BPF: Mitigating the Burstiness-Fairness Tradeoff in Multi-Resource Clusters

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Abstract

Simultaneously supporting latency- and throughout-sensitive workloads in a shared environment is a classic networking challenge that is becoming increasingly more common in big data clusters. Despite many advances, existing cluster schedulers force the same performance goal – fairness in most cases – on all jobs. Latency-sensitive jobs suffer, while throughput-sensitive ones thrive. Using prioritization does the opposite: it opens up a path for latency-sensitive jobs to dominate. In this paper, we tackle the challenges in supporting both short-term performance and long-term fairness simultaneously with high resource utilization by proposing Bounded Priority Fairness (BPF). BPF provides short-term resource guarantees to latency-sensitive jobs and maintains the long-term fairness for throughput-sensitive jobs. The key idea is "bounded" priority for latency-sensitive jobs; meaning, if bursts are not too large to hurt the long-term fairness, they are given higher priority so jobs can be completed as quickly as possible. BPF is the first scheduler that can provide long-term fairness, burst guarantee, and Pareto efficiency in a strategyproof manner for multi-resource scheduling. Deployments and large-scale simulations show that BPF closely approximates the performance of Strict Priority as well as the fairness characteristics of DRF. In deployments, BPF speeds up latency-sensitive jobs by 5.38× compared to DRF, while still maintaining long-term fairness. In the meantime, BPF improves the average completion times of throughput-sensitive jobs by up to 3.05× compared to Strict Priority.

1 Introduction

As distributed data-parallel computing matures, throughput-sensitive batch processing systems [37, 51, 61, 6] are increasingly being complemented by latency-sensitive interactive analytics [72, 15, 4] and online stream processing systems [73, 13, 16, 64, 28]. To enable data sharing and seamless transition between these models, all these applications coexist on shared clusters [10, 8, 5, 49, 69, 9, 24]. Naturally, both systems and networking communities have focused on resource sharing in these clusters [49, 69, 27, 1, 33, 22].

Today's schedulers are multi-resource [43, 45, 57, 32, 19], DAG-aware [31, 45, 72], and allow a variety of constraints [74, 52, 20, 44, 71]. Given all these inputs, they optimize for objectives such as fairness [43, 53, 42, 25], performance [41], efficiency [45], or different combinations of the three [46, 47]. However, all existing schedulers have one thing in common: *they force the same performance goal on all jobs.*

Even though batch, interactive, and streaming computation models all care about performance, their notions of performance are different. For instance, the average completion time can sufficiently capture the performance of a throughout-sensitive batch-job queue (TQ) [45, 46, 20, 74]. However, interactive sessions and streaming applications form latency-sensitive queues (LQ): each LQ is a sequence of small jobs following an ON-OFF pattern. For these jobs [73, 72, 17, 4], individual completion times or latencies are far more important than the average completion time or the throughput of the LQ.

Indeed, existing "fair" schedulers are inherently unfair to LQ jobs: when LQ jobs are present (ON state), they must share the resources equally with TQ jobs, but when they are absent (OFF state), batch jobs get all the resources. The fact that LQ jobs are not using any resources during their OFF periods is completely ignored. In the long run, TQs receive more resources than their fair shares because today's schedulers make *instantaneous* decisions (§2).

One may assume that assigning higher priorities to LQ jobs (Strict Priority, or SP [59]) would resolve this. Although simple and attractive, prioritization cannot address this challenge because it incentivizes LQs to submit arbitrarily large jobs to starve TQs. Consequently, the performance-isolation tradeoff requires a careful consideration.

Additionally, how one reasons about system utilization becomes more complicated in the presence of both LQs and TQs. While it is relatively easy to fill the cluster with many batch jobs to achieve high utilization, LQs often have higher value and are harder to accommodate with resource guarantees. Compared to a simple solution that rejects most of LQs and/or serves them with best efforts, system operators are likely to prefer to maximize the LQs served with resource guarantees, which leads to more predictable performance.

Therefore, we ponder a fundamental question: *can we enable latency-sensitive LQs and throughput-sensitive TQs to coexist, where LQs are permitted short-term resource bursts while ensuring long-term fairness between the two, as well as maximizing LQs served with resource guarantees?*

The need to separate throughput- and latency-sensitive job queues in big data clusters is akin to the classic

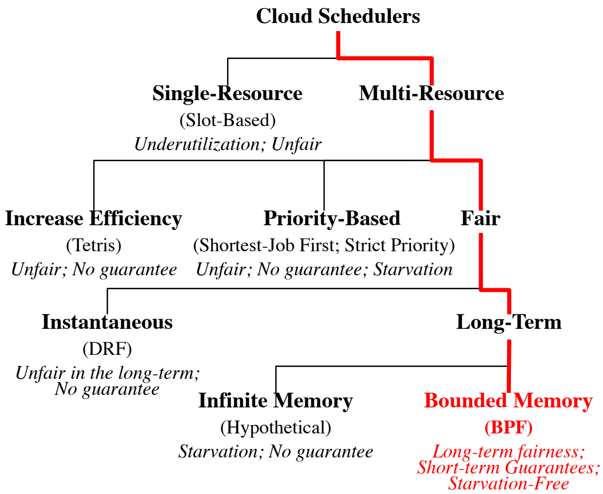


Figure 1: Cluster scheduling design space.

networking problem of supporting throughput-sensitive flows and latency-sensitive realtime communication on network access links [40, 67, 68, 36]. The key difference between the two is the multi-resource nature of cluster scheduling and challenges arising from it. We aim for a solution that can be applied to multi-resource clusters.

In this paper, we first explore opportunities and challenges in achieving four desired properties in this context (§2): (i) allowing LQs to enjoy short-term high resource usage during their ON periods to minimize *individual* job response times; (ii) maintaining the same *long-term* fairness as existing multi-resource fair allocation policies by preventing arbitrarily large bursts; (iii) maximizing system utilization and LQs served with resource guarantees; and (iv) the policy needs to be strategyproof because otherwise LQs may lie about their demands to gain more resources.

The key opportunity lies in the observation that TQs do not care about allocated resources in the short term, as long as the long-term averaged resource share remains the same. This temporal flexibility allows us to accommodate bursts of LQs without hurting TQs. However, there are several challenges to achieve these desired properties (§2). There is a fundamental tradeoff between "hard" resource guarantee to LQs and instantaneous isolation protection for TQs. In addition, naive admission control may result in very few LQs admitted with resource guarantees, leading to suboptimal performance for LQs even with a high system utilization.

Contributions

Algorithm development. We present BPF in Section 3 to find a balance between the potentially conflicting properties. Given the performance-isolation tradeoff, BPF takes long-term fairness as the hard requirement as otherwise TQs may starve, which is not acceptable. Under the isolation requirement, BPF tries to optimize the other two metrics: individual completion time of LQs and number of LQs admitted with resource guarantees.

In BPF, an LQ reports on its arrival the inter-arrival time and maximum allowed processing time (and therefore the deadlines), as well as the amount and duration of (multiple typed) resources requested. An upper limit on the cycle length is set to respect the fair share of TQs in a timely manner. BPF then decides whether to admit the LQ by checking the safety condition, i.e., admitting this LQ does not invalidate any prior resource guarantees committed. Then, if its total requested resources exceed its long-term fair share, the LQ is admitted and provided only with its long-term fair share. Otherwise, the LQ is admitted with resource guarantees. BPF provides both hard and soft guarantees. Intuitively, if there are enough available resources for every burst of the LQ, it is admitted with hard guarantee, i.e., the system guarantees to provide the requested amount of resources during each requested interval accordingly. Otherwise, the LQ is admitted with soft guarantee, i.e., the requested amount of resources are provided as long as there is no conflict with LQs with hard guarantee.

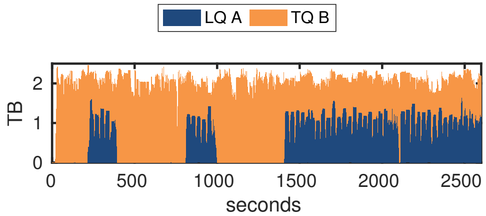
Having the queue with soft guarantee is crucial to minimize the individual completion time of LQs. While LQs with hard guarantee are provided with performance comparable to that under SP, LQs with soft guarantee can still have better performance compared to that under existing fair allocation policies.

For long-term fairness and isolation, BPF guarantees a fixed amount of resources to each admitted LQ instead of extending unlimited resources by prioritization. If some LQ increases their demand beyond its resource guarantee, that demand is only served when the system has unused resources without hurting the isolation for TQs and other LQs.

