Confucius Queue Management: Be Fair But Not Too Fast

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Abstract

When many users and unique applications share a congested edge link (e.g., a home network), everyone wants their own application to continue to perform well despite contention over network resources. Traditionally, network engineers have focused on *fairness* as the key objective to ensure that competing applications are equitably handled by the switch, and hence have deployed fair queueing mechanisms. However, for many network workloads today, strict fairness is directly at odds with equitable application performance. Real-time streaming applications, such as videoconferencing, suffer the most when network performance is volatile (with delay spikes or sudden and dramatic drops in throughput). Unfortunately, 'fair' queueing mechanisms lead to extremely volatile network behavior in the presence of bursty and multi-flow applications such as Web traffic. When a sudden burst of new data arrives, fair queueing algorithms rapidly shift resources away from incumbent flows, leading to severe stalls in real-time applications. In this paper, we present Confucius, the first practical queue management scheme to effectively balance fairness against volatility, providing performance outcomes that benefit all applications sharing the contended link. Confucius outperforms realistic queueing schemes by protecting the real-time streaming flows from stalls in competing with more than 95% of websites. Importantly, Confucius does not assume the collaboration of end-hosts, nor does it require manual parameter tuning to achieve good performance.

1 Introduction

In-network packet scheduling and queue management are powerful tools to ensure that competing networked applications fairly share network resources and achieve their performance objectives (*i.e.*, high throughput, low latency) as best possible. However, emerging real-time streaming applications such as video conferencing, online gaming, and virtual reality suffer from *performance volatility*. Performance volatility manifests as sudden, abrupt drops in throughput or spikes in latency, often as a result of bursty arrival patterns of competing traffic. Performance volatility results in glitches and stalls for applications with *heavy, real-time* (HRT) traffic¹ (such as video conferencing). Indeed, prior work shows that a latency spike of only 200 ms can lead to several seconds of recovery time at the application layer [38].

Troublingly, we observe that many advanced queueing disciplines today not only fail to prevent performance volatility but that they actually *aggravate* volatility. The problem stems from a fundamental tension between two desirable properties: maximizing throughput fairness and minimizing performance volatility. *We observe that strict fairness entails high volatility in the presence of bursty workloads, and that naively mitigating volatility entails weakening fairness.*

To understand the crux of the conflict between fairness and volatility, we consider a motivating example in Figure 2(a). An HRT video connection runs alone over a residential network link, when another user loads a web page (namely, amazon.com, settings in §7.1). In experiments with a range of queueing disciplines, we see that the video connection experiences an unacceptable (¿190ms [46]) frame delay lasting for as much as a second. On the one hand, the worst-performing queueing discipline for the HRT flow is *fair queueing* (FO), which benefits fairness. Indeed, FO rapidly shifts bandwidth resources to the new Web flows, bottlenecking the HRT flow, which will require several RTTs before it receives adequate signals to adjust its video bitrate and its congestion window. On the other hand, the best setting among existing schemes for the HRT flow is the least *fair* one since it simply benefits the HRT flow at the expense of the Web traffic.

An intuitive solution to the volatility vs. fairness tradeoff might involve some sort of priority scheme with surgically computed 'weights' to prioritize sensitive classes of traffic to avoid extreme unfairness. Unfortunately, this is impractical. First, labeling flows (*e.g.*, with DSCP bits [11]) in this way is *not* incentives compatible ² since Internet senders would always benefit from labeling their traffic with higher-priority classes. Worse yet blindly adhering to potentially buggy labeling of various applications will immediately deprive us of any performance guarantee. Second, administrators cannot simply assign weights of classes a priori, because traffic distribution is dynamic and largely unpredictable.

The above discussion leads us to our quest for a queue management scheme that balances three properties that lie in tension with each other. First, we desire a scheme which, in the long run, adheres to traditional flow-rate fairness.

¹HRT represents flows demanding high throughput and low latency at the same time. For example, beyond requiring low latency, videoconferencing applications will also try to increase the bitrate for better quality [34].

²Recent efforts (*e.g.*, L4S [14]) which use incentives-compatible labeling still suffer from practicality and performance issues, as we will later show.

Second, we desire a scheme that tames volatility and enables HRT flows to live side-by-side with bursty traffic patterns (namely, web traffic). Finally, we desire a scheme that is practical, in the sense that it is parameter-free like CoDel [43] and does not require any flow labeling by senders or application-specific configurations such as deadlines [18].

To this end, we designed $Confucius^3$, a parameter-free queue management scheme that balances fairness versus volatility. In the long run, Confucius guarantees fair flow scheduling between competing classes of traffic. However, in the short run, Confucius refuses to abruptly adjust service rates upon bursty traffic arrivals. Instead, when new flows arrive and service rates must be adjusted to ensure fairness, Confucius gradually adjusts the weights to provide HRT flows a few RTTs to detect the change in network conditions and adjust their bitrates and congestion windows appropriately. More specifically, Confucius assigns flow rates according to a simple exponentially weighted moving average (EWMA [36]) which smoothly moves rates towards a fair allocation. We find that this approach provides a good tradeoff between fairness and volatility; in experiments, we measure flow-completion times (FCTs) for web traffic (which benefit from strict fairness) versus frame delays for HRT flows (which benefit from smoothing) to understand the impact of this tradeoff. In trace-driven experimental tests, we find that Confucius typically reduces the duration of frame delay degradation of HRT flows by 90% while maintaining comparable FCTs for web traffic.

We faced several challenges in designing Confucius:

Practicality: Confucius is a classful queueing scheme, which (like many other classful schemes [49, 50]) groups low-latency flows into the same queue to avoid the latency impact of sharing a queue with buffer-filling traffic. This begs the question of how Confucius can be parameterless, correctly classifying flows without the use of labels. In §5, we illustrate how Confucius adaptively migrates flows between classes depending upon their queue occupancy: flows that naturally occupy a small fraction of the buffer are clustered together, while flows that are observed to be buffer-filling compete in a shared buffer with other buffer-filling flows.

Performance Guarantees: It is easy to vaguely describe Confucius as 'balancing fairness and volatility' but it is harder to formulate this into a rigorous service model. By mathematically analyzing the EWMA function which Confucius uses to adjust service rates, we calculate performance bounds for a few classes of applications that might use Confucius. We show that short, FCT-driven flows (such as web traffic) observe a maximum slowdown of 360 ms relative to fair queueing in our setting; HRT flows (such as real-time video) experience more than 90% less stalls compared to fair



Figure 1: Number of TCP flows and their size for loading each of Alexa top 1000 websites (measure time: July 2022 from one vantage point with Chrome and capture the HAR log [1].

queueing, and that long-lived, bulk transfers experience no degradation at all relative to fair queueing (in the limit).

Avoiding Oscilations: Enforcing fairness and consistency in a dynamic environment with multiple control systems (e.g., congestion control, bit-rate adaptation) operating concurrently is dangerous. Seemingly minor changes in queue management could have large collateral damage to applications. By jointly and cautiously assigning the service rate per queue and the flows per queue, Confucius avoids conflicting decisions that will be detrimental to stability. More importantly, Confucius's control is strategically slow-moving, effectively leaving enough time for other control systems, especially congestion control, to kick in to react optimally.

Before moving forward, we consider one issue of setting. Confucius is designed for deployment in residential and end-user access points (*e.g.*, WiFi APs or cellular base stations), and our experiments and data involve application use in those settings where it is well-known that congestion is frequent [10, 27, 38]. There is an open discussion in the networking community in exploring congestion's impact in other settings (*e.g.*, in the Internet core [19] or in datacenters [9]), but these other settings are out of scope for Confucius. Moreover, the computation capability at edge routers also enables us to fine-grained traffic management for flows, as we will demonstrate in §7.5.

2 Motivation

We start by describing recent trends in Internet applications that call for reconsidering queue management. Next, we explain via an intuitive running example why existing approaches in both AQM and scheduling fall short in addressing these challenges.

The rise of HRT brings new challenges to queue management. While the Internet always carried multiple applications, the emergence of prosperous real-time communication applications (*e.g.*, videoconferencing, cloud gaming, virtual reality), in particular, has made sharing of bottleneck links particularly challenging. HRT applications require not just low latency but consistently low latency while also sending at very high bitrates [34, 38]. Despite recent advances in wireless technologies such as 5G and WiFi 6 [13, 38, 54], the HRT consistency requirement is often violated, bringing bad user experience. Facilitating the HRT consistency objectives

³One of Confucius' (the philosopher) educational philosophy is teaching students according to their needs, where in this paper we are going to serve the flows according to their needs.



