancing affects nearly all congestion signals, not only reordering. Thus, to avoid throughput collapse in modern CCAs that rely on several congestion signals, dealing only with reordering is insufficient, and the other congestion signals should be handled as well. Otherwise, if a single path is congested out of n paths, then packets traversing the congested path will cause the sender to reduce its rate, even if all other paths are uncongested. This overreaction can lead to substantial under-utilization of available network capacity and to larger flow completion times (FCTs). The above congested path can affect about any congestion signal, e.g., (a) a large delay in *delay-based CCAs* such as Swift; (b) an ECN-marked packet in *ECN-based CCAs* such as DCTCP; or (c) a congestion signal in *In-band Network Telemetry (INT)-based CCAs* such as Poseidon [25].

In this paper, we argue that there is a need for an approach that is general enough to cover these various congestion signals within the CCA given any per-packet load balancing. We propose a *median-based framework* that is robust enough to address these congestion signals. We further delve into Swift to produce a specific implementation example that can be practically evaluated.

Contributions. We introduce a fundamental model of throughput collapse induced by per-packet load-balancing. We assume a simple round-robin packet spraying scenario, where packets go through a congested path with probability q, while other paths stay uncongested, and exhibit a general rule for additive-increase multiplicative-decrease (AIMD) flows: *Throughput collapses as* $\Theta(1/\sqrt{q})$. We show that it applies to the (1) TCP, (2) DCTCP, and (3) Swift reordering-sensitive CCAs. We also demonstrate that the same asymptotic rule applies to two reordering-insensitive CCAs: (4) FastFlow [26], which uses additive increase and both additive and multiplicative decrease, and relies on *delay* and *ECN* congestion signals, and (5) a reordering-resilient Swift variant, which effectively only uses *delay*. This proves that only solving reordering is insufficient.

We further validate the Swift and reordering-resilient Swift models through simulations and observe a good fit between models and simulations, using both random and round-robin packet-spraying simulations.

To solve the per-packet multi-path collapse, we propose a *median-based framework* that tracks recent congestion signals and responds based on their median value. This simple approach applies to a wide set of signals, and remains robust against varying per-packet multi-path signals.

We focus our implementation and evaluation on Swift. We suggest and implement *MSwift*, where we apply our median-based framework to a reordering-resilient Swift baseline. We also analyze several approaches for the history sizes to be used in the median computation, ultimately proposing a bounded-window one. We examine several multi-path scenarios: permutation scenarios where MSwift is either alone in the network or also suffers from the interference of single-path elephant background flows, and incast scenarios. Extensive evaluations using 3-layer fat-tree topologies show that MSwift improves the mean throughput and 99th-percentile FCT by up to 25% in permutation scenarios compared to our baseline, using both the RPS and AR per-packet routing schemes. We also show that MSwift retains our baseline's tolerance to incast traffic, and retains Swift's performance in single-path scenarios.

In summary, our main contributions are: (1) the fundamental $\Theta(1/\sqrt{q})$ throughput-collapse rule for a large class of CCAs; and (2) the median-based framework solution to fight per-packet multi-path throughput collapse.

We intend to release our code on Github upon publication.

Related Work. A major obstacle to per-packet load balancing is that different paths may experience varying latencies, resulting in packet reordering that triggers congestion avoidance mechanisms and reduces throughput. This phenomenon has been extensively studied for TCP, with numerous solutions proposed over the years. Leung et al. [18] provide an overview of those TCP reordering solutions and discuss them in detail. A first approach [24] either temporarily disables congestion control or performs recovery during congestion avoidance upon reordering. A common technique [20], [21] is to readjust the duplicate ACK threshold. Another mechanism [22] is to delay the congestion response for one RTT after receiving the first duplicate ACK. It is also possible to readjust RTO timer calculations [23]. More recently, it has been suggested to use network coding [19]. Another approach is to completely ignore reordering as a loss signal and rely solely on an RTO timer with adjusted parameters [17]. Finally, Lazy TCP [7] was specifically designed for datacenters. It waits for reordered packets and decreases the window only upon consecutive packet reordering. Unfortunately, these solutions do not provide solutions for congestion signals beyond reordering.

Congestion signals in the literature include ECN, delay, and INT signals. For example, DCTCP [12] uses both loss signals and ECN marking. Swift [15] employs loss signals and incorporates the delay of the last received packet. FastFlow [26] uses only packet trimming and timeouts as loss signals, ignoring reordering altogether, additionally relying on delay and ECN feedback. Poseidon [25] mainly relies on INT signals representing the max per-hop delay (MPD) and on loss signals. DCQCN [27] relies on ECN marking, relayed back through congestion notification packets (CNPs), together with hop-by-hop, link-layer Priority-based Flow Control (PFC).

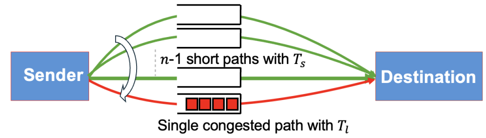


Fig. 1. Periodic round-robin scenario with one congested path.

TABLE I. CCA multi-path throughput models when congestion occurs with probability q and leads to a path delay of T_l rather than T_s. MSS stands for maximum segment size, $mm \equiv max\_mdf$ and ai are Swift parameters. The throughput of all these CCAs falls like $\Theta(1/\sqrt{q})$, experiencing a sharp drop even with little congestion.

Thm.	CCA	Throughput Model
Thm. 1	TCP	$\frac{MSS}{T_s}\frac{1.22}{\sqrt{q}}$
Thm. 2	DCTCP (upper bound)	$\frac{MSS}{T_s}\frac{1.22}{\sqrt{q}}$
Thm. 3	Swift	$\frac{MSS}{T_s}\frac{\sqrt{(1/mm-1/2)\cdot ai}}{\sqrt{q}}$
Thm. 4	FastFlow	$\Theta(1/\sqrt{q})$
Thm. 5	Reordering-resilient Swift	$\Theta(1/\sqrt{q})$

Load balancing solutions such as Hermes [16] try to partially avoid this mismatch of CCA and per-packet load-balancing interaction by limiting the per-packet load balancing rerouting policy. Instead, we want to keep it unchanged.

II. The $\Theta(1/\sqrt{q})$ CCA Multi-Path Rule

A. Outline and assumptions.

Overview. In this section, we model the multi-path performance of a single flow. As Fig. 1 illustrates, it employs round-robin packet spraying across n paths. We assume that a single path out of n experiences congestion, i.e., with probability $q = 1/n$. We also assume a constant-delay congestion to make the model tractable. We denote the large congested RTT as T_l and the short uncongested RTT as T_s.