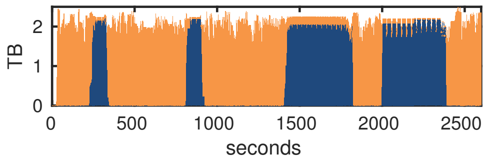
The analysis of BPF is in §3.4, where strategyproofness is proved in addition to the other properties. To the best of our knowledge, BPF is the first multi-resource scheduler that can provide all the five properties.

Design and implementation. We have implemented BPF on Apache YARN [69] (§4). Any framework that runs on YARN can take advantage of BPF. The BPF scheduler is implemented as a new scheduler in Resource Manager that runs on the master node. The scheduling overheads for admitting queues or allocating resources are negligibly less than 1 ms for 20,000 queues.

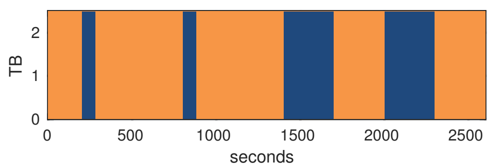
Evaluation based on both testbed experiments and large-scale simulations. We deployed and evaluated BPF on 40 bare-metal machines using the public benchmarks, i.e., BigBench (BB) [3], TPC-DS [11], and TPC-H [12]. In deployments, BPF significantly provides up to 5.38× (totally 9 queues in a cluster) faster performance with smaller variation for LQ jobs than DRF, while maintaining the fairness among the queues (§5.2). In fact, the



(a) DRF: While instantaneous fairness is enforced, the completion time of LQ jobs is much higher than that under SP.



(b) Strict Priority (SP): While the completion time of LQ jobs are reduced, TQ B does not receive its fair share after LQ A increases its demand after 1,400 seconds.



(c) Ideal: The first two LQ jobs finish as quickly as possible. The latter jobs cannot use more resources than LQ A's fair share.

Figure 2: Need for bounded priority and long-term fairness in a shared multi-resource cluster. Although we only focus on memory allocations here, similar observations hold for other resources.

performance of LQ jobs is close to that under SP. On the other hand, BPF maintains the fairness among the queues and does not hurt the long-term averaged resources received by TQs. BPF protects the TQ jobs up to 3.05× compared to SP. Furthermore, BPF performs well even in the presence of moderate misestimations of task demands and without preemption allowed (§5.4).

2 Motivation

2.1 Benefits of Temporal Co-scheduling

Consider Figure 2 that illustrates the inefficiencies of existing resource allocation policies, in particular, DRF [43] and Strict Priority (SP) [59] for coexisting LQs and TQs. For this experiment, we run memory-bound jobs in Tez atop YARN within a cluster of 40 nodes, where each node has 32 CPU cores and 64 GB RAM.

There are two queues: LQ A and TQ B. LQ A has MapReduce jobs submitted every 10 minutes. Its demand increases from its 3rd burst and exceeds its fair share. TQ B has jobs that are generated from the BigBench workload [3] and queued up at the beginning. For simplicity of exposition, all jobs are memory-bound. While LQ A tries to complete each burst as quickly as possible, TQ B cares more about its long-term averaged resources received, e.g., every 10 minutes.

The memory resource consumption under DRF and SP is depicted in Figures 2a and 2b, respectively. DRF enforces instantaneous fair allocation of resources at any time. During the burst of LQ A, LQ A and TQ B share the bottleneck resource (memory) evenly until the jobs from LQ A complete; then TQ B gets all system resources before the next burst of LQ A. Clearly, TQ B is happy at the cost of longer completion times of LQ A's jobs. SP gives LQ A the whole system resources (high priority) whenever it has jobs to run; hence, it provides the lowest possible completion time. The reduction in completion time is significant (around 40%). However, this comes at the expense of TQ B's resource consumption, which is smaller than its fair share after 1,400 seconds (only 1/3). In other words, LQ A can arbitrarily increase its demand without any punishment and as a result, there is no performance isolation for TQ B. The situation for SP becomes even worse when multiple LQs are present.

DRF and SP can be considered as two extremes to resolve the tradeoffs between fairness (for TQs) and performance (for LQs), and both fail to accommodate the requirements from both queues simultaneously. Other existing solutions are incapable of achieving these heterogenous performance metrics as well. For instance, any policy without taking the differences between LQs and TQs into consideration, such as FIFO, renders either LQs or TQs, or even both, unhappy. Any fair scheduler such as DRF and HUG [30] cannot handle the burst of jobs during the ON state of LQs. In contrast, priority-based solutions may lead to the starvation of TQs. Interestingly, DRF allows different weights to be set for each LQ and TQ. In the existing DRF algorithm, however, weights are static over time. Therefore, lower weights for LQs cannot handle the burst, while higher weights may lead to TQ starvation and difficulties with multiple LQs, similar to SP. Nonetheless, it provides a critical control knob that was leveraged in our proposed system BPF.

The ideal allocation is depicted in Figure 2c. The key idea is "bounded" priority for LQs: as long as the burst is not too large to hurt the fair share of TQs, they are given higher priority so jobs can be completed as quickly as possible. In particular, before 1,400 seconds, LQ A's bursts are small, so it gets higher priority, which is similar to SP. After LQ A increases its demand, only a fraction of its demand can be satisfied with the entire system's resources. Then it has to give resources back to TQ B to ensure the long-term fairness.

2.2 Desired Properties

We restrict our attention in this paper to the following, important properties: burst guarantee for LQs, long-term fairness for TQs, strategyproofness, and Pareto efficiency to improve cluster utilization.

Burst guarantee (BG) provides performance guarantee for LQs by allocating guaranteed amount of resources during their bursts. In particular, an LQ requests its minimum required resources for its bursts to satisfy its service level agreements, e.g., percentiles of response time.

Long-term fairness (LF) provides every queue in the system the same amount of resources. Overall, it ensures that TQs progress no slower than any LQ in the long run. LF implies sharing incentive, which requires that each queue should be better off sharing the cluster, than exclusively using its own static share of the cluster. If there are n queues, each queue cannot exceed $\frac{1}{n}$ of all resources under a static sharing.[1]

Strategyproofness (SPF) ensures that queues cannot benefit by lying about their resource demands. This provides incentive compatibility, as a queue cannot improve its allocation by lying.

Pareto efficiency (PE) is about the optimal utilization of the system. A resource allocation is Pareto efficient if it is impossible to increase the allocation/utility of a queue without hurting at least another queue.

2.3 Analysis of Existing Policies

Strict Priority (SP): Strict priority scheduling [59] is also employed to provide performance guarantee for LQs. As the name suggests, an SP scheduler always prioritize LQs. Therefore, when there is only one LQ, SP provides the best possible performance guarantee.

However, when there are more than one LQs, it is impossible to give all of them the highest priority. Meanwhile, TQs may not receive enough resources, which violates long-term fairness. As the LQs may request more resources than what they actually need, strategyproofness is not enforced, and therefore the system may waste some resources – i.e., it is not Pareto efficient.

DRF: DRF [43] is a scheduler designed for multi-resource allocation. It is an extension from max-min fairness to the multi-resource environment, where the dominant share is used to map the resource allocation (as a vector) to a scalar value.

It provides instantaneous fairness, strategyproofness, and Pareto efficiency. In particular, the strategyproofness property is straightforward in the single-resource environment but needs careful treatments in the multi-resource environment.

However, because DRF is an instantaneous allocation policy without any memory, it cannot prioritize jobs with more urgent deadlines. In particular, no burst guarantee is provided. Even DRF with weights is homogeneous over time and cannot provide the burst guarantee needed. In addition, there is no admission control.

[1]For simplicity of presentation, we consider queues with the same weights, which can be easily extended to queues with different weights.

Property	SP	DRF	M-BVT	BPF
Burst Guarantee (BG)	✓*	×	✓*	✓
Long-Term Fairness (LF)	×	✓	✓	✓
Strategyproofness (SPF)	×	✓	×	✓
Pareto Efficiency (PE)	✓	✓	✓	✓
Single Resource Fairness	×	✓	✓	✓
Bottleneck Fairness	×	✓	✓	✓
Population Monotonicity	✓	✓	✓	✓

Table 1: Properties of existing policies and BPF in the presence of burstiness. ✓* means that the property holds when there is only one LQ.

M-BVT: BVT [38] was designed as a scheduler for a mix of real-time and best-effort tasks. The idea is that for real-time tasks, BVT allows them to borrow some virtual time (and therefore resources) from the future and be prioritized for a period without increasing their long-term shares. To make it comparable, we extend it to M-BVT for a multi-resource environment.

