Job Scheduling Mechanisms for Cloud Computing

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<tr>
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</tr>
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</table>

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# Contents

**Abstract** .................................................. 1

**Abbreviations and Notation** .................................. 3

1 Introduction .................................................. 5
   1.1 Motivation .................................................. 5
   1.2 General Model ................................................. 6
   1.3 Thesis Overview ............................................. 8
   1.4 Related Work ................................................ 10

2 Preliminaries ................................................... 12
   2.1 Algorithmic Design .......................................... 12
      2.1.1 Evaluation Metrics ...................................... 12
      2.1.2 The Dual Fitting Technique ................................ 12
   2.2 Algorithmic Mechanism Design ............................... 16
      2.2.1 Definitions ............................................. 16
      2.2.2 Truthfulness and Monotonicity ......................... 17
      2.2.3 Profit Maximization in Bayesian Settings .............. 19
      2.2.4 Related Literature ...................................... 20

3 Near-Optimal Schedulers for Identical Release Times .......... 22
   3.1 Scheduling Model ........................................... 24
   3.2 Approximation Algorithms ................................... 24
      3.2.1 A Simple Greedy Approach ................................ 24
      3.2.2 The GreedyRTL Algorithm ............................... 29
   3.3 Truthfulness ................................................ 35
   3.4 Coping with Demand Uncertainties ........................... 36
   3.5 Empirical Study ............................................. 38
6 Offline Scheduling of DAG-Structured Jobs

6.1 Scheduling Model ................................................. 93
6.2 DAG Scheduling ................................................ 95
  6.2.1 Step 1: Solving a Linear Program ...................... 95
  6.2.2 Step 2: Balancing ....................................... 98
  6.2.3 Step 2: Decomposing a Balanced Solution ............ 100
  6.2.4 Step 4: Randomized Rounding ......................... 103
  6.2.5 Obtaining a Constant Approximation Factor .......... 107
6.3 Model Extensions ................................................ 108
  6.3.1 Monotone Node Allocations ............................ 108
  6.3.2 Multiple Sinks ........................................... 109
6.4 Conclusions .................................................... 109

7 Scheduling Algorithms for Hadoop YARN ..................... 110

7.1 Scheduling Model ................................................. 111
7.2 Planning Algorithms ........................................... 112
  7.2.1 Greedy – The Existing Scheduling Algorithm ......... 113
  7.2.2 LowCost – A New Cost-Based Planning Algorithm .... 114
7.3 Evaluation ....................................................... 117
  7.3.1 Methodology ............................................. 117
  7.3.2 Simulations ............................................... 118
  7.3.3 Experiments on Real Clusters ......................... 120

8 Summary .......................................................... 123
List of Figures

3.1 Average resource utilization over time of GreedyRTL and the Decompose-Randomly-Draw (DRD) mechanism [41] compared to the optimal fractional resource utilization, which is an upper bound to the optimal resource utilization. Results show that GreedyRTL utilizes nearly all of the cloud resources. 40

3.2 Revenue ratio between GreedyRTL and OFP, compared against different input slackness values. The truthful GreedyRTL mechanism is nearly as good as an ideal optimal fixed-price mechanism. For this experiment, we overload the system such that the total demand exceeds the cloud capacity, so that truthful pricing is strictly positive. 41

5.1 Illustration of the proof to Theorem 5.2.1. 77

6.1 A job $j$ and its fractional allocation. (1) DAG structure of job $j$; (2) fractional solution $x$ (only job $j$ shown); (3) weighted decomposition of $x$. 98

7.1 An intermediate execution state of LowCost-A. 116

7.2 Simulation results on a 4K cluster as a function of the number of submitted jobs (300-1000). Results averaged over 5 runs. 118

7.3 Simulation results on a 4K cluster as a function of the number of submitted jobs (1100-1500). Results averaged over 5 runs. 119

7.4 Visualization of the plans at some point throughout the execution of the two algorithms. These snapshots are taken at high-load conditions. 122
Abstract

The rise of cloud computing as a leading platform for large-scale computation has introduced a wide range of challenges to the field of scheduling. In the cloud paradigm, users receive on-demand access to shared pools of computing resources, to which they submit applications. The primary goal of a cloud scheduler is to provide and satisfy service level agreements (SLA) for running applications. For example, businesses run production-level jobs that must meet strict deadlines on their completion time. Since the underlying physical resources are limited, the scheduler must decide which service requests to accept in view of the required SLAs; and furthermore, incorporate clever resource allocation algorithms to increase the utility from completed jobs. In general, designing schedulers for the cloud is challenging. First, jobs differ significantly in their value, urgency, structure and resource requirements. Second, job requests are not always known in advance, and therefore the schedulers must make irreversible decisions on-the-fly. Finally, users may attempt to manipulate the scheduler into processing their own jobs in favor of others.

In this dissertation, we develop deadline-aware job scheduling mechanisms for cloud environments. Our main theoretical study begins with the fundamental problem of online deadline scheduling. In its most general form, the problem admits super-constant lower bounds on the competitive ratio of any scheduler. Nevertheless, we develop constant competitive algorithms under a natural deadline slackness assumption, which requires that no job deadline is tight. Moreover, our worst-case bounds improve as the input jobs exhibit large deadline slackness. We then extend the basic allocation model to handle practical aspects of cloud scheduling, such as scheduling jobs with complex inner dependencies, scheduling jobs with uncertain requirements, and providing upfront commitments on SLAs.

Another aspect of our work studies truthful scheduling mechanisms, where users are incentivized not to manipulate the system by falsely reporting job parameters. Such mechanisms are essential not only for public clouds, but also private clouds shared by entities that belong to the same organization. Based on our allocation algorithms, we develop truthful mechanisms and provide performance guarantees similar to their non-truthful counterparts.

Finally, inspired by our theoretical study, we implement a deadline-aware job scheduling
algorithm for Hadoop YARN. The algorithm was evaluated against existing benchmark algorithms through extensive experiments, and show substantial improvements over state-of-the-art. The algorithm will be incorporated in the upcoming Hadoop 2.8 distribution.
Abbreviations and Notation

System Parameters

\( C \) — capacity; number of servers in the cluster.
\( T \) — number of time slots; for discrete timeline only.
\( \mathcal{T} \) — the timeline.

Job Parameters

\( j \) — an index of a job (user).
\( a_j \) — arrival time of job \( j \).
\( d_j \) — deadline of job \( j \).
\( D_j \) — requested demand (workload) of job \( j \); given in resource units.
\( G_j \) — task dependency graph of job \( j \).
\( k_j \) — parallelism bound of job \( j \).
\( v_j \) — the value of job \( j \).
\( P_j \) — property set of job \( j \).
\( \rho_j \) — value density of job \( j \): \( v_j/D_j \).
\( \tau_j \) — the type of job \( j \).

General Parameters

\( k \) — maximal parallelization bound over jobs: \( \max_j \{k_j\} \).
\( n \) — number of jobs.
\( s \) — deadline slackness.
\( \kappa_D \) — ratio between maximal and minimal job value.
\( \kappa_v \) — ratio between maximal and minimal job demand.
\( \kappa_\rho \) — ratio between maximal and minimal value density.
Algorithm Design

- $\text{cr}(\mathcal{A})$ — competitive ratio of algorithm $\mathcal{A}$.
- $\text{cr}_{\mathcal{A}}(s)$ — competitive ratio of algorithm $\mathcal{A}$ with respect to input instances with slackness $s$.
- $\text{IG}(s)$ — integrality gap of a linear program, with respect to input instances with slackness $s$.
- $\text{OPT}$ — optimal offline algorithm.
- $\text{OPT}^*$ — optimal fractional algorithm.
- $v(\mathcal{A}(\tau))$ — total value of completed jobs by algorithm $\mathcal{A}$ on input instance $\tau$.
- $\mathcal{A}$ — scheduling algorithm.
- $\mathcal{A}(\tau)$ — output allocation of algorithm $\mathcal{A}$ on input $\tau$.
- $\mathcal{J}$ — set of jobs.
- $\tau$ — input instance.

Primal and Dual Variables

- $y^i_j(t)$ — primal variable; allocation indicator of job $j$ on server $i$ at time $t$.
- $y_j(t)$ — primal variable; total amount of resources allocated to job $j$ at time $t$.
- $\alpha_j$ — dual variable; associated with each job $j$.
- $\beta(t)$ — dual variable; associated with time $t$.
- $\pi_j(t)$ — dual variable; by-product of primal gap decreasing program.

Mechanism Design

- $b_j$ — bid of user $j$.
- $f$ — allocation algorithm.
- $p$ — payment scheme.
- $u_j$ — utility function of user $j$.
- $\mathcal{M}$ — mechanism: $\mathcal{M} = (f, p)$. 

4
Chapter 1

Introduction

1.1 Motivation

Batch jobs constitute a significant portion of the computing load across internal clusters and public clouds. Examples include big data analytics, search index updates, video rendering, and eScience applications. The timely execution of such jobs is often crucial for business operation. For instance, financial trading firms must deliver the output of their analytics before the next trading day commences, and delays in uploading website content can lead to a significant loss in revenue. Since end-users do not own the compute infrastructure, they must require strict service level agreements (SLAs) on their job completion time – this can be obtained by enforcing strict deadlines on their completion time. The cloud provider, who only controls a limited amount of physical resources, must implement scheduling mechanisms that decide which job requests to accept, and manage the resource allocation such that no accepted SLA contract is violated.

Unfortunately, the allocation schemes currently used in practice do not provide satisfying solutions for deadline-sensitive jobs. A common approach for internal clusters is to divide computing resources in some fair manner between jobs [37]; yet, this approach completely neglects job deadlines. Another approach is to give strict priority to deadline-sensitive jobs; however, such heavy-handed schemes risk unnecessary termination of low-priority jobs, lowering overall throughput – see [28] for an overview. Public clouds eschew scheduling concerns by only offering on-demand rental of cloud resources (e.g., virtual machines). This leaves users with the task of managing resource utilization levels to guarantee that their jobs are completed by their deadlines. Furthermore, users must pay for their resource consumption, even if their jobs fail to meet their deadline.

The purpose of our work is to develop deadline-aware job scheduling mechanisms for cloud environments. Such mechanisms must cope with diverse jobs that vary by several
dimensions. First, they vary in **urgency**. To exemplify, stock data analysis is crucial to the financial firm and must be performed within several hours; whereas, simulation tasks are typically less urgent and can be completed within a matter of days. Second, they vary in **utility**: some jobs are more important than others, and as a result have higher value assessments for meeting predefined deadlines. Finally, they vary in their **resource requirements**: jobs differ by the amount of resources required to complete them and by their internal structure.

The challenges in designing mechanisms for shared computing clusters spans several research domains.

- **Algorithm Design** – construct efficient algorithms for underlying resource allocation problems. The cloud computing paradigm introduces new intriguing problems that have yet to be studied. Furthermore, well-studied problems in scheduling theory can take new interesting forms when viewed from the perspective of a cloud designer. Our goal is to construct efficient algorithms for cloud allocation problems and provide theoretical worst-case guarantees on their performance.

- **Mechanism Design** – design allocation and pricing schemes for strategic environments, where users may attempt to maximize their personal gain by misreporting their true job parameters. For example, consider a computing cluster which is shared between developers belonging to the same organization. An individual developer may overvalue the urgency of its computing jobs due to personal time constraints. However, personal assessments might not represent the interests of the organization. Our goal is to design *truthful* scheduling mechanisms, in which users are incentivized not to manipulate the system for personal interest by misreporting their true job parameters.

- **System Implementation** – implement deadline-aware mechanisms that schedule jobs on actual computing clusters, and evaluate their performance on real jobs. Unfortunately, providing a model that captures every aspect of real clusters is practically impossible. In our work, we make simplifying assumptions for our theoretical study, and use the derived insights to implement deadline-aware schedulers for real-time systems.

### 1.2 General Model

In the following, we define the main components of the scheduling models studied throughout our work.
System. A computing system that consists of $C$ identical servers (resources) receives job requests over time. The timeline $T$ is either continuous or discrete; in the latter case, the timeline $T$ is divided into $T$ time slots of equal length $\{1,2,...,T\}$. We assume that the servers are fully available throughout time, and that each server can process at any time one job at most.

Jobs. Each job request $j$ submitted to the system is associated with a type $\tau_j$. The type encodes the various parameters of the job, and its definition differs between models. Yet, all definitions share some common components.

Arrival time. The arrival time $a_j$ represents the earliest time during which job $j$ can be processed. Following standard literature, we distinguish between two settings: online and offline. Online scheduling problems assume that jobs are not known to the scheduler in advance, and are only revealed to the scheduler at the time of their arrival. The scheduler must make scheduling decisions without knowledge of future arrivals, and without the ability to modify past allocations. Offline scheduling problems assume that all jobs are known in advance to the scheduler. This is common when scheduling recurring production jobs, e.g., jobs that run on an hourly basis. We discuss evaluation methods for online and offline algorithms in Section 2.1.

Valuation function. In addition, each job type holds a valuation function $v_j : T \rightarrow \mathbb{R}^{+,0}$. The value $v_j(t)$ represents the value gained from completing job $j$ at time $t$. We will mostly focus on deadline valuation functions: step functions which equal to a constant $v_j$ up to a predefined deadline $d_j$ and 0 afterwards; the notation of $v_j$ is abused to simplify exposition. The goal of the scheduler is to maximize the total value gained from completed jobs.

Resource requirements. Finally, the job request includes its resource requirements. We will mostly study a flexible allocation model, where the number of resources allocated per job can change over time. In this model, each job specifies a demand $D_j$, which is the total amount of resource units required to complete the job. The job completion time is the earliest time by which the job is allocated $D_j$ resource units. At each time, the scheduler may allocate job $j$ any number of resources between 0 and a parallelism bound $k_j$ specified by the job type. In Chapter 6, we consider a more general allocation model, where each job consists of multiple stages having execution dependencies.

We introduce several notations used throughout the dissertation. The value-density of job $j$ is defined as $\rho_j = v_j/D_j$. The deadline slackness of the input is defined\(^1\) as the smallest $s \geq 1$ such that $d_j - a_j \geq s(D_j/k_j)$ for every job $j$.

---

\(^1\)When the timeline is discrete, we require $d_j - a_j \geq s\lceil D_j/k_j \rceil$. 

7
1.3 Thesis Overview

This dissertation is organized as follows. We begin by considering a special offline variant of the allocation model, where all jobs share the same arrival time (Chapter 3). This allows us to focus on other aspects of our model. We show that under two realistic assumptions, the resulting resource allocation problem can be solved efficiently using simple greedy-like algorithms. First, we assume that no job can simultaneously accommodate most of the cluster resources, i.e., the parallelism bound of each job is notably smaller than the cluster capacity. Second, we assume that all deadline requirements exhibit a minimal level of slackness; specifically, no job request enforces a tight deadline. To obtain theoretical performance guarantees for our algorithms, we develop a proof methodology based on the dual-fitting technique for our greedy-like algorithms. In addition, we show that these algorithms can be used to construct truthful mechanisms with no performance loss.

We then proceed to study online scheduling with job deadlines (Chapter 4). For the most general form of the problem, several impossibility results are known to rule out the existence of online schedulers that guarantee constant competitive ratios. Nevertheless, we show that under the same deadline slackness assumption as before, we can obtain truthful, online, constant competitive-ratio mechanisms for the problem. Moreover, we provide similar results to a stronger family of committed schedulers, that must guarantee the completion of any admitted job (Chapter 5). We then broaden our allocation model to incorporate DAG-structured jobs, i.e., jobs composed of tasks with inner dependencies (Chapter 6). We show that if the cluster size is significantly larger than the parallelism level of any job, the offline problem can be solved using a randomized rounding algorithm; the online case remains subject to future work. Finally, we use insights from our theoretical study to design and implement a deadline scheduler for Hadoop YARN, which has been accepted by the open-source community (Chapter 7).

In the following, we provide an overview of our results in each chapter.

Chapter 3: Near-Optimal Schedulers for Identical Arrival Times

We first study the special case of identical arrival times. In this simplified model, we assume that all jobs arrive at the same time and that each job \( j \) is associated with a deadline valuation function (i.e., the scheduler must meet a predefined deadline \( d_j \) in order to gain a value \( v_j \) for completing the job). Since all arrival times are identical, the problem reduces to an offline scheduling problem. Our main result is a new near-optimal approximation algorithm for maximizing the social welfare (i.e., total value gained from completed jobs). Based on

\[\text{2For a comprehensive description of dual fitting, see Section 2.1.2.}\]

\[\text{3For more on truthful mechanisms, see Section 2.2.}\]

8
the new approximation algorithm, we construct truthful allocation and pricing mechanisms, in which reporting the true value and other properties of the job (deadline, work volume and the parallelism bound) is a dominant strategy for all users. The mechanisms obtain near-optimal approximation to the social welfare and to the optimal expected profit, respectively; the latter holds under Bayesian assumptions. We empirically evaluate the benefits of our approach through simulations on data-center job traces, and show that the revenues obtained under our mechanism are comparable with an ideal fixed-price mechanism, which sets an on-demand price using oracle knowledge of users’ valuations. Finally, we discuss how our model can be extended to accommodate uncertainties in job work volumes, which is a practical challenge in cloud environments. Joint work with Ishai Menache, Brendan Lucier and Navendu Jain. Results published in [42, 51].

Chapter 4: Online Scheduling with Deadline Slackness

We study the fundamental problem of online deadline scheduling. In this problem, a scheduler receives job requests over time. Each job has an arrival time, deadline, size (demand) and value. The goal of the scheduler is to maximize the total value of jobs that meet their deadline. We circumvent known lower bounds for this problem by assuming that the input has slack, meaning that any job could be delayed and still finish by its deadline. Under the slackness assumption, we design a preemptive scheduler with a constant-factor worst-case performance guarantee. Along the way, we pay close attention to practical aspects, such as runtime efficiency, data locality and demand uncertainty. We then present a truthful variant of the scheduling algorithm which obtains nearly the same competitive ratio. Joint work with Ishai Menache and Brendan Lucier. Results published in [51].

Chapter 5: Online Scheduling with Commitments

We extend our study of online deadline scheduling. We show that if the slackness parameter $s$ is large enough, then we can construct truthful scheduling mechanisms that satisfy a commitment property: the scheduler decides for each job, well in advance before its deadline, whether the job is admitted or rejected. If the job is admitted, then the scheduler guarantees to complete the job by its deadline, and moreover, the required payment is specified at the time of admission. This is notable, since in practice users with strict deadlines may find it unacceptable to discover near their deadline that their job has been rejected. Joint work with Ishai Menache and Brendan Lucier. Results published in [4].
Chapter 6: Offline Scheduling of DAG-Structured Jobs

We generalize our allocation model to accommodate job requests with complex inner structures, as common for most big data jobs. In this work, each job is represented by a Directed Acyclic Graph (DAG) consisting of several stages linked by precedence constraints. The resource allocation per stage is malleable, in the sense that the processing time of a stage depends on the resources allocated to it (the dependency can be arbitrary in general). The goal of the scheduler is to maximize the total value of completed jobs, where the value for each job depends on its completion time. We design a novel offline approximation algorithm for the problem which guarantees an expected constant approximation factor when the cluster capacity is sufficiently high. To the best of our knowledge, this is the first constant-factor approximation algorithm for the problem. However, the algorithm suffers from several shortcomings: it requires solving a large linear program (which is inefficient in practice), and it is not truthful. We note that many open challenges remain regarding DAG scheduling with job deadlines. Joint work with Ishai Menache and Peter Bodík. Results published in [14].

Chapter 7: New Scheduling Algorithm for Hadoop YARN

Apache Hadoop is one of the leading open-source frameworks for cluster resource management and big data processing. Using the Rayon [23] abstraction, we design, implement and evaluate LowCost – a new cost-based planning algorithm for the Hadoop resource negotiator YARN [63]. Through simulations and experiments on a test cluster, we show that LowCost substantially outperforms the existing algorithm on a variety of important performance metrics. Our open-source contributions can be found in YARN-3656 and YARN-4359. LowCost has been recently used as an allocation mechanism for periodic jobs, and is part of the Morpheous system [45]. Joint work with Ishai Menache, Calro Curino and Subru Krishnan.