Our analysis reveals that if the flow uses TCP, DCTCP, Swift, FastFlow, or a reordering-resilient Swift as CCAs, it will experience a throughput collapse that follows a common scaling rule:

$$throughput = \Theta\left(\frac{1}{\sqrt{q}}\right).$$

Table I and Fig. 2 summarize our theoretical models.[1] *The takeaway is that the impact of even a few congested paths is rather dramatic. Having 2% of congested paths rather than 1% decreases the throughput by a factor of $\sqrt{2} \approx 1.4\times$, an awful impact in datacenters, with an even worse effect on 99th-percentile FCTs.*

[1]To plot Fig. 2, we assume that Swift uses parameters $ai = 1$, $mm \equiv max\_mdf = 0.5$, $\beta = 0.8$ (default values in the htsim simulator [28]), $base\_target + topology\_scaling = 21\mu s$ and htsim default flow-based scaling parameters, that FastFlow uses the paper's default parameters $targetRTT = 1.5 \cdot baseRTT$, $mi = 2$, $md = 2$, $fi = 0.25$, $fd = 0.8$ and use $\alpha = \frac{T_s}{baseRTT} = 1.2$. We assume that congestion increases the RTT to be $T_l = 2.5T_s$. We assumed $T_s = 14.4\mu s$ so that $baseRTT = 12\mu s$ for FastFlow to fit the default values.

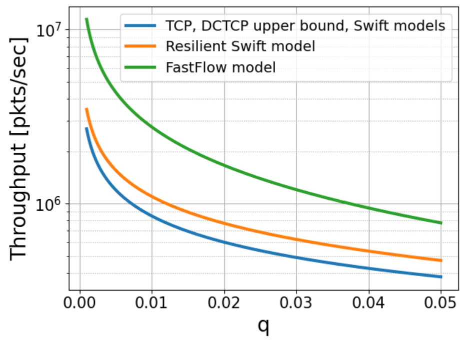


Fig. 2. Model comparison using the theoretical results in Table I. Under all considered CCAs, throughput in round-robin packet spraying collapses when one path out of n is congested, i.e., congestion probability is $q = 1/n$.

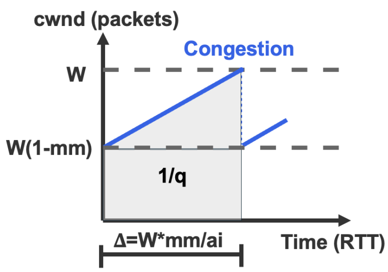


Fig. 3. AIMD dynamics for Swift, providing some intuition for why the grey area of $1/q$ is roughly proportional to $W \times W$.

Intuition. As Fig. 3 illustrates for Swift, our analysis reveals the intuition behind this rule for algorithms employing an *additive increase and multiplicative decrease* (AIMD) policy for their congestion window W. Intuitively, they send a number of packets proportional to W^2 before congestion happens, which occurs every n packets, so $W^2 \propto n = 1/q$ and $W \propto 1/\sqrt{q}$. The rule is closely related to the Mathis $\Theta(1/\sqrt{p})$ throughput model for TCP given a loss rate of p [29]. The reason is that in TCP, both losses and late packets are detected through the same mechanism of three duplicate ACKs. But both rules are not identical. If path delays in the congested path were replaced by drops, as in the Mathis model, the $\Theta(1/\sqrt{p})$ model would not hold for several of our CCAs given some topology parameters. In fact, FastFlow and reordering-resilient Swift sometimes do not even reduce their congestion windows upon packet drop.

Mathis et al. [29] assumptions. We follow the Mathis model assumptions that the flow avoids retransmission timeouts, always has sufficient receiver window and data to send, the receiver is acknowledging every packet without delay, multiple congestion signals within one round trip are treated as a single one, and we can neglect rounding of the congestion window (cwnd) upon reduction, cwnd limits, and details of data recovery and retransmission.

We supplement these with additional assumptions to be able to derive a closed-form model. We assume that the buffer size is large enough that the loss probability is negligible, that the congestion window is sufficiently large that (1) after every packet traversing the long path, three packets from short paths return first, i.e., congestion causes three duplicate ACKs, and (2) the congestion window does not stall while waiting for ACKs of long-path packets. We also assume that n/W is large enough that multiple window increases occur between consecutive decreases. We further assume for all models that all packet sizes are the maximum segment size (MSS).

B. Reordering-sensitive models.

TCP model. We first model the behavior of several reordering-sensitive CCAs, starting with TCP.

Theorem 1 (TCP). *Under the stated assumptions, the throughput of a single TCP flow is*

$$throughput = \frac{MSS}{T_s} \frac{1.22}{\sqrt{q}} \tag{1}$$

Proof Outline: Each packet traversing the congested path returns an ACK only after ACKs from its subsequent three packets arrive, creating three duplicate ACKs and triggering a congestion window reduction by half. This observation demonstrates that packets traversing longer paths produce the *exact* same window size effect as dropped packets in the Mathis model, generating an identical sawtooth pattern. Thus, our TCP flow *exactly* mimics a Mathis TCP flow of RTT T_s that periodically experiences a loss every n packets. The throughput follows the Mathis formula. ■

DCTCP model. For this model of DCTCP [12], we assume that congestion is localized at one buffer, and distinguish the result based on whether the added long-path congestion delay $(T_l - T_s)$ is below the ECN buffer threshold (our default assumption) or not. Note that the ECN threshold is often set around 1 BDP [30]. Both cases yield an $O\left(1/\sqrt{q}\right)$ throughput, with the same main conclusions on throughput collapse.

Theorem 2 (DCTCP). *Under the stated assumptions,*
(i) if a long-path packet doesn't get ECN-marked, the throughput of a single DCTCP flow is

$$throughput = \frac{MSS}{T_s} \frac{1.22}{\sqrt{q}} \tag{2}$$

(ii) else, Eq. (2) *is a* throughput upper bound, *so*

$$throughput = O\left(\frac{1}{\sqrt{q}}\right) \tag{3}$$

Proof Outline: DCTCP uses both packet loss and ECN as congestion signals. If *(i)* ECN marking is not activated, its behavior is identical to TCP. Else, *(ii)* in addition to the reordering-driven window reductions we will have ECN-driven window reductions, yielding even worse performance. ■

Swift model. For this model of Swift [15], we assume that there is no endpoint congestion, that $T_s < target\_delay$ and that we don't reach pacing (i.e., $cwnd \geq 1$).