Under the M-BVT policy, LQ-i is assigned a virtual time warp parameter W_i, which represents the urgency of the queue. Upon an arrival of its burst at A_i, an effective virtual time $E_i = A_i - W_i$ is calculated. This is used as the priority (smaller E_i means higher priority) for scheduling. When LQ-i has the only smallest E_i, it may use the whole system's resources while its W_i is consumed at the rate of its progress calculated by DRF. Eventually, its E_i is no longer the only one that is smallest. Then resources are shared in a DRF-fashion until other queues catch up with LQ-i or there is some change to the system, e.g., a completion or an arrival of the LQs.

The M-BVT policy has some good properties. For instance, the DRF component ensures long-term fairness, and the BVT component strives for performance. Pareto efficiency follows from the work conservation property of the policy.

However, it does not provide general burst guarantees as any new arriving queue (with larger virtual time warp parameter) may occupy the resources of existing LQs or share resources with them, thus hurting their completion time. In addition, it is not strategyproof because queues can lie about their needs in order to get a larger virtual time warp W_i.

Other policies such as the CEEI [63] provide fewer desired properties.

2.4 Summary of the Tradeoffs

As listed in Table 1, no prior policy can simultaneously provide all the desired properties of fairness/isolation for TQs while providing burst guarantees for all the LQs with strategyproofness. In particular, if strict priority is provided to an LQ without any restriction for its best performance (e.g., SP), there is no isolation protection for TQs' performance. On the other hand, if the ideal instantaneous fairness is enforced (e.g., DRF), there is no room to prioritize short-term bursts. While the idea in M-BVT is reasonable, it is not strategyproof and cannot provide burst guarantee.

The key question of the paper is, therefore, how to allocate system resources in a near-optimal way; meaning, satisfying all the critical properties in Table 1.

3 BPF: A Scheduler With Memory

In this section, we first present the problem settings (§3.1) and then formally model the problem in Section 3.2. BPF achieves the desired properties by admission control, guaranteed resource provision, and spare resource allocation presented in Section 3.3. Finally, we prove that BPF satisfies all the properties in Table 1 (§3.4).

3.1 Problem Settings

We consider a system with K types of resources. The capacity of resource k is denoted by C^k. The system resource capacity is therefore a vector $\overrightarrow{C} = \langle C^1, C^2, ..., C^K \rangle$. For ease of exposition, we assume $\overrightarrow{C}$ is a constant over time, while our methodology applies directly to the cases with time-varying $\overrightarrow{C}(t)$ as long as $\overrightarrow{C}(t)$ can be estimated at the beginning. Stochastic optimization [65] and online algorithm design [54] can be leveraged to cases where $\overrightarrow{C}(t)$ is hard to predict.

We restrict our attention to LQs for interactive sessions and streaming applications, and TQs for batch jobs.

LQ-i's demand comes from a series of jobs during its ON status. We denote by $T_i(n)$ and $t_i(n)$ the starting time and allowed processing time specified in its SLA of its n-th ON period, respectively. Therefore, its n-th burst needs to be completed by $T_i(n)+t_i(n)$ (i.e., deadline). We also denote the demand during its n-th ON period by a vector $\overrightarrow{d_i}(n) = \langle d_i^1(n), d_i^2(n), ..., d_i^K(n) \rangle$, where $d_i^k(n)$ is the demand on resource-k.

In practice, the duration of each ON/OFF period (inter-arrival time) $T_i(n+1)-T_i(n)$ can be fixed for some applications such as Spark Streaming [73], or it may vary for interactive user sessions. In general, the duration is quite short, e.g., several minutes. Similarly, the demand vector $\overrightarrow{d_i}(n)$ may contain some uncertainties, and we assume that queues have their own estimations. Therefore, our approach has to be strategyproof so that queues report their estimated demand. Actually, a stochastic optimization problem can be solved by each LQ-i to decide the vector it wants to report. In addition, strategyproofness ensures that queues report their true deadlines.

To enforce the long-term fairness, the total demand of LQ-i during each period $[T_i(n), T_i(n+1)]$, i.e., $\overrightarrow{d_i}(n)t_i(n)$, should not exceed its fair share, which can be calculated by a simple fair scheduler – i.e., $\frac{\overrightarrow{C}}{N}$, when there are N queues admitted by BPF – or a more complicated one such as DRF. We adopt the former in analysis because it provides a more conservative evaluation of the improvements brought by BPF.

Notation	Description
$\mathbb{A}$	Admitted LQs
$\mathbb{B}$	Admitted TQs
$\mathbb{H}$	Admitted LQs with hard guarantee
$\mathbb{S}$	Admitted LQs with soft guarantee
$\mathbb{E}$	Admitted TQs and LQs with fair share only

Table 2: Important notations

TQs' jobs are queued at the beginning with much larger demand than each burst of LQs. In contrast to LQs who wish to finish each burst as quickly as possible in each ON/OFF period lasting for several minutes, TQs only care about the resources received in the long term, e.g., hours.

3.2 Modeling the Problem

Completion time

Let us denote by $R_i(n)$ the average completion time of jobs during LQ-i's n-th ON period. For an admitted LQ in $\mathbb{H}$, we need to ensure the completion time is within the deadline, i.e., $R_i(n) \le T_i(n)+t_i(n), \forall n$. For admitted LQs in $\mathbb{S}$, we want to minimize its average completion time $\frac{1}{|\mathbb{S}|}\sum_{i\in\mathbb{S}}\left(\frac{1}{N_i}\sum_{n=1}^{N_i} R_i(n)\right)$, where N_i is the number of ON/OFF periods within the evaluation interval.

Long-term fairness

Denote by $\overrightarrow{a_i}(t)$ and $\overrightarrow{e_j}(t)$ the resources allocated for LQ-i and TQ-j at time t, respectively. For a possibly long evaluation interval $[t, t+T]$ during which there is no new admission or exit, the average resource guarantees received are calculated as $\frac{1}{T}\int_t^{t+T}\overrightarrow{a_i}(\tau)\mathrm{d}\tau$ and $\frac{1}{T}\int_t^{t+T}\overrightarrow{e_j}(\tau)\mathrm{d}\tau$. We require the allocated dominant resource, i.e., the largest amount of resource allocated across all resource types, received by any TQ queue is no smaller than that received by a LQ. Formally, $\forall i \in \mathbb{A}, \forall j \in \mathbb{B}$, where $\mathbb{A}$ and $\mathbb{B}$ is the set of admitted LQs and TQs, respectively, we need

$$\max_k\left\{\frac{1}{T}\int_t^{t+T} a_i^k(\tau)\mathrm{d}\tau\right\} \le \max_k\left\{\frac{1}{T}\int_t^{t+T} e_j^k(\tau)\mathrm{d}\tau\right\},$$

where $a_i^k(\tau)$ and $e_j^k(\tau)$ are allocated type-k resources for LQ-i and TQ-j at time τ, respectively. This condition provides long-term protections for admitted TQs.

System utilization and LQ utilization

At any time τ, denote by $\overrightarrow{f_i}(\tau)$ and $\overrightarrow{g_j}(\tau)$ the resource consumed by LQ-i and TQ-j, respectively. Over the evaluation interval $[t, t+T]$, the average system utilization for all resources can be calculated as follows:

$$\frac{1}{KT}\sum_k\int_t^{t+T}\frac{\sum_{i\in\mathbb{A}} f_i^k(\tau)+\sum_{i\in\mathbb{B}} g_j^k(\tau)}{C^k}\mathrm{d}\tau,$$

where $f_i^k(\tau)$ and $g_j^k(\tau)$ are allocated type-k resource for LQ-i and TQ-j at time τ, respectively. The LQ utilization is simply the part consumed by LQs with guarantees

$$\frac{1}{KT}\sum_k \int_t^{t+T} \frac{\sum_{i\in\mathbb{H}\cup\mathbb{S}} f_i^k(\tau)}{C^k} \mathrm{d}\tau.$$

