Can't Be Late: Optimizing Spot Instance Savings under Deadlines

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Abstract

Cloud providers offer spot instances alongside on-demand instances to optimize resource utilization. While economically appealing, spot instances' preemptible nature causes them ill-suited for deadline-sensitive jobs. To allow jobs to meet deadlines while leveraging spot instances, we propose a simple idea: use on-demand instances judiciously as a backup resource. However, due to the unpredictable spot instance availability, determining when to switch between spot and on-demand to minimize cost requires careful policy design. In this paper, we first provide an in-depth characterization of spot instances (e.g., availability, pricing, duration), and develop a basic theoretical model to examine the worst and average-case behaviors of baseline policies (e.g., greedy). The model serves as a foundation to motivate our design of a simple and effective policy, Uniform Progress, which is parameter-free and requires no assumptions on spot availability. Our empirical study, based on three-month-long real spot availability traces on AWS, demonstrates that it can (1) outperform the greedy policy by closing the gap to the optimal policy by 2× in both average and bad cases, and (2) further reduce the gap when limited future knowledge is given. These results hold in a variety of conditions ranging from loose to tight deadlines, low to high spot availability, and on single or multiple instances. By implementing this policy on top of SkyPilot, an intercloud broker system, we achieve 27%-84% cost savings across a variety of representative real-world workloads and deadlines. The spot availability traces are open-sourced for future research.[1]

1 Introduction

As organizations continue to migrate their workloads to clouds, the need to minimize operational costs has become a critical concern [41]. One of the top contributors to cloud spending is the cost of compute instances [8], which are typically offered in two pricing models: *on-demand* and *spot*.[2]

On-demand instances are available but come at a premium cost. In contrast, *spot* instances are typically 3–10× cheaper (Table 1), but are less available and they can be preempted unexpectedly. As a result, more applications such as analytics [13], AI [28, 37, 40], HPC [29], and CI/CD workloads [1], are leveraging spot instances to reduce costs. To handle preemptions, these jobs either checkpoint periodically and recover from the last checkpoint on restart [25, 46], or re-execute the entire job.

	V100 GPU	64-core CPU
AWS	3×	2–6×
Azure	3–6×	3–10×
GCP	3×	4–11×

Table 1: Cost savings of spot vs. on-demand instances.

However, while many applications can tolerate uncertainties introduced by spot instance preemptions, others cannot. One such category is delay-sensitive applications where a job needs to finish by a certain deadline [24]. Examples include processing new user data to keep an AI model up-to-date in a recommendation system, or analyzing the latest information to make timely decisions in a trading application. Therefore, most of deadline-sensitive applications eschew spot instances in favor of on-demand instances, thus trading off cost for predictability.

In this paper, we resolve this tradeoff by enabling an application to leverage spot instances while still meeting its deadline. For simplicity, we focus on recoverable jobs running on a single instance, and assume the running time of the job is known, as well as its deadline. A job can be in one of three states: (1) running on a spot instance, (2) running on an on-demand instance, or (3) idle, i.e., waiting for a spot instance to become available. We design scheduling policies that periodically decide whether a job should remain in the same state or switch to another state. When a job switches to a non-idle state we assume there is a delay, e.g., the overhead of provisioning/setting up a new instance, and re-starting from a previous checkpoint. Due to the high unpredictability in spot instance availability (§2.2), the key challenge lies in striking a balance between cost optimization and deadline adherence to effectively leverage the low cost of spot instances without missing the deadline.

A simple solution to this problem would be for a job to

[1] See spot traces: https://github.com/skypilot-org/spot-traces

[2] In this paper, we do not consider "reserved" instances, whose economics involves volume contracts and is more complex.

use a spot instance up to the point at which the remaining computation time equals the remaining time to deadline, and then switch to an on-demand instance until it finishes. While this "greedy" policy (§3.4) guarantees that the job will meet its deadline, we show that it is sub-optimal. We do so by developing a theoretical framework to study the worst-case behavior (e.g., competitive ratio) of the policy (§4).

To address the limitations of "greedy" policy, we propose a simple and effective policy, called *Uniform Progress*, which aims to make uniform progress towards deadline, by distributing the job computation uniformly across the time. Uniform Progress requires no assumption about spot instances' availability and is parameter-free. Using simulations on real-world traces we show that Uniform Progress outperforms greedy policy and approaches an optimal policy with limited knowledge of the future (knowing how long the next spot instance is going to last) in a variety of scenarios—from loose to tight deadlines, and from low to high spot availability. We build a prototype of Uniform Progress and evaluate it in a cloud setting on three real-world workloads: ML training, scientific batch jobs, and data analytics. Results show that Uniform Progress achieves 27–84% cost savings while meeting deadlines.

This paper is organized as follows. First, we provide an in-depth characterization of spot instances across various cloud regions, examining their availability patterns, pricing, and lifetime to inform our policy design (§2). Next, we develop a theoretical model that captures the essential dynamics of spot instances, which enables us to examine the worst-case behavior of a given policy (§3, §4). We then present our policies for jobs with both single and multiple instances (§5) and conduct a comprehensive empirical study on months-long real-world traces of spot instances (§6). We build a prototype implementation that supports the proposed policies in a cloud setting, and evaluate these policies on three real-world workloads (§7). Finally, we review related work in §8.

In summary, this paper makes the following contributions:

1. We introduce a problem of using spot instances to minimize the cost of running a job with deadline adherence.
2. We develop a theoretical framework to study the worst and average-case behavior of baseline policies, providing insights on the tradeoff between cost and deadline.
3. We propose Uniform Progress, a simple but effective policy which is parameter-free and requires no assumptions on spot availability. Empirically, we show the significant improvement of the policy in a wide variety of scenarios.
4. We implement a prototype system with Uniform Progress, and evaluate it on real-world workloads.

Finally, we open source our three-month traces of spot instance availability to encourage future research in this area.

2 Characterization of Spot Instances

In this section, we characterize spot instance availability and pricing over time and across availability zones. We observe high volatility in availability but a smooth pricing pattern. We use these insights to drive the design of our scheduling policy.

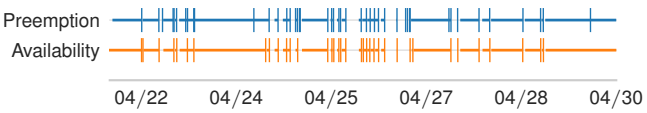


Figure 1: Real spot preemptions and availability are highly correlated. Trace is in AWS us-west-2b. **Upper**: preemptions. Horizontal lines represent a running spot instance. Vertical bars are preemptions. **Lower**: availability. Horizontal lines are spot instance available periods. Vertical bars are changes from availability to unavailability. Grey gaps are unavailability periods. Note that although some vertical bars look immediately followed by a horizontal line, there are still gaps in between.

2.1 Methodology of Spot Trace Collection

We collect *spot availability traces* from public clouds. A trace is a time series showing whether a particular spot instance type is available at a given time in a zone. We collect these traces over a three-month period and in nine AWS availability zones (three in *us-west-2*, four in *us-east-1*, two in *us-east-2*).

A key challenge of trace collection is that it can be prohibitively expensive. For example, a spot V100 instance costs about $1/hour. If we collect a real *preemption* trace where an instance is kept live as much as possible modulo preemptions, collecting three-month long traces in all nine zones could cost over $10,000. Instead, we propose an approximation: we collect *availability* traces, where we try to launch a spot instance every 10 minutes to probe if it is available and then immediately terminate it. To validate this approach, Figure 1 shows a high correlation between the real preemption and availability signals over a week-long period. This approach reduces the cost of trace collection by about 100×. For completeness, we also include real preemption traces in our evaluation of policy performance on multi-instance jobs (§6.6) and real-world workloads (§7.2).

In this work, we focus on a few *scarce* instance types, i.e., Nvidia V100 and K80 GPU instances, which are now in high demand [4] due to the rise of Generative AI and large language models (LLMs). Focusing on these scarce instance types is thus both useful and interesting, as they are frequently preempted, providing a good testing ground for scheduling policies.

2.2 High Variance in Spot Availability

Our analysis reveals that spot availability varies significantly *across zones* and *over time*. Figure 2 (left) shows the availability traces of 9 AWS zones over 2 weeks (4 example zones are in Figure 2 and the rest 5 zones are in §A.1). We observe a large difference across zones (e.g., us-west-2a vs us-east-1a). The periods of unavailability can last for hours or even days.

To understand spot availability distributions, we overlay 6-hour windows on a 2-week period (thus, $14 \times 24/6 = 56$ windows per zone) and count the fraction of availability probes that succeeded in each window. Figure 2 (right) plots the distributions of *spot availability fractions* in the 56 windows per zone, which approximate the fraction of time spot instances are available in each zone. We observe that each

Figure 2: Spot Availability is highly unpredictable and volatile. Traces are across four of nine AWS zones collected. **Left**: Availability. Horizontal lines are available periods. Vertical bars are changes from available to unavailable, followed by grey gaps indicating unavailable period. **Right**: Boxplots of spot availability fraction, *i.e.,* percentage of the time an instance is available in 6-hour windows.

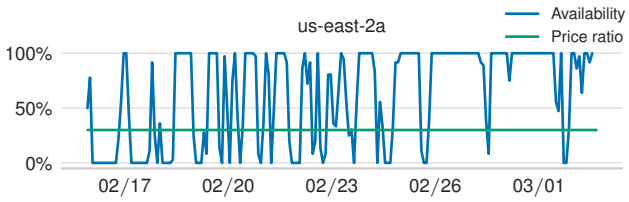


Figure 3: High volatility of spot availability fraction. Availability can jump from 100% to 0% within hours. Price ratio: spot price divided by on-demand price.

zone can go from being highly available to mostly unavailable across time (e.g., in us-east-2b, the difference between p25 and p75 is about 70%) and there is little correlation across zones. In addition, Figure 3 shows changes in spot availability fractions over time. We observe a highly volatile pattern: availability can change from 100% to 0% within hours.

The results above suggest that scheduling policies should be robust to highly unpredictable availability patterns. For generality, in this paper, we make no assumptions on spot availability patterns. We discuss existing prediction-based approaches in §8 and leave this direction to future work.

2.3 Relative Stability in Spot Pricing

In contrast, we observe that spot pricing is much more stable than availability. Figure 3 shows the price ratio of spot to on-demand for AWS stays almost constant despite significant changes in availability. In the three-month-long trace, we observe only a 5% price variation on average over any one-week period, validating the recently introduced smooth pricing model on AWS [5]. GCP's spot instance prices are even more stable as it is guaranteed to only change once every 30 days [3].

2.4 Correlation of Multi-Instance Availability

To understand the behavior of multiple spot instances, we analyze 2-week *preemption* traces and 2-week *availability* traces for clusters of 4 and 16 instances, respectively (see §6.1 for details). Notably, over 94% of the time, either all or none of the instances are available in each cluster. This suggests availability tends to change *simultaneously* for multiple instances (bulk preemption is also observed in [16]), up to a count of 16.