Theorem 3 (Swift). *Under the stated assumptions, the throughput of a single Swift flow is*

$$throughput = \frac{MSS}{T_s} \frac{\sqrt{\left(\frac{1}{mm} - \frac{1}{2}\right) \cdot ai}}{\sqrt{q}} \tag{4}$$

Proof Outline: The Swift loss recovery is based on two main mechanisms: selective ACK (SACK) for fast recovery, and a retransmission timeout (RTO). SACK is implemented using a sequence number bitmap. When a packet is detected as lost via a hole in the bitmap, it is retransmitted, and the congestion window is reduced multiplicatively by $1 - mm$ (where mm stands for max_mdf). Thus, every packet traversing a long path will cause reordering, creating a hole in the SACK bitmap, causing a cwnd reduction. It effectively creates a periodic sawtooth pattern with an additive increase (AI) parameter ai per entire cwnd, multiplicative decrease (MD) parameter $1 - mm$, and a cycle of $n = 1/q$ packets. Let the maximum value of the cwnd be W packets. The minimal value after a decrease is $W(1 - mm)$. The time for an entire cycle will be $\Delta = \frac{W \cdot mm}{ai}$ RTTs, i.e., $\Delta = \frac{W mm}{ai} T_s$ sec. Thus the total data delivered is the area under the sawtooth,

$$\Delta \cdot 1/2 \cdot (W + W \cdot (1 - mm)) = \frac{W^2 \cdot mm \cdot (1 - \frac{1}{2}mm)}{ai}.$$

This total cycle data also equals $\frac{1}{q}$ by definition. Therefore we get $W = \sqrt{\frac{ai}{q \cdot (1 - \frac{1}{2}mm) \cdot mm}}$ Since the throughput is the ratio of the cycle data by Δ, combining with the formula of Δ yields the result. ■

C. Reordering-insensitive models.

We now present two models of CCAs that are reordering-insensitive, and show that they follow *the same* $\Theta(1/\sqrt{q})$ throughput-collapse rule as reordering-sensitive CCAs. This emphasizes that *reordering-only solutions are insufficient*.

FastFlow model. FastFlow [26] uses several layers of congestion control, so it is hard to model. Moreover, its CCA is strongly coupled to an adaptive load-balancer usage, which makes it challenging to disentangle both. Specifically, FastFlow's "wait to decrease" mechanism prevents congestion window reductions unless the moving average of ECN-marked packets per RTT exceeds 25%, and relies instead on an adaptive load-balancer to handle lighter congestion. Since we assume oblivious packet spraying, we always apply window reductions. We assume that packets traversing the congested path experience high delay $T_l \geq 2 \cdot targetRTT$ and get ECN-marked, that packets traversing the short paths do not get ECN marked, and as mentioned previously, that packet drops can be neglected. We follow suggested parameters: $targetRTT = 1.5 \cdot baseRTT$, $mi = 2$, $md = 2$, $fi = 0.25$, $fd = 0.8$, and define α such that $T_s = \alpha \cdot baseRTT$. We assume $1 < \alpha < 1.5$, and that α is big enough so that the Fast Increase component does not activate. We note that FastFlow's multiplicative increase and decrease appear to be effectively additive, while fair decrease appears to be multiplicative.

Theorem 4 (FastFlow). *Under the stated assumptions, the throughput of a single FastFlow flow is*

$$throughput = \Theta(1/\sqrt{q}) \tag{5}$$

Proof Outline: FastFlow's multiplicative and fair increase mechanisms produce an additive increase of $\frac{3-2\alpha}{\alpha}$ MSS and then another additive increase by $\frac{1}{4}$ MSS for a total of $A \equiv \frac{12-7\alpha}{4\alpha}$ MSS per congestion window worth of packets traversing the short paths. The multiplicative and fair decrease mechanisms produce a 1 MSS decrease and then another multiplicative decrease by $\Gamma \equiv 1 - \frac{fd}{BDP}$ per congested-path packet, where BDP is a FastFlow constant. Let the maximum value of the cwnd be W packets. The minimal value after a decrease will be $(W - 1) \cdot \Gamma$. The time for an entire cycle will be $\Delta = \frac{W-(W-1)\Gamma}{A}$ RTTs, which are $\Delta = \frac{W-(W-1)\Gamma}{A} \cdot T_{avg}$ seconds where T_{avg} is the average RTT. The total data delivered is the area under the sawtooth

$$\Delta \cdot 1/2 \cdot (W + (W-1) \cdot \Gamma) = \frac{W^2 \cdot (1 - \Gamma^2) + 2\Gamma^2 \cdot W - \Gamma^2)}{2A}.$$

This total cycle data also equals $1/q$ by definition. Thus $W = \frac{-\Gamma^2 + \sqrt{\Gamma^2 \cdot (1 - \frac{2A}{q}) + \frac{2A}{q}}}{1 - \Gamma^2}$ and after dividing the cycle data by Δ,

$$throughput = \frac{A \cdot MSS}{q \cdot (\Gamma + (1 - \Gamma) \cdot \frac{-\Gamma^2 + \sqrt{\Gamma^2 \cdot (1 - \frac{2A}{q}) + \frac{2A}{q}}}{1 - \Gamma^2}) \cdot T_{avg}}$$

Finally, when $q \to 0$, $throughput = \Theta(1/\sqrt{q})$. ■

Reordering-resilient Swift model. We develop a performance model for a reordering-resilient Swift. For this model, in addition to the previous assumptions made for the regular Swift model, we assume $T_l > target\_delay$.

Theorem 5 (reordering-resilient Swift). *Under the stated assumptions, the throughput of a single reordering-resilient Swift flow is*

$$throughput = \Theta\left(\frac{1}{\sqrt{q}}\right) \tag{6}$$

Proof Outline: The model identifies two key interdependencies between W and $target\_delay$: Swift's delay-driven multiplicative window reduction depends on $target\_delay$, making the steady-state maximum window W a nonlinear function of $target\_delay$. Conversely, Swift's flow-based scaling of $target\_delay$ creates a dependency where $target\_delay$ becomes a non-linear function of W. To solve this coupled equation system, we employ *perturbation theory* to derive an approximate model. The perturbation approach treats the coupling between W and target_delay as a small deviation from the base system, allowing us to systematically improve our approximation through successive orders. ■

Fig. 2 shows that the throughput's $\Theta(1/\sqrt{q})$ behavior is like Swift's, but with a higher constant. Thus, *reordering-resilient Swift improves Swift, but does not solve the throughput drop.* Incidentally, we found that our approximation reaches good results when comparing it to a numerical solution.

III. MSwift

Design goals. We seek a new robust framework that can modify CCAs to let them handle arbitrary per-packet load-balanced traffic. It should (1) be simple; (2) improve (or not degrade) performance for general datacenter traffic scenarios, such as permutation traffic or incast; (3) apply to most advanced CCAs; and (4) maintain compatibility with single-path deployments without performance degradation.

Key idea: using the median. We want to avoid drastic throughput reductions due to intermittent congestion signals. To do so, we propose using *the median value* of recently received congestion signals. The median is well known in robust statistics as a robust measure of central tendency [31]. Our median-based approach intuitively attempts to capture the overall state tendency of the network by generating a coalesced signal that is insensitive to outliers.

This median-based principle can be broadly applied across a variety of congestion signals and algorithms, e.g., *delay measurements* in Swift, *ECN marks* in DCTCP, and *MPD values* from in-network telemetry in Poseidon. Since applying it to all these CCAs is beyond the scope of this single paper, *we will focus on Swift* as an example, as it is an advanced CCA that is used in production datacenters.

LSwift. To show that making Swift reordering-resilient is not sufficient, we also use the core idea of LTCP [7] (using the LTCP-U variant) to design and implement *LSwift*, a reordering-resilient Swift baseline. We choose LTCP because of its specific design for datacenter packet spraying and its SACK-based operation, enabling seamless Swift integration. We adjust the multiplicative window reduction trigger from two to five successive delayed packets, to allow more reordering in congested datacenters.