Optimization problem

We would like to minimize the completion time of jobs for admitted LQs with soft guarantees and maximize the system utilization and LQ utilization while meeting the deadlines of admitted LQs with hard guarantees and keeping the long-term fairness. The problem can be expressed as follows:

$$\begin{aligned}
\min \quad & \frac{1}{|\mathbb{S}|}\sum_{i\in\mathbb{S}}\left(\frac{1}{N_i}\sum_{n=1}^{N_i} R_i(n)\right) \\
\max \quad & \frac{1}{KT}\sum_k \int_t^{t+T} \frac{\sum_{i\in\mathbb{A}} f_i^k(\tau)+\sum_{i\in\mathbb{B}} g_j^k(\tau)}{C^k}\mathrm{d}\tau \\
\max \quad & \frac{1}{KT}\sum_k \int_t^{t+T} \frac{\sum_{i\in\mathbb{H}\cup\mathbb{S}} f_i^k(\tau)}{C^k}\mathrm{d}\tau \qquad (1) \\
\text{s.t.} \quad & R_i(n) \le T_i(n)+t_i(n), \forall n, \forall i\in\mathbb{H} \\
& \max_k\left\{\frac{1}{T}\int_t^{t+T} a_i^k(\tau)\mathrm{d}\tau\right\} \le \\
& \max_k\left\{\frac{1}{T}\int_t^{t+T} e_j^k(\tau)\mathrm{d}\tau\right\}, \forall i\in\mathbb{A}, \forall j\in\mathbb{B}
\end{aligned}$$

The decisions to be made are the set of admitted LQs ($\mathbb{A}$, $\mathbb{H}$, $\mathbb{S}$), the set of admitted TQs ($\mathbb{B}$), and resources allocated to LQ-i and TQ-j ($\overrightarrow{a_i}(t)$ and $\overrightarrow{e_j}(t)$, respectively) over time. The resource consumptions ($\overrightarrow{f_i}(t)$ and $\overrightarrow{g_j}(t)$) are different from resource allocations ($\overrightarrow{a_i}(t)$ and $\overrightarrow{e_j}(t)$) because some queues cannot use up the allocated resource, and if there are some unused/unallocated resources, queues with unsatisfied demand can share them, in addition to their allocated resources. LQ completion time $R_i(n)$ is some non-increasing function of resource consumption $\overrightarrow{f_i}(t)$, i.e., more resources reduce completion time.

3.3 Solution Approach

Our solution BPF consists of three major components for the decision variables: admission control procedure to decide $\mathbb{H}$, $\mathbb{S}$ and $\mathbb{E}$ for long-term fairness, guaranteed resource provisioning procedure for $\overrightarrow{a_i}(t)$ to meet the deadlines or minimize completion time of LQs, and spare resource allocation procedure to decide $\overrightarrow{f_i}(t)$ and $\overrightarrow{g_j}(t)$ to maximize utilization.

Admission control procedure

BPF classifies admitted LQs and TQs into the following three classes:

Algorithm 1 BPF Scheduler

```
procedure PERIODICSCHEDULE()
    if there are new LQs, ℚ then
        {ℍ, 𝕊, 𝔼} = LQADMIT(ℚ)
    end if
    if there are new TQs, ℚ then
        {𝔼} = TQADMIT(ℚ)
    end if
    ALLOCATE(ℍ, 𝕊, 𝔼)
end procedure

function LQADMIT(LQS ℚ)
    for all LQ Q ∈ ℚ do
        if safety condition (2) satisfied then
            if fairness condition (3) satisfied then
                if resource condition (4) satisfied then
                    Admit Q to hard guarantee ℍ
                else
                    Admit Q to soft guarantee 𝕊
                end if
            else
                Admit Q to elastic 𝔼 with long-term fair share
            end if
        else
            Reject Q
        end if
    end for
    return {ℍ, 𝕊, 𝔼}
end function

function TQADMIT(QUEUE ℚ)
    for all TQ Q ∈ ℚ do
        if safety condition (2) satisfied then
            Admit Q to elastic 𝔼 with long-term fair share
        else
            Reject Q
        end if
    end for
    return {𝔼}
end function

function ALLOCATE(ℍ, 𝕊, 𝔼)
    for all LQ Q ∈ ℍ do
        a_i(t) = d_i(n) for t ∈ [T_i(n), T_i(n+1)] until Q's consumption reaches d_i(n)t_i(n).
    end for
    for all LQ Q ∈ 𝕊 do
        allocate C − Σ_{j∈ℍ} d_j(t) based on SRPT until each LQ-i's consumption reaches d_i(n)t_i(n).
    end for
    Obtain the remaining resources L
    DRF(𝔼, L)
end function
```

- $\mathbb{H}$: LQs admitted with hard resource guarantee.
- $\mathbb{S}$: LQs admitted with soft resource guarantee. Similar to hard guarantee, but need to wait when some LQs with hard guarantee are occupying system resources. SRPT [23] based scheduling is leveraged among multiple LQs in $\mathbb{S}$ to minimize the average completion time.
- $\mathbb{E}$: Elastic queues that can be either LQs or TQs. There is no short-term resource guarantee, but long-term fair share is provided.

Before admitting LQ-i, BPF checks if adding it invalidates any resource guarantees committed for LQs in $\mathbb{H} \cup \mathbb{S}$, i.e., the following *safety condition* needs to be satisfied:

$$\vec{d_j}(n)t_j(n) \le \frac{\vec{C}\,(T_j(n+1) - T_j(n))}{|\mathbb{H}| + |\mathbb{S}| + |\mathbb{E}| + 1}, \forall n, \forall j \in \mathbb{H} \cup \mathbb{S}, \tag{2}$$

where $|\mathbb{H}| + |\mathbb{S}| + |\mathbb{E}|$ is the number of already admitted queues. If (2) is not satisfied, LQ-i is rejected. Otherwise, it is safe to admit LQ-i and the next step is to decide which of the three classes it should be added to.

For LQ-i to have some resource guarantee, either hard or soft, its own total demand should not exceed its long-term fair share. Formally, the *fairness condition* is

$$\vec{d_i}(n)t_i(n) \le \frac{\vec{C}\,(T_i(n+1) - T_i(n))}{|\mathbb{H}| + |\mathbb{S}| + |\mathbb{E}| + 1}, \forall n, \tag{3}$$

If only condition (2) is satisfied but (3) is not, LQ-i is added to $\mathbb{E}$. If both conditions (2) and (3) are satisfied, it is safe to admit LQ-i to $\mathbb{H}$ or $\mathbb{S}$. If there are enough uncommitted resources (*resource condition* (4)), LQ-i is admitted to $\mathbb{H}$. Otherwise it is added to $\mathbb{S}$.

$$\vec{d_i}(n) \le \vec{C} - \sum_{j \in \mathbb{H}} \vec{d_j}(t), \forall n, t \in [T_i(n), T_i(n) + t_i(n)]. \tag{4}$$

For TQ-j, BPF simply checks the safety condition (2). If it is satisfied, TQ-j is added to $\mathbb{E}$. Otherwise TQ-j is rejected.

Guaranteed resource provisioning procedure

For each LQ-i in $\mathbb{H}$, during each ON period $[T_i(n), T_i(n) + t_i(n)]$, BPF allocates resources according to its demand $\vec{a_i}(t) = \vec{d_i}(n)$[2]. LQs in $\mathbb{S}$ shares the uncommitted resource $\vec{C} - \sum_{j \in \mathbb{H}} \vec{d_j}(t)$ based on SRPT until each LQ-i's consumption reaches $\vec{d_i}(n)t_i(n)$.

[2]In practice, LQ-i may not fully receive the guaranteed resources. For instance, non-preemption settings do not allow the cluster to kill the running jobs or tasks to give more resources to LQ-i immediately at the beginning of its burst. In such cases, more resources may be provided to LQ-i during the OFF period $[T_i(n) + t_i(n), T_i(n+1)]$ until its resource consumption reaches $\vec{d_i}(n)t_i(n)$.

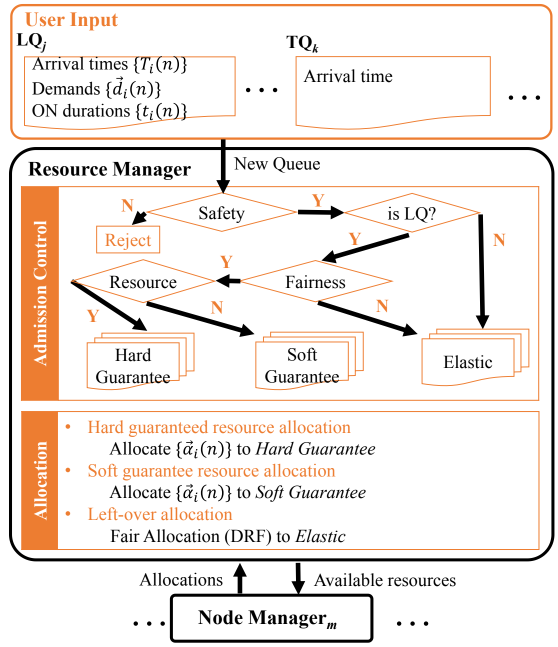


Figure 3: Enabling bounded prioritization with long-term fairness in a multi-resource cluster. BPF-related changes are shown in orange.