3 Using Spot for Deadline-Sensitive Jobs

In this section, we present a simple model to formulate the problem, discuss when a policy matters, and then give three rules for policy design followed by a basic greedy policy.

3.1 Problem Setup

We consider two types of instances with the same hardware: an on-demand instance, which is always available,[3] and a spot instance, whose availability is unpredictable. We assume that spot availability is non-adversarial, meaning that it is independent of the job's choices and observable factors, except for §4.1, where we adopt competitive analysis for the worst case study.

We focus on long-running (hours to days) jobs where preemptions are likely. We firstly assume each job uses one instance. We will extend it to multiple instances in §5.5 and evaluate it in §6.6.

For a deadline-sensitive job, we denote *remaining computation time* at time t as $C(t)$ and *remaining time-to-deadline* as $R(t)$. This implies that the job's total computation time is $C(0)$, and deadline is $R(0)$. Based on the definition, we can derive that $R(t) = R(0) - t$ and when a job is progressing, $\partial C(t)/\partial t = -1$.

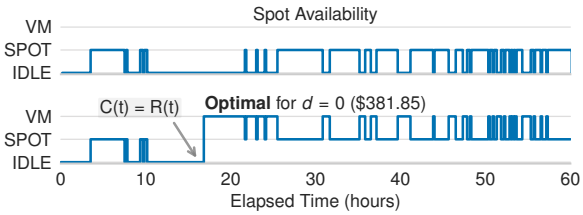
We assume that both $C(0)$ and $R(0)$ are given and the job is fault-tolerant to interruptions. For example, ML training typically has a consistent per-epoch time, indicating a predictable total runtime, and the model weights can be checkpointed and resumed for fault tolerance. Additionally, computation times for many recurring jobs (e.g., data analytics, scientific HPC, CI/CD) can be derived from past executions.

To account for overheads of starting the job on a new instance, we introduce *changeover delay*, d, which includes the time required to launch an instance, set up dependencies, and recover any potential progress loss caused by gaps between checkpoints or restarting the most recent unsaved execution. Whenever a job switches to a new spot or on-demand instance, a changeover delay occurs, meaning that $C(t)$ does not decrease for a duration of d while $R(t)$ continues to decrement. A delay d is charged at the new instance type's price. Switching from an instance to idle (i.e., termination) does not incur a delay. We will extend the model to consider variety with $C(0)$ and d in §5.6, and evaluate it in §6.7.

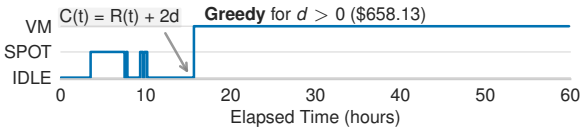
The goal is to minimize the cost for completing job's computation time $C(0)$ before deadline $R(0)$, *i.e.,* $C(R(0)) \leq 0$, using spot and on-demand instances. For simplicity, we define the price for an on-demand instance to be $k > 1$, and a spot instance to be 1. We assume that cloud providers charge every second when an instance is alive.[4] Based on the observation

[3] This is a simplifying assumption. In practice, some on-demand instance types can hit unavailability.

[4] Cloud providers have different billing practices, *e.g.,* AWS does not



(a) Without changeover delay.



(b) With changeover delay.

Figure 4: Example decision traces of policies on real spot availability on AWS.

in §2.3, we assume both the on-demand and spot price are fixed throughout the time before deadline $R(0)$.

3.2 Scheduling Policy

At any time t, a job can be in one of the following three states: idle, running on a spot instance, or running on an on-demand instance. While we assume that on-demand instances are always available, spot instances can be in one of two states: available or unavailable. The job's state space is the combination of any of the instance state and the spot state, except for an impossible case where the instance state is spot with spot state unavailable (Table 2). A scheduling policy is invoked to decide how a job moves across instance states.

Spot State \ Instance State	Idle	Spot	On-Demand
Spot Available	①	③	④
Spot Unavailable	②	-	⑤

Table 2: State space for a job.

In the ideal case where changeover delay $d = 0$, the problem is simple. An optimal policy is to use a spot instance whenever it is available, *i.e.,* transition between state ② and ③, until $C(t) = R(t)$. After that, the job cannot stay idle, as it needs to utilize all the remaining time before deadline to make progress. Since there is no changeover delay, the policy can use spot whenever it is available and switch to on-demand when it is not, *i.e.,* transition between ③ and ⑤. This policy is optimal because it utilizes all available spot instance lifetimes before the deadline, without additional cost. Figure 4a shows an example decision trace of how this policy performs for a job with $C(0) = 48$ hours and $R(0) = 60$ hours on a real spot availability trace, where the policy utilizes every spot lifetime, and runs the remaining computation with on-demand instances.

However, when changeover delay $d > 0$, which is the practical case, the problem becomes non-trivial. The policy now has to decide whether it is worth switching to a different instance at the expense of losing time d without making progress, which increases the risk of missing the deadline. For example, applying the optimal policy above for $d > 0$ would result in missing the deadline, since every switch costs an additional time d.

In the remainder of this paper, we focus on designing policies for the more practical $d > 0$ scenario.

3.3 Rules for Policy Design

Based on the problem setting, we propose three basic rules that all policies without future knowledge should follow to avoid unnecessary cost or missing the deadline.

Thrifty Rule. The job should remain idle after $C(t) = 0$.

Safety Net Rule. When a job is idle and $R(t) < C(t) + 2d$, switch to on-demand and stay on it until the end.

The policy is required to guarantee the job finished by the deadline. After $R(t) < C(t) + 2d$ becomes true, it is no longer safe to move from idle to spot. Otherwise, when the changeover delay of the spot finishes, the remaining time will become $R(t) < C(t) + d$, which means any preemption to the spot instance will result in missing deadline. Note that one could wait until $R(t) = C(t) + d$ then move to on-demand, but there is no gain for waiting an additional d if the job is idle.

Exploitation Rule. Once start using a spot instance, stay on it until it is preempted.

If the job is on a spot instance, any progress made will always cost the minimum price any policy could get, *i.e.,* the spot price. Voluntarily switching from spot to idle or on-demand will have no benefit, but less progress or more cost.

This rule will not violate the deadline because the Safety Net Rule guarantees that $R(t) \geq C(t) + 2d$ holds at the time t when the job is moved to the current spot instance. After the changeover delay is incurred and the job starts progressing, $R(t) - C(t)$ will not change, *i.e.,* $R(t) \geq C(t) + d$ holds, meaning the remaining time is enough for at least one changeover even if the current spot is preempted. The job will be able to switch to on-demand when Safety Net Rule kicks in.

3.4 Greedy Policy

Based on the three rules, we propose a straightforward greedy policy. The greedy policy behaves as follows:

1. Stay on any available spot instance until it is preempted (Exploitation Rule), and keep waiting if no spot instance is available, *i.e.,* transition between ② and ③ in Table 2.
2. (Safety Net Rule) When $R(t) < C(t) + 2d$ holds and the job is idle, move to on-demand and stay there until the end.

In Figure 4b, we show the decision trace of the greedy policy on the same spot availability trace as before (Figure 4a). The greedy policy acts much more conservatively than the previous optimal policy without changeover delay. That is because greedy can no longer afford frequent switches between on-demand and spot instances as before without missing the deadline. Thus, we now turn our attention to: can we do better than greedy while not assuming future knowledge?

4 Theoretical Analysis

In this section, we delve into theoretical aspects of the problem and prove the existence of a policy that is better than greedy in both worst and average cases.

charge for spot instances preempted within the first hour, while GCP does.

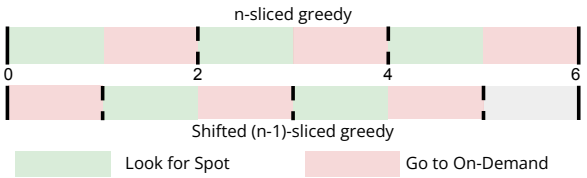


Figure 5: Example slicing for randomized shifted greedy (RSF) policy, where deadline $R(0)=6$, computation time $C(0)=3$, and slices $n=3$. Dashed lines indicate boundaries of slices.

4.1 Worst Case with Competitive Analysis

We first look into the worst case by investigating the competitive ratio c of a policy without knowledge of future spot availability, which is the ratio of the cost of the policy to the best omniscient policy with full knowledge of future spot availability. By "worst" case, we assume that spot instances are chosen by an oblivious adversary, who can base their decisions on complete knowledge of the job's policy but not on random coin flips used by the policy. Our goal is to prove that there is a policy with lower competitive ratio c than greedy, *i.e.,* performs better in the worst case.

To simplify the presentation, we assume changeover delay d is small and ignore the term $O(d)$. Also, we use $R(t)=C(t)+d$ as Safety Net Rule's condition, instead of $R(t)=C(t)+2d$, which will not affect the conclusion, due to negligible $O(d)$.

A natural bound for c is $1\le c\le k$, where k can be reached when the oblivious adversary choose a case that a given policy have to use all on-demand, and the omniscient policy could use all spot instances. We can prove that for any $R(0), C(0)$, a deterministic policy cannot perform better than greedy (see §A.2.1).

Theorem 1. *For any deterministic policy P, $c\ge k-O(d)$.*

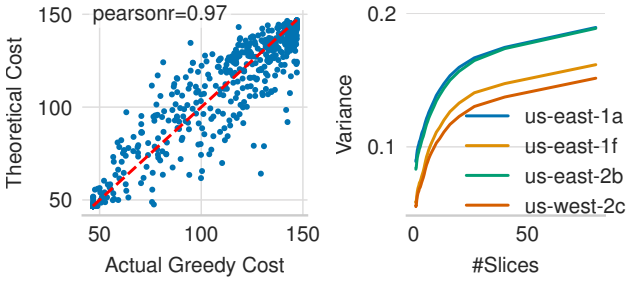
With Theorem 1, we can conclude that a policy has to be randomized to beat greedy, whose competitive ratio $c=k$, as an adversary can simply make spot available from t', where $R(t')=C(t')+d$. We now construct a better policy on top of greedy. We first extend greedy to an *n-sliced greedy* policy, in which we divide the time into n even slices with length $\frac{R(0)}{n}$ and apply greedy in each of these slices with $\frac{C(0)}{n}$ progress to make. The upper figure in Figure 5 is an example of n-sliced greedy, with a deadline $R(0)=6$ and 3 slices. In each slice, the policy enforces the job to make $\ge\frac{C(0)}{n}=1$ units of progress within $\frac{R(0)}{n}=2$.

We then shift the n-sliced greedy policy by $\frac{C(0)}{n}$ to get *shifted* $(n-1)$*-sliced greedy* policy, which uses on-demand for time $\frac{C(0)}{n}$ from start (1 in the example Figure 5) and then applies $(n-1)$-sliced greedy from $t=\frac{C(0)}{n}$ until $t=R(0)-\frac{R(0)-C(0)}{n}$.