Figure 2: (a) A pre-existing HRT flow (*e.g.*, videoconferencing) competes with flows of a Web-page load (namely, amazon.com). The HRT flow experiences transient delay degradation with classless (blue) schemes, while Web traffic experiences long page load times with classful (green) schemes. (b) Each scheme manages a different balance between the HRT (volatility) and web traffic (fairness). (c) The fairness of classful solutions (*e.g.*, CBQ) is heavily sensitive to workload variations. For instance, CBQ with different weights (1:1 or 1:5) will result in poor fairness (JFI<0.9) in certain workloads. Y axis is not lin-scaled.

requires queue management schemes to shift from preventing *fairness* to also preventing performance *volatility*.

Volatility is very hard to avoid in the Internet. While intuitively, providing consistent performance in the Internet could be addressed by recycling good old AQMs, two key characteristics make this task particularly challenging. First, Internet traffic is often bursty. As an intuition, a simple page load results in a burst of responses from multiple sources. In fact, the median number of flows that a webpage load generates is 27, while for 25% of websites that number is 56 flows. As an illustration, we present the number of HTTP requests, concurrent flows (defined by 5-tuples), and source IPs in Fig. 1(a). Second, while most AQMs schemes were designed with loss-based CCAs in mind, today's applications run multiple distinct congestion control algorithms in accordance with their distinct objectives. Importantly, ten distinct algorithms are used by the top Alexa websites [40].

Research Question. Taken together, these trends beg the question: Are today's in-network queue mechanisms (*i.e.*, AQM and scheduling) able to *fairly and consistently* satisfy the heterogeneous objectives of flows sharing a bottleneck link while being practical?

2.1 Motivating Example

To answer this question, we present an intuitive experiment. Assume a user has a video call, thus pulling an HRT (heavy, real-time) flow through a router. At t=0s, another user opens a web page and creates a burst of new short flows on the same bottleneck link as the video flow. The two applications use different CCAs, to achieve their objectives. Concretely, the HRT flow uses Copa [8], a low-latency CCA for videos [29] and the webpage uses TCP Cubic. Fig. 2 illustrates the experience of the two applications (a) over time, (b) on average, and (c) in terms of fairness (JFI), when the bottleneck link is controlled by a variety of schemes. We explain the experimental settings in more detail in §7.2. While simple, our example practically demonstrates the tension between fairness and volatility. Thus, the observations we draw from this example generalize to other traffic mixes and scenarios as we show in §7.

We distinguish existing schemes in *classful* and *classless*.



Figure 3: Illustration of how bandwidth shares change over time with incoming flows for different scheduling algorithms. The dashed red line marks the fair share of the HRT flow.

The former requires end-hosts to label packets per application (videoconferencing, or web). The latter does not need or leverage end-host labels.

Unfortunately, none of the existing solutions can adequately address the tension between fairness and volatility in a realistic setting. Specifically, these existing solutions, respectively, have one or multiple of the following issues:

Performance volatility: the HRT flow suffers from delay degradation when Web flows join. Classless schemes such as FIFO, FQ, RED are unable to avoid performance volatility, effectively hurting the HRT flow. As we observe in Fig. 2(a), when classless schemes (in blue) are managing the bottleneck link, the HRT flow experiences high delays. Concretely the delay of HRT increases by $4 \times$ reaching 400-800 ms. In perspective, an end-to-end delay for video frames of more than 190 ms (dashed line in Fig. 2(a)) causes a stall in video streaming [46]. Fig. 3(a) and 3(b) visually explain why simple classless schemes such as FQ and FIFO are so bad at avoiding volatility. Observe that the available bandwidth for the HRT flow reduces so abruptly when the web flows arrive that the HRT flow cannot adapt.

Failing to offer consistent latency is an unintuitive result for AQM schemes that actually try to control end-to-end latency [17,24,26,43]. However, traditional AQMs cannot balance the performance of heterogeneous flows, as they were designed with loss-based CCAs in mind [23] and cannot effectively communicate congestion to delay-based CCAs, which are adopted by most real-time flows [16]. For multiple latency-sensitive CCA's (including GCC and Copa), a sender does not interpret AQM-induced losses or ECNs as congestion, thus would not reduce its sending rate until the loss rate is very high. Therefore, as shown in Fig. 2(a) and 2(b), AQMs such as CoDel and RED result in significant delay degradation for the HRT flow.

Unfairness: either the Web flows or the HRT flow suffer from extreme performance degradation. Classful schemes such as CBQ, which splits packets into classful queues of configurable service rate or strict priority, which only dequeues packets of lower priority if high priority is empty, protect the HRT flow, as we observe in Fig. 2(a). However, classful schemes also result in unfair allocations (as shown in Fig. 2(b)) because they overpenalize (or even starve) web traffic which experiences high page load times (PLTs) as shown in Fig. 3(c). While, in theory, CBQ could be configured to be fair, that requires knowledge of the exact workload (ratio of flows between classes) over very short time intervals, which is in practice infeasible. For example, we measure the fairness that different schedulers can provide while changing the number of competing flows to the HRT flow in Fig. 2(c). Modifying CBQ's configuration improves JFI for a subset of the workloads: CBQ (1:1) works well when there are two flows competing while CBQ (1:5) achieves a good JFI when there are five competing flows they both degrade as the number of flows changes.

Impracticality: requiring end-hosts to correctly label their traffic is unrealistic in the Internet. Besides the sensitivity to configuration, classful schemes require the endhost to label flows according to their importance or objectives and prioritize traffic based on that. Such label-driven management is unrealistic for home routers for the following reasons. First, labeling incurs substantial coordination overhead. Indeed, users will need to use labels according to their application objectives while also agreeing with routers on the meaning of these labels. Second, label-driven management assumes end hosts are trusted and bug-free. In practice, senders have the incentive to label their flows with a higher priority. Thus, such schemes are mostly practical only for datacenters where both end-hosts and routers are under the control of the same entity (*e.g.*, LSTF [41], pFabric [5]).

While simplistic, our motivating example teaches us two lessons about how we should treat flows of various objectives or CCAs:

Takeaway 1. Immediately enforcing bandwidth fairness e.g., upon arrival of a traffic burst, hurts the performance of existing flows due to the disparity between the CCAs' sending rate and the available bandwidth in the bottleneck link. CCAs might not have information about the dramatic decrease in bandwidth early enough to react gracefully.

Takeaway 2. Flows driven by different CCAs or having distinct objectives should not share the same queue because their perception of congestion differs. As a result, even advanced AQM schemes cannot signal congestion in the right way and at the right time for each of them independently.

3 Confucius Design

In this section, we explain how the takeaways from §2 manifest in the design of Confucius, a scheme that pushes forward the Pareto frontier between fairness and non-volatility. To this end, we explain how Confucius re-allocates bandwidth upon arrival of a burst of new flows to avoid performance volatility. Then, we explain how Confucius splits bandwidth across new and existing (old) flows to achieve equitable performance (fairness).

3.1 Taming volatility through cautious bandwidth re-allocation

To address the performance-volatility problem Confucius leverages a simple yet powerful insight that stems from Takeaway 1: Upon the arrival of a burst, the reduction of the bandwidth that is available to existing (old) flows is inevitable if we want to preserve long-term throughput fairness. Yet, if we gradually and cautiously control the reduction of the bandwidth during the transient period, we can eliminate the disparity between the sending rate of the old flows' CCA and the actual service rate at the bottleneck link, thereby taming volatility.

To understand why there is an advantage in *gradually* controlling the HRT flow's bandwidth allocation compared to directly cutting its available bandwidth to its fair share, we measured the duration of severe delay degradation y. Concretely, y denotes the time interval during which an HRT flow would experience a delay of more than 190 ms of delay⁴. We plot y as a function of the *Available Bandwidth Reduction Factor* (ABRF) for different CCAs in Figure 4(a). We find that CCAs respond very poorly to sudden, large reductions in bandwidth. For instance, reducing GCC's available bandwidth to one-sixteenth of its initial value (i.e., *ABRF* = 16) results in y > 10 seconds stalls of video frames. Interestingly, we observe in Fig. 4(a) that the curve $y = f_{CCA}(ABRF)$, as we denote the relationship between the ABRF and the duration of delay degradation y, follows a super-linear relationship.