After every LQ in $\mathbb{H}$ and $\mathbb{S}$ is allocated, remaining resources are allocated to queues in $\mathbb{E}$ using DRF [43].

Spare resource allocation procedure

If some allocated resources are not used, they are further shared by TQs and LQs with unsatisfied demand. This maximizes system utilization.

3.4 Properties of BPF

We can now make the following formal statements about BPF's properties. Corresponding proofs can be found in the appendix.

Theorem 3.1 *BPF ensures long-term fairness, burst guarantee, and Pareto efficiency.*

Theorem 3.2 *BPF is strategyproof.*

4 Design Details

In this section, we describe how we have implemented BPF on Apache YARN, how we use standard techniques for demand estimation, and additional details related to our implementation.

4.1 Enabling BPF in Cluster Managers

Enabling bounded prioritization with long-term fairness requires implementing the *BPF scheduler* itself along with an additional *admission control* module in cluster managers, and it takes *additional information on demand characteristics* from the users. A key benefit of

BPF is its simplicity of implementation: we have implemented it in YARN using only 600 lines of code. In the following, we describe how and where we have made the necessary changes.

Primer on Data-Parallel Cluster Scheduling

Modern cluster managers typically includes three components: *job manager* or application master (AM), *node manager* (NM), and *resource manager* (RM).

One NM runs on each server in the cluster, and it is responsible for managing resource containers on that server. A container is a unit of allocation and are used to run specific tasks.

For each application, a job manager or AM interacts with the RM to request job demands and receive allocation and progress updates. It can run on any server in the cluster. AM manages and monitors job demands (memory and CPU) and job status (`PENDING`, `IN_PROGRESS`, or `FINISHED`).

The RM is the most important part in terms of scheduling. It receives requests from AMs and then schedules resources using an operator-selected scheduling policy. It asks NM to prepare resource containers for the various tasks of the submitted jobs.

BPF Implementation

We made three changes for taking user input, performing admission control, and calculating resource shares – all in the RM. We do not modify NM and AM. Our implementation also requires more input parameters from the users regarding the demand characteristics of their job queues. Figure 3 depicts our design.

User Input Users submit their jobs to their queues. In our system, there are 2 queue types, i.e., LQs and TQs. We do not need additional parameters for TQs because they are the same as the conventional queues. Hence, we assume that TQs are already available in the system. However, the BPF scheduler needs additional parameters for LQs; namely, arrival times and demands.

Users submit a request job that contains their parameters of the new LQ. After receiving the parameters in the job, the RM sets up a new LQ queue for the user. Users can also ask the cluster administrator to set up the parameters.

Admission Control YARN does not support admission control. We implement an admission control module to classify LQs and TQs into Hard Guarantee, Soft Guarantee, and Elastic classes. A new queue is rejected if it cannot meet the safety condition (2), which invalids the committed performance. If it is a TQ, it is added into the Elastic class. If the new LQ does not satisfy the fairness condition (3), it is also admitted to the Elastic class. If the new LQ meets the fairness condition (3), but fails at the resource condition (4), it will be put in the Soft Guarantee class. If the new LQ meets all the three conditions, i.e., safety, fairness, and resource, it will be admitted to the Hard Guarantee class.

BPF Scheduler We implement BPF as a new scheduling policy to achieve our joint goals of bounded priority with long-term fairness. Upon registering the queues, users submit their jobs to their LQs or TQs. Thanks to admission control, LQs and TQs are classified into Hard Guarantee, Soft Guarantee, and Elastic classes. Note that resource sharing policies are implemented across queues in YARN, jobs in the same queue are scheduled in FIFO manner. Hence, BPF only sets the share at the individual queue level.

BPF Scheduler periodically set the share levels to all LQs in Hard Guarantee and Soft Guarantee classes. These share levels are actually upper-bounds on resource allocation that an LQ can receive from the cluster. Based on the real demand of each LQ, BPF allocates resources until it meets the share levels (whether it is in the ON period or OFF period).

BPF Scheduler allocates the resource to the three classes in the following priority order: (1) Hard Guarantee class, (2) Soft Guarantee class, and (3) Elastic class. The LQs in the Hard Guarantee class are allocated first. Then, the BPF continues allocates the resource to the LQs in Soft Guarantee class. The queues in the Elastic class are allocated with left-over resources using DRF [43].

4.2 Demand Estimation

BPF requires accurate estimates of resource demands and their durations of LQ jobs by users. These estimations can be done by using well-known techniques; e.g., users can use history of prior runs [14, 39, 45] with the assumption that resource requirements for the tasks in the same stage are similar [43, 19, 62]. We do not make any new contributions on demand estimation in this paper. While BPF performs the best with accurate estimations, we have found that BPF is robust to small misestimations in practice (§5.4.1). We consider a more thorough study an important future work.

4.3 Operational Issues

Container Reuse Container reuse is a well-known technique that is used in some application frameworks, such as Apache Tez. The objective of container reuse is to reduce the overheads of allocating and releasing containers. The downside is that it causes resource waste if the container to be reused is larger than the real demand of the new task. Furthermore, container reuse is not possible if the new task requires more resource than existing containers. For our implementation and deployment, we do not enable container reuse because BPF periodically prefers more free resources for LQ jobs, causing its drawbacks to outweigh its benefits in many cases.

Preemption Preemption is a recently introduced setting in the YARN Fair Scheduler [2], and it is used to kill running containers of one job to create free containers for another. By default, preemption is not enabled in YARN. For BPF, using preemption can help in providing guarantees for LQs. However, killing the tasks of running jobs often results in failures and significant delays. We do not use preemption in our system throughout this paper.

5 Evaluation

We evaluated BPF using three widely used big data benchmarks – BigBench (BB), TPC-DS, and TPC-H. We ran experiments on a 40-server CloudLab cluster [7]. We setup Tez atop YARN for the experiment.

To understand performance at a larger scale, we used a trace-driven simulator to replay jobs from the same traces. Our key findings are:

1. BPF can closely approximate the LQ performance of Strict Priority (§5.2.2) and the long-term fairness for TQs of DRF (§5.2.3).

2. BPF can provide similar benefits in the large-scale setting (§5.3).

3. BPF handles multiple LQs to accommodate bounded priority and fairness (§5.2.5).

4. Sensitivity analysis shows that BPF is robust to estimation errors (§5.4.1), and provide benefits to LQs under the increasing impact of non-preemption (§5.4.2).

5.1 Experimental Setup

Workloads Our workloads consist of jobs from public benchmarks – BigBench (BB) [3], TPC-DS [11], and TPC-H [12] traces. A job has multiple phases. A new phase can be executed if its prerequisite phases are finished. A phase has a number of equivalent tasks in terms of resource demand and durations. The cumulative distribution functions (CDFs) task durations across the three benchmarks are presented in Figure 4. In each experiment run, we chose the LQ jobs from one of the traces such that their shortest completion times are less than 30 seconds. We scale these jobs to make sure their instantaneous demands reach the maximum capacity of a single resource. The TQ jobs are randomly chosen from one of the traces. Each TQ job lasts from tens of seconds to tens of minutes. Each cluster experiment has 100 TQ jobs, and each simulation experiment has 500 TQ jobs. Throughout the evaluation, all the TQ jobs are submitted up at the beginning while the LQ jobs arrive sequentially. Unless otherwise specified, our default experimental setup has a single LQ and 8 TQs.

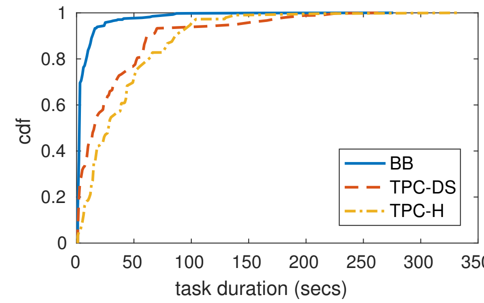


Figure 4: CDFs of task durations across workloads.

User Input Since the traces give us the resource demand and durations of the job tasks, we can set an ON period equal to the shortest completion time of its corresponding LQ job. The average of ON periods is 27 seconds across the traces. Without loss of generality, we assume that the LQ jobs arrive periodically [3]. Unless otherwise noted, the inter-arrival period of two LQ jobs is 300 seconds (1000 seconds) for the cluster experiment (the simulation experiment).