Although both policies have $c=k$, we can define a *randomized shifted greedy (RSF)* policy by using either the n-sliced or the shifted $(n-1)$-sliced greedy with equal probability at any time t. We can prove that the competitive ratio for RSF is bounded and lower than greedy (see §A.2.1).

Theorem 2. *If $R(0)\ge 2C(0)$, then for RSF policy has $c\le\frac{k+1}{2}+\frac{k-1}{2n}+O(d)<k$.*

When deadline $R(0)$ is more than $2\times$ longer than computation time $C(0)$, the worst case (the largest gap to omniscient policy) for RSF policy is bounded, *i.e.,* provably better than greedy.



(a) Theoretical vs actual greedy cost with delay $d=0.01h$.

(b) Variance vs number of slices with an 80-hour deadline.

Figure 6: Numerical results for validating the theoretical greedy cost and the assumption for increasing variance in the stochastic model. Both analysis are conducted on sampling sub-traces from 2-month AWS spot availability traces.

For $R(0)\le 2C(0)$, we can simply use on-demand until $R(t)=2C(t)$ then start using RSF policy. We denote this *modified RSF (MRSF)* policy.

Corollary 1. *Let $a=\frac{R(0)}{C(0)}-1$ for $0<a\le 1$. MRSF policy has:*

$$c\le k-ak+a(\frac{k+1}{2}+\frac{k-1}{2n})+O(d)=k-\frac{a(k-1)(n-1)}{2n}+O(d)<k$$

With MRSF policy, we shown that there exists a policy that performs better than greedy for any $R(0), C(0)$ in worst cases by randomization and distributing job progress.

4.2 Average Case with Stochastic Model

Since spot availability is a complex stochastic process, we propose a simpler model that is analytically tractable for the development of practical policies. With that model, we will show that n-sliced greedy is better than greedy in the average case.

In order to model the spot process, we consider a smoothed version where we assume that a fractional spot is always available, with a ratio $r<1$, *i.e.,* a job running on the fractional spot makes r amount of progress per unit of time. For example, if spots have 4-hour average lifetimes and 1-hour average wait times after preemption. Then, the fractional spot has a ratio, $r=4/(4+1)=0.8$, and a job using it makes 0.8 amount of progress per unit of time.

Similar as §4.1, for simplicity, we assume that d is relatively small and ignore terms of $O(d)$. We first consider greedy policy. It will use the fractional spot until $R(t')=C(t')+O(d)$ and then switch to on-demand. At time t', the job progress on the fractional spot would be $C(0)-C(t')=rt'-O(d)$, *i.e.,* $C(t')=C(0)-rt'+O(d)$, and the remaining time would be $R(t')=R(0)-t'$. We can derive t' and expected payment (total cost) p:

$$R(t')=C(t')\Longrightarrow R(0)-t'=C(0)-rt'+O(d) \quad (1)$$

$$t'=\frac{R(0)-C(0)+O(d)}{1-r} \quad (2)$$

$$p=rt'+(R(0)-t')k+O(d)=(r-k)t'+kR(0)+O(d) \quad (3)$$

We can observe that the payment depends on the fractional spot ratio r. For simplicity, we will drop $O(d)$ in following formulas. Since $r-k<0$, payment p reduces when the time

t' spent on the fractional spot increases.

In Figure 6a, we calculate both actual and theoretical costs, p, for greedy policy on real availability traces for a 48-hour job with various deadlines (52 to 92 hours) and small changeover delays. It illustrates that theoretical costs with the significant simplified stochastic modeling matches well with actual costs.

We now consider the n-sliced greedy policy from §4.1. For a fixed r, the n-sliced greedy has the same expected payment as original greedy. However, when we started considering the expected payment across difference traces, variance for fractional spot involves. We show that n-sliced greedy works better than original greedy in average.

Consider spot fraction $\mathcal{R}$ as a random variable with mean r and variance v. We can prove that the expected time on the fractional spot $E[t']$ increases with the variance v (see A.2.2). With the formula in §A.2.2, we calculate the difference of n-sliced (with variance $\hat{v}$) to original greedy (with variance v):

$$\Delta = \frac{R(0)-C(0)}{(1-r)^3}(\hat{v}-v)$$

where $\hat{v}$ is the variance over slices with length $\frac{R(0)}{n}$ and v is the variance for traces with length $R(0)$. Since $\mathcal{R}$ is averaged over time, we expect $\hat{v} > v$ (shown in Figure 6b), *i.e.*, $\Delta > 0$. We can conclude that n-sliced greedy has larger $E[t']$, leading to a lower expected cost p than original greedy in average case. Also, as v increases with n, n-sliced policy can achieve better performance with more slices, when d is relatively small.

5 Methodology

Building on our theoretical analysis, we now propose policies for real-world cloud settings. In this section, we will examine the performance of a Time Sliced policy derived from the theoretical analysis, and extend it to a parameter-free Uniform Progress policy. Additionally, we present a upper bound of cost savings through the Omniscient policy, which has the knowledge of future spot availability, and a Partial Lookahead Omniscient policy that only has a shorter lookahead of the future (*e.g.*, 6 hours). Then, we will discuss an interesting scenario when the next spot lifetime is given, and propose an extension that combines Uniform Progress with a Next Spot Lifetime Oracle. Lastly, we extend the policies to multiple instances, and relaxed job computation times and changeover delays for generality.

5.1 Time Sliced

Based on the n-sliced greedy policy in §4.1, we propose the Time Sliced policy. We divide the time before deadline, $R(0)$, into slices, and assign each slice a proportionate computation time $C(0)/n$ and deadline $R(0)/n$, denoted as C_i and R_i for slice i. In each time slice, we apply greedy policy – switching to on-demand instances when $R_i(t) < C_i(t) + 2d$. We make two changes compared to the n-sliced greedy policy: (1) jobs can continue on spot instances whenever available after $C_i(t) \leq 0$, and (2) if a slice makes more progress than required, we reduce the required computation in the succeeding slice, C_{i+1}. We do not apply randomness as in the competitive analysis for simplicity based on the assumption that clouds are non-adversarial.

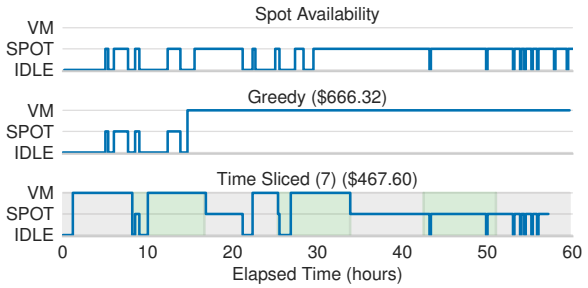


Figure 7: Example decision traces comparing Time Sliced and greedy policy. Time Sliced policy cuts costs by better utilization of available spot near deadline.

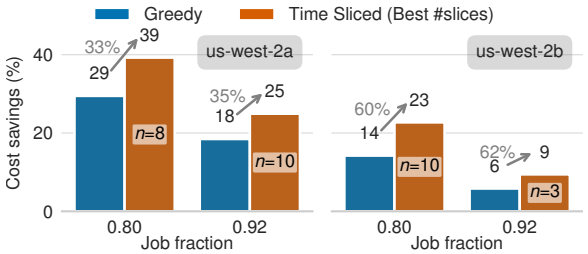


Figure 8: Cost savings (*higher is better*) vs. on-demand with Greedy and Time Sliced policies. Job fraction is $\frac{C(0)}{R(0)}$, and n is the best number of slices chosen for the Time Sliced policy.

Figure 7 presents example decision traces for both greedy and Time Sliced. The spot availability trace shows when spot is available on cloud. The greedy policy utilizes all available spot until $R(t) < C(t) + 2d$. At this point, the job cannot tolerate another changeover delay and must stay on on-demand until the end, rendering available spots close to deadline unusable. In contrast, Time Sliced policy's decision is divided into seven slices (with alternating colors), with greedy applied in each slice. Due to the progress made in earlier slices, Time Sliced allows more slacks to switch between spot and on-demand instances when the deadline is close. This enables better utilization of spot instances, reducing total cost. In this specific example, Time Sliced reduces 30% cost compared to greedy.

In Figure 8, we evaluate Time Sliced by comparing it to greedy in terms of average cost savings across 600 random p3.2xlarge availability traces on AWS. Picking the optimal number of slices enables Time Sliced to achieve 33-62% additional cost savings for relatively tight deadlines. These results suggest that *ensuring uniform progress throughout a job's lifetime* leads to better utilization of spot availability in expectation. We apply this idea in the design of Uniform Progress below.

5.2 Uniform Progress

Although Time Sliced policy with the best slice number n outperforms greedy, selecting the optimal n for different cases is not practical. We take the uniform progress idea from Time Sliced policy and design a parameter-free policy, denoted as Uniform Progress.

5.2.1 Pushing the Slices to the Extreme

Time Sliced policy guarantees uniform progress by enforcing it in discrete slices. While progress can be left behind within a slice, it is ensured by the end of each slice.

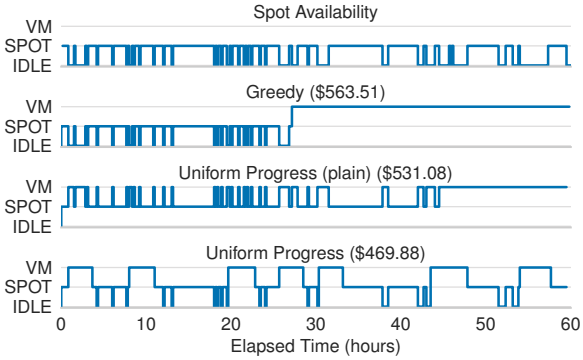


Figure 9: An example decision trace for Uniform Progress.

At the end of a slice i, $t_i = i\frac{R(0)}{n}$, *i.e.,* $i = t_i\frac{n}{R(0)}$. The *current progress*, $cp(t_i) = C(0) - C(t_i)$, is guaranteed to meet the *expected progress*, $ep(t_i)$:

$$cp(t_i) \geq ep(t_i) = i\frac{C(0)}{n} = t_i\frac{C(0)}{R(0)} \tag{4}$$

Note that when the slice number $n = 1$, there is only one t_i, *i.e.,* $t_1 = R(0)$, and Time Sliced becomes greedy policy and only enforces progress $C(0)$ at deadline $R(0)$. When more slices involve, with larger n, (4) applies to more time steps $t \in \{\frac{R(0)}{n}, \frac{2R(0)}{n}, ..., \frac{nR(0)}{n}\}$. According to the stochastic model in §4.2, n-sliced greedy will perform better when n increases, given small changeover delays. Intuitively, this is due to a more aggressive enforcement of progress. For instance, increasing n from 2 to 10 within a 50-hour deadline ensures expected progress made every 5 hours instead of every 25 hours.