To avoid such delay degradation, Confucius *gradually* reduces the available bandwidth for the HRT flow. For instance, to achieve a final ABRF of 16, one might use $log_2(16) = 4$ iterations of bandwidth reduction if the weight is smoothed. Such an exponential (smooth) change in bandwidth share can be achieved by using EWMA and cutting the HRT flow's bandwidth by half at each iteration. This would give the CCA an opportunity to learn about the re-

⁴This is the recommended network delay for video chats by ITU [46]



Figure 4: (a) Duration of delay degradation increases with the available-bandwidth-reduction factor (ABRF). (b) An illustration of how gently reducing available bandwidth helps reduce delay duration. Note that (a) is a log-log plot but (b) is a log-lin plot.



Figure 5: Design overview of Confucius. *w_i* denotes the weight for queue *i* in the scheduling with DWRR.

duced bandwidth allocation through its usual congestion signals while simultaneously mitigating the disparity between the flow's sending rate and available bandwidth at every iteration, thus taming volatility. Figure 4(b) demonstrates, in the ideal case, the value proposition of this approach: instead of scaling *super-linearly*, the duration of delay degradation increases only *logarithmically* with the ABRF (modulated by $f_{CCA}(2)$, a small constant).

Applying a logarithmic dampening factor to the HRT flow's available bandwidth (instead of an instantaneous reduction), Confucius no longer preserves *strict fairness*. Intuitively, that could result in severe damage to short flows. Yet, we prove in §4.2, that Confucius guarantees that the FCT for short flows will *always be within a constant, additive factor* of the FCT under a strictly fair allocation.

3.2 Equitable handling of competing flows

Having explained how Confucius gradually re-allocates bandwidth between old and new flows, we discuss how Confucius actually splits this bandwidth among individual flows. At a high level, Confucius first splits flows to queues and strategically assigns a portion of the available bandwidth to each of them, as illustrated in Figure 5.

Following Takeaway 2, splitting flows into different queues is essential and challenging. Indeed, putting all old flows in a single FIFO queue will lead HRT flows (*e.g.*, Copa) to starvation [8] if flows use heterogeneous CCAs. But, using FQ to split old flows may not be able to provide low latency to the bursty old flows [37].

Confucius splits flows into queues according to their objectives on the premise that flows of similar performance objectives will not hurt each other. To identify the objective of flows in the system, Confucius uses the queue occupancy. We find that flows implicitly demonstrate their preferences and objectives based on how they utilize the bottleneck queue. For example, latency-sensitive applications will choose CCAs that can achieve low latency such as Copa [8] or GCC [16]. Such CCAs achieve low latency by trying to keep the bottleneck queue as short as they can. In contrast, throughput-oriented CCAs (*e.g.*, Cubic) will keep the buffer full to maximize the utilization for the throughput. This allows us to identify the latency preference of flows by their queue occupancy: if one flow has a low queue occupancy, it indicates that (i) that flow tries to not overutilize the queue; and (ii) that flow can co-exist with other flows with similar behaviors.

By grouping flows with similar queue occupancy into the same queue, flows with different queue occupancy will not affect each other. Meanwhile, with a fixed number of queues to schedule between, latency-sensitive flows, no matter bursty or not, will have a consistent latency. Thus, Confucius has a set of queues, each designed to accommodate old flows with different buffer occupancy, and a separate queue dedicated for short flows. Confucius adopts a Deficit-Weighted Round-Robin (DWRR) algorithm to schedule between these queues. When a new flow arrives at the router, Confucius will put it into the short-flow queue. Confucius will periodically measure flow characteristics and reclassify flows as necessary. Doing so allows Confucius to measure flow characteristics accurately. To further increase the robustness of the performance in practice, we introduce hysteresis-based mechanisms for the reclassification of flows. We elaborate on this mechanism in §5.

Having categorized flows according to their objective the next natural question is (i) how to split bandwidth across those categories; and (ii) how long to wait before changing the bandwidth allocation. For the former, our insight is that bandwidth allocation needs to depend on the ratio between the number of old and new flows. For the latter, our insight is to move bandwidth to new flows from old ones so fast as the old flows' CCA has time to react.

In practice, respecting the reaction time of each CCA means that we need to adapt the design of Confucius in various CCAs. To this end, we plot response curves for different CCAs and find that the reaction time of CCAs during bandwidth changes is always above a certain threshold, where Confucius always benefits from gentle adjustments. We could therefore design a uniform weight-adjustment algorithm for flows with different CCAs. In practice, Confucius effectively focuses on the least reactive CCA to make sure all CCAs can have adequate time to react.

4 Age-aware Flow Weights Adjustment

In this section, we dive into Confucius' weight adjustment (§4.1). We then analytically show that this mechanism guarantees bounded performance degradation, both for existing HRT flows and newly-arrived mice flows (§4.2).

4.1 Adjustment Mechanism

Recall that Confucius classifies flows into different queues and uses DWRR to schedule packets across these queues. To assign weights (*i.e.*, service rates) to queues, Confucius uses the following process. For each flow, f, Confucius first computes a weight, w_f ; then, for a given queue, Q, the weight is computed by summing up flow weights of all flows in Q:

$$W_Q = \sum_{f \in Q} w_f \tag{1}$$

A key ingredient in Confucius' design is the computation of per-flow weights. For this purpose, Confucius distinguishes *new flows* from *old flows*. In fact, Confucius groups new flows into a separate queue called Q_{new} (depicted in Figure 5). All old flows which are mapped to $Q_1, Q_2,..,Q_n$ are assigned a flow weight of $w_f = 1$, and are collectively designated by the set \mathscr{F}_{old} . When a new flow arrives, it is first mapped into Q_{new} , and the flow weights of all flows in Q_{new} are then recomputed as follows:

$$w_f = \min\left(\frac{|\mathscr{F}_{old}|}{|Q_{new}|} \cdot 2^{\lambda t}, 1\right), \quad f \in Q_{new}$$
(2)

There are several considerations in the design of Eq. 2:

Age-aware adjustment $(2^{\lambda t})$. As described in §3.1, Confucius gradually reduces the available bandwidth for HRT flows. To achieve this, Confucius gradually increases the weights of the competing new flows. Here, t represents the age (in milliseconds) of the new flow, and λ is a parameter that controls the rate at which the flow weights for mice flows are adjusted – flow weights double every $\frac{1}{\lambda}$ milliseconds. The higher λ is, the faster new flows converge to their fair share of the bandwidth, and the more abrupt the reduction in available bandwidth for HRT flows. We will discuss how λ affects the performance degradation quantitatively in §4.2.

Initial weight $\left(\frac{|\mathscr{F}_{old}|}{|\mathcal{Q}_{new}|}\right)$. If the initial flow weight for new flows is too small, even an exponential growth factor would result in a protracted convergence period for these new flows. In particular, when there are already many old flows, it is hard for few new flows to grab their fair share of bandwidth. Therefore, we scale the initial weight of new flows with the *number of old flows* that are currently active in the router. For each new flow, we set the initial weight to $\frac{|\mathscr{F}_{old}|}{|\mathcal{Q}_{new}|}$, where $|\mathscr{F}_{old}|$ and $|\mathcal{Q}_{new}|$ are the total number of old and new flows, respectively. The intuition behind this particular choice of initial weight is always limiting the bandwidth reduction for old flows to be less aggressive than a factor-of-2 reduction. In this case, the duration of delay degradation can logarithmically scale with the base of $f_{CCA}(2)$, as shown in Figure 4(b).

Upper bound (min(..., 1)). Confucius uses a flow weight threshold of 1 to 'age out' new flows from the Q_{new} queue. Once the flow weight of a flow reaches 1, the flow is no longer considered new, and is moved to one of the other

Parameters and variables:

- *B* Size of each new Web flow.
- *N* Number of new Web flows.
- *k* The responsiveness of a CCA.
- q_0 The delay target that a CCA will try to achieve.
- C The link capacity.
- τ The feedback loop of a CCA (usually one RTT).
- B_0 The initial burst of a new flow (*e.g.*, the initial cwnd [21]).
- PThe scheduling policy.Functions:s(t)Sending rate of the HRT flow of time t.r(t)Available bandwidth of the HRT flow of time t.
- p(t) Number of packets in the queue of the HRT flow.
- q(t) The queueing delay of the HRT flow.

Table 1: Notations

queues based on the output of the Flow Classifier (§5).