1.4 Related Work

Scheduling problems have been extensively studied in operations research and computer science (see [15] for a broad survey). This dissertation focuses on designing deadline-sensitive schedulers which aim to maximize the value of completed jobs. The allocation models we consider, as highlighted in Section 1.2, significantly extends the work on basic problems, such as job interval scheduling [5, 7, 22] and bandwidth allocation [5, 6, 57]. Our review of related literature is spread throughout the dissertation as follows: offline variants of our model are covered in Chapter 3; online variants are overviewed in Chapter 4; literature on DAG-scheduling models is discussed in Chapter 6; and recent work related to datacenter resource allocation can be found in Chapter 7.
Chapter 2

Preliminaries

2.1 Algorithmic Design

2.1.1 Evaluation Metrics

The scheduling algorithms presented in this work are evaluated using standard worst-case performance metrics. Separate metrics are used throughout literature for offline and online settings, though they are similar in nature. In the following, we define these metrics. Denote by \( OPT(\tau) \) the optimal offline solution for an input instance \( \tau \). The performance of an online algorithm \( A \) is measured by the competitive ratio, which is the worst-case ratio between the values gained by the optimal offline solution and the online algorithm. In our work, we are mainly interested in bounding the competitive ratio as a function of the input slackness:

\[
cr_A(s) = \max_{\tau,s(\tau)=s} \left\{ \frac{v(OPT(\tau))}{v(A(\tau))} \right\}.
\]

(2.1)

In general, the competitive ratio of an online algorithm \( A \) is defined as \( cr(A) = \max_s cr_A(s) \). The performance of an offline algorithm \( A \) is measured by the approximation ratio \( ar(A) \), which is also defined as the worst-case ratio between the values gained by the optimal solution and the algorithm. These two definitions are mathematically identical, however have different implications.

2.1.2 The Dual Fitting Technique

A core element in the analysis of our mechanisms is a dual fitting argument. Dual fitting is a common technique for bounding the worst-case performance of algorithms. The technique obtains an upper bound on the value gained by the optimal solution \( OPT(\tau) \) through the
weak duality principle, which originates from optimization theory. In the field of algorithmic design, the dual fitting technique is typically applied over linear programming (LP) relaxations to combinatorial optimization problems. We describe the dual fitting technique through its specific application to the main scheduling model considered in our work.

In the first step of this technique, we describe an optimization problem over linear constraints, called the **primal program**. The primal program is a relaxed formulation of the scheduling problem, i.e., every possible schedule can be translated into a feasible solution to the primal program with an identical total value. The primal program may allow additional solutions. As a consequence, the value of the optimal solution to the primal program may be higher than the value of the optimal schedule. We now describe the primal program used in context of our main scheduling model.

**Primal Program.** The primal program is presented in equations (2.2)-(2.6). The variables of the program are $y_{ij}(t)$ for each job $j$, server $i$ and time $t \in [a_j, d_j]$. We simplify exposition by writing $y_j(t) = \sum_{i=1}^{C} y_{ij}(t)$. However, we note that $y_j(t)$ is not an actual variable of the primal program; it is only used to clarify the constraints of the program.

\[
\text{max} \quad \sum_j \rho_j \int_{a_j}^{d_j} y_j(t) dt \quad (2.2)
\]

\[
\int_{a_j}^{d_j} y_j(t) dt \leq D_j \quad \forall j \quad (2.3)
\]

\[
\sum_{j \in [a_j, d_j]} y_j(t) \leq 1 \quad \forall i, t \quad (2.4)
\]

\[
y_j(t) - k_j \cdot \frac{1}{D_j} \int_{a_j}^{d_j} y_j(t) dt \leq 0 \quad \forall j, t \in [a_j, d_j] \quad (2.5)
\]

\[
y_j(t) \geq 0 \quad \forall j, i, t \in [a_j, d_j] \quad (2.6)
\]

As mentioned, the primal program is a relaxed formulation of the general scheduling problem. For instance, notice that the program does not constrain the variable $y_j(t)$ to be binary. Instead, the variable $y_j(t)$ may receive fractional numbers. For this reason, feasible solutions to the linear program are often called **fractional solutions**.

The first two constraints (2.3) and (2.4) are standard demand and capacity constraints. Constraint (2.5) is a tighter version of the natural parallelism constraint $y_j(t) \leq k_j$. We
further elaborate on this constraint later. Notice that some of the constraints of the original problem are relaxed and replaced by linear constraints. For example, the original constraint $y^i_j(t) \in \{0, 1\}$ is replaced by $y^i_j(t) \geq 0$ (the capacity constraint (2.4) implies that $y^i_j(t) \leq 1$); furthermore, the demand constraint now allows a fractional solution to partially satisfy demand requests. But, constraint relaxation must be done carefully. In general, over-relaxing constraints might cause undesired fractional solutions to become legal. As a result, the relaxed formulation could become meaningless. One way to prevent this is introducing additional constraints that limit the strength of fractional solutions. In our context, the standard parallelism constraint $y_j(t) \leq k_j$ is replaced by a tighter constraint (2.5). This constraint limits the strength of a fractional solution by imposing a tighter restriction on $y_j(t)$. Notice that $\frac{1}{D_j} \int_{a_j}^{d_j} y_j(t) dt$ represents the completed fraction of job $j$. To exemplify, if a fractional solution allocates half of the demand requested by job $j$, then every variable $y_j(t)$ in the fractional solution $y$ cannot exceed $0.5k_j$. The strengthened constraints (2.5) for this problem were first introduced by [41] and are a reminiscent of the knapsack cover inequalities [18].

The objective function (2.2) represents the value gained from completed jobs. However, in this relaxed LP formulation, a fractional solution may gain partial value over partially completed jobs. We denote by $OPT^*(\tau)$ the optimal fractional solution of the primal program for an instance $\tau$. Since the primal program is a relaxed formulation of the scheduling problem, $OPT^*(\tau)$ is super-optimal, meaning that $v(OPT(\tau)) \leq v(OPT^*(\tau))$.

**Dual Program.** The following dual optimization problem is associated with the primal program we described. By weak duality, every feasible solution to the dual program admits an upper bound to $v(OPT^*(\tau))$.

$$\min \sum_{j \in J} D_j \alpha_j + \sum_{i=1}^{C} \int_{0}^{\infty} \beta_i(t) dt \quad \text{(2.7)}$$

s.t. \hspace{1cm} $\alpha_j + \beta_i(t) + \pi_j(t) - \frac{k_j}{D_j} \int_{a_j}^{d_j} \pi_j(\tau) d\tau \geq \rho_j \quad \forall j, i, t \in [a_j, d_j] \quad \text{(2.8)}$

$$\alpha_j, \beta_i(t), \pi_j(t) \geq 0 \quad \forall j, i, t \in [a_j, d_j] \quad \text{(2.9)}$$

The dual program holds a constraint (2.8) for every tuple $(j, i, t)$. We say that a constraint is covered by a dual solution $(\alpha, \beta, \pi)$ if it is satisfied by $(\alpha, \beta, \pi)$. A solution that covers all of the dual constraints is called feasible. We refer to (2.7) as the dual cost of a feasible dual solution. The dual cost of every feasible solution is an upper bound to $v(OPT^*(\tau))$. 

14
There are three kinds of dual variables. Every job \( j \) has a variable \( \alpha_j \) that appears in all of the dual constraints associated with \( j \). Notice that setting \( \alpha_j = \rho_j \) satisfies all of the dual constraints of job \( j \) at a dual cost of \( D_j \alpha_j = D_j \rho_j = v_j \). The second type of dual variable \( \beta_i(t) \) appears in every dual constraint that corresponds to a server \( i \) at time \( t \). We typically think of these variables as continuous functions, one per server. The last set of variables \( \pi_j(t) \) are a result of the strengthened parallelism constraints (2.5). In most cases, we set these variables to 0. However, they can be used to lower the cost of dual solutions.

**Dual Fitting.** The dual fitting technique bounds the competitive ratio (or approximation factor thereof) of an algorithm \( A \) by explicitly constructing a feasible solution to the dual program and bounding its cost, without having to solve the linear program itself. Formally speaking, given an input instance \( \tau \) with slackness \( s = s(\tau) \), we construct a feasible solution \((\alpha, \beta, \pi)\) to the corresponding dual program and bound its dual cost by \( r(s) \cdot v(A(\tau)) \) for some \( r(s) \). This proves that \( \text{cr}_A(s) \leq r(s) \), since by weak duality:

\[
v(A(\tau)) \leq v(OPT(\tau)) \leq v(OPT^*(\tau)) \leq r(s) \cdot v(A(\tau)).
\]

Equation (2.10) reveals an inherent lower bound on the capability of dual fitting arguments.

**Definition 2.1.1.** The integrality gap of the primal program on instances \( \tau \) with slackness \( s = s(\tau) \) is defined as:

\[
\text{IG}(s) = \max_{\tau: s(\tau) = s} \left\{ \frac{v(OPT^*(\tau))}{v(OPT(\tau))} \right\}.
\]

The integrality gap essentially measures the quality of a relaxed formulation. Equation (2.10) indicates that any bound \( r(s) \) that can be proven through dual fitting arguments is limited by the integrality gap \( \text{IG}(s) \) of the primal program. It is important to understand that the integrality gap does not bound the competitive ratio of any algorithm, only those that rely solely on weak duality to prove their performance guarantees. On the other hand, if we are able to prove through dual fitting that \( \text{cr}_A(s) \leq r(s) \) for an algorithm \( A \), then \( r(s) \) is also an upper bound on the integrality gap. The following theorem summarizes the dual fitting technique.

**Theorem 2.1.2 (Dual Fitting [64]).** Consider an online scheduling algorithm \( A \). If for every instance \( \tau \) with slackness \( s = s(\tau) \) there exists a feasible dual solution \((\alpha, \beta, \pi)\) with a dual cost of at most \( r(s) \cdot v(A(\tau)) \), then \( \text{IG}(s) \leq \text{cr}_A(s) \leq r(s) \).
2.2 Algorithmic Mechanism Design

Mechanism design is a sub-field of economic theory which has received recent attention from computer scientists. In its algorithmic aspect, the goal is to design computationally efficient choice mechanisms, such as auctions or resource allocation, while optimizing an objective function. Some examples of objective functions include the social welfare (total value), or the total profit accrued by the mechanism. The difficulty of algorithmic mechanism design is that unlike classic algorithmic design, participants act rationally in a game theoretic sense and may deviate in order to maximize their personal utilities. Since participants’ preferences are usually kept private from the mechanism, we search for efficient mechanisms that implement certain strategic properties to deal with participants’ incentives, e.g., incentivize users to truthfully report their preferences, while attempting to optimize an objective function.

An extensive amount of work has been carried out in the field of algorithmic mechanism design, starting with the seminal paper of Nisan and Ronen [54]. Prior to their paper, mechanism design received much attention by economists who focused on exact solutions or characterizations of truthful mechanisms, mostly under Bayesian settings and typically without taking into account time or communication complexity limitations. The sub-field of algorithmic mechanism design addresses these challenges from the perspective of a computer scientist. In the following, we describe the basic definitions of mechanism design and the main theorems on which we rely in our work. We refer the reader to [55] for a survey book.

2.2.1 Definitions

Every user $j$ is associated with a private true type $\tau_j = (v_j, P_j)$, where $v_j$ is the user value and $P_j$ is a set of properties. In our context, $P_j = (D_j, k_j, a_j, d_j)$ is the set of job properties. The true type of user $j$ is taken from a known type space $T_j$. Denote $T = T_1 \times T_2 \times \cdots \times T_n$. We study direct revelation mechanisms, where each user participates by announcing a reported type (bid type) $b_j \in T_j$ to the mechanism. Note that the reported type $b_j$ may differ from the true type $\tau_j$.

A mechanism $M = (f, p)$ consists of an allocation rule $f : T \to O$, where $O$ is the set of possible outcomes, and a pricing rule $p_j : T \to \mathbb{R}$ for every user $j$. Given a reported bid vector $b = (b_1, b_2, \ldots, b_n)$, the mechanism allocates jobs according $f(b)$ and charges a non-negative payment $p_j(b)$ from each user $j$. The goal of the mechanism is to optimize an objective function $g : O \to \mathbb{R}$ such as the social welfare or the mechanism revenue.

We focus on single-value domains\(^1\), in which user valuation of outcomes is encoded by a single scalar $v_j \in \mathbb{R}$. We define $f_j(b) \in \{0, 1\}$ as a binary function that indicates whether

\(^1\)General value models consider value functions of the form $v_j : O \to \mathbb{R}$ and user utilities of the form $u_j(b) = v_j(f(b)) - p_j(b)$. 

16
job \( j \) is scheduled properly with respect to the job properties; that is, whether \( j \) is allocated \( D_j \) resource units in the interval \([a_j, d_j]\) without violating the parallelism bound \( k_j \). Every user strives to maximize its utility \( u_j(b) \), defined as the following quasilinear function:

\[
u_j(b) = v_j f_j(b) - p_j(b).
\] (2.12)

Notice that the job properties do not affect the value \( v_j \) gained by the user, only the allocation \( f_j(b) \). Models where the user type consists of a single value scalar and multiple type properties (e.g., deadline, demand) are called single-value multi-property models.

### 2.2.2 Truthfulness and Monotonicity

Mechanism design involves additional complications due to the selfish nature of participants. A mechanism must be sensitive to potential manipulation by users, as users striving to maximize their personal gain may attempt to do so by reporting false values or parameters. To prevent false behavior, the mechanism must incentivize users to act truthfully.

Given a vector \( x \), we denote by \( x_{-j} \) the vector \( x \) without entry \( j \). Specifically, \( \tau_{-j} \) represents a type profile of all users except \( j \). We use \((x_j, x_{-j})\) to denote the concatenation of \( x_j \) with \( x_{-j} \).

**Definition 2.2.1 (Truthfulness).** A mechanism \( \mathcal{M} = (f, p) \) is called **truthful** or incentive compatible (IC) if for every user \( j \) and for every choice of \( \tau_{-j} \), truth-telling is a dominant strategy for every user \( j \). Formally, for every type \( \tau'_{j} \in \mathcal{T}_j \):

\[
u_j(\tau_j, \tau_{-j}) \geq u_j(\tau'_{j}, \tau_{-j})
\] (2.13)

If (2.13) holds in expectation, the mechanism is called **truthful-in-expectation**.

Truthful mechanisms in single-value domains have been completely characterized by [52, 2]. For an allocation algorithm \( f \) to be implementable as a truthful mechanism, i.e., for there to exist a corresponding pricing rule \( p \) that admits a truthful mechanism, the allocation algorithm \( f \) must be **monotone**, and vice-versa. This characterization has been extended by [34] for single-value multi-property domains similar to those studied here. In the following, we present their characterization with specific relevance to job scheduling mechanisms. We note that the framework presented in [34] can similarly be extended to other single-value multi-property domains, however we focus here on job scheduling domains alone.

Following [34], we adopt several assumptions on the types \( \tau'_j = (v'_j, D'_j, k'_j, a'_j, d'_j) \) that can be reported to the scheduling mechanism. These assumptions are all justifiable in the context of allocating cloud resources, as we show next.
• **No Early Arrival Times** \((a'_j \geq a_j)\). The true arrival time represents the earliest time in which a job can be processed. The mechanisms we propose require that submitted jobs are ready for execution. Hence, it is natural to assume that a user cannot submit a job before it can be processed.

• **No Late Deadlines** \((d'_j \leq d_j)\). In general, unallocated users might manage to guarantee timely completion by reporting late deadlines. To prevent this behavior, the truthful mechanisms we construct in our work will release the job output only at its reported deadline. This suppresses any incentive to report a late deadline, since by doing so the job would certainly miss its deadline. Henceforth, we assume that users do not report deadlines which are later than their actual deadlines.

• **No Insufficient Demands** \((D'_j \geq D_j)\). Jobs cannot complete without receiving the necessary amount of resources required for completion. As long as the scheduling algorithms do not allocate unnecessary resources to jobs, a user cannot benefit from requesting an insufficient amount of resources.

• **No Overestimated Parallelism Bounds** \((k'_j \leq k_j)\). In practice, bounds on the desired level of parallelism are either enforced by the scheduler or a result of computation overheads (e.g., software limitations, network delays). Exceeding the job resource limitations would result in slower execution, and therefore failure to complete the job within its requested amount of resources.

We now define monotonicity in context of the single-value multi-property scheduling domain studied in this work. We first define a partial order over the job property sets used in our model.

**Definition 2.2.2.** Property set \(P'_j\) is **dominated** by property set \(P''_j\) if \(D'_j \geq D''_j\), \(k'_j \leq k''_j\), \(a'_j \geq a''_j\), and \(d'_j \leq d''_j\). We use \(P'_j \preceq P''_j\) to denote that \(P'_j\) is dominated by \(P''_j\).

Now, we can define monotonicity for single-value multi-property domains.

**Definition 2.2.3.** Type \(\tau_j = \langle v'_j, P'_j \rangle\) is **dominated** by type \(\tau''_j = \langle v''_j, P''_j \rangle\) if \(v'_j \leq v''_j\) and \(P'_j \preceq P''_j\). We use \(\tau'_j \preceq \tau''_j\) to denote that \(\tau'_j\) is dominated by \(\tau''_j\).

**Definition 2.2.4 (Monotonicity).** An allocation algorithm \(f\) is called **monotone** if for every \(j\), \(\tau_{-j}\), and \(\tau'_j \preceq \tau''_j\) we have \(f_j(\tau'_j, \tau_{-j}) \leq f_j(\tau''_j, \tau_{-j})\).

As stated before, monotonicity provides a complete characterization of truthful mechanisms in single-value multi-property domains. This has been proven in [34] for the special case of unit-sized demands. However, their proof extends directly for general demands with restrictions on parallelism.
Theorem 2.2.5 (Restatement of [34]). Let $f$ be an allocation rule. Assume no early arrival times, no late deadlines, no insufficient demands and no overestimated parallelism bounds. Then, there exists a payment rule $p$ such that the mechanism $\mathcal{M} = (f, p)$ is truthful if and only if $f$ is monotone. In the latter case, the pricing rule takes the following form, where $\tau'_j = (v'_j, P'_j)$ is the reported type of job $j$: \[
p_j(\tau'_j, \tau_{-j}) = v'_j \cdot f_j(\tau'_j, \tau_{-j}) - \int_0^{v'_j} f_j(x, P'_j, \tau_{-j}) \, dx. \tag{2.14}
\]

Theorem 2.2.5 also holds for randomized mechanisms. In this case, $f_j$ represents the expected allocation of user $j$. Before continuing, it is worth noting that for binary allocation rules, each allocated user $j$ pays the lowest value which guarantees that $j$ is still allocated.

2.2.3 Profit Maximization in Bayesian Settings
The objective of profit maximizing is of course significant for public commercial clouds. When assuming no a-priori knowledge on clients’ private valuation functions, it is well known that a truthful mechanism might charge very low payments from clients to ensure truthfulness, yielding low revenues. Thus, following a standard approach in game-theory, we consider a Bayesian setting, in which the true value $v_j$ of each user $j$ is assumed to be drawn from a distribution with a probability density function $g_j$, which is common knowledge. We denote by $G_j$ the respective cumulative distribution function (cdf). Job properties are assumed, as before, to be private information with no additional distribution information.

The goal of the mechanism in the current context is to maximize the optimal expected profit, with the expectation taken over the random draws of clients’ values. For single-value domains, it is well known that the problem of maximizing profits can be reduced to the problem of maximizing social welfare over virtual values; this basic property is due to celebrated work by Myerson [52], and has been extended in different contexts (see [55]). To formally state the result, we first need the following definitions.

Definition 2.2.6. Define the revenue curve associated with user $j$ as $R_j(q) = q \cdot G_j^{-1}(1 - q)$. The ironed virtual valuation function $\bar{\phi}_j$ of $j$ is defined as: $\bar{\phi}_j(v) = \frac{d}{dq} \left[ \text{ConcaveClosure} \left( R_j(\cdot) \right) \right]$ for $q = 1 - G_j(v)$.