MSwift. We propose and implement *MSwift*, which builds upon our reordering-resilient baseline LSwift, and applies our proposed median-based approach. For its decisions, *MSwift uses the median delay of recent ACKs* rather than the delay of the latest ACK.

Median history size selection. We denote by *history size* the number of used congestion signals in MSwift's median. It is its only control knob, and balances several considerations.

First, *small vs. large history sizes*. As expected, history size selection presents a fundamental trade-off between sensitivity and responsiveness. As the history size decreases and we only rely on the few latest ACKs, the likelihood of misclassifying localized congestion as network-wide congestion increases, and MSwift can sometimes decrease the global flow rate too aggressively. On the other hand, as the history size increases, the response time to network changes degrades correspondingly, and MSwift may take more time to react to sudden congestion or sudden available capacity.

Second, MSwift needs to decide what its history size should be based on. We consider three alternatives: *a constant size*, *a congestion window (cwnd)-based size*, and *a radix-based size* that derives from the radix of the leaf switch. (1) As we find in the evaluations (§ IV), a constant history size can adapt too slowly to dynamic traffic where window size keeps changing, such as incast traffic. On the other hand, (2) a dynamic window-based history size largely addresses this issue by adapting to current conditions. However, it is also more unfair, as flows with smaller windows, and therefore smaller history sizes, are more sensitive to a few congested paths, and this unfairness impacts 99th-percentile FCTs. Finally, (3) a radix-based approach makes intuitive sense, as the higher the number of leaf switch ports with potential congestion at the source or destination, the more samples we want to take to compute the median. But given a topology, this approach suffers from the same issues as the constant approach. Small radix topologies will be more vulnerable to misjudging network congestion, and large ones will be slow to respond to network changes and incast scenarios. Thus, we abandoned this approach.

To capture the benefits of both constant and window-based approaches while maintaining responsiveness and maximizing potential performance gains, we propose a *bounded window* hybrid method. We essentially take a cwnd-based size, but also bound it below and above to avoid extreme cases:

$$history\ size = \max\left(\min\left(\alpha W, K\right), 3\right).$$

Here, $\alpha > 0$ represents a scaling coefficient for the cwnd W, with smaller α values yielding faster response times. K denotes the constant maximum history size. This bounded-window solution provides rapid response to network changes and incast traffic through its window-based component, while simultaneously reducing unfairness, by ensuring that all flows with sufficiently large windows behave uniformly when the maximum threshold of K is reached. To retain MSwift's median behavior and avoid relying on a single packet, we set a minimum value of 3 for the history size.

Lightweight implementation. Our implementation of the addition of MSwift to baseline LSwift took 25 lines of code.

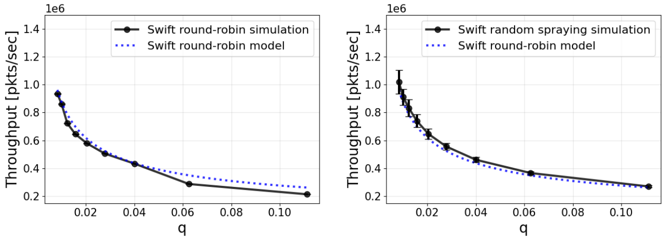
IV. Evaluation

Shared settings. All of our evaluations are performed using (and extending) the htsim packet-level network simulator [28] and its fork with RPS for Swift [32]. They rely on 3-layer, non-blocking fat-tree topologies of various sizes with 100 Gbps links, and compare three algorithms: Swift, LSwift, and our proposed MSwift. They always average 20 runs, except for the model evaluations that use 100 runs. All flow sizes are 20 MB. For Swift, we use $target\_delay$ parameters of $base\_target + topology\_scaling = 15.8\,\mu s$, given the default htsim flow-based scaling and the other parameters.

During our use of htsim, we corrected its Swift implementation to match the Swift mechanisms in the paper, especially (1) the SACK mechanism, and (2) the target delay calculation that should not nullify the topology-based scaling component. We also updated the packet-spraying method in its RPS fork.

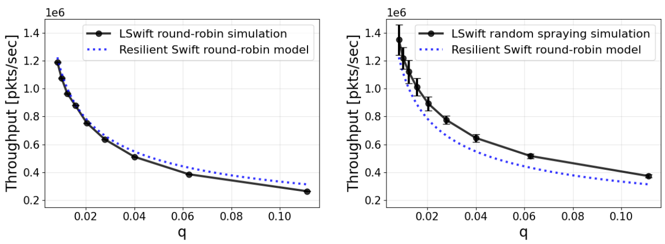
A. Model Verification

Setup. We perform simulations to evaluate the accuracy of our Swift and reordering-resilient Swift models (§ II). Our



(a) Round-robin packet spraying (b) Random packet spraying

Fig. 4. Swift simulation results compared to Swift round-robin model in (a) round-robin and (b) random packet spraying. There is a good fit.



(a) Round-robin packet spraying (b) Random packet spraying

Fig. 5. LSwift simulation results compared to reordering-resilient Swift round-robin model in (a) round-robin and (b) random packet spraying. Since the model is for round-robin, (a) shows a good fit, while (b) only captures well the overall tendency.

setup includes nine empty fat trees, with 54 to 2662 nodes. We implement the model assumptions by introducing an additional single RTT delay in only one path used by our flow, leaving all other paths unmodified (i.e., $T_l = 2T_s$) where $T_s = 14\mu s$. We use the same settings to evaluate both Swift and LSwift, with periodic round-robin and random packet spraying routing.

Results. Fig. 4 compares the *Swift* flow round-robin and random packet spraying results vs. our round-robin *Swift model* prediction. Fig. 5 shows a similar comparison for *LSwift* and our round-robin *reordering-resilient Swift model*. In all cases, we see a good fit between the results and the models.

B. MSwift Evaluation

Setup. We evaluate MSwift against the existing reordering-only solution LSwift using both random packet spraying (RPS) and adaptive routing (AR). We use the default AR in htsim fat-tree topologies. It is based on quantized shortest outgoing queue. We primarily conduct evaluations using a 250-node fat tree for permutation and incast scenarios. We then analyze the trade-offs inherent in different history size approaches, ultimately developing a hybrid method that combines the strengths of the constant and window-based approaches.

Scenario 1: Permutation traffic. Like FastFlow [26], we use htsim to add a scenario with permutation traffic, where each source sends a single flow to a single destination. Our permutation is randomly generated. The goal of this scenario is to check the CCA performance when all flows use per-packet load-balancing, with no other CCAs or uncooperative flows, and the congestion derives from temporary imbalance.