Parameter configuration. The choice of λ is an important consideration in the design of Confucius. A large λ (*e.g.*, $\lambda \to \infty$) leads to abrupt reductions in available bandwidth, causing volatility, while a small λ (*e.g.*, $\lambda \to 0$) results in unfairness (or even starvation) for new flows. Moreover, in setting this parameter, we need to be aware that different flows, particularly flows with different CCAs, respond differently to the same congestion signals (*e.g.*, Copa requires 5 RTTs to effectively reduce its sending rate, while BBR's response time is dictated by its probing interval of 6-8 RTTs). Consequently, we seek to configure λ so that the available bandwidth drops as fast as possible, subject to the responsiveness of the underlying CCAs.

To deal with the heterogeneity of CCAs on the Internet [40], we set λ as the inverse of *the probing period of the least responsive, latency-sensitive CCA*. This ensures that even the least responsive CCA can smoothly react to bandwidth changes. Based on the experiments depicted in Figure 4(a), BBR is the least responsive CCA with a probing period of 6-8 RTTs. Therefore, given a typical RTT of 30-50 ms for Web services [55], we set λ =0.004 (ms⁻¹) to have a doubling interval of $\frac{1}{\lambda}$ =250 ms. Experiments in §7.2 demonstrate satisfactory results for not only BBR but also several other CCAs.

4.2 Theoretical Analysis

In this subsection, we demonstrate analytically that Confucius can provide consistent performance for both HRT and Web flows. In the scenario of a single HRT flow competing with N new flows (*e.g.*, Figure 2(a)), we show that Confucius guarantees bounded delay degradation for the existing flow, while yielding FCTs for Web flows that are within a constant additive factor of what FQ provides. We list the notations we will use in Table 1.

Scenario overview. Consider a single HRT flow running by itself on a bottleneck link. At t = 0, N new flows (e.g., Web flows), each with size B, join the same bottleneck link and share the buffer with the existing flow. We analyze the performance degradation for both the existing and new flows.

CCA model. We adopt a simplified delay-convergent CCA model [4, 7], where the delay-sensitive CCA has a target queueing delay, q_0 . The CCA seeks to maintain its queueing delay around this target, increasing or decreasing its sending rate proportional to the difference between the current delay and the target:

$$\frac{\mathrm{d}s(t)}{\mathrm{d}t} = -k \cdot (q(t-\tau) - q_0) \tag{3}$$

Here, s(t) is the flow's instantaneous sending rate, q(t) the instantaneous queueing delay it experiences, and τ is the feedback loop of the CCA. Finally, k is a coefficient representing the CCA's responsiveness. We discuss how k varies for different CCA's in Appendix A.5.

Delay model. Next, we analyze the number of packets in the queue, p(t), at time *t*. At any t > 0, this quantity satisfies the following relationship:

$$p(t) = p(0) + \int_0^t \left(s(t') - r(t') \right) dt'$$
(4)

where $p(0) = q_0 \cdot C$ is the buffer occupancy in steady state with *C* being the link capacity. If r(t) represents the instantaneous service rate (*i.e.*, available bandwidth) for the HRT flow at time *t*, then the queueing delay can be written as follows:

$$q(t) = \frac{p(t)}{r(t)} = \frac{1}{r(t)} \left(p(0) + \int_0^t \left(s(t') - r(t') \right) dt' \right)$$
(5)

There are two metrics that we focus on. The first is the **maximum queueuing delay** experienced by the HRT flow, q_P^{max} , for a given scheduling policy *P*:

$$q_P^{max} = \max_{t>0} q(t) \tag{6}$$

In this context, we find that q_P^{max} serves as a good proxy for the duration of delay degradation since it establishes a *lower bound* on how quickly previously-queued packets of the HRT flow drain from the bottleneck queue.

The second metric is the **FCT**, T, for the new flows, which can be expressed as follows:

$$\int_0^T \left(C - r(t') \right) \mathrm{d}t' = N \cdot B \tag{7}$$

Since FQ provides the 'fairest' bandwidth allocation (representing one extreme of the fairness vs. non-volatility tradeoff), we use the FCT for Web flows under FQ, T_{FQ} , as our baseline. We then calculate $T_P - T_{FQ}$ as the degree to which policy *P* degrades Web flow performance relative to FQ.

Having established our two figures of merit (*maximum* queueuing delay and FCT degradation to FQ), we evaluate four scheduling policies: FQ, FIFO, CBQ (1:1), and Confucius. We find that the available bandwidths for these policies



Table 2: Approximations for different schedulers on their maximum delay (q_P^{max}) and FCT degradation $(T_P - T_{FQ})$. In the transient scenarios, existing scheduling policies have either unbounded delay degradation, or unbounded flow completion time degradation. The unbounded terms with workload changes (*N* and *B*) are marked in red.

satisfy the following relationships:

$$r_{FQ}(t) = \frac{C}{N+1} \qquad (t>0) \qquad (8a)$$

$$r_{FIFO}(t) \leqslant C \cdot \frac{Cq_0}{Cq_0 + NB_0} \qquad (t > 0) \qquad (8b)$$

$$r_{CBQ}(t) = \frac{C}{2} \qquad (t > 0) \qquad (8c)$$

$$r_{\text{Confucius}}(t) = \max\left(\frac{C}{2} \cdot 2^{-\lambda t}, \frac{C}{N+1}\right)$$
 (t > 0) (8d)

where for FIFO, B_0 is the initial burst size of these new flows (*e.g.*, the initial congestion window in TCP). We then solve for the performance degradation of the HRT flow, q_P^{max} , and FCT degradation of mice flows, $T_P - T_{FQ}$, with the differential equation in Eq. 5 using Laplacian transforms. We summarize the *approximate* results in Table 2 and leave the analytical details to Appendix A.

For FQ and FIFO, we observe that the duration of delay degradation scales linearly with the number of new flows, N, and is therefore unbounded, where N can go to more than 100 in some Web pages (Fig. 1(a)). Intuitively, as the number of flows joining the bottleneck link increases, the more drastically the available bandwidth for the HRT flow drops, resulting in significant volatility.

In the case of CBQ, pre-labelling the HRT flow enables the policy to give it a fixed share of bandwidth, resulting in bounded delay degradation. However, if the weights are not appropriated precisely (i.e., do not match the number of flows in each queue), CBQ converges to an unfair solution, and the degradation in FCT for mice flows becomes unbounded (§2).

Finally, Confucius yields bounded performance degradation for *both sets of flows*. On one hand, Confucius ensures that the delay degradation for HRT flows is a constant that depends only on the CCA's queueing delay target (q_0), the responsiveness of the CCA (k), the duration of its feedback loop (τ), and the decay parameter (λ)⁵. On the other hand, Confucius can also ensure the FCT degradation for mice flows is bounded by an additive constant factor with respect to the decay parameter (λ), which goes to negligible with the

⁵In practice, when using Copa with an RTT of 40ms, the approximation bound $q_{Confucius}^{max}$ from Table 2 is roughly 640ms. As we show experimentally in §7.2, the delay degradation using Confucius is much lower than this.





Figure 6: The relationship between queue utilization and delay in difare simulated with real WiFi traces from [38].

Figure 7: Confucius's hysteresis reclassification mechanism for flows. Only when the buffer occupancy of a ferent CCAs. Experiments flow has significantly deviated from the current class will it be moved to another class.

increase of the flow sizes.

5 **Occupancy-aware Flow Classification**

As described in §3.2, Confucius seeks to classify flows into groups, each with a dedicated queue based on how aggressively they consume buffer space. In this section, we first present our design consideration when classifying flows into different queues (§5.1). We then present our hysteresisbased mechanism to robustly classify the flows (§5.2).

Design Considerations 5.1

Confucius puts short flows into a separate queue Q_{new} and classifies long flows with different buffer occupancy aggressiveness into separated queues. Therefore, we need to set up a series of queues Q_1, Q_2, \dots, Q_n to accommodate flows with different buffer occupancy.⁶ Queue indices increase with buffer target *i.e.*, Q_1 will be shorter than Q_3 , as shown in Fig. 5. Specifically, we denote the buffer occupancy that queue Q_i targets as $q_0^{(i)}$. Realizing this brings with two questions. First, how many queues we should set for routers to accommodate heterogeneous flows. Second, how to match the flow's buffer occupancy with the target $q_0^{(i)}$ that queue Q_i tries to maintain. We will answer these two questions in the following.