That is, $\bar{\phi}_j(v)$ the derivative of the concave closure\(^2\) of $R(\cdot)$. Note that $\bar{\phi}_j(\cdot)$ is monotonically non-decreasing. Thus, if a single-value allocation rule $f^{sv}$ is monotone, then so is $f^{sv}(\bar{\phi}(\cdot))$.

\(^2\)The concave closure of a function $f(\cdot)$ is the pointwise supremum of the set of convex functions that lie below $f$. 

19
Theorem 2.2.7 ([52, 55]). For any single-value truthful mechanism $M^{sv}$ that guarantees an $\alpha$-approximation to the optimal social surplus, the mechanism $M^{sv}(\phi(\cdot))$ guarantees an $\alpha$-approximation to the optimal expected profit.

For our purposes, we prove that the reduction proposed by Myerson [52] extends to domains of single value and multiple properties. Formally:

Theorem 2.2.8. Let $f$ be a binary allocation rule for a single-value multi-property problem, such that $f$ is monotone and guarantees an $\alpha$-approximation to the optimal social welfare. Let $f_{\phi}$ be an allocation rule that replaces every type $\langle v_j, P_j \rangle$ with $\langle \phi_j(v_j), P_j \rangle$ and calls $f$. Then, the mechanism $M_{\phi}$ with allocation rule $f_{\phi}$ that charges payments according to (2.14), with respect to $f_{\phi}$, is truthful, and is an $\alpha$-approximation to the optimal expected profit under Bayesian assumptions.

Proof. Fix the set of properties $P_j$ of each job $j$. This makes $f$ a single-value allocation rule. By the characterization theorem of single-value allocation functions [2], since $f$ is monotone, the mechanism $M = (f, p)$ with $p$ set as in (2.14) is truthful. By Theorem 2.2.7, the mechanism $M_{\phi}$ gives an $\alpha$-approximation to the optimal expected profit.

It remains to show that $f_{\phi}$ admits a truthful mechanism. Notice that since $\phi_j(\cdot)$ is monotone for every $j$, $f_{\phi}$ is a monotone allocation rule. Therefore, we can apply Theorem 2.2.5 and conclude that the mechanism $M_{\phi}$ is truthful.

■

2.2.4 Related Literature

We focus on the algorithmic aspect of designing implementable allocation rules, i.e., allocation rules that can be transformed into truthful mechanisms. For an extensive study on algorithmic mechanism design, we refer the reader to [55].

Characterization of Truthful Mechanisms. As discussed, monotonicity provides a full characterization of implementable allocation rules for single-value domains [52, 2], as well as for single-value multiple-property domains [34]. However, much less is known for the general multiple-value domain, where the valuation function of each user is not necessarily scalar. Rochet [59] presented an equivalent property to monotonicity called cyclic monotonicity, which is a necessary and sufficient condition for truthfulness. Yet, it is unclear how to use this property to easily construct truthful mechanisms from it and only few successful efforts are known (for example, [49]). Saks and Yu [60] showed that for deterministic settings, cyclic monotonicity is equivalent to a simpler property called weak monotonicity, which conditions only on cycles of length 2 (see also [3]). However, this result is not valid for randomized mechanisms [13].
**Black-Box Reductions.** Much work has been dedicated to the existence of black-box reductions from algorithmic mechanism design to algorithm design; namely, reductions that can convert any (approximation) algorithm into a truthful (approximation) mechanism, preferably without loss of performance. Unfortunately, recent work by Chawla, Immorlica and Lucier [21] disproved the existence of many types of black-box reductions. For social welfare maximization, [21] proved that there cannot exist a general reduction that preserves the worst-case approximation ratio by a subpolynomial factor, even for truthfulness in expectation. For makespan minimization, the same bound applies even for average-case guarantees and under Bayesian assumptions. General reductions for social welfare maximization are only known to exist under Bayesian assumptions. Hartline and Lucier [36] showed that any approximation algorithm for a single-value problem can be transformed into a Bayesian Incentive-Compatible (BIC) mechanism. This result has been improved since then for multiple-value settings by Hartline, Kleinberg and Malekian [35], and by Bei and Huang [11] independently.

Several black-box reductions have been suggested for large classes of social welfare maximization problems, without prior assumptions on the input. Lavi and Swamy [48] constructed a truthful-in-expectation mechanism for packing problems that are solved through LP-based approximation algorithms. Their reduction maintains the approximation factor of the original algorithm. However, for their reduction to work, the approximation algorithm must bound the integrality gap of the "natural" LP for the problem - and this is not always possible. Dughmi and Roughgarden [26] proved that packing problems that admit an FPTAS can be turned into a truthful-in-expectation mechanism which is also an FPTAS. Finally, we mention that any optimal algorithm for welfare maximization problems can be converted into a truthful mechanism via the celebrated VCG mechanism [55].
Chapter 3

Near-Optimal Schedulers for Identical Release Times

Nowadays, cloud providers offer three pricing schemes to users: (i) on-demand instances, where a user pays a fixed price for a virtual machine (VM) per unit time (e.g., an hour) and can acquire or release VMs on demand, (ii) spot-instances, where users bid for spot instances and get allocation when the spot market price falls below their bid, and (iii) reservations, where users pay a flat fee for long term reservation (e.g., 1-3 years) of instances and a discounted price during actual use. Despite their simplicity, these approaches have several shortcomings for batch computing. First, they offer only best-effort execution without any guarantees on the job completion time. This might not be adequate for all users. For example, the financial firm discussed in the introduction requires SLA on the job completion time rather than how VMs are allocated over time. Second, current resource allocation schemes do not differentiate jobs based on their importance. For instance, financial applications have (and are willing to pay for) strict job deadlines, while scientific jobs are likely willing to trade a bounded delay for lower costs. As a result, cloud systems lose the opportunity to increase profits (e.g., by prioritizing jobs with strict SLAs), improve utilization (e.g., by running low priority jobs at night), or both. Finally, existing schemes do not have in-built incentives to prevent fluctuations between high and low resource utilization. Perhaps the most desired goal of cloud operators is to keep all their resources constantly utilized.

In this chapter, we consider an alternative approach to resource allocation and pricing in cloud computing environments based on an offline scheduling problem of multiple batch jobs. In our approach, we explicitly incorporate the importance of the completion time of a job to its owner, rather than the number of instances allocated to the job at any given time. We exemplify the benefits of our approach through a special case of the general scheduling
problem (Section 1.2) of identical release (arrival) times. In this case, all jobs are available for execution when the scheduler computes the allocation. This scenario is common when the resource plan is computed periodically.

We develop novel truthful mechanisms for the problem. Our main result is a truthful mechanism called GreedyRTL, which guarantees a \((\frac{C}{k}) \left(\frac{s}{s-1}\right)\)-approximation for social welfare maximization, where \(k\) is the maximal parallelism bound over all jobs, \(C\) is the cloud capacity, and \(s\) is the input slackness. Note that the approximation factor approaches 1 under the (plausible) assumptions that \(k \ll C\) and \(s\) is sufficiently large. Our results are presented as follows. We first focus on the pure algorithmic problem, disregarding incentive concerns. We present in Section 3.2.1 a simple greedy algorithm that obtains the desired competitive ratio, however with an additional +1 factor. Based on the simple greedy approach, we develop the GreedyRTL algorithm in Section 3.2.2.

Related Work. The identical arrival model has been studied in our prior work [41] for general user valuation functions. The paper proposed the first algorithm for the objective of maximizing social welfare, which obtained a \((1 + \frac{C}{C-k})(1 + \varepsilon)\)-approximation factor. The algorithm served as the basis for designing a truthful-in-expectation mechanism where reporting valuations truthfully maximized the expected utility for each user. However, it has four key practical shortcomings. First, from the mechanism design perspective, job work volume and parallelism bounds are assumed to be truthfully reported and hence it is only necessary to guarantee truthfulness with respect to values and deadlines. Second, to guarantee truthfulness, the proposed mechanism risks low utilization with at least half of the resources unutilized. Further, the solution cannot be extended to deal with uncertainties in job resource demand. Finally, the solution requires solving a linear program, which might be computationally expensive to run frequently for a large number of jobs.

Of specific relevance to our work is the work of Lawler [50]. In his work, Lawler studied the problem of designing a preemptive job scheduler on a single server to maximize the social welfare. We note that the model can be simply generalized to multiple servers without parallelism bounds. Lawler solved the problem optimally in pseudo-polynomial time via dynamic programming. However, his algorithm cannot be extended to the case where jobs have parallelization limits. The model studied here significantly extends the basic job interval scheduling problem studied by [5, 7]. In this problem, each job is associated with a set of time intervals. Allocating a job corresponds to selecting one of the intervals, and executing the job during that interval. The overall set of selected intervals must not intersect (this corresponds to allocating jobs on a single server). The best known approximation factor for this problem is 2. For identical values, the approximation ratio was improved by Chuzoy et al. [22] to 1.582. Several papers extended the interval scheduling problem by associated
each interval with a width (corresponds to parallelism requirements). When each job has only one interval, Calinescu et al. [16] developed a \((2 + \varepsilon)\) approximation algorithm. For multiple intervals, Phillips et al. [57] and Bar-Noy et al. [5] obtain constant approximations.

### 3.1 Scheduling Model

We consider a single cloud provider which allocates resources (CPUs) to jobs over time. The cloud capacity \(C\) is fixed throughout time. The time horizon is divided into \(T\) time slots \(T = \{1, 2, \ldots, T\}\) of equal size. There are \(n\) jobs, denoted \(1, 2, \ldots, n\). Our focus in this chapter is the identical release time model, where all jobs arrive to the system by time 0 and can be executed immediately. Every job \(j\) is associated with a type \(\tau_j = (v_j, D_j, k_j, d_j)\), where \(v_j\) is the job value, \(d_j\) is the job deadline, \(D_j\) is the job demand, and \(k_j\) is the job parallelism bound. An input to the problem is a type profile \(\tau = \{\tau_1, \ldots, \tau_n\}\). We consider a flexible allocation model. For each job \(j\), the amount of resources allocated to a job can change over time, given that it does not exceed \(k_j\). A feasible allocation of resources to job \(j\) is a function \(y_j : [0, d_j] \rightarrow [0, k_j]\) in which \(j\) is allocated a total of \(D_j\) resources by its deadline \(d_j\). Our goal is to maximize the social welfare, which is the aggregate value of jobs that are completed before their deadline. We remind that partial execution of a job does not yield partial value.

Before we describe our approximation algorithms, we give some definitions and notations that we will use later on. Given a solution consisting of allocations \(y_j\), we define \(W(t) = \sum_{j=1}^{n} y_j(t)\) to be the total workload at time \(t\) and \(\bar{W}(t) = C - W(t)\) to be the amount of available resources at time \(t\). A time slot is saturated if \(\bar{W}(t) < k\) and unsaturated otherwise. Finally, given a time slot \(t\), we define:

\[
R(t) = \max \left\{ t' : t' \geq t, \forall t'' \in (t, t'), \bar{W}(t'') < k \right\}.
\] (3.1)

Intuitively, if there are saturated time slots adjacent to \(t\) to the right, \(R(t)\) is the rightmost time slot out of the saturated block to the right of \(t\). Otherwise, \(R(t) = t\).

### 3.2 Approximation Algorithms

#### 3.2.1 A Simple Greedy Approach

We present a simple greedy algorithm which serves as a basis for developing GreedyRTL. The full implementation of the simple greedy algorithm is given in Algorithm 1. Notice that several lines have been faded out. These lines are only necessary for the analysis, and they can be omitted from the implementation.
The algorithm works as follows. An empty solution $y \leftarrow 0$ is initialized. The jobs are then sorted in non-increasing order of their value-densities $\rho_j$; we assume thereof that jobs are numbered such that $\rho_1 \geq \rho_2 \geq \cdots \geq \rho_n$. For every job $j$ in this order, the algorithm checks whether the request of job $j$ can be satisfied without violating any constraint; that is, whether $D_j$ resource units can be allocated by time $d_j$ without exceeding the maximum allocation $k_j$ per time unit. If so, job $j$ is accepted and scheduled resources arbitrarily, without violating constraints. Otherwise, job $j$ is rejected. In the latter case, the algorithm calls an auxiliary procedure called $\beta$-cover($j$) (line 4.2.1). We describe the $\beta$-cover procedure later, however we note that $\beta$-cover does not affect the scheduling algorithm.

**Algorithm 1:** The simple greedy algorithm

**SimpleGreedy($\tau$)**
1. initialize $\alpha \leftarrow 0$, $\beta \leftarrow 0$, $\xi \leftarrow 0$
2. initialize an empty allocation $y \leftarrow 0$.
3. sort jobs in non-increasing order of value-densities ($\rho_1 \geq \rho_2 \geq \cdots \geq \rho_n$).
4. for $(j = 1, \ldots, n)$ do
   4.1. if ($j$ can be allocated) then
      4.1.1. Allocate($j$)
   4.2. else if ($\beta(d_j) = 0$) then
      4.2.1. $\beta$-cover($j$)

**Allocate($j$)**
1. Allocate $D_j$ resource units arbitrarily to job $j$ in $[0, d_j)$, without violating the parallelism bound $k_j$ at each time slot.
2. $\alpha_j \leftarrow \rho_j$

**$\beta$-cover($j$)**
1. for $(t = 0 \ldots R(d_j))$ do
   1.1. set $\beta(t) \leftarrow \min\{\beta(t), \rho_j\}$
   1.2. for $(i = 1 \ldots j - 1)$ do
      1.2.1. if ($y_i(t) > 0$ and $\xi_i(t) = 0$) then
           1.2.1.1. set $\xi_i(t) \leftarrow \left[\frac{C}{(s-1)} \cdot \frac{s}{s-1}\right] \cdot p_j \cdot y_i(t)$

At this point, one might consider the job allocation phase of the algorithm to be too permitting, since allocated jobs are assigned resources arbitrarily. Nevertheless, in the following we prove a relatively good bound on the guaranteed social welfare.
Analysis. We bound the total value gained by the simple greedy algorithm using the dual fitting technique. Let $\tau = \{\tau_1, \ldots, \tau_n\}$ be an input instance and consider the dual program for an input $\tau$. We construct a feasible solution $(\alpha, \beta, \pi)$ to the dual program and bound its dual cost. Recall the dual constraints (2.8). Each constraint that corresponds to a job $j$ and time slot $t \leq d_j$ must be covered by the variables $\alpha_j$, $\beta(t)$ and $\pi_j(t)$ by at least $\rho_j$. Initially, we set all dual variables to be 0. For allocated jobs $j$, we set $\alpha_j = \rho_j$. This covers all the dual constraints associated with $j$, since the variable $\alpha_j$ is common to all of them. Note that the cost added to the dual objective function is exactly $D_j \alpha_j = v_j$.

Dual constraints of unallocated jobs are covered by the $\beta(t)$ variables. Note that the variable $\beta(t)$ appears in all of the dual constraints associated with $t$. Setting $\beta(t)$ allows us to cover all dual constraints of unallocated jobs at time $t$. To that end, consider an unallocated job $j$. When $j$ is rejected, the algorithm calls a method called $\beta$-cover($j$) used to construct the dual solution. The method guarantees that each variable $\beta(t)$ in the range $[0, R(d_j)]$ is set to at least $\rho_j$. As a result, all of the dual constraints corresponding to $j$ are covered, since $d_j \leq R(d_j)$ and all $\pi$ variables are set to 0. We note that the feasibility of the dual solution can be ensured by only increasing $\beta(t)$ only in the range $[0, d_j]$. However, extending the range to $R(d_j)$ will be critical when we analyze GreedyRTL. To simplify exposition, we perform this extension here.

Corollary 3.2.1. The dual solution $(\alpha, \beta, \pi)$ constructed by the greedy algorithm is feasible.

Before continuing, it is important to understand the form $\beta(t)$ takes. Notice that a variable $\beta(t)$ is always set as the value density of a rejected job. We claim that since jobs are considered in non-increasing order of value densities, the $\beta(t)$ function obtains the form of a decreasing step function.

Claim 3.2.2. The $\beta(t)$ variables are monotonically non-increasing in $t$.

Proof. We prove the claim by induction on the number of jobs considered by the algorithm. Initially, $\beta(t) = 0$ for every $t$ and the claim trivially holds. Let $j$ be a job considered by the algorithm and assume that $\beta(t)$ is monotonically non-increasing in $t$. If $j$ is allocated, then the claim holds since $\beta(t)$ is not modified. Now, assume that $j$ is rejected by the algorithm due to insufficient free resources. Define $t_{cov} = \max\{t \mid \beta(t) > 0\}$. Recall that the algorithm sets entries of $\beta(t)$ to be value densities of rejected jobs. Since the algorithm considers jobs in non-increasing order of value densities, any job $j'$ rejected by now satisfies $\rho_{j'} \geq \rho_j$. Specifically, $\beta(t_{cov}) \geq \rho_j$. Moreover, the inductive assumption implies that $\beta(t) \geq \rho_j$ for every $t \leq t_{cov}$. Therefore, the call to $\beta$-cover($j$) only sets $\beta(t) = \rho_j$ for every $t \in (t_{cov}, R(d_j)]$. We conclude that $\beta(t)$ is monotonically non-increasing in $t$. ■
It remains to bound the dual cost of the constructed dual solution. Let $S$ denote the set of jobs allocated by the algorithm. The cost of covering the dual constraints associated with allocated jobs is exactly $\sum_{j=1}^{n} D_j \alpha_j = \sum_{j \in S} v_j$. The remaining cost $\sum_{t} C\beta(t)$ is bounded through a charging argument. Namely, we charge allocated jobs for the dual cost of setting the $\beta(t)$ variables, and then prove that the total amount charged is at least $\sum_{t} C\beta(t)$; finally, we bound the total amount charged through relatively simple arguments.

We charge allocated jobs at time slots in which they were allocated resources. Formally, denote by $\xi_{i}(t)$ the amount charged from job $i$ in time slot $t$. We charge job $i$ at time $t$ an amount proportional to $y_{i}(t)$, the number of resources it received at time $t$. Every pair $(i, t)$ will be charged only once, according to the following rule: whenever a job $j$ is rejected and $\beta\text{-cover}(j)$ is called, the pair $(i, t)$ is charged:

$$
\xi_{i}(t) \leftarrow \left[ \frac{C}{C-k} \cdot \frac{s}{s-1} \right] \cdot \rho_{j} \cdot y_{i}(t).
$$

Notice that $\rho_{i} \geq \rho_{j}$, since $i$ has been allocated before $j$ was considered by the algorithm. This implies that the total amount charged from all jobs is at most:

$$
\sum_{i \in S} \sum_{t \leq d_{i}} \xi_{i}(t) \leq \left[ \frac{C}{C-k} \cdot \frac{s}{s-1} \right] \sum_{i \in S} \sum_{t \leq d_{i}} \rho_{i} \cdot y_{i}(t)
= \left[ \frac{C}{C-k} \cdot \frac{s}{s-1} \right] \cdot \sum_{i \in S} v_{i}.
$$

It remains to prove that total amount charged from jobs is an upper bound to $\sum_{t} C\beta(t)$. Define $E_{j}$ to be the set of unsaturated time slots (i.e., $\bar{W}(t) \geq k$) up to time $R(d_{j})$ during the call to $\beta\text{-cover}(j)$.