Experimental Cluster We setup Apache Hadoop 2.7.2 (YARN) on a cluster having 40 worker nodes on CloudLab [7] (40-node cluster). Each node has 32 CPU cores, 64 GB RAM, a 10 Gbps NIC, and runs Ubuntu 16.04. Totally, the cluster has 1280 CPU cores and 2.5 TB memory. The cluster also has a master node with the same specification running the resource manager (RM).

Trace-driven Simulator To have the experimental results on a larger scale, we build a simulator that mimics the system like Tez atop YARN. The simulator can replay the directed acyclic graph jobs (like Tez does), and simulate the fair scheduler of YARN at queue level. For the jobs in the same queue, we allocate the resource to them in a FIFO manner. Unlike YARN, the simulator supports 6 resources, i.e., CPU, memory, disk in/out throughputs, and network in/out throughputs.

Compared baselines We compare BPF against the following approaches

1. **Dominant Resource Fairness (DRF)**: DRF algorithm is implemented in YARN Fair Scheduler [2]. DRF uses the concept of the dominant resource to compare multi-dimensional resources [43]. The idea is that resource allocation should be determined by the dominant share of a queue, which is the maximum share of any resource (memory or CPU). Essentially, DRF seeks to maximize the minimum dominant share across all queues.

2. **Strict Priority (SP)**: We use Strict Priority to provide the best performance for LQ jobs. In fact, we

[3]The case of aperiodic LQ jobs is similar to multiple LQs with different periods.

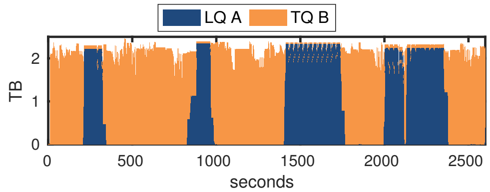


Figure 5: [Cluster] BPF's solution for the motivational problem (§2.1). The first two jobs of LQ A quickly finish and the last two jobs are prevented from using too much resource. This solution is close to the optimal one.

borrow the concept of "Strict Priority" from network traffic scheduling that enables Strict Priority queues to get bandwidth before other queues [59]. Similarly, we enable the LQs to receive all resources they need first, and then allocate the remaining resources to other queues. If there are conflicts among the LQs, we use DRF to share the resources among them.

3. **Naive-BPF (N-BPF)**: N-BPF is a simple version of BPF that can provide bounded performance guarantee and fairness. However, N-BPF does not support admission to Soft Guarantee. For the queues that satisfy the safety condition 2, N-BPF decides to admit them to Hard Guarantee if they meet the fairness condition 3 and resource condition 4. Otherwise, it put the queues into the Elastic class. We use N-BPF as a baseline when there are multiple LQs (§5.2.5).

Overall, SP is the upper bound in terms of performance guarantee, and DRF is the upper bound of fairness guarantee for our proposed approach.

Metrics Our primary metric is the *average completion times* (avg. compl.) of LQ jobs or TQ jobs. To show the performance improvement, we use the average completion times of LQ jobs across the three approaches. On the other hand, we use average completion times of TQ jobs to show that BPF also protects the TQ jobs. Additionally, we use *factor of improvement* to show how much BPF can speed up the LQ jobs compared to DRF as

$$\text{Factor of improvement} = \frac{\text{avg. compl. of DRF}}{\text{avg. compl. of BPF}}.$$

5.2 BPF in Testbed Experiments

5.2.1 BPF in practice

Before diving into the details of our evaluation, recall the motivational problem from Section 2.1. Figure 5 depicts how BPF solves it in the testbed. BPF enables the first two jobs of LQ A to quickly finish in 141 and 180 seconds. For the two large jobs arriving at 1400 and 2000 seconds, the share is very large only in roughly 335 seconds but it is cut down to give back resource to TQ B.

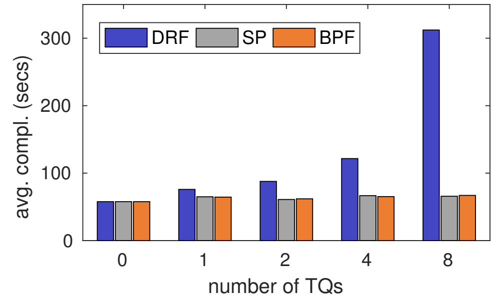


Figure 6: [Cluster] Average completion time of LQ jobs in a single LQ across the 3 schedulers when varying the number of TQs. BPF and SP guarantee the average completion time of the LQ jobs while DRF significantly suffers from the increase of number of TQs.

Table 3: [Cluster] Factor of improvement by BPF across various workload with respect to the number of TQs.

Workload	1 TQ	2 TQs	4 TQs	8 TQs
BB	1.18	1.42	1.86	4.66
TPC-DS	1.35	1.61	2.29	5.38
TPC-H	1.10	1.37	2.01	5.12

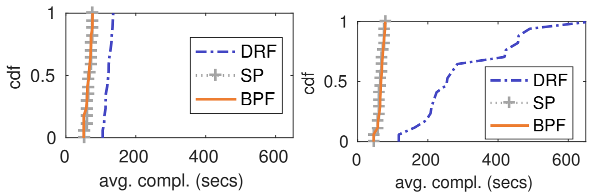
5.2.2 Performance guarantee

Next, we focus on what happens when there are more than one TQ. Figure 6 shows that average completion time of LQ jobs in the 40-node cluster on the BB workload. In this setting, there are a single LQ and multiple TQs. The x-axis shows the number of TQs in the cluster.

When there are no TQs, the average completion times of LQ jobs across three schedulers are the same (57 seconds). The completion times are greater than the average ON period (27 seconds) because of inefficient resource packing and allocation overheads. In practice, the resource demand of tasks cannot utilize all resources of a node that results in large unallocated resources across multiple nodes. Hence, the LQ jobs are not able to receive the whole cluster capacity as expected. More importantly, this delay is also caused by allocation overheads, such as waiting for containers to be allocated or launching containers.

As the number of TQs increases, the performance of DRF significantly degrades because DRF tends to allocate less resource to LQ jobs. DRF is the worst among three schedulers. In contrast, BPF and SP give the highest priority to LQs that guarantees the performance of LQ jobs. The average completion times, when TQs are available (1,2,4, and 8), are almost the same (65 seconds). These average completion times are still larger than the case of no TQs because of non-preemption. The LQ jobs are not able to receive the resources that are still used by the running tasks.

To understand how well BPF performs on various workload traces, we carried out the same experiments on TPC-DS and TPC-H. As SP and BPF achieve the similar performance, we only present the factors of improvement



(a) 1 LQ & 4 TQs **(b)** 1 LQ & 8 TQs

Figure 7: [Cluster] The completion time of LQ jobs is predictable using BPF.

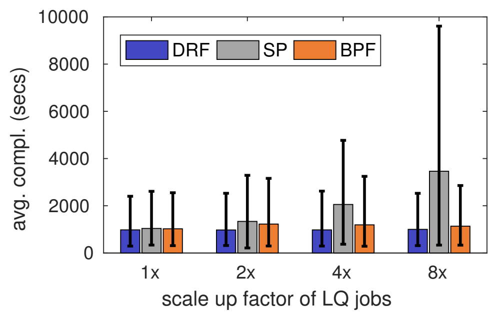


Figure 8: [Cluster] BPF protects the batch jobs up to 3.05× compared to SP.

of BPF across the various workloads in Table 3. The numbers on the table show the consistent improvement on the average completion time of LQ jobs.

In addition to the average completion time, we evaluated the performance of individual LQ jobs. Figure 7 shows that cumulative distribution functions (cdf) of the completion times across 3 approaches. Figure 7a and 7b are the experimental results for the cases of 4 TQs and 8 TQs, respectively. We observe that the completion times of LQ jobs in DRF are not stable and vary a lot when the number of LQs becomes large as in Figure 7b. The unstable performance is caused by the instantaneous fairness and the variance of total resource demand.

5.2.3 Fairness guarantee

Figure 8 shows the average completion time of TQ jobs when we scale up the number of tasks of LQ jobs are by 1x, 2x, 4x, and 8x. In this experiment, there are a single LQ and 8 TQs.

Since DRF is a fair scheduler, the average completion times of TQ jobs are almost not affected by the size of LQ jobs. However, SP allocates too much resource to LQ jobs that significantly hurts TQ jobs. Since SP provides the highest priority for the LQ jobs, it makes the TQ jobs to starve for resources. BPF performs closely to DRF. While DRF maintains instantaneous fairness, BPF maintains the long-term fairness among the queues.