Number of queues to set. The first thing to determine for instantiating Confucius is how many queues we should set on the router. To answer this, we need to estimate how many CCA groups of distinct queue behavior there are in the wild. To this end, we measure the buffer occupancy of 7 CCAs (the top-5 CCAs used in websites [40] plus two recent latencysensitive CCAs, namely GCC and Copa), over real-world bandwidth traces [38]. We further measure the network RTT at the sender, and the application-layer performance (including the delay in the socket buffer and retransmissions). A lower RTT and application delay indicate that such a given CCA is more latency-sensitive. As we can see in Fig. 6, GCC, Copa, and Vegas have a low network RTT and application delay. Thus, delay-sensitive applications can choose these CCAs to achieve lower latency. Cubic, Yeah, and Illinois have a much higher delay, while BBR is in-between. We observe that the CCAs concentrated in three clusters (dashed

⁶We use per-queue buffer occupancy as maximum queue length.

circles in Fig. 6). Concretely, GCC, Copa, and Vegas have a queue occupancy of less than 20%; Cubic, Illinois, and Yeah have a queue occupancy of more than 80%; and BBR's queue occupancy stays in-between. Therefore, we set three queues and use the average queue occupancy in these three clusters as our targets $\{q_0^{(i)}\}$. We expect other CCAs to fall into one of these three representative categories, if not we can configure Confucius to work with more queues.

Practical challenges. While one can characterize flows offline as we did above, Confucius cannot use the same approach online. Indeed, Confucius works at line-rate and flows will not come prelabeled with their CCA. Inferring the buffer aggressiveness of a flow is challenging in practice for the following reasons. First, the buffer aggressiveness of flow may take a long time to manifest. For example, Confucius will not be able to characterize short flows lasting only a few RTTs (§2). Second, the network conditions will also affect the measurement, effectively deceiving Confucius. For example, a drop in the available bandwidth will result in an increase in the buffer occupancy [38], which does not necessarily mean that flow is aggressive in occupying the buffer. Finally, a flow's buffer aggressiveness can change over time. For example, a Cubic flow throttled/congested elsewhere (on a different router) will not be aggressive in buffer occupancy (although Cubic would). Such a cubic flow can share the queue with other delay-sensitive flows. However, when the bottleneck moves to the current router, this Cubic flow will be aggressive on the buffer occupancy. Therefore, we need to periodically monitor the buffer share that each flow occupies within its current queue and re-consider its classification. We elaborate on our algorithm in the next subsection.

5.2 Hysteresis-based Adjustment

To allow re-classifications while avoiding oscillations in flows' classification, we introduce a hysteresis mechanism. The overall classification steps are as follows:

Classification of new flows. For the flow *f* in the new-flow queue \mathscr{F}_{new} , when the flow is ready (its weight reaching one) to be moved out from the new-flow queue Q_{new} to one of the old queues (which we elaborate on in §4.1), we measure the buffer occupancy of that flow q_f *i.e.*, the number of packets of this queue that belong to flow f. We then find the queue iwith the nearest O_i to accommodate this flow.

Periodic adaptation. Confucius periodically examines flows and queues and moves flows accordingly. First, intraqueue examination identifies and moves flows that are outstanding among flows in the current queue (e.g., a flow that is more aggressive compared to the other flows). Second, the queue-level examination checks if the length of a queue fits the queue's control target.

1. Intra-queue examination. Confucius examines the buffer each flow occupies and compares it with its fair share. Specifically, if the buffer occupancy of a flow $\left(\frac{q_f}{\sum_{g \in Q_i} q_g}\right)$ is larger than its fair share $\left(\frac{1}{|Q_i|}\right)$, i.e.:

$$\frac{q_f}{\sum_{f \in Q_i} q_f} \ge \frac{1}{|Q_i|} + \alpha \tag{9}$$

where $\alpha > 0$ is a hysteresis, that flow is too aggressive in the current queue. Confucius wll promote that flow from queue Q_i to Q_{i+1} to keep Q_i near its control target. Similarly, a flow with an outstandingly lower buffer occupancy that its fair share in the queue, i.e.:

$$\frac{q_f}{\sum_{f \in Q_i} q_f} \leqslant \frac{1}{|Q_i|} - \alpha \tag{10}$$

will be demoted from queue Q_i to Q_{i-1} . Here we set α to 10% based on our previous observations in Fig. 6. Our evaluation in §7 shows that the performance of Confucius is not sensitive to the workloads and CCAs.

2. Queue-level examination. Confucius verifies that the length of each queue is within the target. If the length of a queue exceeds a safe region between the control target of any of the two neighbor queues, Confucius moves all flows in the current queue to a higher or lower queue, as shown in Figure 7. This is needed because the intraqueue examination only focuses on cross-flow relative occupancy. Thus, it cannot identify instances in which flows in the current queue are comparably aggressive but more aggressive than the target of this queue. For example, assume that there are two Cubic flows that were previously classified to Q_1 (the least aggressive) due to being throttled elsewhere or measurement errors. When these Cubic flows start to be aggressive in buffer occupancy, Confucius would need to move them to a different queue to protect latency-sensitive flows that may join.

While seemingly complex, these operations are well within the capabilities of Linux-based edge routers. In fact, we have implemented a complete prototype in §6.

6 Confucius implementation

Implementing Confucius in Linux kernel has some challenges. We discuss them and our solutions below.

Order-preserving during reclassification. Flows can be moved to another class in the runtime. Thus, we need to ensure the order-preservation during the reclassification of Confucius of a certain flow. In response, we adopt a virtual class design in Confucius. During the enqueue process of new packets, we bind the sk_buff to each flow. During the dequeue process, we search for all flows that are bound to the determined class and dequeue the packet with the earliest enqueue time. In this way, when moving a flow to another class, we can just rebind the pointer of the flow from the previous class to the new class.

Reducing computational overhead. To implement Confucius in Linux kernel and optimize the execution overhead, we need to strictly optimize the computational overhead. Specifically, we have the following two implementations: (*i*) Bit-shifting for exponential operations. Confucius reweights flows based on their ages with an exponential function, yet the floating number calculation in the kernel is expensive. Therefore, we quantize the weight of new flows with the unit of $\frac{1}{128}$. We follow the implementation of EWMA and use bit shifts for the exponential changes of the weights, i.e., left shifting the weight by one bit every $\frac{1}{\lambda}$ milliseconds.

(ii) Periodical reweighting and reclassification. The reweighting and reclassification do not necessarily need to happen for each packet. For the reweighting, as we discussed before, we only need to reweight for a certain flow every $\frac{1}{\lambda}$ milliseconds. When we set $\lambda = 0.004$, this means to reweight every 250 ms. For the reclassification, we should at least observe the results after moving one flow to a new class for a certain period to measure the queue utilization, which should at least be more than one RTT to fully observe the behavior of the sender in the new class. Therefore, we also reclassify the flows in a periodic way – we set the reclassification period to 100ms.

7 Evaluation

We first present our experimental setup (§7.1); then we evaluate Confucius by answering the following questions:

- How does Confucius navigate the fairness-volatility tradeoff compared to baselines on real-world Web traces? Confucius protects an HRT flow from delay degradation when competing with loading 95% of websites with various CCAs. In contrast, with classless schemes such as FQ or FIFO, the percentage is less than 30% (§7.2).
- How sensitive is Confucius to changes in workload? We vary the size and number of flows and find that Confucius remains consistently performant (in terms of delay degradation for the HRT flow and PLT degradation for Web flows) always following our theoretical analysis (§7.3).
- How does Confucius scale if there are multiple flows with different CCAs? We test Confucius under the coexistence of flows with different CCAs, and demonstrate that Confucius can correctly separate flows based on their behaviors and provide consistent performance to all of them (§7.4).
- How does Confucius perform in the testbed prototype? We integrate Confucius into the qdisc module in Linux kernel 4.4.0 and evaluate Confucius with real HTTP request traces. Confucius can reduce the duration of delay degradation by more than 60% with reasonable overhead (§7.5).
- How does Confucius perform in different settings? We show that Confucius is still able to outperform baselines when working with multiple HRT flow competition, bandwidth-probing CCAs, and different bottlenecks (§7.6).