We adapt this idea into Time Sliced by pushing $n \to \infty$, making each slice infinitesimal. That enforces (4) at any $t \leq R(0)$, *i.e.,* fully distributing progress within the deadline:

$$cp(t) \geq ep(t) = t\frac{C(0)}{R(0)}, \forall t \leq R(0) \tag{5}$$

5.2.2 Uniform Progress Policy

We propose a parameter-free policy, called *Uniform Progress (plain)*, that switches among three instance states: idle, spot, and on-demand. The policy, based on (5) and the rules in §3, has the following rules:

1. Uniform Progress: When the job is idle and $cp(t) < ep(t)$, switch to on-demand and stay on it to catch up progress.
2. Taking Risks: Switch to spot whenever it is available (even when $cp(t) < ep(t)$). Stay on the spot until it is preempted (Exploitation Rule).

To avoid missing deadline, we also apply Safety Net Rule on top. The first rule asks the policy to maintain steady progress, while *Taking Risks* rule allows the policy to utilize any available spot instances by taking the risk of changeover delays.

In Figure 9, we show an example decision trace. Similar to Time Sliced, Uniform Progress (plain) can achieve better cost savings compared to the greedy policy by evenly distributing progress within the deadline. However, during periods when spot life/wait time are relatively short, the policy suffers from frequent switches between spot and on-demand instances. When the job is on on-demand, and a spot becomes available,

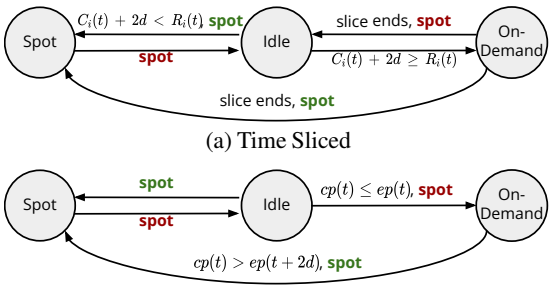


Figure 10: State machine diagram for Time Sliced and Uniform Progress. **spot** means spot unavailable and **spot** means spot available. The Safety Net Rule is left out for simplicity.

our policy will immediately switch to spot. If the spot is preempted by the cloud shortly, the job may make little progress. When that happens, $cp(t) < ep(t)$ can still hold and the job will be scheduled to on-demand again, wasting two changeover delays, $2d$ (one for spot and one for on-demand).

To address that, we propose adding hysteresis to the policy. Although the policy does not know or control the lifetime of a spot instance, it can ensure that the progress made on on-demand instances is sufficient to compensate for potential losses in the worst-case scenario. We thus add another rule:

3. Hysteresis: When the job is on on-demand, stay on it until $cp(t) \geq ep(t+2d)$.

We call the resulting policy *Uniform Progress*. Figure 9 shows that the hysteresis mitigates frequent switching by enforcing more progress on on-demand, and improves cost savings.

Figure 10 compares the state transitions of Uniform Progress and Time Sliced. Both policies share the uniform progress idea, but Time Sliced is discretized, relying on Safety Net Rule within each slice and slice boundaries to jump off an on-demand instance. In comparison, Uniform Progress replaces slice parameters with a global uniform progress checker, $cp(t) \geq ep(t)$, and a hysteresis, $cp(t) \geq ep(t+2d)$.

We will evaluate the policies above in §6. In order to properly assess a policy's performance relative to the best cost savings, we next discuss several policies, which have access to future knowledge, and use them as cost saving upper bounds.

5.3 Omniscient

First, we propose the Omniscient policy, which assumes full future knowledge and generates the theoretically optimal plan.

5.3.1 Omniscient Policy

The Omniscient policy minimizes cost for a given availability trace and deadline $R(0)$. We define some binary variables:

- $a(t)$ whether a spot instance is available at time t.
- $s(t)$, $v(t)$ indicate the policy choose to use a spot/on-demand instance at time t.
- $x(t)$, $y(t)$ represent changeover delays happen to a spot/on-demand instance at time t.

By discretizing time, we can represent the policy as a cost

minimization problem:

$$\min_{s(t),v(t)} \sum_{t=0}^{R(0)} [s(t)+v(t)k] \tag{6}$$

$$\forall t, s(t)+v(t) \le 1, s(t) \le a(t) \tag{7}$$

$$\sum_{t=0}^{R(0)} [s(t)+v(t)] \ge d \sum_{t=1}^{R(0)} (x(t)+y(t))+C(0) \tag{8}$$

$$\forall t, x(t) \le s(t), x(t) \le 1-s(t-1), x(t) \ge s(t)-s(t-1) \tag{9}$$

$$\forall t, y(t) \le v(t), y(t) \le 1-v(t-1), y(t) \ge v(t)-v(t-1) \tag{10}$$

(7) ensures the policy to choose only one instance at a time and only use spot when it is available; (8) requires the total time on spot and on-demand instances to be larger than sum of the time spent on changeover delays and the job runtime; (9) and (10) set variables $x(t)$ and $y(t)$ to 1 when a changeover occurs for spot and on-demand instances, respectively. The resulting formula is an integer linear programming (ILP) problem and can be solved using ILP solvers [14, 31].

5.3.2 Partial Lookahead Omniscient Policy

Omniscient, with complete knowledge of future spot availability, produces an unachievable bound. To better understand the impact of partial knowledge, we propose Partial Lookahead Omniscient, which has limited foresight into future spot availability. By partitioning the deadline into n slices, it can only see complete availability within each slice. To incorporate that knowledge, we modify Omniscient formula to minimize the average cost of progress made in a slice i while ensuring the job progress at the end to be at least $iC(0)/n$. Further details can be found in §A.3.

5.4 Next Spot Lifetime Oracle

Both Omniscient and Partial Lookahead Omniscient policies assume complete knowledge of future availability with different lookahead windows. We propose a more realistic scenario where cloud providers offer an oracle $o(t)$ that returns the lifetime of the next spot instance a job can acquire at the current time t. This assumption is reasonable as providers can determine when to reclaim a spot instance.

Uniform Progress can be extended to leverage this oracle. We introduce two new conditions to replace the hysteresis:

1. If the job is idle, we only switch to spot when the average cost per unit of progress is lower than on-demand cost $\frac{o(t)}{o(t)-d} < k$, *i.e.,* $o(t) > \frac{kd}{k-1}$.
2. If the job is on on-demand instance, we switch to spot only when the average cost per unit of progress, considering switching to spot and back to on-demand, is less than staying on the current on-demand: $\frac{o(t)+kd}{o(t)-d} < k$, *i.e.,* $o(t) > \frac{2kd}{k-1}$.

5.5 Extending to Multiple Instances

All the discussions above are based on single-instance scenario. We now extend the policies to multiple instances. We assume gang-scheduling is required, *i.e.,* all instances must be running for a job to progress. This is typical in distributed ML training [22, 23, 36] and HPC workloads [11]. A cluster may consist solely of spot instances, on-demand instances, or a mix of both. We call clusters with an identical resource type *homogeneous* and those with a mix *heterogeneous*. Changeover delays are incurred when a cluster is reconfigured, *i.e.,* the number of spot/on-demand instances in it changes, unless it has no instance after reconfiguration.

We introduce a new rule for all multi-instance policies:

Polarization Rule. For a job requiring $N > 1$ instances, a policy should either use no instance or N instances at any time.

Since gang-scheduling is required, a cluster with fewer than N instances incurs unnecessary costs without job progress. Thus, once any instance is preempted, a policy should immediately reconfigure the cluster to either 0 or N instances.

We now extend previous policies to multiple instances.

Extending Greedy and Uniform Progress. First, observing that spot availability tends to change simultaneously for multiple instances (§2.4), we propose each policy should produce homogeneous clusters. We will show that this assumption does not harm performance on reasonably large clusters (§6.6). Combining this with *Polarization Rule*, the action space for a policy is simplified to either: N spot, N on-demand, or no instances at any time t.

The problem for multiple instances is now equivalent to the single instance, with the one-to-one mapping of states (§3.2):

- *Cluster state*: N spot, N on-demand, or no instances map to spot, on-demand or idle states for single-instance jobs.
- *Spot state*: If available spot instances $a(t) < N$, it is equivalent to a spot being unavailable in the single-instance scenario, and $a(t) = N$ maps to a spot being available.

Thus, for multi-instance jobs, we directly execute greedy and Uniform Progress using the mappings above.

Extending Omniscient. For Omniscient, we can also restrict it to produce homogeneous clusters and get Omniscient (Homogeneous). The detailed formulation is in §A.7.2. To obtain a better theoretical upper bound for cost savings, however, we further adapt Omniscient to support heterogeneous clusters, denoted as Omniscient (Heterogeneous), by modifying the ILP (6) to factor in a mixed cluster configuration (§A.7.3).

5.6 Relaxing Computation Time and Changeover Delay

In real-world scenarios, exact computation times and changeover delays may be uncertain. We generalize our model to accommodate such variability.

Computation time. To account for the inaccuracies of a user-provided job computation time $\bar{C}(0)$, we denote the difference to the actual job computation time as $\delta = C(0) - \bar{C}(0)$. Given that no policy can predict $C(0)$ precisely beforehand, we adjust the deadline guarantee of the policies to be best effort, ensuring a finish time within the original deadline plus the difference, $R(0)+\delta$. This is guaranteed by having all policies stay on the current instance and switch to on-demand,[5] after the job does not finish but has already made $\bar{C}(0)$ progress, *i.e.,* $\bar{C}(t) \le 0$. When a user overestimates a job's computation time $\bar{C}(0) > C(0)$, it should finish before the original deadline.

[5] If the job was on a spot instance, it should switch to on-demand after the spot instance is preempted (Exploitation Rule).

Otherwise, if the job computation time is underestimated $\bar{C}(0) < C(0)$, the job should finish within the original deadline plus the difference. Note that there is no additional d, as Safety Net Rule guarantees that when $\bar{C}(t) \to 0$, the job should either be on on-demand already or $R(t) \geq \bar{C}(t) + d$, *i.e.,* there is a spare d for the job to switch to on-demand.

Changeover delay. We now adjust the model to factor in system stragglers and variations in changeover delay. We assume that no policies can foresee the exact changeover delay until its occurrence, though the average changeover delay is given. If the maximum possible changeover delay, $\hat{d}$, is also given (*e.g.,* the most significant possible progress loss is triggered), we can prove that policies should be able to ensure a deadline of $R(0) + 2(\hat{d} - d)$. The proof can be found in §A.4. If a user would like to ensure the original deadline with a given maximum changeover delay, they can specify a new deadline $R(0) - 2(\hat{d} - d)$.

With the new model, policies can account for the variety, by guaranteeing a bounded relaxed deadline $R(0) + \delta + 2(\hat{d} - d)$.