**Lemma 3.2.3.** After every call to $\beta\text{-cover}(j)$:

$$
\sum_{i=1}^{j-1} \sum_{t \leq d_{i} : \bar{W}(t) < k} \xi_{i}(t) - \sum_{t=1}^{T} C\beta(t) \geq C \cdot \rho_{j} \cdot \frac{s}{s-1} \cdot \left[ \frac{R(d_{j})}{s} - |E_{j}| \right].
$$

**Proof.** By Induction. Initially, both sides equal 0 and the claim trivially holds. Let $j'$ be the last unallocated job for which $\beta\text{-cover}(j')$ was called prior to $j$ and assume that the claim holds after $\beta\text{-cover}(j')$ was called. We examine the change in both sides of the inequality from after the call to $\beta\text{-cover}(j')$ and until after the call to $\beta\text{-cover}(j)$. We begin with the left hand side (LHS). Note that the set of saturated time slots $t$ satisfying $\bar{W}(t) < k$ can only grow, since saturated time slots cannot become unsaturated. Between the two calls,
LHS is updated as follows:

- \( R(d_j) - R(d_{j'}) - |E_j \setminus E_{j'}| \) new saturated time slots in the interval \( (R(d_{j'}), R(d_j)) \) are included in the LHS. Let \( t \) be such a time slot. Every job \( i \) allocated job during time slot \( t \) is either charged when \( \beta\text{-cover}(j) \) is called or during a previous call. In both cases, it is charged at least \( (\frac{C}{C-k} \cdot \frac{s}{s-1}) \cdot \rho_j \cdot y_i(t) \). Therefore:

\[
\sum_{i=1}^{j-1} \xi_i(t) \geq \frac{C}{C-k} \cdot \frac{s}{s-1} \cdot \sum_{i=1}^{j-1} \rho_j \cdot y_i(t) \geq C \cdot \frac{s}{s-1} \cdot \rho_j.
\]

The inequality follows since \( t \) is saturated. The cost of setting \( \beta(t) = \rho_j \) for a time slot \( t \) is \( C \cdot \rho_j \). Overall, LHS increases by at least:

\[
(R(d_j) - R(d_{j'}) - |E_j \setminus E_{j'}|) \cdot C \cdot \left(\frac{1}{s-1}\right) \cdot \rho_j.
\]

- \( |E_{j'} \setminus E_j| \) time slots in the interval \([1, R(d_{j'})]\) became saturated. Since \( \beta(t) \) has already been set for such time slots, LHS increases by at least:

\[
|E_{j'} \setminus E_j| \cdot C \cdot \left(\frac{s}{s-1}\right) \cdot \rho_j.
\]

- \( |E_j \setminus E_{j'}| \) unsaturated time slots have been covered at cost:

\[
|E_j \setminus E_{j'}| \cdot C \cdot \rho_j.
\]

By applying the inductive assumption on the value of LHS before the call to \( \beta\text{-cover}(j) \) and rearranging terms, we have:

\[
\text{LHS} \geq C \cdot \rho_j \cdot \frac{s}{s-1} \cdot \left[ \frac{R(d_j)}{s} - |E_{j'}| \right] +
C \cdot \rho_j \cdot \left[ \frac{R(d_j) - R(d_{j'})}{s-1} - \frac{|E_j \setminus E_{j'}|}{s-1} \right] +
C \cdot \rho_j \cdot \left[ \frac{s}{s-1} \cdot |E_{j'} \setminus E_j| - |E_j \setminus E_{j'}| \right] \geq
C \cdot \rho_j \cdot \left[ \frac{R(d_j) - s}{s-1} \cdot |E_j| \right] +
C \cdot \rho_j \cdot \frac{s}{s-1} \cdot \left[ |E_j| - |E_{j'}| - |E_j \setminus E_{j'}| + |E_{j'} \setminus E_j| \right]
\]

28
\[ C \cdot \rho_j = \frac{s}{s-1} \left[ \frac{R(d_j)}{s} - |E_j| \right], \]
since \(|E_j| - |E_j'| = |E_j \setminus E_j'| - |E_j' \setminus E_j|\).

**Theorem 3.2.4.** The simple greedy algorithm guarantees a \((1 + \frac{C}{C-k} \cdot \frac{s}{s-1})\)-approximation.

**Proof.** Denote by \(S\) the set of jobs allocated by the simple greedy algorithm. Let \(j\) be the last job for which \(\beta\)-cover has been called. Since \(j\) was not allocated, we must have \(|E_j| < len_j\), otherwise \(j\) could have been allocated. By the slackness assumption and since by definition, \(d_j \leq R(d_j)\), we have \(s \cdot |E_j| < s \cdot len_j \leq d_j \leq R(d_j)\). By Lemma 3.2.3 and by (3.3), the dual cost of the dual solution constructed by the algorithm is at most \((1 + \frac{C}{C-k} \cdot \frac{s}{s-1}) \cdot \sum_{j \in S} v_j\).

In Appendix 3.A we show that the analysis of the simple greedy algorithm can be further improved, and that it actually guarantees an approximation factor of \(1 + \frac{s}{s-1}\). Nevertheless, the proof of the weaker bound presented in this section is essential to the analysis of GreedyRTL, which guarantees near optimal performance. We leave the improved analysis of the simple greedy algorithm to the appendix.

### 3.2.2 The GreedyRTL Algorithm

The GreedyRTL algorithm presented here is similar in nature to the simple greedy algorithm. GreedyRTL (Algorithm 2) sorts the jobs according to their value densities in non-increasing order. Also, a job is scheduled if a feasible allocation for it exists. The main difference between the two algorithms is the allocation rule of a single job. In the previous section, we allowed any arbitrary allocation of resources to scheduled jobs. Here, we construct a specific single-job allocation rule called AllocateRTL. Also, we allow AllocateRTL to reallocate previously scheduled jobs; to be described later.

Before beginning, we provide some intuition. Our goal is to reduce the dual cost associated with an allocated job \(j\). This consists of \(D_j \alpha_j\) and \(\xi_j(t)\) for every time slot \(t\) in which resources are allocated to \(j\). Consider the monotonically non-increasing vector \(\beta\) and ignore for now the \(\pi\) variables. To satisfy the dual constraints of an allocated job \(j\), we must set \(\alpha_j\) as \(\rho_j - \beta(d_j)\); the monotonicity of \(\beta\) implies that all constraints are covered. However, \(\beta(d_j)\) might be 0, hence the dual cost might not decrease. An alternative approach would be to allocate \(j\) during later time slots, where jobs are charged less to cover the \(\beta\) variables. Ideally, we would want job allocations to be *aligned to the right* as much as possible; formally, each job \(j\) would be allocated \(k_j\) resources from the deadline \(d_j\) backwards, perhaps less during the earliest time slot if \(k_j\) does not divide \(D_j\). This makes sense, since fewer jobs can be allocated during later time slots. However, a solution in which all jobs are allocated
ideally does not always exist. Moreover, it is still unclear how to reduce the dual cost by only using $\alpha$ and $\beta$.

We start by defining a “nearly ideal” form of allocation, called $\beta$-consistent allocations. The GreedyRTL algorithm we design maintains a $\beta$-consistent allocation for each job. To define $\beta$-consistency, we require a preliminary definition.

**Definition 3.2.5.** The breakpoint $bp(y_j)$ of an allocation $y_j$ of job $j$ is defined as:

$$bp(y_j) = \max\left\{ t \mid y_j(t) < k_j \right\} \cup \{st(y_j)\}.$$  \hfill (3.5)

The breakpoint $bp(y_j)$ is essentially the first time slot $t$, starting from the deadline moving towards earlier time slots, during which $y_j(t)$ does not coincide with the ideal aligned-to-right form of allocation. If such a time slot does not exist, $bp(y_j) = st(y_j)$. Alternatively, $bp(y_j)$ is defined such that each $y_j(t) = k_j$ for every $t \in (bp(y_j), d_j]$.

**Definition 3.2.6.** A job allocation $y_j$ is called $\beta$-consistent if every $t \in (st(y_j), bp(y_j)]$ is either saturated or satisfies $\beta(t) > 0$.

The single job allocation algorithm AllocateRTL($j$) produces a $\beta$-consistent allocation for a job $j$, while preserving the $\beta$-consistency of existing allocations. The algorithm works as follows. First, an empty allocation $y_j \leftarrow 0$ is initialized. The algorithm iterates over the time slots from the deadline $d_j$ backwards (hence, the name Right-To-Left). During each time slot $t$, the algorithm attempts to allocate $\Delta = \min\{k_j, D_j - \sum_{t \leq d_j} y_j(t)\}$ resource units to job $j$; this is either the maximal amount of resources $k_j$ that can be allocated to $j$ at a time slot $t$, or the remaining resources required to complete $j$. If there are at least $\Delta$ free resources at time $t$, then the algorithm sets $y_j(t) = \Delta$ and continues. Otherwise, the algorithm attempts to free resources allocated at time $t$ by moving workload from $t$ to earlier time slots. This is done as follows. AllocateRTL searches for the latest unsaturated time slot $t'$ in the range $(R(t_{fix}), t]$ where $t_{fix}$ is the latest deadline of an unallocated job. Notice that $R(t_{fix})$ is also the maximal time slot in the support of $\beta$. Hence, $t'$ is the latest unsaturated time slot that also satisfies $\beta(t') = 0$. If no such $t'$ exists, then the allocation is guaranteed to be $\beta$-consistent. In this case, the algorithm can allocate the remaining portion of $j$ arbitrarily in the interval $[1, t]$ (for the sake of consistency, we will keep allocating $j$ from right to left, giving $j$ in each time slot the maximal amount of resources it can get). Otherwise, the key idea is that there must be a job $j'$ with $y_{j'}(t) > y_{j'}(t')$, since $t$ is saturated and $t'$ is unsaturated. As long as this condition holds, we increase $y_{j'}(t)$ in expense of $y_j(t)$, until either (i) $\bar{W}(t) = \Delta$, in which case we set $y_j(t) = \Delta$ and continue; or (ii) $j'$ is exhausted ($y_{j'}(t) = 0$ or $y_{j'}(t') = k_{j'}$), for which we keep repeating this process. It is easy to see that
Algorithm 2: GreedyRTL

GreedyRTL(τ) 1. call SimpleGreedy(τ); replace Allocate(j) with AllocateRTL(j) 2. foreach (allocated job j) do 2.1. call α-correct(j)

AllocateRTL(j) 1. initialize y_j ← 0 2. set t ← d_j 3. while (j has not been fully allocated) do 3.1. set Δ ← min \{k_j, D_j - \sum_{t'=t+1}^{d_j} y_j(t')\} 3.2. while (W(t) < Δ) do 3.2.1. set t_{fix} ← max\{d_{j'} | j' has been rejected\} 3.2.1. set t' ← latest unsaturated time slot earlier in \(R(t_{fix}, t]\) 3.2.2. if (t' does not exist) then 3.2.2.1. Δ ← W(t) 3.2.2.2. break 3.2.3. set j' ← job satisfying \(y_{j'}(t) > y_{j'}(t')\) 3.2.4. set ϵ ← min \{Δ - W(t), y_{j'}(t), k_{j'} - y_{j'}(t')\} 3.2.5. call Reallocate(j, j', t, t', ϵ) 3.3. set y_j(t) ← Δ 3.4. set t ← t - 1

Reallocate(j, j', t, t', ϵ) 1. set y_{j'}(t) ← y_{j'}(t) - ϵ 2. set y_{j'}(t') ← y_{j'}(t') + ϵ 3. set y_j(t) ← y_j(t) + ϵ 4. set y_j(t') ← y_j(t') - ϵ

α-correct(j) 1. set α(j) ← ρ_j - β(bp(y_j)) 2. for (t = (bp(y_j) + 1) \ldots d_j) do 2.1. set π_j(t) ← β(bp(y_j)) - β(t) 2.2. set α_j ← α_j + \frac{k_j}{D_j} \cdot π_j(t)
this operation does not violate the parallelism bound of $j'$. The completion time of $j'$ might decrease, however this does not violate the deadline $d_{j'}$.

**Analysis of GreedyRTL**

We first prove that GreedyRTL maintains the $\beta$-consistency of all job allocations throughout its execution. For this, we need to make two preliminary observations.

**Claim 3.2.7.** The total workload $W(t)$ of every time slot $t$ does not decrease after a call to $\text{AllocateRTL}(j)$. Specifically, GreedyRTL does not turn a saturated time slot into an unsaturated one.

**Proof.** The only stage of the algorithm in which we decrease the total workload $W(t)$ for some time slot $t$ is when we cannot allocate $\Delta$ resource units during a call to $\text{AllocateRTL}$. Since we decrease $W(t)$ up to the point where $W(t) = C - \Delta$ and then allocate $\Delta$ resource units to $j$, time slot $t$ becomes full. Specifically, saturated time slots remain saturated throughout the algorithm.

**Claim 3.2.8.** Let $j$ be an uncharged job with a $\beta$-consistent allocation $y_j$. Once $j$ is charged by GreedyRTL, $y_j$ remains fixed during the remainder of the execution of GreedyRTL.

**Proof.** Consider the call $\beta\text{-cover}(j')$ in which $j$ is charged for the first time. Recall that an allocation $y_j$ is modified by GreedyRTL only if there exists two time slots $t, t'$ such that: (1) $t'$ is the latest unsaturated time slot for which $t' < t$ and $\beta(t') = 0$; and (2) $y_j(t) > y_j(t')$. The monotonicity of $\beta$ implies that $\beta(t) = 0$.

We claim that it suffices to prove that $\beta(\text{bp}(y_j)) > 0$ after the call to $\beta\text{-cover}(j')$. This would imply that $\text{bp}(y_j) < t', t$, since $\beta$ is monotonic, and therefore $y_j(t') = y_j(t) = k_j$. Hence, once $\beta(\text{bp}(y_j)) > 0$ the algorithm does not modify $j$ anymore. We prove that $\beta(\text{bp}(y_j)) > 0$. Since $j$ is charged after the call to $\beta\text{-cover}(j')$, we must have $\text{st}(y_j) \leq R(d_{j'})$. By the definition of $\text{bp}(y_j)$, all of the time slots in the range $(\text{st}(y_j), \text{bp}(y_j)]$ are saturated. This implies that $\text{bp}(y_j) \leq R(d_j)$, by the definition of $R(\cdot)$. Therefore, after the call to $\beta\text{-cover}(j')$, we have $\beta(\text{bp}(y_j)) \geq \rho_{j'} > 0$, as desired.

**Claim 3.2.9.** The GreedyRTL algorithm guarantees that all job allocations are $\beta$-consistent throughout its execution.

**Proof.** By induction on the number of jobs considered by the algorithm. The claim trivially holds initially and when the considered job is rejected. Consider the case where a job $j$ is scheduled and assume that all existing allocations are $\beta$-consistent. We first claim that $\text{AllocateRTL}$ produces a $\beta$-consistent allocation for job $j$. If at the end of the call
Theorem 3.2.10. The GreedyRTL algorithm guarantees a \( \left( \frac{C}{C-k} \cdot \frac{s}{s-1} \right) \)-approximation to the optimal social welfare.

Proof. First we show that the dual solution \((\alpha, \beta, \pi)\) constructed by GreedyRTL is feasible. The dual constraints of an unallocated job are covered by the \(\beta(t)\) variables; this follows from the correctness of \(\beta\)-cover. Now, consider an allocated job \(j\). We set \(\pi_j(t) = \beta(bp(y_j)) - \beta(t)\) for every time slot \(t \in [bp(y_j), d_j]\). Notice that whenever a variable \(\pi_j(t)\) is set to some value \(\varepsilon\), every time slot (including \(t\)) incurs a "punishment" of \(-k_j/D_j \cdot \varepsilon\). To balance this, the routine \(\alpha\)-correct increases \(\alpha_j\) by \(k_j/D_j \cdot \varepsilon\). Notice that every such time slot \(t\) also satisfies
\( y_j(t) = k_j \). As a result, \( \alpha_j \) is increased by a total of at most \( \rho_j - \beta(bp(y_j)) \). Overall, covered each dual constraint by at least \( \beta(bp(y_j)) \) (by the monotonicity of \( \beta \)). Increasing \( \alpha_j \) by an additional amount of \( \rho_j - \beta(bp(y_j)) \) guarantees that all dual constraints are covered. We conclude that \((\alpha, \beta, \pi)\) is feasible.

We now bound the cost of the dual solution \((\alpha, \beta, \pi)\). Notice that unallocated jobs do not contribute to the dual objective function, since they are not charged and their \( \alpha \) value is 0. By Claim 3.2.8, once an allocated job is charged for the first time, its allocation becomes fixed and is not modified by GreedyRTL. Therefore, we can apply Lemma 3.2.3 and bound the total dual cost by:

\[
\sum_{j=1}^{n} D_j \alpha_j + \sum_{j=1}^{n} \sum_{t \leq d_j, W(t) < k} \xi(t) \leq \sum_{j=1}^{n} D_j \alpha_j + \sum_{j=1}^{n} \sum_{t \leq d_j} \xi(t). \tag{3.6}
\]

An unallocated job \( j \) does not contribute to (3.6), since \( \alpha_j = 0 \) and \( \xi(t) = 0 \) for every \( t \). Consider an allocated job \( j \). The first contribution of \( j \) to (3.6) is \( D_j \alpha_j \), which equals:

\[
D_j \left[ \rho_j - \beta(bp(y_j)) \right] + \sum_{t=bp(y_j)+1}^{d_j} k_j \cdot \beta(bp(y_j)) - \beta(t) = v_j - \sum_{t=bp(y_j)+1}^{d_j} k_j \beta(t). \tag{3.7}
\]

The equality follows since \( y_j \) is \( \beta \)-consistent (Claim 3.2.9). It remains to bound the total amount charged from \( j \). Let \( j' \) be the first job for which the call to \( \beta\)-cover\((j')\) charges \( j \), and let \( y_j \) denote the allocation of \( j \) at that point. Claim 3.2.8 states that the allocation \( y_j \) remains fixed henceforth. The call to \( \beta\)-cover\((j')\) charges \( j \) up until time \( R(d_{j'}) \). As in the proof of Claim 3.2.8, we have \( \beta(bp(y_j)) \leq R(d_{j'}) \). Hence, we have \( \xi_j(t) = \frac{C}{C-k} \cdot \frac{s}{s-1} \cdot \rho_j' \cdot y_j(t) \) and \( \beta(t) = \rho_j' \) for every \( t \in [st(y_j), bp(y_j)] \). We can deduce that the total amount charged from job \( j \) is:

\[
\left( \frac{C}{C-k} \cdot \frac{s}{s-1} \right) \cdot \left[ \sum_{t \leq bp(y_j)} \beta(bp(y_j)) y_j(t) + \sum_{t=bp(y_j)+1}^{d_j} \beta(t) y_j(t) \right]. \tag{3.8}
\]

Moreover, the previous paragraph implies that \( \beta(t) \leq \rho_j \) for every \( t \in [st(y_j), d_j] \). Combine-
ing this with (3.7) and (3.8) gives us:

\[ D_j \alpha_j + \sum_{t \leq d_j} \xi_j(t) \leq \left( \frac{C}{C - k} : \frac{s}{s - 1} \right) \cdot v_j. \]  

(3.9)

The theorem follows by summing (3.9) over the jobs allocated by GreedyRTL.

\[ \blacksquare \]

### 3.3 Truthfulness

We prove that the GreedyRTL allocation rule is monotone, and therefore it can be implemented as a truthful mechanism.

**Claim 3.3.1.** GreedyRTL is monotone.

**Proof.** Consider some job \( j \). Throughout the proof, we fix the types \( \tau_{-j} \) of all jobs beside \( j \). Let \( f_j(\tau_j, \tau_{-j}) \) indicate whether \( j \) is completed or not by GreedyRTL when reporting type \( \tau_j \). Our goal is to prove that for any two types \( \tau'_j \preceq \tau''_j \) the inequality \( f_j(\tau'_j, \tau_{-j}) \leq f_j(\tau''_j, \tau_{-j}) \) holds. Since \( f_j \) is binary, it is enough to prove that if \( j \) is scheduled when reporting \( \tau'_j \), then \( j \) is also scheduled when reporting \( \tau''_j \).