Scenario 2: Permutation with background traffic. To assess MSwift's performance in the presence of background flows that use single-path routing, we further introduce background uncooperative elephant flows by converting up to six multi-path flows into single-path flows that keep sending traffic using UDP at a constant pace of 50% of the line rate. We evaluate four scenarios that progressively increase network-wide interference from these elephant flows, with particular focus on their impact on the most affected 1% of flows:

- *Zero elephants*: Baseline performance (scenario 1).
- *One elephant*: The most affected 1% of flows share the same leaf switch with the elephant at either source or destination.
- *Two & three elephants*: The most affected 1% of flows share the same leaf switch with an elephant at one endpoint and the same pod at the other endpoint.
- *Six elephants*: The most affected 1% of flows share the same leaf switch with elephants at both source and destination endpoints.

Scenario 3: 50-to-1 incast traffic. Like FastFlow, we add a scenario with incast traffic. We use 50-to-1 incast where 50 randomly selected servers transmit to a single destination, each sending one long data flow. The evaluation contains no background elephant flows.

Permutation traffic: MSwift vs. LSwift. First, we evaluate MSwift with a simple constant history size, and compare it to the reordering-only solution LSwift using the permutation traffic scenarios (with and without elephant flows).

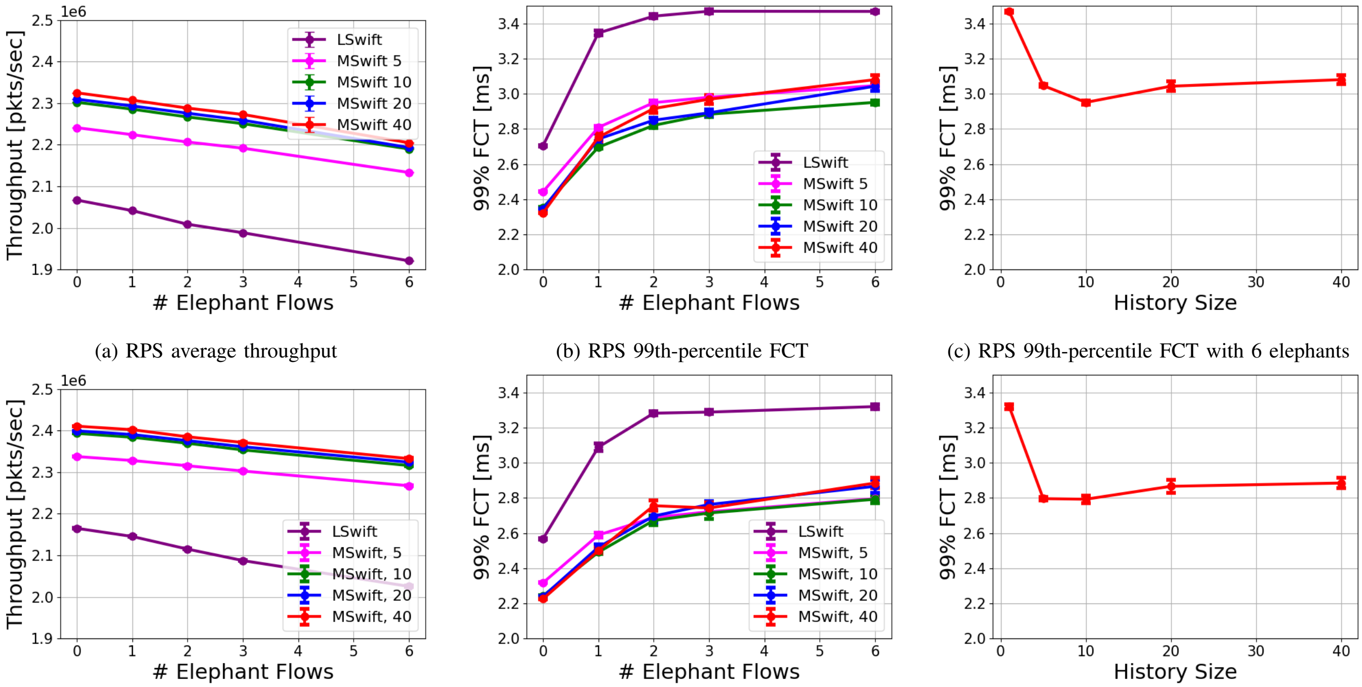
Fig. 6 demonstrates that MSwift improves both the mean-throughput and 99th-percentile FCT performance, with both RPS and AR. This improvement holds across a wide range of history sizes, though Figs. 6(b) and 6(e) show that performance gains for 99th-percentile FCT can deteriorate when history sizes are too low (5 ACKs) or too high (40 ACKs). Figs. 6(c) and 6(f) clearly demonstrate it for the 6-elephant scenario, where a history size of 1 corresponds to LSwift. All figures show an optimal history size around 10.

Constant vs. radix-based history size. We check our radix-based history size approach. In this evaluation only, we use a 54-node fat-tree with a radix of 6 (rather than a radix of 10), applying AR and permutation traffic with one elephant flow.

Figure 7 shows the 99th-percentile FCT results across different history sizes A history size of 10 again slightly outperforms a history size of 6 (which would have matched the radix), thus equaling the history size to the radix does not necessarily reach optimal results.

Constant history size suffers with incast. We evaluate whether MSwift with constant history size adversely affects incast performance.

Fig. 8 reveals a poor performance for the constant history size on 99th-percentile FCT, scaling exponentially with the chosen history size. Even with a history size of 10, we observe a deterioration of more than 20% in 99th-percentile FCT in both RPS and AR environments vs. the LSwift baseline with a history size of 1. This is because a larger constant



(a) RPS average throughput (b) RPS 99th-percentile FCT (c) RPS 99th-percentile FCT with 6 elephants

(d) AR average throughput (e) AR 99th-percentile FCT (f) AR 99th-percentile FCT with 6 elephants

Fig. 6. Median-based *MSwift* with different constant history sizes vs. baseline reordering-resilient *LSwift*, using permutation traffic. MSwift clearly outperforms LSwift. All figures show an optimal history size around 10.

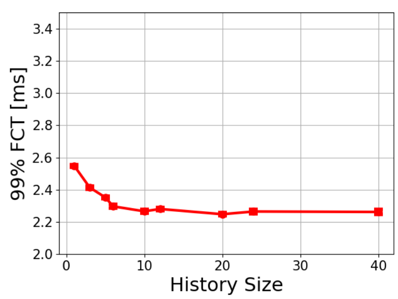
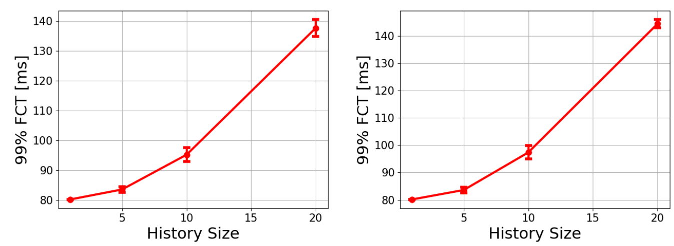


Fig. 7. MSwift using AR with different constant history sizes, given a small radix of 6 and permutation traffic with one elephant. The minimum is not 6 or lower, so it is unclear that a lower radix implies a smaller history size.