6 Evaluation

In this section, we conduct experiments to assess the performance of the proposed policies using real spot instance traces collected from the cloud.

6.1 Datasets and Setup

We collected spot availability traces on AWS (§2.1). These traces include a 2-week availability trace started on 10/26/2022, with four instance types: p3.2xlarge/p3.16xlarge (1/8 V100), p2.2xlarge/p2.16xlarge (1/8 K80), and two availability zones: us-west-2a and us-west-2b. Moreover, we collect a 2-month long availability trace started on 02/15/2023 for p3.2xlarge instances across nine zones from regions, us-east-1, us-east-2, and us-west-2. For multiple instances, we collect 2-week *preemption* traces for 4 p3.2xlarge in 3 AWS zones (*us-east-1f*, *us-east-2a*, *us-west-2c*), and 2-week *availability* traces for 16 p3.2xlarge in 3 zones (*us-east-2a*, *us-west-2b*, *us-west-2c*). All the availability traces were collected with a 10-minute probe interval. As demonstrated in §2.1, availability and preemption traces are highly correlated, indicating that the performance of the policies on availability traces should reflect their real-world performance. We will use preemption traces in §6.6 for multiple instances benchmark and §7.2 for real system evaluation.

We evaluate the policies on both 2-week traces, and 2-month traces. For all experiments, we randomly sample 300 starting points for each trace, considering each pair of instance type and zone. We consider cases where the *job fraction* $\frac{C(0)}{R(0)} > 0.6$, *i.e.,* the deadline is relatively tight, as the problem becomes less interesting when deadlines are loose and available spot instances within deadline are sufficient to complete the job. For loose deadlines, jobs can utilize spot instances whenever they are available until the remaining time-to-deadline $R(t)$ is relatively tight compared to the remaining computation time $C(t)$, and then start applying policies (details in §A.8). The computation time is set to 48 hours for consistent comparison across different settings (experiments for different computation times can be found in §A.9). Unless noted, changeover delays d are set to 0.2 hours and costs are normalized by on-demand costs in all experiments.

Policy	**On-Demand** (hours)	**Spot** (hours)	**Spot Util.**
On-Demand	48.0 ± 0.0	0.0 ± 0.0	0%
Greedy	30.8 ± 17.7	17.2 ± 17.7	63%
Uniform Progress	25.1 ± 15.3	22.9 ± 15.4	84%
Omniscient	20.7 ± 15.5	27.4 ± 15.5	100%

Table 3: Compute time spent on on-demand and spot instances, averaged across 8 scenarios for a job fraction of 0.8. "Spot Util." indicates the fraction of compute time on spot leveraged by a policy vs. the Omniscient policy.

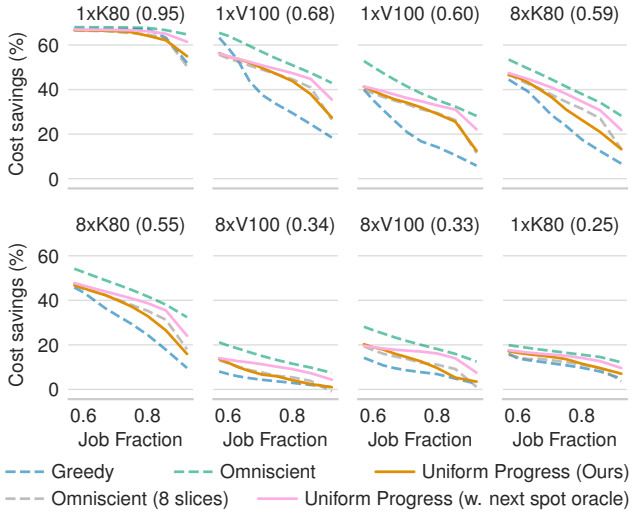


Figure 11: Cost savings (*higher is better*) against on-demand instances on real spot availability traces. Omniscient (8 slices) is Partial Lookahead Omniscient. Larger job fraction means tighter deadline. Each sub-plot is on a (instance type, zone) trace. Values in '(x)' are average spot fractions (percentages of time a spot instance is available) across all samples in the trace.

Baselines. To our knowledge, existing methods in literature (§8) do not consider switching between spot and on-demand in a cost optimization and deadline adherence setting for batch jobs. Thus, we compare our results against policies with future knowledge, which serve as strong upper bounds.

6.2 Time Spent on On-demand and Spot Instances

We first show different policies' overall compute times on on-demand vs. spot instances, which exclude changeover delays. Such breakdowns examine how well spot instances are utilized. Table 3 shows the results with a fixed job fraction $\frac{C(0)}{R(0)} = 0.8$ on the 2-week traces, averaging across eight (instance type, availability zone) pairs, each with 300 randomly sampled traces. We observe that our Uniform Progress runs on spot instances 21% longer than greedy policy on average, reducing the gap to Omniscient's spot usage by 57%.

6.3 Various Deadlines

Figure 11 evaluates the cost savings achieved by the policies across various deadlines (represented as job fractions)

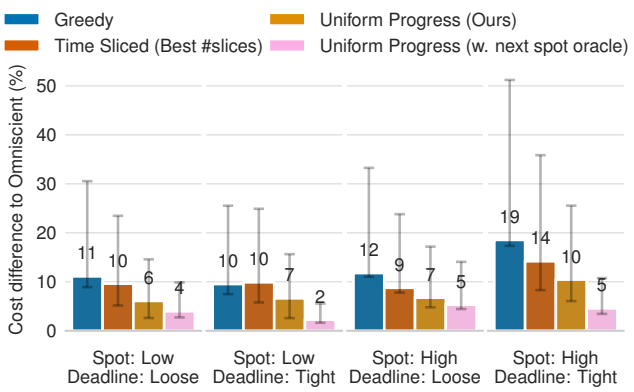


Figure 12: Cost difference compared to Omniscient policy (normalized by on-demand cost, *lower is better*), measuring a policy's proximity to Omniscient. Error bars range from p25 to p75. "Spot" represents spot fraction. It is on 2-week availability traces, aggregated on 300×8=2400 sampled traces.

on the 2-week availability traces. Our Uniform Progress consistently surpasses the greedy in cost savings in all cases, while approaching savings of Omniscient policy.

While Uniform Progress excels, there is still a gap to Omniscient. We compare Uniform Progress with Partial Lookahead Omniscient policy with 8 slices, which assumes strong knowledge of the future (around 6 hours of lookahead): Uniform Progress achieves similar performance in most cases, despite lacking future knowledge. This suggests any other policy without future knowledge may not yield much higher savings.

We also investigate the potential improvement of Uniform Progress policy by assuming cloud providers offering an oracle for the lifetime of the next spot instance (§5.4). With such knowledge, cost savings improve significantly, nearing the theoretical optimum when deadlines are tighter.

The conclusions also hold on the 2-month traces (§A.5).

6.4 Impact of Spot Fraction and Deadline

To better understand the influence of *spot fractions* (the percentage of time a spot instance is available) and deadlines on policy performance, we categorize them into two dimensions: low or high spot fraction, and loose or tight deadline. Tight deadline represents job fraction $\frac{C(0)}{R(0)} > 75\%$, while high spot fractions are defined as those exceeding 50%. Our 2-week traces have an even distribution between high and low spot fractions, while the 2-month traces show a dominance of high spot fractions, which forms 72% of all cases. This aligns with our earlier observation of the volatile nature of spot instance availability (§2.2). Figure 12 presents the performance of the policies compared to Omniscient policy (theoretical upper bounds for cost savings) in the four categories. Results based on the 2-month traces are covered in §A.5.

For tight deadlines, the number of feasible instance switches is limited to at most $\frac{R(0)-C(0)}{d}$, demanding strategic planning of each changeover. When spot availability is high and deadline tight (the rightmost group of bars), all policies lacking future knowledge exhibit a relatively large gap to the optimal.

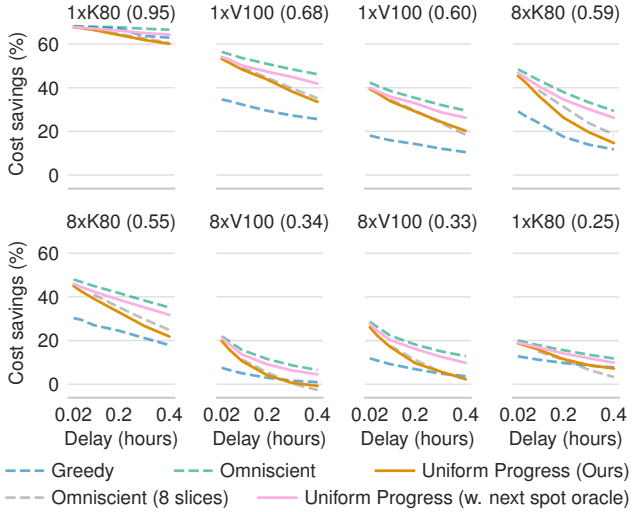


Figure 13: Impact of changeover delays (d). Values in '(x)' are average spot fractions over all samples in the trace.

Nevertheless, Uniform Progress still reduces the gap by ∼2× compared to the greedy policy. This efficiency arises from its uniform progress guarantee and hysteresis, which optimize spot utilization within the deadline while avoiding frequent changeovers. The small gap between Uniform Progress with the next spot lifetime oracle and Omniscient policy confirms that the ability to skip short spot lifetimes and strategically switching from on-demand to spot with the opportunity cost in mind is crucial to achieve close to optimal performance.

As deadlines loosen and spot availability increases, all policies perform closer to Omniscient policy, as jobs have greater flexibility to wait for spot instances and switch between resource types, *i.e.,* judicious planning becomes less important.

Additionally, we show the performance of Time Sliced policy with the best number of slices (within 50 slices). Time Sliced policy outperforms Greedy because of uniform progress it guarantees, but worse than Uniform Progress, potentially due to a higher overhead between slice switches.

Regardless of the different categories, our Uniform Progress policy reduces the gap to optimal by nearly 2× compared to greedy policy for both average and tail (p75) cases.

6.5 Different Changeover Delays

In Figure 13, we evaluate the performance of policies across various changeover delays. Our Uniform Progress performs consistently similar to the Partial Lookahead Omniscient policy. As changeover delays increase, cost savings compared to on-demand instances are reduced. This is because for each spot instance being used, a larger changeover delay means we pay the same price for less actual progress, so that switching to spot instances becomes less economical. Both Uniform Progress and Partial Lookahead Omniscient approach the greedy policy as d increases. However, Uniform Progress combined with the next spot lifetime oracle consistently remains close to the upper bound, due to its ability to skip short spot lifetimes and judiciously calculate the opportunity

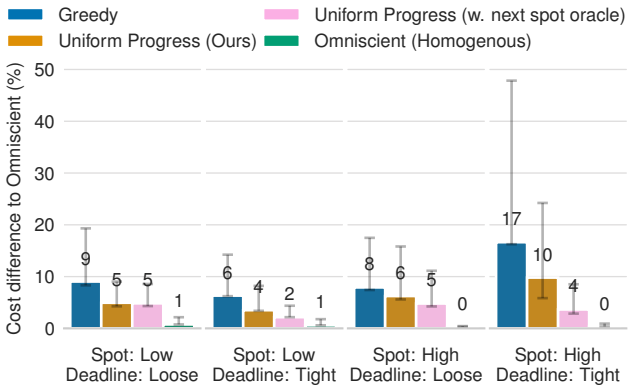


Figure 14: Cost savings for jobs on 4 instances, compared to Omniscient with heterogeneous clusters.