We prove that \( f_j \) is monotone with respect to each parameter individually. We begin with the job value. Consider some property set \( P_j = (d_j, D_j, k_j) \) and let \( v'_j \leq v''_j \) be two job values. Assume that \( j \) is scheduled by GreedyRTL when reporting \( \langle v'_j, P_j \rangle \) and assume towards contradiction that \( j \) is rejected when reporting \( \langle v''_j, P_j \rangle \). Recall that GreedyRTL iterates over all jobs in decreasing order of their value-densities. Therefore, both executions of GreedyRTL behave identically for jobs with value-densities of at least \( v''_j / D_j \). Consider the case where \( \langle v''_j, P_j \rangle \) is reported by job \( j \). The job is rejected since GreedyRTL cannot complete it using the remaining available resources. Claim 3.2.7 states that the workload \( W(t) \) at any time \( t \) does not decrease between calls to AllocateRTL. Hence, \( j \) must also be rejected when it reports a lower value \( v'_j \). This contradicts the initial assumption.

We now prove the monotonicity of \( f \) on each job parameter. Consider two demands \( D'_j \geq D''_j \). Notice that reporting a lower demand \( D''_j \) increases the value-density of the job. Moreover, a lower demand request is easier to satisfy. Hence, if job \( j \) is scheduled when requesting \( D'_j \) demand units, it will also be scheduled when requesting \( D''_j \) demand units. Finally, consider the case where an earlier arrival time \( a''_j \leq a'_j \) or a later deadline \( d''_j \geq d'_j \) is reported. This does not change the value-density of the job. In both cases, satisfying the demand request of \( j \) becomes easier, since more time slots become available. The monotonicity of \( f \) follows.

\[ \blacksquare \]

This leads to the main result of this section.
Corollary 3.3.2. GreedyRTL implements a truthful mechanism obtaining a \( \left( \frac{C}{C-k} \cdot \frac{s}{s-1} \right) \)-approximation to the optimal social welfare. Moreover, if the value \( v_j \) of every user is drawn from a known distribution \( G_j \), then GreedyRTL applied on virtual values \( \tilde{\phi}_j(v_j) \) implements an incentive compatible mechanism obtaining a \( \left( \frac{C}{C-k} \cdot \frac{s}{s-1} \right) \)-approximation to the optimal expected profit.

3.4 Coping with Demand Uncertainties

Up until now, we have assumed that the job work volume (or demand) \( D_j \) is a deterministic quantity. However, this might be a restrictive assumption in practice, as the exact volume is either unknown, predicted based on prior executions, or often overestimated. Further, the demand might be sensitive to stochastic fluctuations, especially in jobs where some tasks have dependencies on the completion of other tasks (see, e.g., [1] and references therein). From a theoretical perspective, these demand uncertainties introduce new challenges for mechanism design and impossibility results can indeed be shown ([27]). In this section, we discuss how to address demand uncertainties, while still maintaining the benefits of our scheduling framework. We study below one plausible model for representing user knowledge of job demand. A more comprehensive study of alternative models is left for future work.

We consider a more general job model where the true demand \( D_j \) of each job \( j \) is taken from a range \([D^L_j, D^H_j]\) which is known to the scheduler (either reported by the user, or estimated by the scheduler). However, the exact amount of resource units required by the job is only revealed upon completion of the job. We propose the following solution. We incorporate demand uncertainties into the GreedyRTL allocation rule by taking the requested demand of each job \( j \) to be \( D^H_j \). On one hand, this guarantees that the mechanism can always complete scheduled jobs. If the mechanism allocates an insufficient amount of resources to scheduled jobs, it may not always be able to provide additional resources due to cluster congestion. The lack of additional assumptions on the true demand justifies allocating resources according to the worst-case scenario, where all \( D^H_j \) resources are needed. On the other hand, this approach can lead to a considerable amount of unused resources, which in hindsight could have been used to process other jobs. In practice, real-time systems can use these resources to process jobs ad-hoc, thus improving the resource utilization. Yet, we focus our analysis on the offline scheduling phase alone.

Theorem 3.4.1. Assume the demand of each job \( j \) satisfies \( D_j \in [D^L_j, D^H_j] \), and denote by \( \mu = \max_j \{D^H_j/D^L_j\} \) the input demand uncertainty factor. Running GreedyRTL with demands \( D^H_j \) provides a \( \mu \cdot \left( \frac{C}{C-k} \right) \left( \frac{s}{s-1} \right) \)-approximation to the optimal offline schedule with true demands \( D_j \).
Proof. As before, our proof relies on the dual fitting technique. Specifically, we generate a feasible dual solution \((\alpha, \beta, \pi)\) to the dual program with true demands \(D_j\), and bound the dual cost of the solution in terms of \(v(S)\), where we recall that \(S\) denotes the set of jobs completed by GreedyRTL. Consider the execution of GreedyRTL with job demands \(D_j^H\). By the analysis of GreedyRTL (Theorem 3.2.10), there exists a dual solution \((\alpha^H, \beta^H, \pi^H)\) that satisfies the following dual constraint:

\[
\alpha_j^H + \beta^H(t) + \pi_j^H(t) - \frac{k_j}{D_j^H} \sum_{t' \leq d_j} \pi_j(t') \geq \frac{v_j}{D_j^H} \quad \forall j, t \leq d_j
\]  

(3.10)

with a dual cost \(\sum_{j=1}^n D_j^H \alpha_j^H + \sum_t C\beta^H(t)\) which is at most \((\frac{C}{c-k})(\frac{s}{s-t})\cdot v(S)\).

We define the following dual solution. For every job \(j\), we define \(\alpha_j = \mu \cdot (D_j^H / D_j) \cdot \alpha_j^H\). For every time slot \(t\), we define \(\beta(t) = \mu \cdot \beta^H(t)\). Finally, for every job \(j\) and time slot \(t \leq d_j\), we define \(\pi_j(t) = \mu \cdot \pi_j^H(t)\). We claim that \((\alpha, \beta, \pi)\) is a feasible dual solution for the dual program corresponding to true demands \(D_j\). This implies that the dual cost of \((\alpha, \beta, \pi)\) is an upper bound on the optimal offline schedule with true demands \(D_j\). Notice that:

\[
\mu \cdot \frac{v_j}{D_j^H} \geq \frac{D_j^H}{D_j} \cdot \frac{v_j}{D_j^H} \geq \frac{D_j^H}{D_j} \cdot \frac{v_j}{D_j} = \frac{v_j}{D_j} = \rho_j
\]  

(3.11)

which implies that \(\mu \cdot [\alpha_j^H + \beta^H(t) + \pi_j^H(t) - \frac{k_j}{D_j^H} \sum_{t' \leq d_j} \pi_j^H(t')] \geq \rho_j\). Therefore, for each job \(j\) and \(t \leq d_j\):

\[
\alpha_j + \beta(t) + \pi_j(t) - \frac{k_j}{D_j} \sum_{t' \leq d_j} \pi_j(t') \geq \rho_j + \mu \cdot \left(\frac{D_j^H}{D_j} - 1\right) \alpha_j^H - \mu \cdot \left(\frac{k_j}{D_j} - \frac{k_j}{D_j^H}\right) \sum_{t' \leq d_j} \pi_j^H(t') = \\
= \rho_j + \mu \cdot \left(\frac{D_j^H}{D_j} - 1\right) \alpha_j^H - \mu \cdot \left(\frac{D_j^H}{D_j} - 1\right) \cdot \frac{k_j}{D_j} \cdot \sum_{t' \leq d_j} \pi_j^H(t') \geq \rho_j
\]  

(3.12)

The last inequality follows since \(\alpha_j^H\) satisfies \(\alpha_j^H \geq \frac{k_j}{D_j^H} \sum_{t' \leq d_j} \pi_j^H(t')\). Hence, we conclude that \((\alpha, \beta, \pi)\) is a feasible dual solution for demands \(D_j\). It remains to bound the dual cost:

\[
\sum_{j=1}^n D_j \alpha_j + \sum_t C\beta(t) \leq \sum_{j=1}^n D_j \cdot \mu \cdot \frac{D_j^H}{D_j} \cdot \alpha_j^H + \sum_t C \cdot \mu \cdot \beta^H(t)
\]  

(3.13)
\[
\leq \mu \cdot \sum_{j=1}^{n} D_j^H \alpha_j^H + \mu \sum_t C \beta^H(t) \\
\leq \mu \left( \frac{C}{C-k} \right) \left( \frac{s}{s-1} \right) \cdot v(S)
\]

and therefore we obtain a \(\mu \cdot \left( \frac{C}{C-k} \right) \left( \frac{s}{s-1} \right)\) approximation.

We note that the approximation quality depends linearly on the uncertainty factor \(\mu\). This is an appealing property, as we expect the uncertainty factor to be less than 1.15, as current execution engines can utilize fairly accurate job profiling tools (see, e.g., [23] and reference therein).

### 3.5 Empirical Study

In this section, we describe some of the experiments we carried out to further evaluate the benefits of our scheduling framework. We begin by describing the simulation setup that has been used throughout this section.

#### 3.5.1 Simulation Setup

Our simulations evaluate the performance of the mechanisms over a set of 529 jobs, taken from empirical job traces of a large batch computing cluster. The original workload consisted of MapReduce jobs, comprising multiple phases with the constraint that phase \(i+1\) can only start after phase \(i\) has finished. The available information included the runtime of the job (\(\text{totTime}\)), the overall amount of consumed CPU hours (\(\text{totCPUHours}\)), the total number of servers allocated to it (\(\text{totServers}\)), the number of phases (\(\text{numPhases}\)) and the maximum number of servers allocated to a phase (\(\text{maxServersPerPhase}\)). Since our model is not a MapReduce model, we need to adjust the raw data that was available to us, while preserving the workload characteristics. We describe below the details of the simulation choices we make.

**Demand \(D_j\).** The \(\text{totCPUHours}\) field is used to represent the demand of the job.  

**Parallelism bound \(k_j\).** Since the cloud capacity is given in units of server hours per time slot, the parallelism bound must be given in server CPU hour units as well. The data available to us does not contain information on the actual running time per job of each of servers allocated to it. Thus, we use the available information to estimate the parallelism bound. Our estimation of \(k_j\) mainly relies on the \(\text{maxServersPerPhase}\) field, which gives the closest indication to the real parallelism bound. However, the \(\text{maxServersPerPhase}\)
field indicates the maximum amount of servers that have been allocated to a phase, whereas the units of $k_j$ should be CPU hour per time slot. To set $k_j$, we first estimate the maximal number of servers allocated per time unit by dividing $\text{maxServersPerPhase}$ by the average execution time of a phase $\text{totTime/numPhases}$. Then, we multiply the result by the average runtime of a server $\text{totCPUHours/totServers}$. To conclude, the parallelism bound is estimated via the following formula:

$$k_j = \frac{\text{maxServersPerPhase}}{(\text{totTime/numPhases})} \cdot \frac{\text{totCPUHours}}{\text{totServers}}.$$

Values $v_j$ and deadlines $d_j$. Our job traces do not contain any information regarding job deadlines nor any indication on job value. Hence, they are synthetically generated as follows. The deadline is set according the effective length of the job, defined as $\text{len}_j = \lceil \frac{D_j}{k_j} \rceil$, multiplied by the slackness parameter $s$. The value of the job is uniformly drawn from $[0, 1]$.

Cloud parameters $C, T$. The capacity $C$ is set so that the total demand exceeds the total amount of available resources. $T$ is set according to the maximal deadline.

3.5.2 Resource Utilization

High utilization is certainly one of the main goals in the area of cloud computing (see, e.g., [32]). For the scheduling model studied in this paper, the only truthful mechanism known until now is the Decompose-Randomly-Draw (DRD) mechanism, presented in [41]. The main practical drawback of the DRD mechanism is that on average, the mechanism leaves at least half of the resources unallocated. In fact, this property is essential for proving the truthfulness of DRD. We note that without considering incentives, the utilization of DRD could be improved by adding unscheduled jobs to the solution in a greedy manner, whenever possible. Yet, it is unclear how to improve utilization under the framework of [41] without affecting the truthfulness of the mechanism.

In our first experiment, we compare the average utilization of the DRD and GreedyRTL mechanisms. Since the maximum possible utilization level generally depends on the job characteristics, we should compare the resource utilization with the optimal resource allocation. However, finding the optimal resource allocation is an NP-hard problem. Instead, we compare the resource utilization of DRD and GreedyRTL with the optimal fractional resource utilization, which is obtained by solving the relaxed primal program (P) with $v_j := D_j$ for every job $j$ (equivalently, the marginal value of each job is 1). We denote the optimal fractional resource utilization by $OPT^\ast_{\text{Util}}$ and notice that it is an upper bound on the optimal resource allocation.

Figure 3.1 compares the average resource utilization of DRD and GreedyRTL with the
optimal fractional resource utilization, as a function of the number of jobs. Each point was averaged over 20 runs, in which the set of jobs were randomly selected from our dataset. We see that GreedyRTL reaches a utilization level which is very close to $OPT^{\ast}_{\text{Util}}$ (within 2% thereof), while the mechanism of [41] achieves around 35% of the upper bound on utilization. The results are consistent regardless of the number of jobs that we consider. The utilization results not only provide an explanation to the social welfare improvements we obtain, but also stand on their own – given the significance of achieving high utilization in large cloud clusters. The same behavior was observed when measuring the average resource utilization as a function of the deadline slackness.

### 3.5.3 Revenue Maximization

In the next experiment, we evaluate the potential revenue gain of the GreedyRTL mechanism. In Section 3.3 we showed that given distribution knowledge on the input job types (Bayesian model), GreedyRTL can be modified such that it nearly gains the optimal expected revenue. Yet, in many cases such distribution knowledge is unavailable. The unmodified GreedyRTL mechanism does not set prices to maximize revenue. Instead, prices are set to guarantee truthfulness, with the mechanism goal being social welfare maximization. Nonetheless, it is interesting to see how high can the revenue of GreedyRTL be compared to currently deployed pricing schemes. Nowadays, most cloud providers incorporate fixed-price schemes, in which
Figure 3.2: Revenue ratio between GreedyRTL and OFP, compared against different input slackness values. The truthful GreedyRTL mechanism is nearly as good as an ideal optimal fixed-price mechanism. For this experiment, we overload the system such that the total demand exceeds the cloud capacity, so that truthful pricing is strictly positive.
the system sets a price per resource unit (e.g., CPU hour) and users are charged according to their resource usage. GreedyRTL differs from fixed-price schemes, since prices are set to enforce truthfulness and are not necessarily proportional to the requested demands.

We examine the revenues of GreedyRTL against an idealized fixed-price mechanism, which we term the Optimal Fixed Price (OFP) mechanism. In general, fixed-price mechanisms charges each scheduled job some fixed price \( q \) per server CPU hour, regardless of the job identity. Given that the mechanism charges a fixed price \( q \), it would only schedule a job \( j \) with non-negative net utility, namely, \( v_j \geq q \cdot D_j \). Define \( J(q) = \{ j \in [n] \mid v_j \geq q \cdot D_j \} \). Notice that given a fixed price \( q \), maximizing revenue is equivalent to maximizing resource utilization over the jobs in \( J(q) \). To maximize revenues, the OFP mechanism charges a fixed price \( q^* \) which maximizes the revenue gained by a resource utilization maximization algorithm on \( J(q^*) \). As stated in Section 3.5.2, finding the optimal resource utilization is an NP-hard problem. However, notice that the resource utilization problem is equivalent to maximizing social welfare when the value of each job equals its size. Hence, OFP approximates the resource utilization problem by running the near-optimal GreedyRTL allocation algorithm on \( J(q^*) \), with the value of each job \( j \) taken as \( D_j \). Notice that \( q^* \) must equal \( \rho_j \) for some input job \( j \); otherwise, the revenue of OFP can be increased. Therefore, we can effectively determine \( q^* \) by repeating the allocation algorithm for \( n \) different prices \( \{ \rho_j \}_{j=1}^n \), and setting \( q^* \) to be the revenue-maximizing price among this set. We emphasize that OFP is an ideal mechanism. First, OFP sets the fixed price \( q^* \) only after users submit their jobs to the mechanism. In practice, it is unlikely that users would agree to participate in such a mechanism. Second, OFP uses full knowledge of the private values of users (and other job parameters). That is, users are assumed to report true values, although the mechanism does not guarantee that.

Figure 3.2 depicts the ratio of revenues between GreedyRTL and OFP as a function of the slackness parameter \( s \) for two different cluster sizes. Each point in the graph corresponds to an average of 20 runs; each run uses a different subset of 400 jobs, which are randomly selected from our dataset. Surprisingly, despite the fact that OFP has significant value information that GreedyRTL is not assumed to have, GreedyRTL revenues are comparable with those of OFP (roughly between 90% and 105% of the optimal fixed price revenue).

3.6 Summary

In this chapter, we designed truthful mechanisms for scheduling deadline-sensitive jobs with identical arrival times under a flexible allocation model with parallelism bounds. Assuming deadline slackness, we provided near-optimal performance guarantees when implementing
our mechanisms on large computing clusters. In addition, these mechanisms are efficient and easy to implement, which makes them appealing solutions for practical applications.

Yet, while the “identical arrival times” assumption is justifiable for many practical scenarios, in general job requests are submitted to computing clusters over time in an online manner. Developing truthful online mechanisms for social welfare maximization is one of the key challenges in the field. However, as we discuss in the next chapters, online truthful mechanisms are inherently limited due to algorithmic impossibility results for online scheduling. Interestingly, these impossibility results assume tightness of deadlines ($s = 1$). In Chapter 4, we prove that constant-competitive algorithms exist for online scheduling, provided that the input jobs exhibit some level of deadline slackness ($s > 1$).

3.A Appendix A: Improved Analysis of the Simple Greedy Approach

We improve the analysis of the the simple greedy algorithm. Our improved analysis rids the assumption that $k \ll C$, thus providing a constant approximation for any $s > 1$.

**Theorem 3.A.1.** The simple greedy algorithm guarantees a $\left(1 + \frac{s}{s-1}\right)$-approximation to the optimal social welfare.

**Proof.** We improve our original analysis by providing an improved bound to the total cost of $\beta(t)$, i.e., $\sum_{t=1}^{T} C_{\beta(t)}$. We do so by improving the bound stated in Lemma 3.2.3. First, we simplify the charging process performed by $\beta$-cover. Now, we charge from each allocated job $i$ at any time $t$ an amount of $\xi_i(t) \leftarrow \frac{s}{s-1} \cdot \rho_i \cdot y_i(t)$. Notice that the overall charge is exactly $\frac{s}{s-1} \cdot \sum_{i \in S} v_i$, where $S$ is the set of allocated jobs. To complete the analysis, we show that at the end of each call to $\beta$-cover($j$), the following inequality holds:

$$
\sum_{i=1}^{j} \sum_{t \leq d_i} \xi_i(t) - \sum_{t=1}^{T} C_{\beta(t)} \geq \sum_{i=1}^{j} \sum_{t \leq d_i} \rho_j \cdot \frac{s}{s-1} \cdot y_i(t) - C_{\rho_j} d_j.
$$

(3.16)

The remainder is twofold: first, we need to prove that the right hand side of (3.16) is non-negative; and second, that (3.16) holds after every call to $\beta$-cover($j$). The later can be proven by a simple induction similar to Lemma 3.2.3. Let $j'$ be the job for which $\beta$-cover was called previously to $j$. The inductive claim follows since jobs are ordered according to their value-demand ratio in non-increasing order, and since the expression $\sum_{t=1}^{T} C_{\beta(t)}$ changes by exactly $C_{\rho_j}(d_j - d_{j'})$. 