(a) RPS (b) AR

Fig. 8. MSwift with different constant history sizes using 50-to-1 incast (a size of 1 corresponds to the LSwift baseline). MSwift clearly performs worse than the baseline with incast when using constant history sizes.

history size responds slowly to changing network conditions. For example, when incast ends and cwnd can increase, it will require numerous RTTs to detect this, leading to a large FCT.

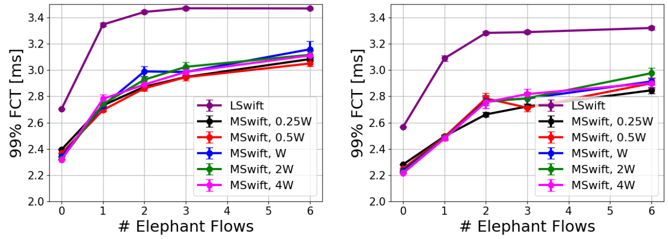
A window-based history size handles incast. We next evaluate a window-based history size, hypothesizing that it can outperform the reordering-only solution LSwift while providing better incast handling than a constant history size. The rationale is that flows exiting incast scenarios operate with small congestion windows, leading to correspondingly small history sizes that enable rapid adaptation to changing network conditions. We test solutions of the form $history\ size = \max(\alpha W, 3)$, where smaller α values provide enhanced responsiveness. The minimal history size of 3 avoids relying on a single ACK for the median.

Fig. 9 shows that $\alpha = 0.5$ works best. Half a window roughly corresponds to half an RTT of memory.

Fig. 10 compares the 99th-percentile FCT for the chosen constant and window-based history sizes. It confirms that window-based history size outperforms LSwift, although the best window-based performance falls short of the best constant history size approach.

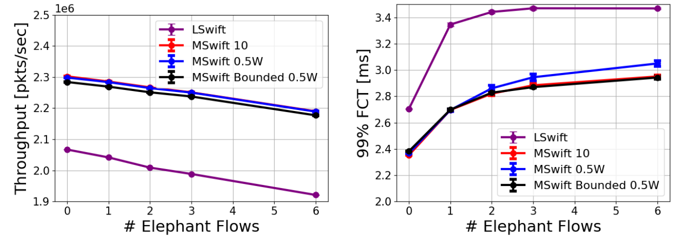
In additional evaluations with incast scenarios, we also found that window-based history size performance degrades by less than 1% across all the aforementioned history size options, meeting the approach's objectives.

A window-based history size is unfair. While window-based history sizes provide clear benefits through enhanced responsiveness and superior incast handling, they cause increased unfairness. Flows with smaller congestion windows detect and



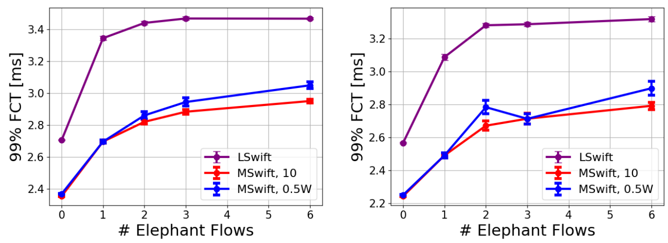
(a) RPS (b) AR

Fig. 9. MSwift with window-based history size using permutation traffic. MSwift outperforms the baseline.



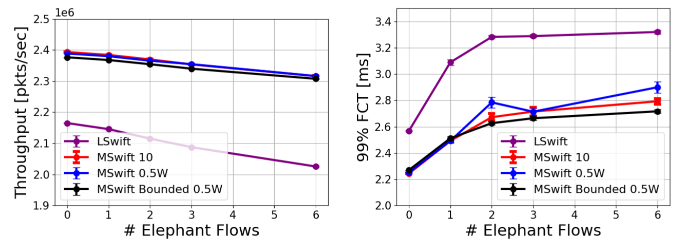
(a) Average throughput (b) 99th-percentile FCT

Fig. 12. Sensitivity to history-size method using permutation traffic with RPS. MSwift with bounded window performs well with RPS.



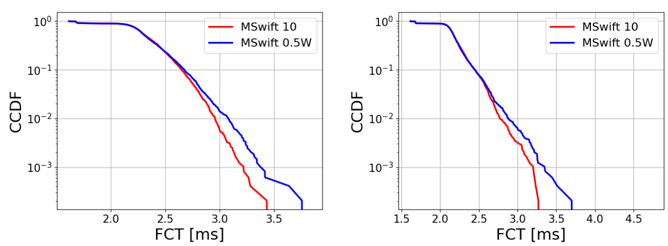
(a) RPS (b) AR

Fig. 10. MSwift with best constant and window-based history sizes using permutation traffic. Window-based history sizes seem a bit worse than constant for permutation traffic.



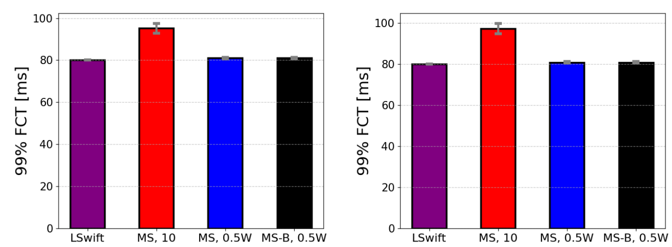
(a) average throughput (b) 99th-percentile FCT

Fig. 13. Sensitivity to history-size method using permutation traffic with AR. MSwift with bounded window also performs well with AR.



(a) RPS (b) AR

Fig. 11. MSwift with constant vs. window-based history size using permutation traffic with 6 elephants: CCDF of FCT. Window-based history sizes have poor performance for the last flows, exhibiting unfairness between flows.



(a) RPS (b) AR

Fig. 14. 50-to-1 incast scenario comparison between LSwift and MSwift with constant, window-based and bounded window history size approaches. MSwift with bounded window also performs well with incast.

respond to congestion signals earlier than those with larger windows.

Fig. 11 illustrates this unfairness through CCDF comparisons of window-based vs. constant history size in a permutation traffic with six elephant flows. In the window-based approach late flows perform worse, even though previous flows perform well or even better, demonstrating the unfairness.

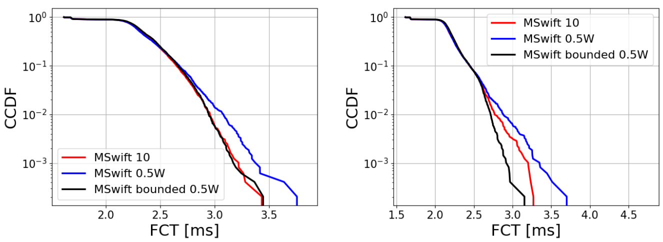
Hybrid bounded window. We now evaluate our hybrid bounded-window approach. Figs. 12 and 13 present comprehensive comparisons for mean throughput and 99th-percentile FCT in both RPS and AR environments. Our bounded-window technique achieves mean throughput performance comparable to both alternatives. However, for 99th-percentile FCT, it outperforms window-based with RPS, and surpasses both alternatives with AR under elephant interference while maintaining comparable performance without elephants.