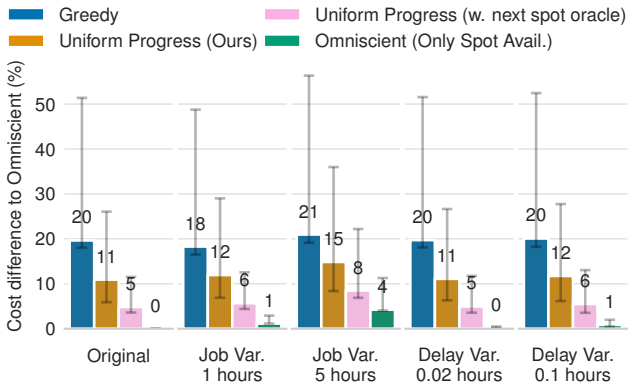


Figure 15: Cost savings with relaxed job computation time or changeover delays. All policies are compared against Omniscient knowing exact spot availability, computation time, and changeover delays in advance. Omniscient (Only Spot Avail.) only has the information of spot availability.

cost of switching from an on-demand to a spot instance.

6.6 Multiple Instances

We now evaluate the policies on multi-instance jobs. Figure 14 shows the cost savings on 4-instance clusters for various policies compared to the theoretical upper bound set by our Omniscient (Heterogeneous) policy (§5.5). The difference between Omniscient (Homogeneous) and Omniscient (Heterogeneous) is negligible (at most 1%), which validates the use of homogeneous clusters in our policy formulation. Our Uniform Progress consistently outperforms the greedy policy, especially in high-spot-availability, tight-deadline conditions, which agrees with the conclusion on single-instance jobs (§6.4). We observe a similar win for clusters with 16 instances (§A.7.4). Due to monetary budget limits, we leave the extension to larger clusters ($N > 16$) to future work.

6.7 Relaxed Computation Time and Changeover Delay

We show that the variations for computation time and changeover delays introduced in §5.6, marginally influence the cost savings. In Figure 15, we apply a uniformly distributed variance to the computation time and changeover delays, and compare all policies with Omniscient policy, which possesses exact knowledge of the job and delays. The experiments are conducted in the same settings as §6.4, with a single instance, high spot fraction, and tight deadline. All policies can guarantee deadlines in the new model. The performance of Omniscient with only spot availability information degrades when the variance of computation time increases. When a user-provided job computation time is larger than the actual one $\bar{C}(0) > C(0)$ (overestimate), it cannot fully utilize spot instances close to the deadline, while, for $\bar{C}(0) < C(0)$ (underestimate), it has to use on-demand after exceeding the original deadline $R(0)$. Similarly, it performs worse when the variance of changeover delay increases, due to sub-optimal decisions made with partial information. However, in all cases, we observe Uniform Progress outperforms greedy with a relatively stable gap, indicating its robustness.

7 Practical Usage

In this section, we discuss our implementation of the prototype and evaluate it with three real-workload: machine learning training, bioinformatics (HPC), and data analytics.

7.1 Implementation

We implemented the policies on top of a real multi-cloud system, SkyPilot [44], that supports launching instances on the public cloud providers. Given an availability zone and an instance type to use, our policies drive a job's resource provisioning and switching decisions.

In the system, a controller is in charge of monitoring spot availability and managing the job with heartbeats. All policies are invoked by the controller behind a simple interface as follows. Periodically, the policy observes current_instance_state (in {idle, spot, on-demand}) and a boolean is_spot_available through the controller, and then uses them to compute a decision (in the same state set). If the decided state differs from the current instance state, the decision is executed by the system's provisioner module (*e.g.,* switch from on-demand to spot). To obtain the boolean is_spot_available, the controller invokes cloud-specific capacity reservation APIs (*e.g.,* AWS EC2 offers a create_capacity_reservation API) which return whether a zone has capacity for a spot instance type.

7.2 Real Workloads

We validate our policy across AWS and GCP platforms using real-world preemption traces with spot availabilities ranging from 70% to 90%. Metrics like changeover delays and other system lags are measured directly from the implementation and included in the evaluation. We summarize the settings of the three workloads, Machine Learning (ML) Training, Bioinformatics, Data Analytics, in Table 4 and explain details in §A.6.

We consider two different deadlines (job fractions 90% and 75%) for each workload. We first present detailed cost breakdowns for the ML workload with loose deadlines in Figure 16. Uniform Progress achieves 48% cost savings compared to only using on-demand. It outperforms Greedy (15%) and approaches the optimal (55%). Similar patterns are observed in the other two workloads. We show the cost savings in Table 5. For Bioinfo's c3-highcpu-88, the spot price is 91%

Workload	Location	Instance Type	Spot Price (Discount)	Computation	Deadlines	Changeover Delay
ML Training	AWS (us-west-2b)	p3.2xlarge	$0.92/hr (-67%)	72 hrs	84/100 hrs	4+5+9 mins ≈0.3 hrs
Bioinformatics	GCP (us-east1-b)	c3-highcpu-88	$0.34/hr (-91%)	22.5 hrs	24/28 hrs	2+1+8 mins ≈0.2 hrs
Data Analytics	AWS (us-east-1c)	r5.16xlarge	$1.85/hr (-55%)	27 hrs	30/36 hrs	4+1+7 mins ≈0.2 hrs

Table 4: Detailed characteristics of real workloads. Deadlines are derived from job fractions 90% and 75%, and changeover delays are the sum of VM provisioning, environment setup, and job recovery progress loss time.

		Uniform Progress	
Workload	On-demand	Tight DDL (0.9)	Loose DDL (0.75)
ML	$233.5	$138.2 (**-41%**)	$122.0 (**-48%**)
Bioinfo	$140.5	$51.9 (**-63%**)	$22.8 (**-84%**)
Analytics	$109.6	$80.0 (**-27%**)	$74.1 (**-32%**)

Table 5: Cost savings for real workloads. Results of two deadlines are shown (job fractions 0.9 and 0.75).

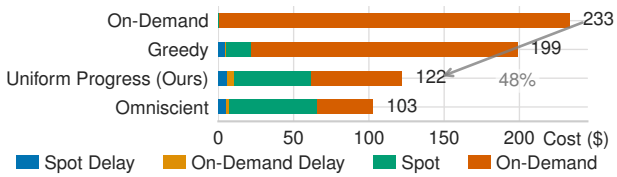


Figure 16: Cost breakdown of each policy for ML workload.

cheaper than on-demand. This allows Uniform Progress to achieve 63% cost savings even when the deadline is tight and 84% savings when the deadline is loose. For the analytics workload, the spot price discount is much smaller (55%). In this case, Uniform Progress achieved 27% and 32% savings for tight and loose deadlines, respectively. Note, however, these savings still approach those achieved by the Omniscient (32% and 46%, for tight and loose deadlines).

8 Related Work

Spot pricing and availability modeling. AWS pioneered spot instances in 2009, using a bidding mechanism to monetize unused cloud capacity [5]. The pricing model has evolved to offer more stability, diminishing bidding, with other cloud providers adopting similar strategies, such as GCP's constant 30-day spot price [2], Oracle Cloud's fixed 50% discount for preemptible instances [6], and Azure's stable regional pricing [21]. While spot pricing is relatively stable, modeling spot availability remains challenging due to its black box nature. While prior work attempted to model preemption patterns [20] and employed ML prediction methods [16, 42, 43], we design our policy to be robust against potential changes in spot eviction strategies of the cloud providers.

Applications using spot instances. The cost-effective nature of spot instances has driven their adoption for savings. Frameworks like Bamboo [38], Spotnik [40], and Srifty [28], was developed for machine learning on spot instances. Narayanan *et al.* [33] showed significant reductions in machine learning training costs using spot instances across multiple clouds. CompuCache [47] leverages spot instances for in-memory data caching. However, preemptions can negatively impact application performance [10, 43], and deadline-constrained applications may struggle to effectively utilize spot instances.

Job scheduling with preemptions. Running jobs on preemptive devices is investigated on intermittent systems, where jobs can be interrupted due to sporadic harvestable energy. Many studies [12, 15, 18] focus on scheduling multiple real-time IoT tasks, due to the limited computation resources on these devices. Spot instances introduce preemption to resource-demanding batch jobs on clouds. From the cloud providers' perspective, existing work [9, 17, 19] investigates how to maximize revenue, or enhance runtime guarantees. For end-users, earlier studies explored bidding-based policies for bag of tasks with deadlines [30, 35, 39, 45], but these approaches are less applicable to current spot markets due to changes in pricing model. Recently, Snape [43] investigates using a mix of spot and on-demand instances for long-running services. It optimizes for SLO which require the number of instances available to be close to the target one at any time. It is different from deadline-sensitive batch jobs studied in this paper, where the job can stay idle for long periods, as long as it can meet the deadline.

9 Conclusion

Spot instances are economically appealing, but unreliable due to the preemptions. In this paper, we resolve a critical challenge of minimizing the cost for delay-sensitive jobs by utilizing a mix of spot and on-demand instances. Our work features a comprehensive analysis of spot instances and presents a theoretical framework to assess policies in both worst and average cases. This inspires the development of our proposed policy, Uniform Progress, which is simple, parameter-free, and effective without relying on assumptions of spot availability. Our empirical study using 3-month real-world traces demonstrates a significant improvement in cost savings compared to the greedy policy, closing gaps with the optimal policy by approximately 2× on both single or multiple instances. We also find that if cloud providers were willing to offer an oracle for the next spot instance's lifetime, it could further improve applications' cost efficiency, by enabling our Uniform Progress to approach the upper bound of cost savings. We implemented a prototype on top of SkyPilot, and showcased the effectiveness of Uniform Progress on three real workloads, reducing the cost by 27%-84%. We open source the spot traces for future research.

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A Appendix

A.1 Spot Availability and Preemption Traces

In Section 2.2, we highlighted the variability in spot availability across four out of nine AWS availability zones. For a comprehensive view, Figure 17 presents data for all nine zones. It demonstrates the fluctuations in spot availability both across zones and over time.

A.2 Proofs for Theoretical Analysis

In this section, we show the detailed proofs for the theorems and statements in our theoretical analysis (§4).

A.2.1 Worst Case with Competitive Analysis

We first prove Theorem 1 (see §4.1), which states that a deterministic policy cannot perform better than the greedy policy in competitive analysis.