7.1 Experiment Setup

Ns-3 **setup.** In §7.2-7.4, we evaluate the performance of Confucius with ns-3.34. We set up a linear topology and limit the capacity of the bottleneck link to 20Mbps, which is the average bandwidth in the WiFi traces from [38], as shown in Figure 8. The round-trip propagation delay is set to 40ms in total based on measurements from [38]. We further change the RTT and the bottleneck in §7.6. We adopt a videoconferencing application in ns-3, of which the flow is an HRT flow. We connect the HRT flows to different delay-sensitive CCAs, including Copa [8], GCC [16], BBR [15] etc. The Web flows use the default CCA in Linux kernel – Cubic [31].

Linux kernel setup. In §7.5, we implement Confucius as a kernel module of queue disciplines (qdisc) in traffic control in Linux kernel 4.4.0 and evaluate the performance of Confucius on a machine with Intel Xeon E5-2620 v4 CPU. We run the official CCP-based implementation of Copa [6].

Web traces. To compose a realistic and relevant dataset of web traffic, we followed two steps. First, we collected the Alexa Top-1000 websites [2] (July 2022, distribution in Fig. 1). Second, we loaded each of these websites and measured the size of the HTTP requests they trigger. Having this dataset we replay the traces from these 1000 websites to test a variety of scenarios. We plan to release our dataset.

Baselines. We compare the performance of Confucius with multiple scheduling and AQM baselines. For the parameters in these baselines, we use the default parameters in the Linux kernel 4.4.0 or ns-3.34.

- (1) FIFO and (2) FQ, the two most used schedulers.
- (3) SJF (shortest job first) prioritizes short flows over long flows. Since we cannot know which job is shorter, we approximate a job's length with its age (namely, PIAS [9]), *i.e.*, always prioritizing flows that are newer, which is exactly opposite to what Confucius tries to do.
- (4) HHF [22] heavy-hitter filter differentiates between small flows and heavy-hitters, giving each category a fixed share of bandwidth.
- (5) CoDel [43] and (6) RED [26] will drop packets before the queue overflows to notify the sender about the congestion.
- (7) CBQ puts flows from different applications into different classes based on their labels. We set the weights for two classes to 1:1 and 1:5 and evaluate performance, respectively.
- (8) StrictPriority strictly prioritizes traffic from HRT flows if they are labeled accordingly.

(9) DualQ [49] is a recently proposed scheduler in L4S [14] that protects latency-sensitive flows with labels.

Metrics. We focus on the following metrics in experiments.

- **Duration of delay degradation** for video frames is the duration for which the delay of the video frame is greater than 190 ms. This directly reflects users' experiences on video stalls [38, 46, 56]. We use this metric to evaluate how volatility affects the performance of the HRT flow.
- **Page Load Time (PLT)** is the time till the last HTTP request in a web page is completed. We use this metric to evaluate the performance of web traffic. PLT degradation refers to the increase of delay compared to FQ.

Besides, we also evaluate other metrics in different experiments, which we will elaborate on accordingly.

7.2 Confucius under a realistic workload

Simulation scenario. At t=0 we start an HRT flow from the videoconferencing application. At t=10s we reconstruct the requests associated with one of the Alexa Top websites. All flows are active *i.e.*, we are not replaying pre-recorded traffic. We run the same scenario 1000 times, once per website. In each run, we measure the duration where the frame delay of the video flow is larger than 190 ms (delay degradation). We also measure the loading time of the web pages from different websites. We repeat the whole experiment three times, each considering a different CCA for the HRT flow. We summarize and present the average results in Figure 9.

Confucius strikes a balance between video and web performance that is consistent across CCAs. In Figure 9(a), we observe that classless schedulers (*i.e.*, those that do not use a label from the end host and are marked in blue) suffer from long video stalls. For example, when using FQ and FIFO, the video flow experiences delay degradation for 600 ms on average. Classful schedulers (i.e., those that require labels on packets and are marked in green) protect prelabeled video flows, but considerably degrade the PLT for the Web traffic. Worse yet, as we discussed in §2, it is unrealistic to assume that an end-host will correctly label all traffic. Confucius not only reduces the duration of stuttering compared to existing classless schemes, but is almost on par with classful schemes. Moreover, Confucius maintains a low PLT for Web flows. Notably, Confucius pushing the Pareto front of the classless schedulers (the dashed blue line) forward. The results are similar for Confucius when the video flow uses other CCAs such as BBR or GCC, as shown in Figures 9(b) and 9(c).

Confucius protects the HRT flow from traffic from more than 95% of the websites, while not sacrificing their per-formance. We further break down the distribution for different websites in Figure 9(a) into Figure 10. Figure 10(a) which presents the distribution of delay- degradation duration when the video flow encounters Web flows from different websites in the dataset. With FQ or FIFO, the HRT flow will experience delay degradation (frame delay >190ms) for



Figure 9: The trade-off between the performance of the HRT flow (duration of delay degradation) and Web flows (page loading time). The dashed line denotes the Pareto front of classless baselines. We change the CCA that the HRT flow uses in different subfigures and observe similar performance improvements of Confucius in all experiments.



Duration of delay degradation (ms) (a) Duration of delay degradation of the HRT flow (CDF over websites).





(b) PLT degradation of Web flows to FQ (CDF over websites).



the period when Web flows arrive

(CDF over packets, log-scaled).

(c) The max frame delay of the HRT flow when Web flows arrive (CDF over websites).

Figure 10: The distribution of results in Fig. 9(a).

more than 70% of websites, half of which will even last 520 ms (in the case of FIFO) and 660 ms (in the case of FQ). In contrast, with Confucius, the HRT flow will not experience any delay degradation when encountered with 95% of the websites, comparable to CBQ. Importantly, Confucius does not over-penalize web traffic – the PLT of 90% of websites are only increased by less than 360 ms against FQ, as shown in Figure 10(b), which mostly corroborate our previous theoretical analysis. We further present the distribution of maximum experienced delay, and the delay of all packets of the HRT flow when competing with different websites in Figures 10(c) and 10(d). This further demonstrates that Confucius is able to control the latency volatility in not only the duration of delay degradation but also directly the raw delay. The results when using GCC and BBR are similar.

7.3 Confucius under workload changes

In this subsection, we test our theoretical analysis in a more practical setting. Concretely, we investigate whether Confucius can provide consistent performance in different workloads. To this end, we vary the workload by changing the number of flows in a Web page and the size of Web flows. We measure the duration of delay degradation in different scenarios and the degradation on the PLT against FQ. **Confucius delay degradation is bounded by a theoretically-estimated threshold,** confirming our analysis. We vary the number of flows in the Web page from 5 to 100, each with the size of 15KB and summarize our results in Figure 12(a). The duration of delay degradation for FQ and FIF0 increases with the number of flows. For example, when the number of Web flows goes to 60, the HRT flow experiences a degraded delay for more than half a second when using FQ or FIF0. On the contrary, Confucius maintains zero delay degradation in this setting, similar to CBQ (which uses labels). We further compare the experimental results with our previous analysis in §4.2. As we can see in the yellow dashed line in Figure 12, the experimental results corroborate our previous theoretical analysis on the performance of Confucius in Table 2.

We further change the size of Web flows (from short flows to long flows) and see if Confucius is capable of handling all types of competing traffic. We vary the size of Web flows from 15KB to 9MB, and run 5 flows with the same size to compete with the HRT flow. With the increase of the size of flows, the competing flows are changing from short flows (e.g., Web) to long flows (e.g., FTP). In this case, when using FIFO, the HRT flow will suffer from drastic delay degradation due to failure to provide inter-CCA fairness across flows, as shown in Fig. 13(a). The HRT flow using FQ also has a long delay degradation of hundreds of milliseconds. In contrast, Confucius is still able to achieve both negligible duration of delay degradation for the HRT flow and bounded degradation of the PLT for the Web flows in the same time.

7.4 Heterogeneous Flow Classification

In this subsection, we zoom in on Confucius's flow classification mechanism and investigate its effect on delay and fairness. We find that Confucius groups flows of the same CCA together, without any prior knowledge, which in turn leads to better performance compared to the baselines.

We simultaneously run HRT flows of four different CCAs: one Cubic flow, one BBR flow, one GCC flow, and one Copa flow for 100 seconds. We plot the frame delay for each flow over time in Figure 11(a). In this experiment, we also measure the JFI in Figure 11(c) to present the fairness when using different schemes. We also compare the results (the delay of the Copa and GCC flow, and the JFI among all flows) of the same experimental settings with other sched-



Figure 11: Four flows with different CCAs (Cubic, BBR, Copa, and GCC) run in the same bottleneck router. We present the frame delay and classification results of these flows when using Confucius over time in Figure 11(a) and 11(b). We also compare the fairness (JFI) and the delay of latency-sensitive flows (Copa and GCC) of Confucius and baselines in Figure 11(c).