Fig. 14 further demonstrates that our hybrid approach matches the LSwift baseline with incast.

Fig. 15 reveals significantly better fairness than the window-based solution using permutation traffic. Thus, these results confirm that our bounded window technique successfully synthesizes the strengths of both constant and window-based methods while mitigating their respective limitations.

MSwift still works with single path. We run our permutation setting without elephants *using single-path routing*, for both regular Swift and MSwift. Fig. 16 shows that the MSwift multi-path solution performs similarly to Swift, which was designed for single-path only. Thus, an operator can use MSwift even if the routing policy is unknown, since it performs well on both single-path and multi-path.

Bounded-window parameter sensitivity. We also evaluated the bounded-window solution's sensitivity to α and K in permutation traffic, as can be seen in Figs. 17 and 18 . We found that our solution exhibits robust performance across



(a) RPS (b) AR

Fig. 15. MSwift with constant, window-based and bounded-window-based history size using permutation traffic with 6 elephants. CCDF of FCT for (a) RPS and (b) AR. MSwift with bounded window also performs well with regards to fairness and late flows.

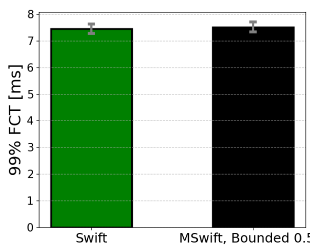
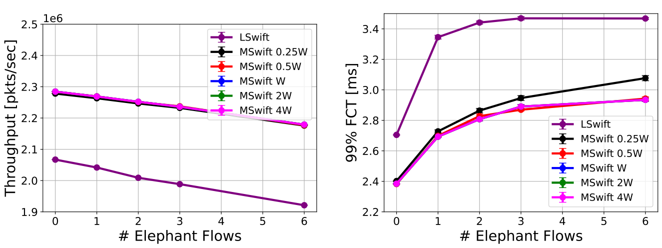
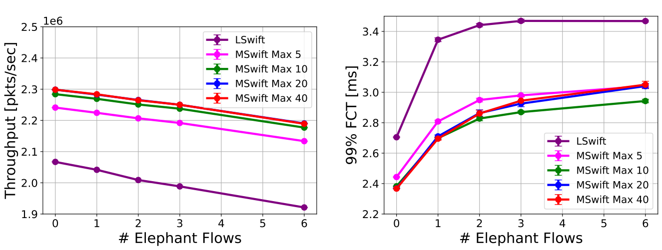


Fig. 16. Single-path routing using permutation traffic without elephants. MSwift with bounded window, which is designed for multi-path, does not experience degradation in single-path.



(a) average throughput (b) 99th-percentile FCT

Fig. 17. MSwift with bounded-window: history size sensitivity to α using permutation traffic in RPS.



(a) average throughput (b) 99th-percentile FCT

Fig. 18. MSwift with bounded-window: history size sensitivity to K using permutation traffic in RPS.

different α and K values close to $\alpha = 0.5$ and $K = 10$. In additional evaluations with incast traffic, we also confirmed a robustness of values to incast.

Drop rate analysis. Our evaluation setup employs constant-paced UDP elephant flows as single-path background traffic. We selected UDP to avoid complex interaction effects of reactive CCAs with our Swift variants, and configured small buffer sizes to maintain low network delays. However, this combination produces a huge drop rate of $\approx 7\%$ for the elephant flows (while MSwift drop rates are under 1%).

To validate this decision, we also evaluated *using Swift* for elephant flows, as a more cooperative alternative. In additional evaluations, we observed that they experienced no drops. However, their throughput significantly decreased to only 55% of that of the UDP elephants, using both RPS and AR. Importantly, we found that even in this permutation traffic with Swift elephants, MSwift consistently outperformed baseline LSwift, achieving 10% improvement in mean throughput and 16% improvement in 99th-percentile FCT. Thus, MSwift appears as more aggressive against background traffic, but also more efficient when left with similar flows. This would seem to fit the operator's goal of maximizing the total throughput, and in particular the throughput of preferred flows vs. background flows. Of course, if the operator has different fairness goals, it is possible to use WFQ as suggested in the Swift paper [15].

V. Discussion

Multi-path implicit priority. We acknowledge that in protecting multi-path traffic from performance degradation, *we deliberately shift the design point* to favor the emerging technology of adaptive per-packet load-balanced flows over legacy single-path flows. This design choice optimizes for multi-path flow performance and may encourage migration toward multi-path routing, advancing the vision of fully multi-path datacenter networks. We realize that it is contrary to much work on CCA fairness that explicitly attempts to be fair to previous CCAs. As a datacenter belongs to an operator, we feel it is the right of this operator to make such a choice.

Optimal fairness. A central design question we considered is defining optimal fairness in mixed scenarios with both single-path and multi-path flows. To be fair, should the *total* rate of a flow with n paths be equal to that of a single-path flow, or should it be its *per-path* rate? How does the answer change if multi-path is defined as the norm, or if prioritizing multi-path increases the overall utilization? These are questions we wrestled with.

The limits to a universal median framework. While our median-based solution integrates easily with many CCA designs, we found that it is not universally applicable. For example, DCQCN sends congestion notification packets to senders at most once per $50\mu s$, coalescing ECN marks at the receiver. In such cases, applying median filtering to these sparse and coalesced signals could prove counterproductive.

VI. Conclusion

As per-packet load balancing becomes widely deployed in datacenter networks, its interaction with CCAs is increasingly critical, since it causes a throughput collapse for many modern CCAs. In this paper, we modeled the throughput collapse for a variety of CCAs when some of the paths are congested.

Our model emphasized the crucial importance of not relying only on the latest congestion signal in these CCAs. Instead, we proposed using the median feedback as a more robust alternative. Building on this insight, we introduced MSwift, which applies our median solution to make Swift robust to per-packet load-balancing, and at the same time retains Swift's single-path performance. Thus, MSwift makes Swift compatible with both RPS and AR while being entirely oblivious to them. Finally, we demonstrated that MSwift improves the 99th-percentile FCT by up to 25% in both RPS and AR scenarios vs. a reordering-resilient Swift, providing evidence that using the median is a practical solution that enables existing CCAs to work effectively in modern per-packet load-balancing datacenter networks.

REFERENCES

[1] D. Abts and J. Kim, *High Performance Datacenter Networks: Architectures, Algorithms, and Opportunities*, ser. Synthesis Lectures on Computer Architecture. Springer International Publishing, 2022. [Online]. Available: https://books.google.ca/books?id=NYZyEAAAQBAJ

[2] NVIDIA, "NVIDIA InfiniBand Adaptive Routing Technology Accelerating HPC and AI Applications," https://www.amax.com/content/files/2023/12/NVIDIA_InfiniBand_Adaptive_Routing_Technology_Insights_Whitepaper.pdf, 2023.

[3] M. Voloshin, "Introduction to Congestion Control for RoCE," Broadcom Inc., Tech. Rep., 2023. [Online]. Available: "https://docs.broadcom.com/doc/NCC-WP1XX"

[4] NVIDIA, "NVIDIA Spectrum-X Network Platform Architecture," https://resources.nvidia.com/en-us-networking-ai/nvidia-spectrum-x, 2024.