43
Hence, it remains to show that the right hand side of (3.16) is non-negative. To do so, we bound the amount of unallocated resources in the interval \([1, d_j]\) when considering an unscheduled job \(j\). Recall that \(E_j\) represents the time slots that are not saturated when the algorithm considers job \(j\), and that \(|E_j| < D_j/k\), otherwise \(j\) could have been scheduled. The amount of free resources at this point is at most: \(C \cdot |E_j| + (D_j - k|E_j|)\). This follows since only time slots in \(E_j\) can be completely empty. This expression is maximized when \(|E_j| = D_j/k\). Since \(D_j/k \leq d_j/s\) (slackness assumption), the total amount of free resources in the interval \([1, d_j]\) is at most: \(C \cdot (d_j/s)\). Therefore:

\[
\sum_{i=1}^{j} \sum_{t \leq d_i} y_i(t) \geq C d_j \cdot \frac{s - 1}{s}
\]

which means that the right hand side of (3.16) is non-negative. \(\blacksquare\)
Chapter 4

Online Scheduling with Deadline Slackness

The mismatch between current approaches for resource allocation and the evident need for deadline-aware scheduling mechanisms is due, in part, to the algorithmic difficulties of online deadline scheduling. The problem, even in its most basic form, admits several impossibility results on the existence of online schedulers. Interestingly, these impossibility results are valid only when all deadlines are tight ($s = 1$). In this chapter, we revisit the basic scheduling problem under a deadline slackness assumption ($s > 1$), which has strong evidence in practice. Under this assumption, we design the first algorithm to obtain a constant competitive-ratio for general job values and demands. Then, we present a truthful variant of the algorithm with a slightly worse guarantee on its competitive ratio. Our algorithmic approach is efficient, robust, and simple to implement. Therefore, we believe that these results may provide a foundation for developing an efficient deadline-aware ecosystem for computing clusters.

The scheduling problem studied in the current and next chapters is a basic online scheduling problem. In this problem, a scheduler receives job requests over time which are only revealed upon arrival. Each job request $j$ is associated with an arrival time $a_j$, a demand $D_j$, a deadline $d_j$ and a value $v_j$. The goal is to maximize the total value of jobs that meet their deadline. Preemption is allowed; that is, the scheduler may stop the execution of a running job in favor of other jobs. Note that allowing preemption is necessary, since non-preemptive schedulers cannot accept jobs that arrive and depart while the cluster is busy – this can lead to arbitrarily high loss.

Without making any input restrictions, it is well known that no scheduler for the problem can provide any worst-case guarantees on the value it gains. This has initiated a search for
simplifying assumptions that induce meaningful results. The most common assumptions limit on one of the parameters \( \kappa_v, \kappa_D \) and \( \kappa_\rho \), which denote the ratio between the maximal and minimal value (for \( \kappa_v \)), demand (for \( \kappa_D \)) and value-density (for \( \kappa_\rho \)) across jobs. We summarize here the main results for the various restrictions.

- **Restricted values:** Canetti and Irani [17] designed a randomized \( O(\log \kappa_v) \)-competitive algorithm that assumes a priori knowledge of \( \kappa_v \). On the other hand, they proved that the competitive ratio of any randomized algorithm must be at least \( \Omega\left(\sqrt{\frac{\log \kappa_v}{\log \log \kappa_v}}\right) \). For deterministic algorithms, their lower bound is \( \kappa_v \).

- **Restricted demands:** The work of Canetti and Irani [17] also proved a randomized lower bound of \( \Omega\left(\sqrt{\frac{\log \kappa_D}{\log \log \kappa_D}}\right) \) and a deterministic lower bound of \( \sqrt{\frac{\kappa_D}{2\ln(\kappa_D)}} - 1 \). Canetti and Irani gave a randomized \( O(\log \kappa_D) \)-competitive algorithm when \( \kappa_D \) is known in advance. Hajihaghayi et al. [34] designed an \( O(\log \kappa_D) \)-competitive randomized truthful mechanism. Their work also introduced a 5-competitive truthful deterministic mechanism and a corresponding lower bound of 2 for the special case of unit demands (\( \kappa_D = 1 \)).

- **Restricted value-densities:** Baruah et al. [10] established a lower bound of \( (1 + \sqrt{\kappa_\rho})^2 \) for the competitive ratio of any algorithm, whereas Koren and Shasha [46] constructed an optimal \( (1 + \sqrt{\kappa_\rho})^2 \) algorithm when \( \kappa_\rho \) is known in advance. For truthful mechanisms, Porter [58] proved a tight deterministic bound of \( (1 + \sqrt{\kappa_\rho})^2 + 1 \). The special case of identical value-densities\(^1\) (\( \kappa_\rho = 1 \)) has also been studied [30, 24, 31]. The best known result for \( \kappa_\rho = 1 \) is by Garay et al. [30], who constructed a 5.828-competitive algorithm for identical value-densities. A lower bound of 4 for deterministic algorithms can be deduced by the work of Baruah et al. [10].

Unfortunately, the worst-case algorithmic guarantees that are obtained under these restricted models are insufficient for practical use, since \( \kappa_v, \kappa_D \) and \( \kappa_\rho \) can all be arbitrarily high. This has lead the community to use heuristic methods which do not have explicit worst-case guarantees, but turn out to work reasonably well, empirically. The question is: what aspects of practical inputs enable such heuristics to perform well? It turns out that the lower bounds [17, 62, 10, 58] only apply when all job deadlines are tight (i.e., \( d_j = a_j + D_j \) for every job \( j \)). Practical inputs, on the other hand, rarely exhibit tight deadlines. Thus, one might suspect that the loose time restrictions allow heuristic methods to perform well in general.

Our contribution is based on the following idea: if the existence of slackness in deadline constraints provides an empirical mean for escaping worst-case lower bounds, then one can

\(^1\)The case of \( \kappa_\rho = 1 \) is referred in literature as throughput/busy-time maximization.
revisit the general theoretical problem under the same slackness assumption. Specifically, we will assume that no job pressures the system by requiring immediate and continuous execution in order to meet its deadline – a natural and justifiable in practice.

Slackness assumptions have been used in the past to obtain improved results for deadline scheduling. Dasgupta and Palis [24] developed a \((1 + \frac{1}{s-1})\)-competitive algorithm for the case of identical value-densities \((\kappa_\rho = 1)\), which improves the known constant competitive ratio 5.83 when \(s > 1.207\). Our work generalizes the scheduling model to incorporate arbitrary job values and demands, where it is necessary to circumvent the known barriers to obtain constant factor approximations.

Any reasonable solution, in addition to overcoming the theoretical difficulties, must cope with practical constraints, such as inaccurate estimation of resource requirements, data locality (i.e., resuming preempted jobs on the same physical location, to avoid large data transfers) and provider commitments (i.e., completion guarantees for admitted jobs). In this chapter, we will focus on preserving data locality and handling inaccurate demand estimations. Provider commitments are the focus of Chapter 5.

**Our Results.** We design new scheduling algorithms and truthful mechanisms for online scheduling with job deadlines, and prove worst-case bounds on their competitive ratios of the form:

\[
2 + O\left(\frac{1}{\sqrt{s} - 1}\right) + O\left(\frac{1}{(\sqrt{5} - 1)^d}\right)
\]

where \(d = 2, 3\) for non-truthful and truthful scheduling, respectively. We emphasize that algorithms that obtain constant competitive ratios under slackness assumptions and general job specifications have not been previously known, and that our work closes a large gap open for nearly a decade between positive and negative results related to this fundamental online scheduling problem.

To obtain the main results, we rely on a proof methodology developed in Chapter 3 for the special case of identical arrival times. First, we formulate the scheduling problem as a linear program with additional gap-reducing constraints, which are somewhat reminiscent of knapsack constraints [18]. Then, using insights from Chapter 3, we develop new algorithms for the more challenging online scheduling problem. To bound the competitive ratio of the suggested algorithms, we utilize the dual fitting technique together with sophisticated charging arguments tailored to this specific context.
4.1 Preliminaries

4.1.1 Scheduling Model

A computing cluster that consists of $C$ identical servers, denoted $1, 2, \ldots, C$, receives job requests over time. The $C$ servers are available throughout time and each server can process at most one job at any given time. The cluster is managed by a service provider (scheduler) which determines the resource allocation.

The input is a finite set$^2$ of batch jobs, represented by the set $J$. These jobs arrive to the system online, over the (continuous) time interval $[0, \infty)$. Each job in $J$ is associated with a type $\tau_j = (v_j, D_j, k_j, a_j, d_j)$, which is revealed to the system only upon its arrival time $a_j$. The interval $[a_j, d_j]$ is called the availability window of job $j$.

The goal of the scheduler is to maximize the total value of jobs fully completed by their deadlines. The scheduler is not required to complete all jobs. Specifically, if a job reaches its deadline without being completed, there is no benefit to allocating additional servers to it. We assume that at most $k$ servers can be allocated to a single job at any given time. This parameter may stand for a common parallelism bound across jobs$^3$, or represent a management constraint such as a virtual cluster. For example, $k = 1$ means that every job can be processed on at most one server at any time. At any given time, the scheduler may allocate any number of servers between 0 and $k$ to any job, subject to the capacity constraint $C$. In particular, jobs may be preempted. Execution of preempted jobs may be resumed from the point during which they were preempted (assuming proper checkpointing of intermediate states).

4.1.2 Definitions

The following definitions refer to the execution of an online allocation algorithm $A$ over an input set $J$ of jobs. We drop $A$ and $J$ from notation when they are clear from context.

**Job Allocations.** Denote by $j_A^i(t)$ the job running on server $i$ at time $t$ and by $\rho_A^i(t)$ its value-density. Denote by $J_A(t)$ the set of all jobs running at time $t$. We use $y_j^i(t)$ as a binary variable indicating whether job $j$ is running on server $i$ at time $t$, i.e., whether $j = j_A^i(t)$ or not. We often refer to the function $y_j^i$ as the allocation of job $j$ on server $i$. Define $y_j(t) = \sum_{i=1}^C y_j^i(t)$ to be the total number of servers allocated to $j$ at time $t$. The starting

$^2$Algorithms described in this chapter are well-defined for infinite job sequences; we assume finiteness for notational convenience.

$^3$E.g., if jobs have different parallelism bounds, then $k$ is the minimum thereof. We note that more involved parallelism models, such as Amdahl’s law, are beyond the scope of this work. Nevertheless, we believe that the insights and design principles obtained here may carry over to such models.
point \( st(y^j_i) = \min \{ \{ t \mid y^j_i(t) = 1 \} \cup \{ \infty \} \} \) of job \( j \) on server \( i \) is the first time during which \( j \) is allocated to server \( i \). If no such \( t \) exists, \( st(y^j_i) = \infty \).

**Job Final Execution Status.** We divide the job set \( J \) into three sets \( \mathcal{J}^F, \mathcal{J}^P \) and \( \mathcal{J}^E \), depending on the jobs’ final execution status: (1) \( \mathcal{J}^F \) - fully processed (completed) jobs, which have been completed by their corresponding job deadlines; (2) \( \mathcal{J}^P \) - partially processed jobs, which have been allocated resources, yet not enough to complete by their corresponding deadlines; and (3) \( \mathcal{J}^E \) - unprocessed (empty) jobs, which have not been allocated resources at all. We say that a job is admitted if it has been allocated resources, i.e., it is in \( \mathcal{J} \setminus \mathcal{J}^E \). We denote by \( \mathcal{J}^P_i \) the set of jobs that have been partially processed on server \( i \).

### 4.2 The Necessity of Preemption and Resume

As mentioned, preemption is mandatory for obtaining bounded competitive ratios, since non-preemptive schedulers might lose jobs of arbitrarily high value while the system is busy. To complete a preempted job, the scheduler must either save its intermediate state to allow its resumption later on, or terminate and restart its execution. In the following, we prove (for deterministic schedulers) that supporting “job resume” is also mandatory for proving theoretical worst-case bounds.

**Theorem 4.2.1.** Any deterministic scheduling algorithm that supports preemption, but not job resume, cannot guarantee a constant competitive ratio for any slackness \( s \).

**Proof.** Let \( A \) be a deterministic online scheduler which can only restart the execution of preempted jobs, and assume that the system consists of a single server. We prove that \( \text{cr}_A(s) \geq x \) for any constant \( x \). To do so, consider an adversary which controls the flow of input jobs to the algorithm. The adversary begins by submitting a single job \( A \) of type \( (v_A, D_A, a_A, d_A) = (1, 1, 0, s) \). Note that if the algorithm does not process \( A \), then the competitive ratio is clearly unbounded. Therefore, we can assume that the algorithm attempts to complete \( A \).

Whenever the algorithm completes 50% of \( A \), the adversary starts to submit a stream of small type \( B \) jobs. A stream of jobs is defined as a collection of \( N \) jobs submitted consecutively, that is, the next job in the stream is submitted at the deadline of its predecessor. Here, the stream includes \( N_B = 2sx(x + 1) \) type \( B \) jobs, each with demand \( D_B = (2sN)^{-1} \) and deadline slackness \( s \). Notice that each stream stretches throughout half a time unit. Each type \( B \) job in the stream has a value of \( v_B = (2sx)^{-1} \). Notice that the total value of jobs in the stream is larger than \( x \). If, at some point, the algorithm decides to preempt \( A \).
and run a type $B$ job, the adversary immediately stops submitting the stream of $B$ jobs. Therefore, whenever the algorithm preempts $A$, it can only gain $v_B$ value.

Consider the possible cases. Notice that job $A$ can be preempted at most $2s$ times, since each preemption occurs after half of job $A$ was processed. If the algorithm completes job $A$, then it can gain at most $(2s - 1)v_B + v_A \leq 1 + 1/x$. However, the optimal solution could have completed a single stream, which has a total value of $x + 1$. If the algorithm does not complete job $A$, then it can gain at most $2sv_B = 1/x$. However, completing $A$ would have yielded a value of 1. We can conclude that $cr_A(s) \geq x$.

4.3 Online Algorithms

In this section we present our main theoretical result - an online scheduling algorithm with guaranteed constant competitive ratios for every $s > 1$. We first present an algorithm $A$ for the single server case in Section 4.3.1. Then, we extend $A$ to incorporate multiple identical servers in Section 4.3.2.

4.3.1 Single Server

4.3.1.1 Algorithm

Throughout this subsection we assume that the computing system is composed of a single server ($C = 1$), therefore we drop the server index $i$ from our notation. We define two parameters $\gamma$ and $\mu$, each representing a simple principle that our scheduling algorithm will follow. The first principle incorporates the conditions for preempting a running job, and it is characterized by a threshold parameter $\gamma > 1$.

**Principle 4.3.1.** A pending job $j'$ can preempt a running job $j$ only if $\rho_j' > \gamma \rho_j$.

Roughly speaking, the algorithm prioritizes jobs by their value-densities. This may seem counter-intuitive at first, since large high-valued jobs might be preempted by small low-valued jobs that have much higher value densities. Nevertheless, we shall see that our algorithms produce overall high values, mainly due to the slackness assumption. To do so, we incorporate a second principle, which restricts the starting time of jobs and is parameterized by a gap parameter $\mu$ ($1 \leq \mu \leq s$).

**Principle 4.3.2.** A job $j$ may not begin its execution after time $d_j - \mu D_j$.

We provide brief intuition for the selection of these two principles. First, if some job $j$ has not been processed at all, any other job that has been processed during $[a_j, d_j - \mu D_j]$ must have a value-density of at least $\rho_j/\gamma$. Second, for a job $j$ to be partially processed (i.e.,
began execution, yet incompletely), any other job executed during \([d_j - \mu D_j, d_j]\) must have a value-density of at least \(\gamma \rho_j\). This will become more clear once we analyze the performance of the algorithm.

### Algorithm 3: Algorithm \(\mathcal{A}\) (single server)

\[\forall t, \quad J^P(t) = \{ j \in \mathcal{J} \mid j \text{ partially processed by } \mathcal{A} \text{ at time } t \land t \in [a_j, d_j]\}\]

\[J^E(t) = \{ j \in \mathcal{J} \mid j \text{ unallocated by } \mathcal{A} \text{ at time } t \land t \in [a_j, d_j - \mu D_j]\}\]

**Event:** On arrival of job \(j\) at time \(t = a_j\):
1. call \(\text{ThresholdPreemptionRule}(t)\)

**Event:** On job completion at time \(t\):
1. resume execution of job \(j' = \arg \max \{ \rho_{j'} \mid j' \in J^P(t)\}\)
2. call \(\text{ThresholdPreemptionRule}(t)\)

**Threshold Preemption Rule \((t)\):**
1. \(j \leftarrow \text{job currently being processed}\).
2. \(j^* \leftarrow \arg \max \{ \rho_{j^*} \mid j^* \in J^E(t)\}\)
3. if \((\rho_{j^*} > \gamma \cdot \rho_j)\) then
   3.1. preempt \(j\) and run \(j^*\)

The algorithm \(\mathcal{A}\) presented here for online preemptive single server scheduling (Algorithm 3) follows these two principles. The algorithm maintains two job sets. The first set \(J^E(t)\) represents jobs \(j\) that have been partially processed by time \(t\) and can still be executed, whereas the second set \(J^E(t)\) represents all jobs \(j\) that have not been allocated by time \(t\) such that \(t \leq d_j - \mu D_j\). The decision points of the algorithm occur at one of two events: either when a new job arrives, or when a processed job is completed. The algorithm handles both events similarly. When a new job arrives, the algorithm invokes a threshold preemption rule, which decides whether to preempt the running job or not. The preemption rule selects the pending job \(j^* \in J^E(t)\) of maximal value-density (ties broken arbitrarily) and replaces the currently running job \(j\) with \(j^*\) only if \(\rho_{j^*} > \gamma \cdot \rho_j\). Note that it is always possible to complete any \(j^* \in J^E(t)\) before its deadline, since \(\mu \geq 1\). The second type of event refers to a completion of a job. In this case, the algorithm temporarily resumes the preempted job in \(J^P(t)\) of highest value-density and calls the threshold preemption rule. Before we proceed to analyze the competitive factor of \(\mathcal{A}\), we summarize some of the properties of the algorithm in the following claims.

**Claim 4.3.3.** Any job \(j \not\in J^E\) allocated by \(\mathcal{A}\) satisfies \(s(t_j) \leq d_j - \mu D_j\).
Proof. The claim follows directly from the threshold preemption rule. For job $j$ to start at time $t$ it must satisfy $j \in J^E(t)$, which implies that $t \leq d_j - \mu D_j$. ■

Claim 4.3.4. Consider some time $t$. Let $j = j_A(t)$ denote the job processed at time $t$ by $A$ and let $j'$ either be an allocated job such that $t \in [a_{j'}, d_{j'}]$, or an unallocated job such that $t \in [a_{j'}, d_{j'} - \mu D_j]$. Then, $\rho_{j'} \leq \gamma \rho_j$.

Proof. Assume towards contradiction that $\rho_{j'} > \gamma \rho_j$. Let $t^*$ denote the earliest time job inside the interval $[a_{j'}, t]$ during which $j$ is allocated. Note that $t^*$ must exist, since the claim assumes that $j$ has being processed at time $t$. At time $t^*$, the algorithm $A$ either started processing $j$ or resumed the execution of $j$. For $A$ to start $j$, the threshold preemption rule must have preferred $j$ over $j'$, which is impossible. The second case where $A$ resumed the execution of job $j$ is also impossible, since either $j'$ would have been resumed instead of $j$, or the threshold preemption rule would have immediately preempted $j$. We conclude that $\rho_{j'} \leq \gamma \rho_j$. ■

Claim 4.3.5. Let $j'$ be a job partially processed by $A$. Any job $j \neq j'$ running during $[\text{st}(y_{j'}), d_{j'}]$ satisfies $\rho_j > \gamma \rho_{j'}$ and $\text{st}(y_{j'}) < \text{st}(y_j)$.

Proof. Assume towards contradiction that $\text{st}(y_j) < \text{st}(y_{j'})$. The assumption implies that the execution of job $j$ is paused at time $\text{st}(y_{j'})$. Hence, $\rho_{j'} > \gamma \rho_j$; otherwise, $j'$ would not start. Denote by $t$ the earliest time after $\text{st}(y_{j'})$ during which $j$ is allocated. Following the initial assumption that $\text{st}(y_j) < \text{st}(y_{j'})$, we can deduce that job $j$ resumed execution at time $t$. Since $j$ can only resume execution once another job completes, and since $j'$ is never completed, we can also deduce that job $j'$ was paused at time $t$. Since $j$ was eventually selected, we have $\rho_j > \rho_{j'}$, which is a contradiction. Therefore, $\text{st}(y_{j'}) < \text{st}(y_j)$. The claim that $\rho_j > \gamma \rho_{j'}$ follows since at time $\text{st}(y_j)$ job $j$ starts execution while job $j$ has not been completed. ■

4.3.1.2 Analysis

We bound the competitive ratio of the single server algorithm $A$. Our analysis is post factum, meaning, we measure the performance of the online algorithm only after all jobs have been considered. As we soon show, we strongly rely on the dual fitting technique described in Section 2.1.2 to bound the competitive ratio of the algorithm. The analysis proceeds in two parts. In the first part of our analysis we show how to construct a feasible solution to the dual program, and bound its dual cost in terms of $\int_0^\infty \rho_A(t)dt$ (recall that $\rho_A(t)$ represents the value-density of the job processed by $A$ at time $t$). Notice that the integral does not necessarily represent the total value gained by the algorithm, as it may include times $t$ during
which incomplete jobs were processed. Hence, the second part of our analysis bounds the ratio between $\int_0^\infty \rho_A(t)dt$ and the total value $v(J^F)$ gained by the algorithm.