Figure 13: Performance consistency in workloads with different *size* of Web flows, each experiment having 5 flows.

ulers in Figure 11(c). We find that with Confucius the Copa and GCC flows maintain a low end-to-end delay even though they share the bottleneck link with Cubic and BBR. Mean-while, they also enjoy a reasonable fair share of the band-width – the JFI in this experiment is 0.98 in Figure 11(c).

To understand Confucius's superior performance, we look at its classifications over time and verify that Confucius works in practice as we expect. We make two observations. First, Confucius can classify flows using different CCAs into different queues. As shown in Figure 11(b), the Copa and GCC flows can be stably classified into the low occupancy queue $(Q_1, blue)$, the BBR flow into the median occupancy queue (Q_2 , yellow), and the Cubic flow into the high occupancy queue (Q_3 , green). This follows our previous observation in Figure 6 – Copa and GCC both demonstrate similar low buffer occupancy, while Cubic occupies the buffer aggressively, and BBR in the middle. In this way, flows with different queue occupancy can be isolated from each other. Moreover, we notice that the Cubic flow can temporarily be in the same queue as BBR, as shown in the yellow lines in the green bar in Figure 11(b). This is, in fact, beneficial for Confucius as the Cubic flow has (at times) a low queue oc-



Figure 14: Results over our Linux kernel-based testbed.

cupancy in its probing period. Second, flows with different CCAs can co-exist in the same queue as long as they have similar buffer occupancy. In this experiment, Copa and GCC flows are put into the same queue since they have similar buffer occupancy. As we can see in Figure 11(a), these two flows still have consistent low latency all the time.

7.5 Testbed Experiments

We also evaluate the performance of Confucius in the Linux kernel. We find that Confucius is capable of achieving significant benefits in kernel-based implementations while only adding marginal processing delay.

We run an iperf3 flow, set the CCA to Copa, and measure the delay reported by iperf3 for the latency-sensitive flow. We then set up an HTTP server based on Python to serve the client with the Web traces we collected. We also measure the computational overhead of Confucius and the baselines. We log the processing time for the enqueue and dequeue operation in Linux tc, where the reweight and reclassification in Confucius are both implemented.

As shown in Figure 14(a), Confucius reduces the duration of delay degradation by more than 60% without the need for labels on each packet. This result is similar to our simulation in Figure 9(a). Moreover, 86% of websites when using Confucius do not suffer from delay degradation. Notably, this number is only 56% and 30% for FIFO and FQ.

We vary the number of long-running flows to observe how the processing time changes. Note that the processing time of Confucius is insensitive to the number of short flows, as they all belong to the new-flow queue. As shown in Figure 14(b), Confucius slightly increases the processing time for each packet compared to FQ. However, even if there are 100 concurrent long-running flows on the same queue discipline, the per-packet processing time is still 5 μ s, indicating a processing rate of 200 kpps, or a bitrate of 100 Mbps~2.4 Gbps (depending on the packet size). Note that Confucius is mainly designed to be deployed on the last-mile routers such as home routers. This can satisfy the daily usage of home access points or last-mile routers. We stress that the kernel implementation of Confucius can be further optimized for high-performance execution in the future. We leave the further exploration of Confucius over numerous flows (*e.g.*, in the routers in the core network) in the future.

7.6 Microbenchmarks

We further evaluate the performance of Confucius in a series of microbenchmarking settings. In Appx. B.1, we demonstrate that the hysteresis mechanism of Confucius (§5.2) is able to work with bandwidth-probing CCAs (e.g., BBR) and stably and correctly classify flows. We further show that Confucius will not have any side effects if the bottleneck is not the router where Confucius is deployed in Appx. B.2. Finally, we also show that even if there are multiple HRT flows competing at the same time, Confucius is still able to handle those flows simultaneously and provide significant performance improvements against baselines (Appx. B.3).

8 Related Work

Queue management solutions. There are numerous of efforts on queue management for routers. Besides the solutions we introduced in §2 and §7.1, there are even more AQMs proposed back to 2000s [17, 24, 25, 35, 44]. As we discussed in §2, these AQMs cannot meet the requirement of providing consistent performance and fairness during transient events. At the same time, recent delay- or rate-based CCAs, which are commonly used in real-time flows, are not responsive to such dropping-based or ECN marking-based AQMs. Further, datacenter flow scheduling schemes [5,9] or buffer management [3] are designed for homogeneous flows (sometimes with labelled packets) and are not suitable for heterogeneous flows in home routers in the wide-area network.

Optimizations for latency consistency. Multiple schemes aim at offering consistent low latency for latency-sensitive applications such as videoconferencing either at the end hosts [8, 16, 28], and/or in-network [30, 38]. Besides, there are also application-specific solutions such as frame-rate or bit-rate adaption [28, 39] and latency compensation [47]. Confucius is orthogonal to such solutions.

Inter-flow fairness. The fairness across flows dates back to the birth of congestion control [33]. Recent work analyzes fairness in different scenarios [45] or defines fairness with different applications [51,52]. There are also measurements investigating the inter-CCA fairness with emerging CCAs [32,42,48]. Instead, Confucius is also able to maintain the long-term fairness across flows.

9 Conclusion

In this paper, we propose Confucius, the first queue management scheme to balance fairness against volatility. Confucius achieves this by grouping flows based on their latency preferences, which it infers by observing their buffer occupancy over time. Confucius gradually adjusts per-flow weight, and uses those weights to devise the per-queue service rate. Doing so allows Confucius to mitigate volatility that degrades the performance of HRT flows. Linux kernel-based emulation and ns-3 based simulations show that Confucius can reduce the number of websites causing delay degradation for video flows from 70% to 5% with negligible overhead.

This work does not raise any ethical issues.

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A Fluid Model Analysis

In this section, we present the details about how we get the results in Table 2.

A.1 Fair Queueing (FQ)

Substituting Eq. 8a into Eq. 3, and taking the derivatives, we have:

$$\frac{\mathrm{d}^2}{\mathrm{d}t^2}s(t) + k \cdot s(t-\tau) = k\frac{C}{N+1} \tag{11}$$

With loss of generality, we assume $s(\tau) = C$, meaning that before *N* flows join, the sending rate has converged to the link capacity. Note that the measurement loop is usually much smaller than the control loop, i.e. $\tau \ll 1/k$, we then solve the differential equation above as:

$$s(t) = \left(1 - \frac{1}{N+1}\right) \cos\left(\sqrt{k}(t-\tau)\right) + \frac{1}{N+1}C \quad (t > \tau) \quad (12)$$

Since we are considering the transient conditions with a small *t*, where *t* is less than the first time of s(t) = r(t), we approximate the formula above with Taylor's expression:

$$s(t) = C - C \frac{N}{N+1} \cdot \frac{k}{2} \cdot (t-\tau)^2 \quad (t > \tau)$$
(13)

Combine with Eq. 5, we have

$$q(t) = N\left(q_0 + \tau - \frac{N}{6k(N+1)}(t-\tau)^2\right)$$
(14)

We then have the maximum queue delay as:

$$q_{FQ}^{max} \ge q\left(\tau + \sqrt{2}k\right) = N\left(\frac{2}{3}\sqrt{\frac{2}{k}} + q_0 + \tau\right)$$
(15)

As N increases, q_{FIFO}^{max} will also increase.

Meanwhile, by substituting the available bandwidth in Eq. 7 with Eq. 8a, we have T_{FO} :

$$T_{FQ} = \left(1 + \frac{1}{N}\right) \cdot \frac{NB}{C} \tag{16}$$

A.2 FIFO

Since the share of available bandwidth is proportional to the share of buffer occupancy, we estimate $r_{FIFO}(t)$ as in Eq. 8b. Similar to FQ, we can get:

$$q(t) \ge \frac{1}{C} \left(\frac{NB}{q_0 C}\right) \left(q_0 C + \int_0^t s(t') dt' - tC \frac{1}{\frac{NB}{q_0 C} + 1}\right)$$
(17)

and then

$$q_{FIFO}^{max} \ge q\left(\tau + \sqrt{\frac{2}{k}}\right) \tag{18}$$

Consequently

$$q_{FIFO}^{max} \ge \left(\frac{NB_0}{q_0C} + 1\right) \left(\frac{2}{3}\sqrt{\frac{2}{k}} + q_0 + \tau\right) \tag{19}$$

A.3 DRR

As we can see from Eq. 8c, the $r_{DRR}(t)$ is a special case of $r_{FQ}(t)$ with N = 1. Therefore, according to the delay degradation result in Eq. 15, we have:

$$q_{DRR}^{max} \ge \frac{2}{3}\sqrt{\frac{2}{k}} + q_0 + \tau \tag{20}$$

The FCT satisfies:

$$T_{DRR} = \frac{2NB}{C} \tag{21}$$

In this case,

$$T_{DRR} - T_{FQ} = \frac{(N-1)B}{C}$$

diverges with N and B.