Theorem 1. *For any deterministic policy P, $c \geq k - O(d)$.*

Proof. Since the policy P is deterministic, the adversary can choose spot availability as follows. It makes the spot available only when P starts using on-demand or $R(t) = C(t) + d$. If P switches to the spot, the adversary waits for d units of time, then preempts the spot, so P makes no progress on any spot instances, *i.e.,* must use at least $C(0)$ units of on-demand.

With that adversary, we examine P have to use all on-demand while omniscient policy can finish the job with all spots. Consider the first time t', where $R(t') = C(t') + d$. Over $t' \leq t \leq R(0)$, P cannot switch to spot, but the omniscient policy could as it knows the spot will remain available, *i.e., P* makes $C(t')$ progress on on-demand, while omniscient is on spot. Next, P must have accumulated the $C(0) - C(t')$ before t'. Due to the adversary, any work accumulated before t' should be on on-demand when a spot is available. Thus, the omniscient policy can make $C(0) - C(t')$ of progress on those spots before t'. □

We now show the proof for Theorem 2, *i.e.,* the competitive ratio for randomized shifted greedy (RSF) policy is bounded and lower than greedy.

Theorem 2. *If $R(0) \geq 2C(0)$, then for RSF policy has $c < k$.*

Proof. By ignoring the terms of $O(d)$, at any time t before the last split, at least one of the policies is looking to use a spot (as shown in Figure 5), so any available spot is used for at least half of the time. Thus, except for the last $C(0)/n$ progress, at least half of the remaining progress is done on spot instances:

$$c \leq (\frac{1}{n} + \frac{1-1/n}{2})k + \frac{1-1/n}{2} + O(d) = \frac{k+1}{2} + \frac{k-1}{2n} + O(d) < k \quad \square$$

A.2.2 Average Case with Stochastic Model

In §4.2, we inferred that the expected payment (total cost), p, for greedy policy in the stochastic model decreases (lower the better) when the time t' spent on the fractional spot increases. Consider spot fraction $\mathcal{R}$ as a random variable with mean r and variance v. We now prove that the expected time spent on the fraction spot $E[t']$ increases when v increases, *i.e.,* larger v indicates lower expected cost.

Proof. Let $\mathcal{R} = r + \delta$. Based on (2), we have $E[t']$:

$$E[t'] = E[\frac{R(0) - C(0)}{1 - (r+\delta)}] = \frac{R(0) - C(0)}{1-r} E[1 + \frac{\delta}{1-r} + \frac{\delta^2}{(1-r)^2} + \cdots]$$

where the second equation is derived from Taylor expansion for $\delta \to 0$. By construction, $E[\delta] = 0$ and $E[\delta^2] = v > 0$. When we take the first three terms, we get an approximation:

$$E[t'] = \frac{R(0) - C(0)}{1-r}(1 + \frac{v}{(1-r)^2})$$

We calculate the difference of the expected time on the fractional spot $E[t']$ for policies with variance v_1 and v_2

$$\Delta = \frac{R(0) - C(0)}{(1-r)^3}(v_1 - v_2)$$

Since $\Delta > 0$ when $v_1 > v_2$, we can conclude that $E[t']$ increases with the variance v. □

A.3 Partial Lookahead Omniscient Formulation

Instead of minimizing the total cost for the progress, in Partial Lookahead Omniscient policy, a job can make more progress than it is assigned in each slice and reduce the computation time required in the next slice by the additional

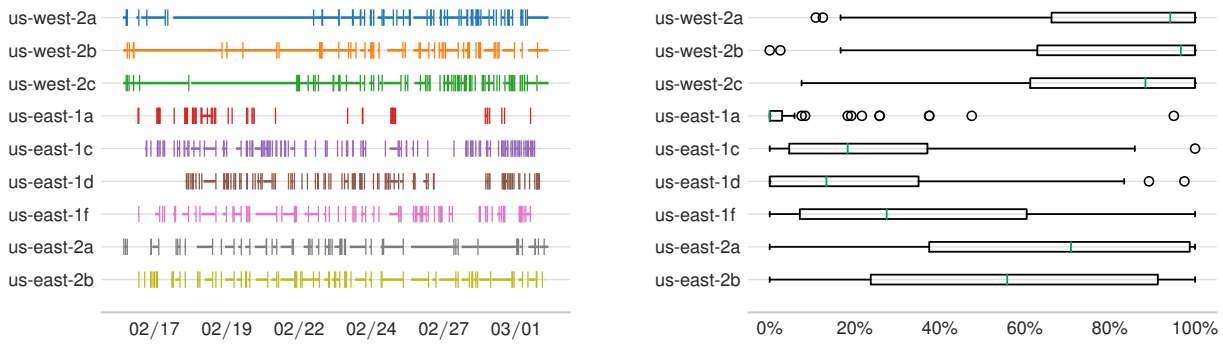

Figure 17: Spot availability is highly unpredictable and volatile. Traces are across nine AWS zones collected.

progress made. Therefore, we modify the ILP formula for the Omniscient policy with the following formula for a slice i to minimize the average cost of the progress made in that slice:

$$\min_{s(t>t_{i-1}),v(t>t_{i-1})} \sum_{t=t_{i-1}}^{t_i} [s(t)+v(t)k]/P_i \tag{11}$$

$$\forall t, s(t)+v(t)\le 1, s(t)\le a(t) \tag{12}$$

$$P_i = \sum_{t=t_{i-1}}^{t_i} [s(t)+v(t)] - d \sum_{t=t_{i-1}+1}^{t_i} (x(t)+y(t)) \tag{13}$$

$$P_i \ge \frac{iC(0)}{n} - \sum_{j=1}^{i-1} P_j \tag{14}$$

$$\sum_{j=1}^{i} P_i \le C(0) \tag{15}$$

$$\forall t, x(t)\le s(t), x(t)\le 1-s(t-1), x(t)\ge s(t)-s(t-1) \tag{16}$$

$$\forall t, y(t)\le v(t), y(t)\le 1-v(t-1), y(t)\ge v(t)-v(t-1) \tag{17}$$

where the (13) ensures the total progress at the end of the slice is at least $cp(t_i)\ge iC(0)/n$, and the (15) avoids making more total progress than the job computation time.

A.4 Deadline for Changeover Delay Extension

In §5.6, we relaxed the model to account for the variations of the changeover delay. We now prove that with the extension, the deadline guaranteed by all policies should be $R(0)+2(\hat{d}-d)$.

Proof. With the assumptions, all variance of changeover delay will be directly reflected in $C(t)$.

We consider the last moment a job is idle before it finishes (at time t), there are three cases:

1. $R(t) > C(t) + 2d$: Safety Net Rule should never be triggered, causing the maximum time the job finishes to be $R(0)-R(t)+C(t)+\hat{d}<R(0)+\hat{d}-2d$.
2. $R(t)=C(t)+2d$: Safety Net Rule kicks in at $t+\varepsilon$, and the guaranteed deadline should be $R(0)-R(t)+C(t)+\hat{d}$, *i.e.*, $R(0)+\hat{d}-2d$.
3. $R(t) < C(t) + 2d$: It means the job was on a spot instance and got preempted. In this case, at the time t' the job jumped onto the spot instance, we have $R(t') \ge C(t') + 2d$. Thus, the worst case for the guaranteed deadline would be the job experience two maximum changeover delays, once for jumping onto a spot, and once for jumping onto an on-demand instance. That said, the bound for the finish time would be $R(0)-R(t')+C(t')+2\hat{d}\le R(0)+2(\hat{d}-d)$.

Combining the three cases, the bound for the deadline guaranteed should be $R(0)+2(\hat{d}-d)$ □

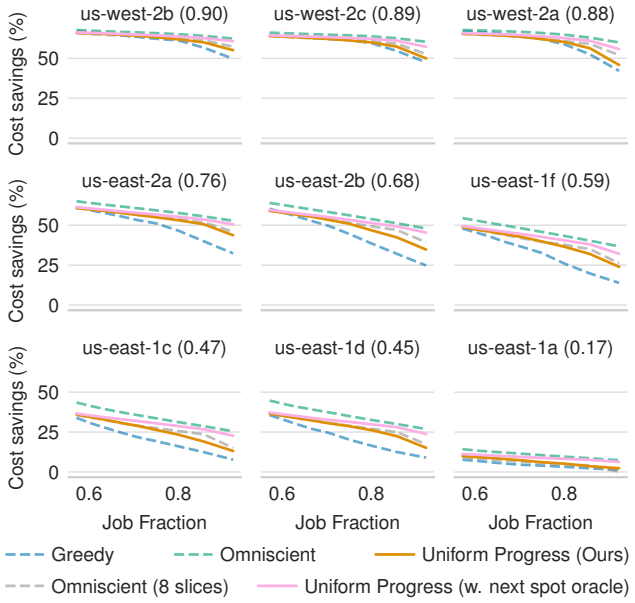

Figure 18: Cost Savings against on-demand instance for different policies on 2 months of spot availability traces.

A.5 Performance on 2-month Availability Traces

Various Deadlines. Figure 18 shows the cost savings of different policies we consider on the 2-month spot availability trace. Similar conclusions as §6.3 can be drawn from the figure that our Uniform Progress has a much lower gap to the Omniscient policy, with similar performance as the Partial Lookahead Omniscient policy in various cases, including loose and tight deadline as well as low and high spot fraction. The Next Spot Lifetime Oracle improves our Uniform Progress even further making the performance approach to the theoretical optimum.

Impact of Spot Fraction and Deadline. Figure 20 compares the cost saving difference of the policies against Omniscient policy on 2-month spot availability traces. Similar conclusions as in §6.4 can be drawn that Uniform Progress consistently outperforms greedy policy in all the scenarios, and applying

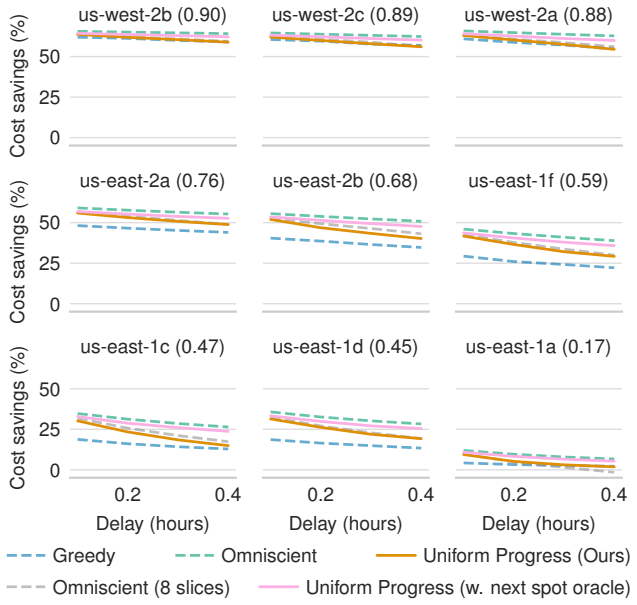

Figure 19: Cost savings against on-demand instances for different changeover delays.