To better see the long-term fairness in resource allocation, we present average resource usage across 3 approaches in Figure 9. There are totally 9 queues (1 LQ and 8 TQ). The x-axis is the normalized capacity. SP is dominant in both memory and CPU. BPF and DRF can achieve the fairness in resource allocation for LQs and

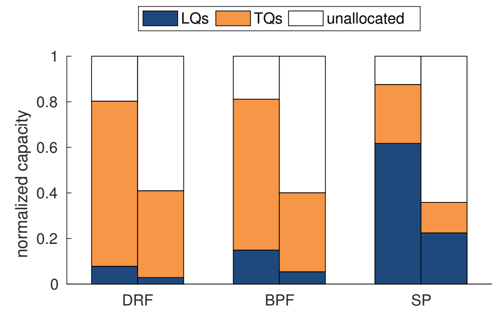


Figure 9: [Cluster] The average resource consumption of the cases of scaling up LQ jobs at 8x. The left bar is memory usage, and the right bar is CPU usage. All three policies have similar utilization.

TQs. All of them have similar resource utilization.

5.2.4 Scheduling overheads

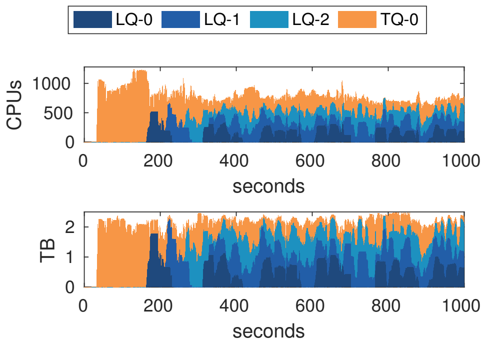
Recall from Section 4 that the BPF scheduler has three components: user input, admission control, and allocation. Compared to the default schedulers in YARN, our scheduler has additional scheduling overheads for admission control and additional computation in allocation.

Since we only implement our scheduler in the Resource Manager, the scheduling overheads occur at the master node. To measure the scheduling overheads, we run admission control for 10000 LQ queues and 10000 TQ queues on a master node – Intel Xeon E3 2.4 GHz (with 12 cores). Each LQ queue has 500 ON/OFF cycles. Recall the LQADMIT and TQADMIT functions in Algorithm 1, the admission overheads increase linearly to the number of queues. The total admission overheads are approximately 1 ms, which is much less than the default update interval in YARN Fair Scheduler, i.e., 500 ms [2]. The additional computation in allocation is also negligibly less than 1 ms.

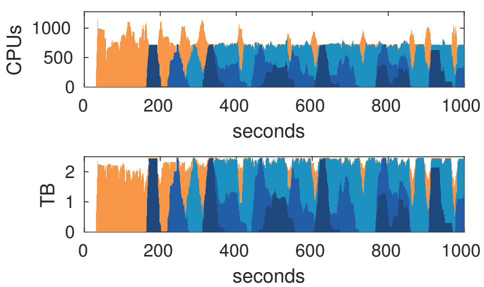
5.2.5 Admission control for multiple LQs

To demonstrate how BPF works with multiple LQs, we set up 3 LQs (LQ-0, LQ-1, and LQ-2) and a single TQ (TQ-0). The jobs TQ-0 are queued up at the beginning while LQ-0, LQ-1, and LQ-2 arrive at 50, 100, and 150 seconds, respectively. The periods of LQ-0, LQ-1, and LQ-2 are 150, 110, and 60 secs. All the LQs jobs have the identical demand and task durations. The TQ jobs are chosen from the BB benchmark. BPF admits LQ-0 to the Hard Guarantee class, LQ-1 to the Soft Guarantee class, and LQ-2 to the Elastic class.

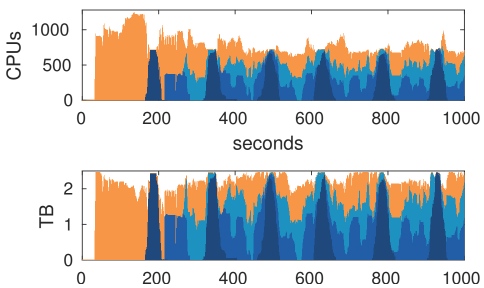
Figure 10a shows the resource usage (CPU and memory) for each queue across four schedulers, i.e., DRF, SP, N-BPF and BPF. As an instantaneously fair scheduler, DRF continuously maintains the fair share for all queues as in Figure 10a. Since LQ-2 requires a lot of resources, SP makes TQ-0 starving for resources (Figure 10b). N-BPF provides LQ-0 with resource guarantee and it fairly share the resources to LQ-1, LQ-2, and TQ-0



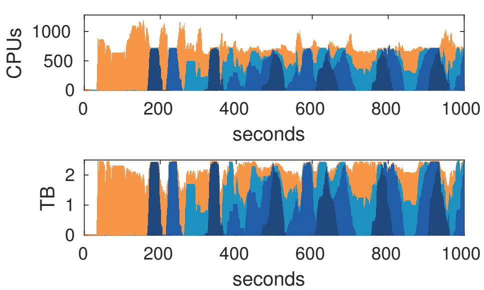
(a) DRF: LQ-0, LQ-1, LQ-2 are unhappy with high latency.



(b) SP: TQ-0 is starving of resources.



(c) N-BPF: Only LQ-0 and TQ-0 are happy.



(d) BPF: LQ-0, LQ-1 and TQ-1 are happy.

Figure 10: [Cluster]. DRF and SP fail to guarantee both performance and fairness simultaneously. BPF gives the best performance to LQ-0, near optimal performance for LQ-1, and maintains fairness among 4 queues. LQ-2 requires too much resource, so its performance cannot be guaranteed.

(Figure 10c). BPF provides hard guarantee to LQ-0 and soft guarantee to LQ-1 as in Figure 10d. The soft guarantee allows LQ-1 performs better than using N-BPF. Since LQ-2 demands too much resources, BPF treats it like TQ-0.

Workload	Number of TQs					
	1	2	4	8	16	32
BB	1.08	1.56	2.32	4.09	7.28	16.61
TPC-DS	1.06	1.38	1.66	2.93	5.16	10.40
TPC-H	1.01	1.28	1.92	3.04	5.50	11.35

Table 4: [Simulation] Factors of improvement by BPF across various workloads w.r.t the number of TQs.

Figure 11 shows the average completion time of jobs on each queue across the four schedulers. The performance of DRF for LQ jobs is the worst among the four schedulers but it is the best for only TQ-0. The performance of SP is good for LQ jobs but it is the worst for TQ jobs. N-BPF provides the best performance for LQ-0 but not LQ-1 and LQ-2. BPF is the best among the four schedulers. The three of four queues, i.e., LQ-0, LQ-1, and TQ-0, significantly benefit from BPF. BPF even outperforms SP for LQ-0 and LQ-1 jobs and does not hurt any TQ.

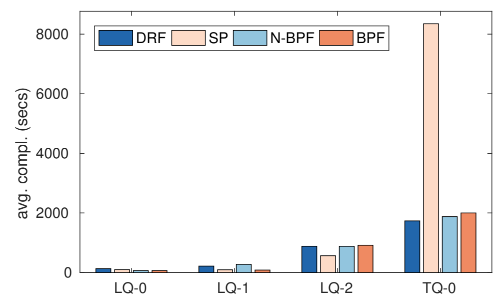


Figure 11: [Cluster] BPF provides with better performance for LQs than DRF and N-BPF. Unlike SP, BPF protects the performance of TQ jobs.

5.3 Performance in Trace-Driven Simulations

To verify the correctness of the large-scale simulator, we replayed the BB trace logs from cluster experiments in the simulator. Table 4 shows the factors of improvement in completion times of LQ jobs for BB workload in simulation that are consistent with that from our cluster experiments (Table 3).

BPF significantly improves over DRF when we have more TQs. We note that the factors of improvement for TPC-DS and TPC-H in the simulation are less that of the cluster experiments. It turns out that DRF in TCP-DS and TPC-H suffers from the allocation overheads that our simulation does not capture. The allocation overheads for the LQ jobs in TPC-DS and TPC-H are large because they have more phases than the LQ jobs in BB (only 2 phases).

5.4 Sensitivity Analysis

We use the large-scale simulator to study the impact of estimation errors and non-preemption on LQ jobs.