A.4 Confucius

For Confucius, we have:

$$r_{\text{Confucius}}(t) = \frac{C}{2}e^{-\lambda t} \quad (t > 0)$$
(22)

we could then solve out (using Laplacian transform, and solve with undetermined coefficients):

$$s(t) = Ae^{-\lambda(t-\tau)} + B\cos\sqrt{k}(t-\tau)$$
(23)

where

$$A = C \cdot \frac{k}{2} \cdot \frac{1}{\lambda^2 + k \cdot e^{\lambda \tau}}$$
(24)

$$B = C - A \tag{25}$$

Still using Taylor's approximation:

$$\begin{aligned} (t) &= A \left(1 - \lambda (t - \tau) \right) + B \left(1 - \frac{1}{2} k (t - \tau)^2 \right) \\ &= -\frac{B}{2} k (t - \tau)^2 - \lambda A (t - \tau) + A + B \end{aligned}$$
 (26)

Denote the root of s(t) = 0 on $t > \tau$ as $t_0 + \tau$ ($t_0 > 0$), we then have

$$q(t_0 + \tau) = 2e^{\lambda(t_0 + \tau)} \left(q_0 + \tau - \left(t_0 - \frac{\lambda A}{2C} t_0 - \frac{kB}{6C} t_0^3 \right) \right)$$
(27)

where t_0 satisfies:

S

$$t_0 = \frac{-\lambda A + \sqrt{(\lambda A)^2 + 2Bk(A+B)}}{Bk}$$
(28)

Thus, we have a bound of $q_{Confucius}^{max}$:

$$q_{\mathsf{Confucius}}^{max} \approx q(t_0 + \tau) = f(\lambda; k, \tau, q_0)$$
(29)

independent of B or N. bounded. We expand the series as:

$$f(\lambda) = F_0 + F_1 \lambda + F_2 \lambda^2 + o(\lambda^2)$$

$$F_0 = 2q_0 + 6\tau + \frac{8}{2\sqrt{k}}$$

$$F_1 = \frac{10}{3k} + 2q_0 \tau + 2\tau^2 + \frac{4q_0}{\sqrt{k}} + \frac{16\tau}{3\sqrt{k}}$$

$$F_2 = \frac{4q_0}{k} + \frac{6\tau}{k} + q_0 \tau^2 + \tau^3 + \frac{6q_o \tau}{\sqrt{k}} + \frac{11\tau^2}{\sqrt{k}}$$
(30)



Figure 15: The theoretical estimation from Confucius under different parameter settings.





Figure 16: The hysteresis design in Confucius (§5.2) is able to absorb the fluctuations caused by probing from CCAs.

Figure 17: When the bottleneck is elsewhere, Confucius maintains the same performance as existing mechanisms.

Given that $\frac{1}{k} \ll q_0, \tau$, we can simplify and upper bound them into:

$$q_{\mathsf{Confucius}}^{max} \leqslant 6q_0 + 15\tau + \frac{8\lambda}{k} + \frac{(10q_0 + 15\tau)\lambda^2}{k} \tag{31}$$

We further plot the unsimplified bound in different k and other parameter settings:

The FCT difference over the fair share for new flows is also bounded compared to other baselines. The FCT of N flows with B bytes, T for each flow basically follows:

Recall that $r(t) = \max(C - \frac{C}{2}2^{-\lambda t}, \frac{N}{N+1}C)$, we thus have

$$T_{\text{Confucius}} = \frac{(N+1)B}{C} + \frac{1}{\lambda} \cdot \left(\frac{1}{2} - \frac{1}{N}\log_2\frac{N+1}{2} - \frac{1}{2N}\right) \quad (32)$$

where $t \ge \frac{1}{\lambda} \log_2 \frac{N+1}{2}$. In this case,

$$T_{\mathsf{Confucius}} - T_{FQ} \leqslant \frac{1}{\lambda} \cdot \left(\frac{1}{2} - \frac{1}{N}\log_2\frac{N+1}{2} - \frac{1}{2N}\right) \leqslant \frac{\log_2 e}{\lambda}$$
(33)

A.5 Responsiveness for CCAs

For different CCAs, we can fit their responsiveness k based on their probing period in the steady state. From the differential equations in Eq. 3 and Eq. 5, during the steady state where $r(t) \equiv C$, we can solve that the sending rate s(t) follows:

$$s(t) = C + A\cos(\sqrt{kt} + \varphi) \tag{34}$$

where A and φ are undetermined coefficients. In this case, we can know that the probing period of a CCA is $\frac{2\pi}{\sqrt{k}}$. From the respective design of CCAs, the probing period for Copa is 5 RTTs, and for BBR is 8 RTTs. For example, when RTT is 40 ms, we will have $k_{Copa} = 0.001 \ (ms^{-2})$, $k_{BBR} = 0.0004 \ (ms^{-2})$.

B Supplementary Experiments

We further evaluate the performance of Confucius in a series of microbenchmarking settings.

B.1 Working with Bandwidth Probing

Some recent CCAs proposed to periodically probe the available bandwidth by overshooting the network, which might introduce noises in classifying the buffer occupancy of flows in Confucius. Some recent examples for video streaming include Sprout [53], PCC (probing up to 5%) [20], and BBR (probing 25%) [15]. We evaluate how Confucius is able to handle the bandwidth probing from CCAs. We first run one BBR flow, which is the most aggressive one among these bandwidth probing CCAs, and change the RTT from 20 ms to 160 ms since the probing period is counted in the unit of RTT. As shown in Figure 16, with the other settings the same as Figure 8, the queue fluctuations never go across the threshold of reclassification of the flow. This is due to the hysteresis design in §5.2 – Confucius deliberately makes conservative decisions in the classification of flows to smoothize the noises out. This can also be validated from Figure 11(b): the classification results are stable all the time even if BBR periodically probes the bandwidth. Therefore, Confucius is able to work well with bandwidth-probing CCAs.

B.2 Working with Different Bottleneck

We further evaluate the end-to-end performance when the bottleneck is not where Confucius is deployed. Confucius is able to reduce the latency volatility when it is deployed on the bottleneck router. Our further experiments show that Confucius does not introduce side effects when the bottleneck is before or after the router deployed with Confucius. We still deploy queue management mechanisms to the router before link B and respectively rate-limit the link A, B, and C in Figure 8 to 20 Mbps:

- Btlnk-A. When link A is limited while the other two links are set to 100 Mbps, the bottleneck is before the place of Confucius.
- Btlnk-B. The case when link B is limited is what we mainly evaluated in this section, where Confucius is at the bottleneck.
- Btlnk-C. When link C is limited, the bottleneck is after the place of Confucius.

For those unmanaged routers, they adopt FIFO as their default mechanism. As shown in Figure 17, the performance is only affected by the mechanism deployed at the bottleneck. When Confucius is not at the bottleneck (e.g., link A or C), the performance is the same no matter what mechanism is deployed at link B. It is worth to note that as discussed in a series of papers [12, 38], the last-mile routers (e.g., cellular base stations, home wireless APs) are the bottleneck for most of the congestions, in which case deploying Confucius will achieve significant performance benefits.

B.3 Multiple HRT Flows Competition

We further evaluate the performance when there are multiple HRT flows running simultaneously. We reproduce the experiments in Figure 9(a) but change the number of HRT



tion of the HRT (old) flow.

Figure 18: We increase the number of simultaneous HRT flows, and measure the results again with the Alexa dataset.

flows from 1 to 5. The average duration of delay degradation of HRT flows, and the PLT of Web flows are presented in Figure 18. Confucius is able to provide a consistent performance for multiple HRT flows in the same time – the delay degradation is consistently negligible independent of the number of concurrent HRT flows and the PLT stays roughly the same place compared to the baselines. Note that since Confucius is designed for last-mile routers, 5 concurrent flows should be able to cover most scenarios [38].