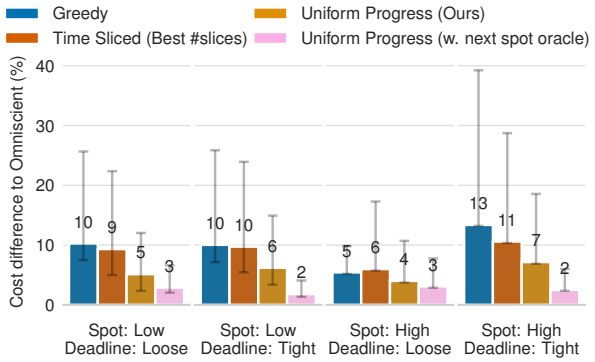

Figure 20: Cost difference compared to the Omniscient policy (normalized by on-demand cost, *lower is better*). It is on 2-month availability traces starting from 2/15/2023, aggregated on 300×9=2700 sampled traces.

Next Spot Lifetime Oracle further increases the cost savings.

Different Changeover Delays. We also evaluate the performance of the policies for different changeover delays on the 2-month availability trace. Figure 19 illustrates that our policy performs consistently better than the greedy policy for different changeover delays. Similarly as §6.5, the gap of Uniform Progress to the Omniscient policy increases while the Next Spot Lifetime Oracle helps it regain the advantage.

A.6 Setup of Real Workloads

We benchmark all policies on real workloads in §7.2. We describe detailed setups of the workloads in this section.

Machine Learning Training. We consider pre-training a RoBERTa [27] model on a subset of Wikipedia, WikiText-103, with a V100 GPU instance (p3.2xlarge) on AWS. We follow the configuration of FairSeq's reproduction [7, 34] to train the model for around 110 epochs (each takes about 40 minutes). To be fault-tolerant, we checkpoint the model weights twice per epoch to a cloud object store (AWS S3). The average progress loss and the time to reload the model into GPU are included in the changeover delay.

Bioinformatics. We run a bioinformatics workload of mapping DNA cells of sequencing data [26] on GCP. The workload has 90 independent tasks, each with a relatively short duration (15 minutes). Each task requires a powerful multi-core CPUs for parallelization. We use GCP's latest C3 generation of compute instance, c3-highcpu-88. In this workload, interrupted tasks need to be recomputed entirely after recovery. We use the average task duration as the changeover delay (see Table 4).

Data Analytics. We run Apache Spark [46] (v3.2.0) on a widely-used benchmark, TPC-DS [32]. We use scale factor 1000 to generate 300 GB of data on a 64-core CPU instance (r5.16xlarge). The data is stored on a persistent disk, which is attachable for future instances. We run all queries 10 times. Similar to the bioinformatics workload, each query needs to start over if interrupted. We add a weighted average of query runtimes (7 mins) as progress loss into the changeover delay.

A.7 Extending to Multiple Instances

We extend Omniscient policy to gang-scheduling jobs with multiple instances as mentioned in §5.5.

A.7.1 Omniscient policy

We extend Omniscient's ILP (6) to multiple instances.

A.7.2 Omniscient with homogeneous clusters.

We first extend the formula for the homogeneous cluster case, where all instances in a cluster with N instances should be the same type (all spot, all on-demand, or none). We revise the semantics of the original variables:

- $a(t)$: the number of spot instances available at time t.
- $s(t), v(t)$ indicate the policy chooses to use all spot or all on-demand for the cluster at time t.
- $x(t), y(t)$ represent the changeover delay that happens to the spot/on-demand cluster at time t.

The Omniscient policy with the same instance type can be represented as:

$$\min_{s(t),v(t)} \sum_{t=0}^{R(0)} N[s(t)+v(t)k] \tag{18}$$

$$\forall t, s(t)+v(t) \le 1, s(t) \le a(t)/N \tag{19}$$

$$\sum_{t=0}^{R(0)} [s(t)+v(t)] \ge d \sum_{t=1}^{R(0)} (x(t)+y(t)) + C(0) \tag{20}$$

$$\forall t, x(t) \le s(t), x(t) \le 1-s(t-1), x(t) \ge s(t)-s(t-1) \tag{21}$$

$$\forall t, y(t) \le v(t), y(t) \le 1-v(t-1), y(t) \ge v(t)-v(t-1) \tag{22}$$

A.7.3 Omniscient with heterogeneous clusters.

We further generalize the Omniscient policy to support heterogeneous clusters, allowing a mix of spot and on-demand instances in a cluster. This is the theoretical upper bound of the cost saving we can achieve under the problem setting in §5.5. We update the definition of variables as follows:

- $s(t), v(t)$: the number of spot and on-demand instances in the cluster at time t.

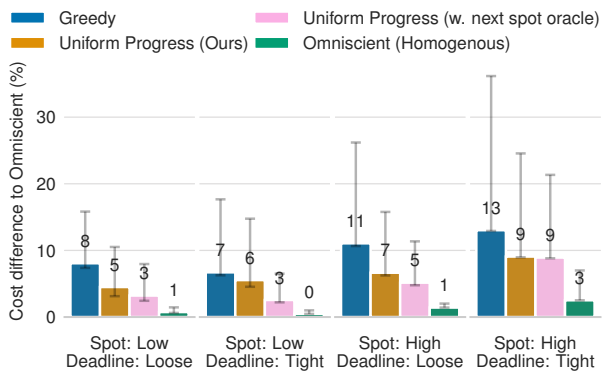

Figure 21: Cost savings for gang-scheduling jobs on 16-instance clusters, compared against theoretical upper bound (Omniscient policy allowing heterogeneous clusters). Uniform Progress consistently outperforms greedy policy.

- $p(t)$: whether the cluster is UP at time t.
- $z(t)$: whether changeover delay is triggered at time t.
- $m(t), n(t), j(t), k(t)$: intermediate binary variables.

The following is the Omniscient policy for multi-nodes with gang scheduling.

$$\min_{s(t),v(t)} \sum_{t=0}^{R(0)} [s(t)+v(t)k] \tag{23}$$

$$\forall t, s(t)+v(t)-N\cdot p(t)=0, s(t)\le a(t) \tag{24}$$

$$\sum_{t=0}^{R(0)} [s(t)+v(t)] \ge d \sum_{t=1}^{R(0)} z(t)+C(0) \tag{25}$$

$$\forall t, s(t)-s(t-1)\le N\cdot z(t) \tag{26}$$

$$\forall t, v(t)-v(t-1)\le N\cdot z(t) \tag{27}$$

$$\forall t, m(t)\le s(t)-s(t-1)+(N+1)\cdot j(t) \tag{28}$$

$$\forall t, m(t)\le s(t-1)-s(t)+(N+1)\cdot(1-j(t)) \tag{29}$$

$$\forall t, n(t)\le v(t)-v(t-1)+(N+1)\cdot k(t) \tag{30}$$

$$\forall t, n(t)\le v(t-1)-v(t)+(N+1)\cdot(1-k(t)) \tag{31}$$

$$\forall t, z(t)\le m(t)+n(t) \tag{32}$$

(26) and (27) set $z(t)=1$, when either the number of spot or on-demand increases in the cluster; (28) to (32) enforces $z(t)=0$ when $s(t)=s(t-1)\wedge v(t)=v(t-1)$, *i.e.,* the number of spot or on-demand used by the job does not change. That said, (26) to (32) make sure $z(t)=1$ iff changeover delay happens at time t.

A.7.4 Cost Savings on 16 Instances

We scale up the experiments to 16 instances using real spot preemption traces. In Figure 21, we can observe that the homogeneous cluster constraint only has negligible influence on the Omniscient policy on 16-instance clusters, which is also because the spot market is efficient enough, similar availability of all the 16 instances in a cluster. Our Uniform Progress still outperforms greedy policy on all 4 different scenarios with a smaller gap to the best cost savings a system can achieve.

A.8 Loose Deadline

In this paper, we mainly discuss policy design for jobs with relatively tight deadlines, as very loose deadlines will likely lead to jobs able to finish on spot instances only. As mentioned in §6.1, when a loose deadline is given, a job can utilize spot instances whenever available until timestamp t_0, when the remaining time to deadline $R(t_0)$ becomes tight compared to the job progress $C(t_0)$, and apply the policy. We conduct experiments for loose deadlines, by setting the switch point at $\frac{C(t_0)}{R(t_0)}=0.7$.

In Figure 22, we can see that greedy policy gets close to the upper bound of the cost savings for very loose deadlines, as jobs are likely to be able to finish on spot instances only. It is worth noticing that job fraction 0.25 represents the deadline

Figure 22: Cost savings for policies with very loose deadlines.

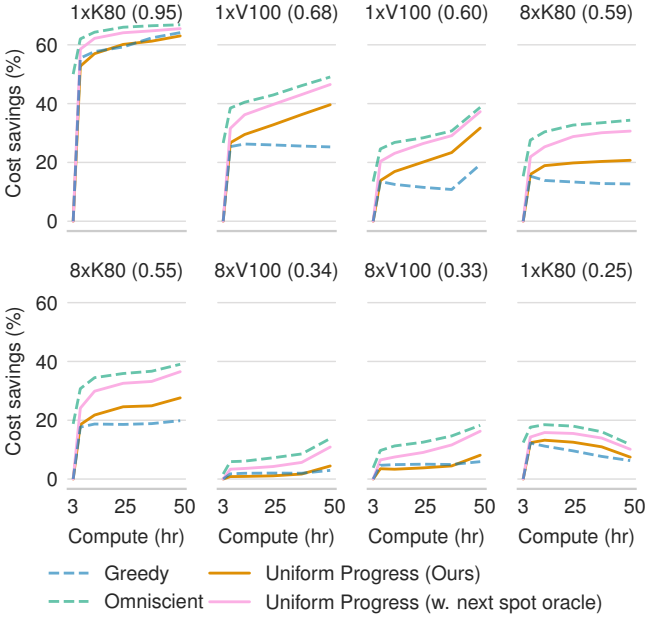

Figure 23: Cost savings with various job computation time. Job fraction (computation time/deadline) is set to 85%.

is 4x longer than the job duration. By allowing jobs to utilize as many spot instances as possible when the remaining time is abundant, all policies perform similarly in cases where loose deadlines are given.

A.9 Various Job Computation Time

We compare the cost savings for the policies across different job computation times with the same job fraction 85% in Figure 23. When job computation time is very small (comparable to the changeover delay), all policies' cost savings drop quickly, as switching between spot and on-demand instances is not worth the cost caused by the changeover delay. However, when the job computation time increases, there is more optimization opportunity for the policies, as more changeover delay can be tolerated, leading to a larger gap between Uniform Progress and greedy policy.