5.4.1 Impact of estimation errors

BPF requires users to report their estimated demand for LQ jobs. However, it is challenging to estimate the demand accurately, which naturally results in estimation errors. To understand the impact of estimation errors on BPF, we assume that estimation errors $e(\%)$ follow the standard normal distribution with zero mean. The standard deviation (std.) of estimation errors lines in $[0, 50]$. To adopt the estimation errors, we update the task demand and durations of LQ jobs as $task_{new} = task_{original} * (1 + e/100)$.

Figure 12 shows the impact of estimation errors on the average completion time of LQ jobs. There are 1 single LQ and 8 TQs. LQ jobs arrive every 350 seconds. BPF is robust when the standard deviation of estimation errors vary 0 to 20. The LQ jobs in BB suffer more from the large estimation errors (std. > 30) than that of TPC-DS and TPC-H. The delays are caused by the underestimated jobs because the excessive demand is not guaranteed by the system. Meanwhile, the overestimated jobs do not suffer any delays as the guaranteed resource is more than needed. Although estimation errors result in performance degradation, the performance of LQ jobs is still much better than that of DRF (162 seconds).

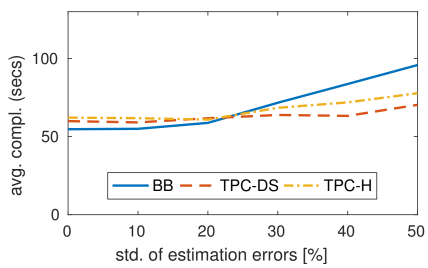


Figure 12: [Simulation] BPF's performance degrades with larger estimation errors, yet is still significantly better than DRF (162 secs).

5.4.2 Impact of non-preemption

To evaluate the impact of non-preemption, we vary the average task durations of TQ jobs. The longer task duration is, the longer the task holds its resources. In this evaluation, we set up 1 LQ and 8 TQs on the simulator. Each LQ job arrives every 350 secs. The evaluation is run on three workloads BB, TPC-DS, and TPC-H.

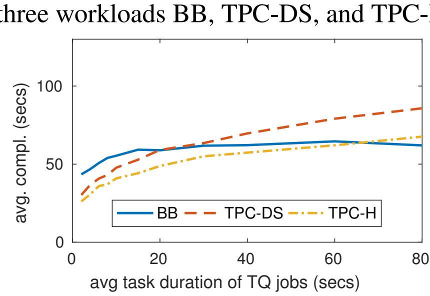


Figure 13: [Simulation] With longer average task durations, the impact of non-preemption on the performance of LQ jobs becomes larger. However, the average completion time is still significantly better than that of DRF (162 secs).

Figure 13 shows the impact of average task durations of TQ jobs on the average completion time of LQ jobs. When we increase the average task durations, the performance of LQ jobs is degraded. Due to the variations of task durations, the BB curve stops increasing from 20, while the TPC-DS and TPC-H curves keep going up. Recall the distributions of the task durations in Figure 4: 70 percent of tasks in BB are very short. When the average task durations are more than 20 seconds, there are still a large number of short tasks in BB that allows BPF to allocate more resources to LQ jobs. TPC-DS and TPC-H have more variations of task durations that result in increasing delay for LQ jobs.

6 Related Work

Bursty Applications in Big Data Clusters Big data clusters experience burstiness from a variety of sources, including periodic jobs [39, 14, 18, 66], interactive user sessions [17], as well as streaming applications [73, 16, 13]. Some of them show predictability in terms of inter-arrival times between successive jobs (e.g., Spark Streaming [73] runs periodic mini batches in regular intervals), while some others follow different arrival processes (e.g., user interactions with large datasets [17]). Similarly, resource requirements of the successive jobs can sometimes be predictable, but often it can be difficult to predict due to external load variations (e.g., time-of-day or similar patterns); the latter, without BPF, can inadvertently hurt batch queues (§2).

Multi-Resource Job Schedulers Although early jobs schedulers dealt with a single resource [74, 20, 52], modern cluster resource managers, e.g., Mesos [49], YARN [69], and others [66, 70, 29], employ multi-resource schedulers [43, 41, 45, 46, 27, 58, 25] to handle multiple resources and optimize diverse objectives. These objectives can be fairness (e.g., DRF [43]), performance (e.g., shortest-job-first (SJF) [41]), efficiency (e.g., Tetris [45]), or different combinations of the three (e.g., Carbyne [46]). However, *all* of these focus on instantaneous objectives, with instantaneous fairness being the most common goal. To the best of our knowledge, BPF is the first multi-resource job scheduler with long-term memory.

Handling Burstiness Supporting multiple classes of traffic is a classic networking problem that, over the years, have arisen in local area networks [40, 67, 68, 26], wide area networks [60, 55, 50], and in datacenter networks [56, 48]. All of them employ some form of admission control to provide quality-of-service guarantees. They also consider only a single link (i.e., a single resource). In contrast, BPF considers multi-resource jobs and builds on top this large body of existing literature.

BVT [38] was designed to work with both real-time and best-effort tasks. Although it prioritizes the real-time tasks, it cannot guarantee performance and fairness.

Expressing Burstiness Requirements BPF is not the first system that allows users to express their time-varying resource requirements. Similar challenges have appeared in traditional networks [68], network calculus [34, 35], datacenters [56, 21], and wide-area networks [60]. Akin to them, BPF requires users to explicitly provide their burst durations and sizes; BPF tries to enforce those requirements in short and long terms. Unlike them, however, BPF explores how to allow users to express their requirements in a multi-dimensional space, where each dimension corresponds to individual resources. One possible way to collapse the multi-dimensional interface to a single dimension is using the notion of *progress* [30, 43]; however, progress only applies to scenarios when a user's utility can be captured using Leontief preferences.

7 Conclusion

We observe that all existing schedulers force the same performance goal on all jobs, which fails to serve both latency-sensitive LQs and throughput-sensitive TQs. In fact, existing "fair" schedulers [43, 42, 25, 53] only make instantaneous decisions causing high latency for LQs. On the other hand, just giving high priority to LQs does not solve the problem because it may starve the TQ jobs. To enable the coexist of latency-sensitive LQs and the TQs, we proposed BPF (Bounded Priority Fairness). BPF provides bounded performance guarantee to LQs and maintains the long-term fairness for TQs. BPF classifies the queues into three classes: Hard Guarantee, Soft Guarantee and Elastic. BPF provides the best performance to LQs in the Hard Guarantee class and the better performance for LQs in the Soft Guarantee class. The scheduling is executed in a strategyproof manner, which is critical for public clouds. The queues in the Elastic class share the left-over resources to maximize the system utilization. In the deployments, we show that BPF not only outperforms the DRF up to 5.38× for LQ jobs but also protects TQ jobs up to 3.05× compared to Strict Priority. The sensitivity analysis shows that our scheduler is robust to estimation errors and non-preemption.

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8 Sigcomm comments

- The proposed solution does not really present any difficult technical challenge.

- BPF requires as input the duration of the ON periods for low latency traffic. It is unclear to me whether jobs can know this in advance so that they can submit it to the scheduler. BFP needs accurate estimates of resource demands and their duration to schedule jobs properly. This looks like a very strong assumption. Tan says: We can argue for this assumption as our solution is robust to estimation errors and strategyproofness. So, users may not need to report these parameters and they can be estimated instead. This must be justified in the approach section.

- BPF addresses scheduling in one specific scenario. If new applications or computing abstractions come along, BPF might not generalize.

- There is a large body of work we could draw on to schedule latency-sensitive applications on datacenters, but the paper does not seem to take it into account. Tan says: We indeed have this in related work.

- You should compare BFP to "SP+DRF", e.g., latency-sensitive jobs get high priority and throughput-sensitive jobs get low priority, the job scheduling within the same priority uses DRF. To guard against latency-sensitive jobs that become too large (e.g., exceeding certain pre-defined threshold), they can be converted into throughput-sensitive jobs. To me, this simple two-tier scheduler will likely achieve the same effect as BFP, and is much easier to implement. Tan says: This is similar to DRF-W, but it won't provide performance guarantee and it is not fair as latency-sensitive jobs may dominate the resources for a long time.

9 What we can do?

- 1.5 page reduction. We can remove the Algorithm 1 pseudo code due to page limit and it is covered by Figure Figure 2 as well as text (0.5 pages). We can remove paragraphs at the beginning of section (0.25 pages). Shrink the figures (0.25 pages). Need 0.5 page for simulation results in section 5.3 that duplicate the results in implementation.

- Currently we have simulation results and implementation that support long-term fairness, burst guarantee but NOT for pareto efficiency and strategyproofness. There is no easy way to show pareto efficiency in simulation. We can have results for strategyproofness when LQ users report more resources than they need. However, is it too straighforward?