[5] P. Rizk, "Turbocharging Generative AI Workloads with NVIDIA Spectrum-X Networking Platform," https://developer.nvidia.com/blog/turbocharging-ai-workloads-with-nvidia-spectrum-x-networking-platform/, 2023.

[6] A. Dixit, P. Prakash, Y. C. Hu, and R. R. Kompella, "On the impact of packet spraying in data center networks," in *IEEE Infocom*, 2013, pp. 2130–2138.

[7] J. Zhang, D. Zhang, and K. Huang, "Improving datacenter throughput and robustness with Lazy TCP over packet spraying," *Computer Communications*, vol. 62, pp. 23–33, 2015.

[8] J. Hu, J. Huang, W. Lv, Y. Zhou, J. Wang, and T. He, "CAPS: Coding-based adaptive packet spraying to reduce flow completion time in data center," *IEEE/ACM Transactions on Networking*, vol. 27, no. 6, pp. 2338–2353, 2019.

[9] T. Bonato, A. Kabbani, A. Ghalayini, M. Papamichael, M. Dohadwala, L. Gianinazzi, M. Khalilov, E. Achermann, D. D. Sensi, and T. Hoefler, "Reps: Recycled entropy packet spraying for adaptive load balancing and failure mitigation," 2025. [Online]. Available: https://arxiv.org/abs/2407.21625

[10] Y. Le, R. Pan, P. Newman, J. Blendin, A. Kabbani, V. Jain, R. Sivaramu, and F. Matus, "Strack: A reliable multipath transport for ai/ml clusters," *arXiv preprint arXiv:2407.15266*, 2024.

[11] Ultra Ethernet Consortium, "Ultra EthernetTM Specification v1.0," https://ultraethernet.org/wp-content/uploads/sites/20/2025/06/UE-Specification-6.11.25.pdf, 2025.

[12] M. Alizadeh, A. Greenberg, D. A. Maltz, J. Padhye, P. Patel, B. Prabhakar, S. Sengupta, and M. Sridharan, "Data Center TCP (DCTCP)," in *SIGCOMM*, 2010.

[13] G. Judd, "Attaining the Promise and Avoiding the Pitfalls of TCP in the Datacenter," in *12th USENIX Symposium on Networked Systems Design and Implementation (NSDI 15)*, 2015, pp. 145–157.

[14] A. Dhamija, B. Madhavan, H. Li, J. Meng, S. Khare, M. Rao, L. Brakmo, N. Spring, P. Kannan, S. Sundaresan *et al.*, "A large-scale deployment of DCTCP," in *Usenix NSDI*, 2024, pp. 239–252.

[15] G. Kumar, N. Dukkipati, K. Jang, H. M. Wassel, X. Wu, B. Montazeri, Y. Wang, K. Springborn, C. Alfeld, M. Ryan *et al.*, "Swift: Delay is simple and effective for congestion control in the datacenter," in *ACM SIGCOMM*, 2020, pp. 514–528.

[16] H. Zhang, J. Zhang, W. Bai, K. Chen, and M. Chowdhury, "Resilient datacenter load balancing in the wild," in *Proceedings of the Conference of the ACM Special Interest Group on Data Communication*, 2017, pp. 253–266.

[17] T. Chang and L. Cai, "Multipath Routing Compatible Congestion Control," in *2024 IEEE 100th Vehicular Technology Conference (VTC2024-Fall)*. IEEE, 2024, pp. 1–5.

[18] K.-C. Leung, V. O. Li, and D. Yang, "An overview of packet reordering in transmission control protocol (TCP): problems, solutions, and challenges," *IEEE transactions on parallel and distributed systems*, vol. 18, no. 4, pp. 522–535, 2007.

[19] N. V. Ha and M. Tsuru, "TCP with network coding performance under packet reordering," in *International Conference on Emerging Internetworking, Data & Web Technologies*. Springer, 2019, pp. 552–563.

[20] Y. Lee, I. Park, and Y. Choi, "Improving TCP performance in multipath packet forwarding networks," *Journal of Communications and Networks*, vol. 4, no. 2, pp. 148–157, 2002.

[21] K.-C. Leung and C. Ma, "Enhancing TCP performance to persistent packet reordering," *Journal of Communications and Networks*, vol. 7, no. 3, pp. 385–393, 2005.

[22] S. Bhandarkar and A. N. Reddy, "TCP-DCR: Making TCP robust to non-congestion events," in *International Conference on Research in Networking*. Springer, 2004, pp. 712–724.

[23] S. Bohacek, J. P. Hespanha, J. Lee, C. Lim, and K. Obraczka, "A new TCP for persistent packet reordering," *IEEE/ACM Transactions on networking*, vol. 14, no. 2, pp. 369–382, 2006.

[24] F. Wang and Y. Zhang, "Improving TCP performance over mobile ad-hoc networks with out-of-order detection and response," in *Proceedings of the 3rd ACM international symposium on Mobile ad hoc networking & computing*, 2002, pp. 217–225.

[25] W. Wang, M. Moshref, Y. Li, G. Kumar, T. E. Ng, N. Cardwell, and N. Dukkipati, "Poseidon: efficient, robust, and practical datacenter CC via deployable INT," in *Usenix NSDI*, 2023, pp. 255–274.

[26] T. Bonato, A. Kabbani, D. De Sensi, R. Pan, Y. Le, C. Raiciu, M. Handley, T. Schneider, N. Blach, A. Ghalayini *et al.*, "FASTFLOW: Flexible Adaptive Congestion Control for High-Performance Datacenters," *arXiv preprint arXiv:2404.01630*, 2024.

[27] Y. Zhu, H. Eran, D. Firestone, C. Guo, M. Lipshteyn, Y. Liron, J. Padhye, S. Raindel, M. H. Yahia, and M. Zhang, "Congestion control for large-scale RDMA deployments," *ACM SIGCOMM Computer Communication Review*, vol. 45, no. 4, pp. 523–536, 2015.

[28] (2025) htsim Network Simulator. [Online]. Available: https://github.com/Broadcom/csg-htsim

[29] M. Mathis, J. Semke, J. Mahdavi, and T. Ott, "The macroscopic behavior of the TCP congestion avoidance algorithm," *ACM SIGCOMM Computer Communication Review*, vol. 27, no. 3, pp. 67–82, 1997.

[30] Y. Zhu, M. Motiwala, Y. Li, M. Yu, and J. Rexford, "Tuning ECN for data center networks," in *Usenix NSDI*, 2015, pp. 507–520.

[31] F. R. Hampel, "Robust statistics: A brief introduction and overview," in *Research Report/Seminar für Statistik, Eidgenössische Technische Hochschule (ETH)*, vol. 94. Seminar für Statistik, Eidgenössische Technische Hochschule, 2001.

[32] (2025) htsim fork. [Online]. Available: https://github.com/smcclure20/csg-htsim