**Dual Fitting** The first part of our analysis can be summarized by the following theorem.

**Theorem 4.3.6.** Consider an execution of the online algorithm $A$ over a set of arriving jobs $J$. Let $\rho_A : \mathbb{R} \rightarrow \mathbb{R}$ be a function representing the value-density of the job executed by $A$ at time $t$. Then, there exists a solution $(\alpha, \beta, \pi)$ to the dual program with a dual cost of at most:

$$v(J^F) + \gamma \cdot \frac{s}{s - \mu} \cdot \int_0^\infty \rho_A(t)dt.$$  (4.1)

Before proving Theorem 4.3.6 we need to make several preliminary observations and develop additional machinery. The $\pi_j(t)$ variables are not necessary for the single server analysis of our algorithm, so for the remainder of this section we set them to 0. As a result, the dual constraints reduce to the following form:

$$\alpha_j + \beta(t) \geq \rho_j \quad \forall j, t \in [a_j, d_j]$$  (4.2)

We proceed to construct a feasible solution to the dual program that satisfies (covers) the dual constraints (4.2). Notice that the dual constraints of each completed job $j \in J^F$ can be covered by setting $\alpha_j = \rho_j$. This increases the dual cost by exactly $\sum_{j \in J^F} D_j \alpha_j = \sum_{j \in J^F} D_j = v(J^F)$. Hence, it remains to cover the dual constraints corresponding to incomplete jobs. To do so, we use the $\beta(t)$ function. Notice that the variable $\beta(t)$ is common to all of the dual constraints (4.2) corresponding to time $t$. This allows us to cover the dual constraints of incomplete jobs $j \notin J^F$ all at once without having to cover them separately using their corresponding $\alpha_j$ variables, as done for completed jobs. To obtain a feasible solution to the dual program, we require that $\beta(t)$ satisfies $\beta(t) \geq \rho_j$ for every job $j \notin J^F$ and time $t \in [a_j, d_j]$. The requirement can be written alternatively as $\beta(t) \geq \max \{ \rho_j \mid j \notin J^F \land t \in [a_j, d_j] \}$ for every $t$. Now, consider the following function $\beta^{-\mu} : \mathbb{R}^+ \rightarrow \mathbb{R}^+$, defined by:

$$\beta^{-\mu}(t) = \max \{ \rho_j \mid j \notin J^F \land t \in [a_j, d_j - \mu D_j] \}.$$  (4.3)

The function $\beta^{-\mu}$ satisfies two useful properties. First, the function satisfies $\beta^{-\mu}(t) \leq \gamma \cdot \rho_A(t)$ for every time $t$ by Claim 4.3.4. Second, the function $\beta^{-\mu}$ covers the dual constraints of every incomplete job $j \notin J^F$ and time $t \in [a_j, d_j - \mu D_j]$. This nearly completes the analysis, since most of the dual constraints (4.2) can be covered by the $\beta^{-\mu}$ function, and we can bound its cost in terms of $\rho_A$. Yet, it remains to cover the constraints corresponding to
times \([d_j - \mu D_j, d_j]\). To cover the remaining constraints, we “stretch” the function \(\beta^{-\mu}\) by using the following lemma.

**Lemma 4.3.7** (Stretching Lemma). Assume that a function \(\beta^{-\mu} : \mathbb{R}^+ \rightarrow \mathbb{R}^+\) satisfies \(\beta^{-\mu}(t) \geq \rho_j\) for every incomplete job \(j \notin J^F\) and time \(t \in [a_j, d_j - \mu D_j]\). Then, there exists a function \(\beta : \mathbb{R}^+ \rightarrow \mathbb{R}^+\) satisfying: \(\beta(t) \geq \rho_j\) for every \(j \notin J^F\) and \(t \in [a_j, d_j]\), such that:

\[
\int_0^\infty \beta(t) dt \leq \frac{s}{s - \mu} \int_0^\infty \beta^{-\mu}(t) dt.
\]

In fact, we prove a stronger variant of the stretching lemma, where the assumption on \(\beta^{-\mu}\) for every job \(j \notin J^F\) only holds for the interval \([a_j, a_j + \frac{s - \mu}{s} \cdot (d_j - a_j)]\). Due to its technicality, the proof can be found in Appendix 4.A. We can now prove Theorem 4.3.6 by incorporating the stretching lemma into the construction of the dual solution. The remaining details are given next.

**Proof of Theorem 4.3.6.** Set \(\alpha_j = \rho_j\) for every completed job \(j \in J^F\) and \(\alpha_j = 0\) otherwise. To cover the remaining dual constraints, we apply the stretching lemma on the function \(\beta^{-\mu}\) defined in (4.3) to obtain \(\beta\). The \(\pi_j(t)\) variables are all set to 0. It follows that the constructed solution is feasible. The total cost of the dual solution \((\alpha, \beta, \pi)\) is bounded by:

\[
\sum_{j \in J} D_j \alpha_j + \int_0^\infty \beta(t) dt \leq v(J^F) + \frac{s}{s - \mu} \int_0^\infty \beta^{-\mu}(t) dt
\]

\[
\leq v(J^F) + \gamma \cdot \frac{s}{s - \mu} \int_0^\infty \rho_A(t) dt.
\]

The last inequality follows since \(\beta^{-\mu}(t) \leq \gamma \cdot \rho_A(t)\) for every \(t \in \mathbb{R}^+\).

**Cost Analysis** The second part of our analysis bounds the integral \(\int_0^\infty \rho_A(t) dt\) in terms of \(v(J^F)\). Theorem 4.3.8 summarizes our result.

**Theorem 4.3.8.** Let \(\rho_A : \mathbb{R}^+ \rightarrow \mathbb{R}^+\) be a function representing the value-density of the job executed by \(A\) at time \(t\). Let \(J^F\) be the set of jobs completed by \(A\) with input \(J\), and denote by \(v(J^F)\) the total value gained by the algorithm. Then:

\[
\int_0^\infty \rho_A(t) dt \leq v(J^F) \cdot \left[\frac{(\gamma - 1)(\mu - 1)}{(\gamma - 1)(\mu - 1) - 1}\right].
\]
We divide the timeline $T$ into two disjoint sets $T^F = \{ t \in T \mid j_A(t) \in J^F \}$ and $T^P = T \setminus T^F$. Notice that integrating $\rho_A(t)$ over $T^F$ gives us exactly $v(J^F)$. To prove the theorem, it remains to bound $\int_{T^P} \rho_A(t) dt$, which is the total partial value lost by the algorithm for not completing partially processed jobs, i.e., jobs in $J^P$.

Consider a partially processed job $j \in J^P$. Define the admission window of job $j$ as $Ad_j = [st(y_j), d_j]$ as the interval between the job start time (admission time) and its deadline. By Claim 4.3.3, the size of the admission window is at least $\mu D_j$. Let $I_j \subseteq Ad_j$ represent the times during which job $j$ has been processed. Since job $j$ has not been completed, its total execution time is at most $D_j$. Hence, the total time in $Ad_j$ during which $A$ processed jobs different than $j$ is at least $(\mu - 1)D_j$; denote this set of times by $O_j$. According to Claim 4.3.5, each of the jobs executed during $O_j$ has a value-density of at least $\gamma \rho_j$. Integrating $\rho_A(t)$ over $O_j$ gives us a total value of at least $\gamma (\mu - 1) v_j$. Intuitively, we would like $O_j$ to account for the partial value corresponding to $I_j$, during which the algorithm processed the incompletely job $j$. However, the jobs processed during $O_j$ have not necessarily been completed; specifically, we cannot directly link between the value gained during $O_j$ and the value gained by the algorithm. Thus, a more rigorous analysis is required.

We bound $\int_0^\infty \rho_A(t) dt$ using a charging argument motivated by the previous discussion. Initially, we charge every job running at some time $t$ a value of $\rho_A(t)$. We then apply a charging procedure that iteratively transfers charges away from incomplete jobs, until finally only completed jobs are charged. Finally, we bound the total amount each completed job is charged for (Lemma 4.3.9).

The Charging Procedure. Let $\xi : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ be a charging function, representing an amount charged from the job that has been processed per time $t$. Initially, we set $\xi(t) = \rho_A(t)$ for every time $t$. We describe a procedure that shifts values of $\xi(t)$ towards completed jobs, that is, time slots in $T^F$. After initializing $ch$, we sort the partially executed jobs in $J^P$ according to their starting time $st(y_j)$. For each job $j \in J^P$ in this order, we do the following:

1. Define: $I_j = \{ t \in \mathbb{R}^+ \mid j = j_A(t) \}$.
2. Define: $O_j = Ad_j \setminus I_j$.
3. Let $\psi_j : I_j \rightarrow O_j$ be some bijection from $I_j$ to $O_j$.
4. For every $t \in I_j$, increase $\xi(\psi(t))$ by $(|I_j| / |O_j|) \xi(t)$ and set $\xi(t)$ to 0.

Let $\xi'(t)$ denote the value of $\xi(t)$ at the end of the procedure. At each iteration of the charging procedure, some incomplete job $j \in J^P$ transfers all of the charges associated with
it towards jobs that execute during $O_j$. Claim 4.3.5 implies that jobs processed in $O_j$ have either been completed or have started executing after $j$. Since we sorted jobs by start times, this implies that after we transfer charges away from a job $j \in J^F$, we never subsequently transfer charges back to $j$. This will imply that, at the end of the procedure, only jobs in $J^F$ are charged. Our goal now is to obtain a good bound on $ch'(t)$ as a function of $\xi(t)$. This goal is complicated by the fact that charges can be transferred multiple times, and along multiple paths, before reaching jobs from $J^F$. The following is our main technical lemma, which analyzes the structure of the charging procedure in order to bound $ch'(t)$.

**Lemma 4.3.9.** At the end of the charging procedure:

1. \[
\int_0^\infty \rho_A(t) dt = \int_0^\infty \xi'(t) dt.
\]

2. For every $t \in T^F$, $\xi'(t) \leq \rho_A(t) \cdot \frac{(\gamma-1)(\mu-1)}{(\gamma-1)(\mu-1)-1}$.

3. For every $t \notin T^F$, $\xi'(t) = 0$.

**Proof.** Clause 1 holds since every iteration of the charging procedure (lines 1-4) does not change the value of $\int_0^\infty \xi(t) dt$. We now prove clause 3. Recall that the charging procedure sorts jobs in $J^F$ according to their starting times. Every job $j \in J^F$ transfers all of its charges towards jobs in $A_d_j$, which are either completed jobs or other jobs in $J^F$. Claim 4.3.5 states that a job in $J^F$ processed in $A_d_j$ must have started after job $j$. This guarantees that at the end of the charging procedure, $\xi'(t) = 0$ for every $t \notin T^F$.

The rest of the proof is dedicated to proving clause 2. Our goal is to bound the ratio between $ch'(t)$ and $\rho_A(t)$ for every time $t \in T^F$. Up until now we treated entries of the function $\rho_A$ as value that has or has not been gained by the algorithm. However, the notion of value may be confusing in the current context of analyzing a charging argument. To avoid confusion, in this proof we refer to entries of $\rho_A$ as costs that need to be paid for. Specifically, we are interested in costs that eventually affect $ch'(t)$.

Consider some time $t_i \in T^P$. The role of $i$ will be explained later on, and at this point can be ignored. Let $j_i$ be the job that has been processed at time $t_i$. Consider the cost $\rho_A(t_i)$. Initially, $\xi(t_i)$ is charged for the cost of $\rho_A(t_i)$. When the iterative loop of the charging procedure reaches job $j_i$, the cost $\rho_A(t_i)$ is transferred to a different time $t_{i-1} = \psi_{j_i}(t_i)$ and scaled down by a factor of $1/(\mu-1)$, at least\(^4\). Let $i$ represent how many times the cost $\rho_A(t_i)$ has been transferred, and let $t_i^F$ represent the final time to which the cost is transferred. By clause 3, the job processed at $t_i^F$ must have been completed by the algorithm.

\(^4\)We note that the transferred value, $\xi(t_i)$, may be larger than $\rho_A(t_i)$, because of other costs transferred to $t_i$ at an earlier stage. However, at this point in the analysis we are only interested in the portion of the transferred value corresponding to $\rho_A(t_i)$.
Now consider an incomplete job \( j' \in \mathcal{J}^P \), and some time \( t \). We say that job \( j' \) *charges time \( t \) after \( i \) transfers* if there some time \( t_i \) for which \( t_i^F = t \). We would like to understand how much of the final charge at \( t \), \( \text{ch}'(t) \), was transferred from job \( j' \). A complication is that \( j' \) can charge time \( t \) in multiple ways. For example, it may be that \( t \in O_{j'} \), so that the charge at \( t \) increases when \( j' \) is handled by the charging procedure. However, there may be another job incomplete \( j'' \) that was also being processed in the interval \( O_{j'} \), which receives part of the charge of \( j' \); when \( j'' \) is handled by the charging procedure, it might also transfer some of its charge – which includes charge received from \( j' \) – to time \( t \). In general, charge may transfer from \( j' \) to time \( t \) via multiple paths of varying lengths; we will bound this transfer over all possible paths.

Let \( k \) be the number of incomplete jobs that have started between \( st(y_{j'}) \) and \( t \) (not including \( j' \)). We are interested in bounding the number of times that job \( j' \) charges \( t \) after \( i \) transfers. We claim this number is at most \( \binom{k}{i-1} \). To see this, consider a cost \( \rho_A(t_i) \). Let \( t_i \rightarrow t_{i-1} \rightarrow \cdots \rightarrow t_0 = t_i^F \) denote the path through which the cost \( \rho_A(t_i) \) is transferred, and by \( j_i, j_{i-1}, \ldots, j_0 \) the corresponding jobs processed during those times. Notice that the set \( j_i, j_{i-1}, \ldots, j_0 \) is unique for each such \( t_i \), since every \( \psi \) is a bijection. Moreover, notice that the jobs \( j_i, j_{i-1}, j_1 \) must be sorted in ascending order of starting time, since by Claim 4.3.5 an incomplete job only charges jobs that have started after it. Hence, the number of options for such a \( t_i \) is the number of unique paths from \( j_i \) to \( j_0 \), which is the number of options to choose \( j_{i-1}, \ldots, j_1 \) out of \( k \) jobs. Notice that \( i \) can range between 1 and \( k+1 \).

The last step of the proof is to bound \( \rho_{j'} \). Without loss of generality, we assume that \( j' \) actually charges \( t \) after some amount of transfers, otherwise \( j' \) is irrelevant for the discussion. Consider the \( k \) incomplete jobs that started between \( st(y_{j'}) \) and \( t \) in ascending order of their starting times. Each job in this order must be contained in the admission window of its predecessor. By Claim 4.3.4, we get that \( \rho_{j'} \leq \frac{\rho_A(t)}{\gamma^{k+1}} \). Since each job \( j' \) is uniquely identified by the number \( k \) of jobs that start between time \( t \) and the start of \( j' \), and each path to such a \( j' \) from \( t \) has length at most \( k+1 \), this gives us the following:

\[
\xi'(t) \leq \rho_A(t) + \sum_{k=0}^{\infty} \sum_{i=1}^{k+1} \left( \begin{array}{c} k \\ i-1 \end{array} \right) \frac{\rho_A(t)}{\gamma^{k+1}(\mu-1)^i}
\]

\[
= \rho_A(t) + \sum_{k=0}^{\infty} \frac{\rho_A(t)}{\gamma^{k+1}(\mu-1)} \sum_{i=1}^{k+1} \left( \begin{array}{c} k \\ i-1 \end{array} \right) \frac{1}{(\mu-1)^{i-1}}
\]

\[
= \rho_A(t) + \sum_{k=0}^{\infty} \frac{\rho_A(t)}{\gamma^{k+1}(\mu-1)} \left( 1 + \frac{1}{\mu-1} \right)^k
\]

57
\[
\rho_A(t) \left[ 1 + \frac{1}{\gamma(\mu - 1)} \sum_{k=0}^{\infty} \left( \frac{\mu}{\gamma(\mu - 1)} \right)^k \right] \\
= \rho_A(t) \left[ 1 + \frac{1}{(\gamma(\mu - 1) - \mu)} \right] \\
= \rho_A(t) \frac{(\gamma - 1)(\mu - 1)}{(\gamma - 1)(\mu - 1) - 1},
\]

which is exactly what was required in clause 2, thus completing the lemma.

Theorem 4.3.8 follows by simply integrating over \( t \) and applying Lemma 4.3.9. Combining Theorems 4.3.6 and 4.3.8 leads to our main result.

**Corollary 4.3.10.** The competitive ratio of \( A \) for the single server case is at most:

\[
\text{cr}(A) \leq 1 + \gamma \cdot \frac{s}{s - \mu} \cdot \frac{(\gamma - 1)(\mu - 1)}{(\gamma - 1)(\mu - 1) - 1}.
\]

In fact, we can obtain a stronger variant of Theorem 4.3.8 by making minor adjustments to our proof. Instead of bounding \( \int_0^{\infty} \rho_A(t) \, dt \), we can prove the exact upper bound on \( v(\mathcal{J}^F) + v(\mathcal{J}^P) \), the total value of jobs that have been either fully or partially processed. The strengthened variant will be useful in subsequent sections. Before continuing our analysis, we describe the changes required to strengthen the theorem.

**Theorem 4.3.11.** Let \( \mathcal{J}^F \) and \( \mathcal{J}^P \) be the set of jobs fully completed and partially completed by \( A \) with input \( \mathcal{J} \), respectively, and let \( v(\mathcal{J}^F) \) and \( v(\mathcal{J}^P) \) denote their overall values. Then:

\[
v(\mathcal{J}^F) + v(\mathcal{J}^P) \leq v(\mathcal{J}^F) \cdot \frac{(\gamma - 1)(\mu - 1)}{(\gamma - 1)(\mu - 1) - 1}.
\]

**Proof.** We revisit the charging procedure and slightly modify it to obtain the tighter bound stated in this lemma. Instead of initializing the charge vector to \( \xi(t) = \rho_A(t) \), we set the initial values differently. Initially, we set \( \xi(t) = v_j / |I_j| \) for every time \( t \), where \( j = j_A(t) \). Notice first that after initializing, we have \( \int_0^{\infty} \xi(t) \, dt = v(\mathcal{J}^F) + v(\mathcal{J}^P) \). Consider the point where the charging procedure iterates over a partially completed job \( j \in \mathcal{J}^P \). Note that the factor added to \( \xi(\psi(t)) \) in step 4 is exactly \( (|I_j|/|O_j|)\xi(t) = v_j/|O_j| \). By Claim 4.3.3, this expression is at most \( \rho_j/(\mu - 1) \). Notice that original proof of the charging lemma obtains the same bound on the added factor. The theorem follows.

**Optimizing the bound** The bound on \( \text{cr}(A) \) given in Corollary 4.3.12 can be further optimized. A straightforward calculation shows that for any value of \( \mu \), the bound is minimized for a unique optimal value of \( \gamma^*(\mu) = \sqrt{\pi} / \sqrt{\mu - 1} \); at this value, the bound becomes:
\[ \text{cr}(A) \leq 1 + \frac{s}{s - \mu} \cdot \sqrt{\mu + 1} / \sqrt{\mu - 1}. \]

There are two ways to interpret the above result. One may think of \( \mu \) as a constraint set by the service provider. For example, by setting \( \mu = s/2 \), the service provider can limit the starting time of jobs to the first half of their availability window; as a result, the bound becomes \( 3 + O \left( \frac{1}{\sqrt{s}} \right) \) for \( s > 2 \). On the other hand, the bound can be further minimized by setting \( \mu \approx s^{2/3} \); this leads to the following form:

\[ \text{cr}(A) = 2 + O \left( \frac{1}{\sqrt[3]{s} - 1} \right) + O \left( \frac{1}{(\sqrt[3]{s} - 1)^2} \right). \]

The analysis follows from basic calculus, hence we omit details for brevity.

### 4.3.2 Multiple Servers

In the next following sections we extend our solution to handle multiple servers. We first consider the non-parallel allocation model \((k = 1)\), where a job cannot be simultaneously processed on more than one server. We then extend our solution to a general allocation model, where each job can be allocated any number of servers between 0 and a parallelism bound \( k \) common to all jobs.

#### 4.3.2.1 No Parallel Execution \((k = 1)\)

The algorithm works as follows. Each server runs a local copy of the single server algorithm. In addition, we enforce an additional restriction called job locality (no migration) rule. The job locality rule forbids a preempted job to resume execution on a different server; specifically, a job preempted from server \( i \) may only resume execution on server \( i \). The detailed implementation of the algorithm is given fully in Algorithm 4. The algorithm follows the general approach described here in an efficient manner. Upon arrival of a job \( j \) at time \( t \), we only invoke the threshold preemption rule on server \( i_{\text{min}}(t) \), which is the server running the job with lowest value-density (unused servers run idle jobs of value-density 0). Notice that it suffices to invoke the threshold preemption rule of server \( i_{\text{min}}(t) \): if job \( j \) is rejected, it would be rejected by the threshold preemption rule of any other server. When job \( j \) completes on server \( i \), we first load the job with maximal value-density out of \( J_i^P(t) \), the jobs preempted from server \( i \) by time \( t \) (event 2, line 1), and then invoke the threshold preemption rule. Following the job locality rule, the threshold preemption rule only considers completely unallocated jobs as candidates for \( j^* \) (line 2). Specifically, a job preempted from
server $i$ can only resume execution once it is the job with the highest value-density among those preempted from server $i$.

**Algorithm 4:** Algorithm $\mathcal{A}$ (multiple servers; no parallelism)

$\forall t$, $J^P(t) = \{ j \in \mathcal{J} \mid j$ partially processed on server $i$ by $\mathcal{A}$ at time $t \land t \in [a_j, d_j]\}$.  
$J^E(t) = \{ j \in \mathcal{J} \mid j$ unallocated by $\mathcal{A}$ at time $t \land t \in [a_j, d_j - \mu D_j]\}$.

**Event:** On arrival of job $j$ at time $t = a_j$:
1. call **ThresholdPreemptionRule**($i_{\min}(t), t$), where:
   $$i_{\min}(t) = \arg\min \{ \rho_{iA}(t) \mid 1 \leq i \leq C \}$$

**Event:** On completion of job $j$ on server $i$ at time $t$:
1. resume execution of job $j' = \arg\max \{ \rho_{j'} \mid j' \in J^P_i(t) \}$
2. call **ThresholdPreemptionRule**($i, t$).

**ThresholdPreemptionRule**($i, t$):
1. $j \leftarrow$ job currently processed on server $i$.
2. $j^* \leftarrow \arg\max \{ \rho_{j^*} \mid j^* \in J^E(t) \}$.
3. if $(\rho_{j^*} > \gamma \cdot \rho_j)$ then
   3.1. preempt $j$ and run $j^*$ on server $i$.

The competitive ratio analysis of the multiple server algorithm is quite similar to its single server counterpart. As before, we bound the competitive ratio by constructing a feasible solution to the dual program and bounding its dual cost. Notice that the dual program now holds a constraint for each tuple $(j, i, t)$. One would hope that the dual solution for a single server could be simply extended to a dual solution for multiple servers. Unfortunately, this is not the case. We explain this intuitively. Consider an incomplete job $j \in \mathcal{J}^P$ and assume that the job was processed on server $i$ at time $t$. Recall that we set $\alpha_j = 0$ and $\pi(t') = 0$ for all $t' \in [a_j, d_j]$. Hence, we must require that $\beta_i(t) \geq \rho_j$ for every server $i'$. When analyzing the single server algorithm, we obtained the values for the $\beta(t)$ function by applying the stretching lemma on $\beta^{-\mu}(t) = \gamma \rho_{A}(t)$. Similarly, for the multiple server case, we can stretch the function $\beta^{-\mu}(t) = \gamma \cdot \rho_{A}(t)$ to obtain $\beta_{i}(t)$. Obviously, $\beta_{i}(t) \geq \rho_j$. However, this does not necessarily guarantee that $\beta_{i'}(t) \geq \rho_j$ on any other server $i' \neq i$. Fixing the $\beta_{i'}(t)$ functions to cover the dual constraints of job $j$ may increase the dual cost of our solution drastically. Luckily, we can resolve this issue by setting $\alpha_j = \rho_j$ for every incomplete job $j \in \mathcal{J}^P$; this increases the dual cost by $v(\mathcal{J}^P)$, which we have already bounded (Theorem 4.3.11). The bound we obtain on the competitive ratio of the multiple server algorithm is presented in the following theorem.
Theorem 4.3.12. The competitive ratio of the multiple server algorithm $A$ is at most:

$$cr(A) \leq \left[ 1 + \gamma \cdot \frac{s}{s - \mu} \right] \cdot \left[ \frac{(\gamma - 1)(\mu - 1)}{(\gamma - 1)(\mu - 1) - 1} \right].$$

Proof. We construct a feasible dual solution $(\alpha, \beta, \pi)$ as follows. For each job $j \in J_F \cup J_P$, set $\alpha_j = 0$. We generate the values of $\beta_i(t)$ for each server $i$ by applying the stretching lemma on $\beta_i^{-\mu}(t) = \gamma \cdot \rho_A(t)$. All $\pi$ variables are set to 0. The feasibility of the dual solution follows from the correctness of the stretching lemma. The dual cost of the obtained solution is at most:

$$v(J_F) + v(J_P) + \gamma \cdot \frac{s}{s - \mu} \cdot \sum_{i=1}^{C} \int_{0}^{\infty} \rho_A(t)dt.$$  \hspace{1cm} (4.4)

By Theorem 4.3.11, we have:

$$v(J_F) + v(J_P) \leq v(J_F) \cdot \left[ \frac{(\gamma - 1)(\mu - 1)}{(\gamma - 1)(\mu - 1) - 1} \right].$$

The remainder of (4.4) can be bounded by applying Theorem 4.3.8 on each server separately and aggregating over all servers. This gives us:

$$\sum_{i=1}^{C} \int_{0}^{\infty} \rho_A(t)dt \leq v(J_F) \cdot \left[ \frac{(\gamma - 1)(\mu - 1)}{(\gamma - 1)(\mu - 1) - 1} \right].$$

Combining the two inequalities leads to our result.

4.3.2.2 Identical Parallelism Bounds ($k > 1$)

Up to now we have restricted the execution of every job to at most one server at any moment. In the following, we consider a more general model, in which each job may be processed simultaneously on any number of servers between 0 and a parallelism bound $k$ set by the service provider. The service provider may flexibly change the resource usage of each job at any point.

Our solution is based on a simple reduction to the non-parallel case. We divide the $C$ servers into $C/k$ equal-sized “virtual clusters” (VCs); we assume $k$ divides $C$ for ease of exposition. In our solution, jobs are allocated to VCs rather than to individual servers. When a job is allocated to a VC, it runs on all of its $k$ servers in parallel. Note the difference between the model assumptions and the obtained allocations in terms of parallelism. The model allows any job to receive any amount of resources between 0 and $k$, whereas Algorithm 5 either allocates $k$ resources to a job or none at all. Nevertheless,
Algorithm 5: Algorithm $\mathcal{A}$ (multiple servers; identical parallelism bound)

1. divide the $C$ servers into $C/k$ equal-sized virtual clusters.
2. run Algorithm 4 under the following modifications:
   - capacity: $C' = C/k$.
   - demand: $D'_{j} = D_{j}/k$ for each job $j$.

the reduction preserves the competitive ratio guaranteed by the algorithm. The analysis is
rather straightforward due to the use of the dual fitting technique. A dual solution $(\alpha', \beta', \pi')$
to the reduced problem ($k = 1$) can be easily transformed into a feasible solution $(\alpha, \beta, \pi)$
to the general case ($k > 1$). First, set $\alpha = \alpha'$ and $\pi = \pi'$. Then, for each server $i$
associated with a virtual cluster $i'$, set $\beta_i(t) = \beta'_i(t)/k$. Notice that $\rho'_j = k\rho_j$ and $s' = s$. This implies
that the dual solution is feasible and that the cost is preserved.

We note that the algorithm we provide overcomes some concerns that may arise in
practical settings. For example, the dynamic allocation of resources might in principle
incur high network costs due to large data transfers. However, the job locality feature of
our algorithm prevents jobs from migrating across VCs, thereby minimizing communication
overheads. We emphasize that imposing this feature does not affect performance, as we
guarantee the same competitive ratio of the single server algorithm. In other words, while
our algorithm does not migrate jobs across VCs, and only ever allocates 0 or $k$ resources to
a job at any given time, our performance bounds are with respect to an optimal schedule
without any such restrictions.

4.4 Truthful Mechanisms

Unfortunately, the scheduling algorithm $\mathcal{A}$ developed in Section 4.3 does not implement a
truthful mechanism, since it is not monotone. We refer the reader to Appendix 4.A for a
counterexample, in which a job that would otherwise not be completed can manipulate the
mechanism by reporting a lower value and consequently be completed by its deadline.

In the following, we suggest a variant $\mathcal{A}_T$ of $\mathcal{A}$ which implements a truthful mechanism
and guarantees a constant competitive ratio for every $s > 1$. We first present $\mathcal{A}_T$ for the
single server case, and then extend the algorithm to accommodate multiple servers.

4.4.1 Single Server

We divide the jobs into classes $\mathcal{C}_\ell = \{j \mid \rho_j \in [\gamma^\ell, \gamma^{\ell+1})\}$ that are characterized by the range
of value-densities they accept. Notice that every job $j$ belongs to class $\mathcal{C}_\ell$ for $\ell = \lfloor \log_\gamma(\rho_j) \rfloor$. 62
We think of a job \( j' \) as dominating another job \( j \) if \( j' \) belongs to a higher class. More formally, we use the following notation throughout the section.

**Definition 4.4.1.** We write \( j' \succ j \) if \( \lfloor \log_\gamma (\rho_{j'}) \rfloor > \lfloor \log_\gamma (\rho_j) \rfloor \).

The truthful scheduling algorithm \( A_T \) is obtained by making the following two modifications to \( A \). First, we refine the threshold preemption rule to prioritize jobs according to \( \succ \). The preemption rule guarantees that the running jobs belong to the highest classes out of all available jobs (proven later, see Claim 4.4.2). This prevents users from benefiting from a misreport of their values. Second, we prevent jobs from completing before their deadline. Namely, when a job completes, we do not immediately send its output to the user. Instead, we delay the completion of the job until its submitted deadline \( d_j \). Intuitively, this prevents job \( j \) from potentially reporting a later deadline \( d_j' > d_j \). We explain this intuitively. Assume that when reporting a deadline of \( d_j \) the job is not allocated at all until time \( d_j - \mu D_j \). Consequently, \( j \) is rejected by the algorithm. However, if the job reports a later deadline \( d_j' \), the algorithm might choose to allocate resources to \( j \) before time \( d_j' - \mu D_j \). As a result, \( j \) may continue to receive allocations even after time \( d_j' - \mu D_j \). If \( j \) is allocated enough resources by time \( d_j \), then it would meet its actual deadline. By deliberately delaying outputs to the reported deadlines, we eliminate any incentive to report a false late deadlines.

**Algorithm 6:** Algorithm \( A_T \) (truthful; single server)

\[
\forall t, \quad (J^P(t) = \{ j \in J \mid j \text{ partially processed by } A_T \text{ at time } t \land t \in [a_j, d_j] \}) .
\]

\[
J^E(t) = \{ j \in J \mid j \text{ unallocated by } A_T \text{ at time } t \land t \in [a_j, d_j - \mu D_j] \}.
\]

**Event:** On arrival of job \( j \) at time \( t = a_j \):
1. call ClassPreemptionRule\((t)\).

**Event:** On completion of job \( j \) at time \( t \):
1. resume execution of job \( j' = \arg \max \{ \rho_{j'} \mid j' \in J^P(t) \} \).
2. call ClassPreemptionRule\((t)\).
3. delay the output response of \( j \) until time \( d_j \).

**ClassPreemptionRule \((t)\):**
1. \( j \leftarrow \text{job currently being processed} \).
2. \( j^* \leftarrow \arg \max \{ \rho_{j^*} \mid j^* \in J^E(t) \} \).
3. if \( (j^* \succ j) \):
   3.1. preempt \( j \) and run \( j^* \).

The full implementation of \( A_T \) appears in Algorithm 6. Notice that the threshold preemption rule of \( A \) has been replaced by a class preemption rule, which favors jobs of higher
Claim 4.4.2. Let \( j = j_{\mathcal{A}}(t) \) be the job processed at time \( t \) by \( \mathcal{A} \). Let \( j' \in J^P(t) \cup J^E(t) \) be an allocated job such that \( t \in [a_{j'}, d_{j'\text{}}] \) or an unallocated job such that \( t \in [a_{j'}, d_{j'} - \mu D_{j'}] \). Then, \( j' \neq j \).

Proof. Assume towards contradiction that \( j' \succ j \). Let \( t^* \) denote the earliest time job inside the interval \([a_{j'}, t]\) during which \( j \) is allocated. Note that \( t^* \) must exist, since the claim assumes that \( j \) is processed at time \( t \). At time \( t^* \), the algorithm \( \mathcal{A} \) either started processing \( j \) or resumed the execution of \( j \). For \( \mathcal{A} \) to start \( j \), the class preemption rule must have preferred \( j \) over \( j' \), which is impossible. The second case where \( \mathcal{A} \) resumed the execution of job \( j \) is also impossible, since either \( j' \) would have been resumed instead of \( j \) or the class preemption rule would have immediately preempted \( j \). We conclude that \( j' \neq j \). □

Claim 4.4.2 implies that at any point in time, the job allocated by \( \mathcal{A} \) belongs to the highest class among the jobs that can be processed, i.e., either an unallocated job \( j \) such that \( t \in [a_j, d_j - \mu D_j] \) or a partially processed job \( j \) such that \( t \in [a_j, d_j] \). Notice further that equalities in job classes are broken in favor of partially processed jobs. This feature is crucial for proving the truthfulness and the performance guarantees of our algorithm. Using Claim 4.4.2 we prove an additional property, which is also required for establishing truthfulness.

Claim 4.4.3. At any time \( t \), the set \( J^P(t) \) contains at most one job from each class.

Proof. By induction. Assume the claim holds and consider one of the possible events. Upon arrival of a new job \( j^* \) at time \( t \), the threshold preemption rule allocates \( j^* \) only if \( j^* \succ j \). Since \( j \) is the maximal job in \( J^P(t) \), with respect to \( \succ \), if \( j^* \) is allocated then it is the single job in \( J^P(t) \) from its class. Upon completion of job \( j \), it is removed from \( J^P(t) \) and the threshold preemption rule is invoked. As before, if a new job is allocated, it belongs to a unique class. □

We now prove that \( \mathcal{A} \) is truthful, i.e., \( \mathcal{A} \) can be used to design a truthful online scheduling mechanism.

Theorem 4.4.4. The algorithm \( \mathcal{A} \) (single server) is truthful.

Proof. By Theorem 2.2.5, it suffices to show that \( \mathcal{A} \) is monotone. Consider some job \( j \). Throughout the proof, we fix the types \( \tau_{-j} \) of all jobs beside \( j \). To ease exposition, we drop \( \tau_{-j} \) from our notation. Write \( \tau_j = \langle v_j, D_j, a_j, d_j \rangle \) for the true type of job \( j \). Suppose that \( \mathcal{A}(\tau_j, \tau_{-j}) \) completes job \( j \). We must show that \( \mathcal{A} \) will still complete job \( j \) under a reported type of \( \tau'_j \), where \( \tau'_j \succ \tau_j \). Since one can modify each component of a reported
type in sequence, it will suffice to establish monotonicity with respect to each coordinate independently.

**Step 1: Value Monotonicity.** Let us first establish value monotonicity. Consider some $v'_j > v_j$ and assume $j$ is completed when reporting $v_j$. Let $\rho'_j = v'_j/D_j$ be the value-density and let $\ell'_j = \lfloor \log_\gamma (\rho'_j) \rfloor$ be the class of job $j$ when reporting $v'_j$. Let $st'(y_j)$ be the starting time of $j$ when reporting $v'_j$. Similarly, denote $\rho_j$, $\ell_j$ and $st(y_j)$ with respect to $v_j$. Notice that if $\ell_j = \ell'_j$, then the behavior of $A_T$ is identical regardless of value reported; hence $j$ is completed. We therefore assume $\ell'_j > \ell_j$. Note then that $st'(y_j) \leq st(y_j)$, since if $j$ does not start by time $st(y_j)$ under reported value $v'_j$, then it will start at that time since it has only a higher class.

Now, consider the case where $j$ reports a value of $v'_j$. Observe $J^P(t)$ at time $t = st'(y_j)$. Claims 4.4.2 and 4.4.3 imply that no existing job can preempt job $j$. Specifically, any job that can run instead of $j$ during the interval $[st'(y_j), d_j]$ must have arrived after time $st'(y_j)$. If $j$ did not complete, then during this interval the algorithm processed higher priority jobs during more than $d_j - st'(y_j) - D_j$ time units. These jobs would also be preferred by $A_T$ when $j$ reports a lower value of $v_j$. Hence, $j$ could not have been completed when the value $v_j$ was reported, a contradiction.

**Step 2: Monotonicity of Other Properties.** Next consider misreporting a demand $D'_j \leq D_j$, and suppose the job completes under report $D_j$. Then the job’s value density is higher under report $D'_j$, and its latest possible starting time is increased to $d_j - \mu D'_j$. This only extends the possibilities of $j$ being completed, and hence job $j$ would be completed under report $D'_j$ as well. Following similar arguments, a later deadline $d'_j$ instead of $d_j$ only increases the latest possible start time of $j$, and increases the time slots in which the job can be completed, which again can only increase the allocation to $j$. Finally, we show that a later arrival time $a'_j \leq a_j$ cannot be detrimental. We assume that $j$ is completed when the job is submitted at time $a_j$. It remains to prove that $j$ is completed when submitting at time $a'_j$. This follows in a similar fashion to our argument for value monotonicity. If when reporting $a'_j$ the job is not processed until $a_j$, then both executions of $A_T$ are identical, hence $j$ is completed. Otherwise, $j$ necessarily begins earlier than when $a_j$ is reported, and again job $j$ is completed. We reach the same conclusion as before.

Since $A_T$ satisfies all required monotonicity conditions, we conclude that $A_T$ is truthful.

The competitive-ratio analysis of $A_T$ is similar to the analysis of the non-truthful algorithm $A$ [51], and proceeds via the dual fitting methodology. Our result is the following.
Theorem 4.4.5. The algorithm $A_T$ (single-server) obtains a competitive ratio of:

$$cr(A_T) \leq 1 + \gamma \cdot \frac{s}{s - \mu} \cdot \left[ \frac{(\gamma - 1)\mu}{(\gamma - 1)(\mu - 1) - 1} \right].$$

For $\gamma^*(\mu) = \sqrt[\mu]{\mu}$ and $\mu = s^{2/3}$, the bound takes the following form.

$$cr_{A_T}(s) = 2 + \Theta \left( \frac{1}{\sqrt{3s - 1}} \right) + \Theta \left( \frac{1}{(\sqrt{s - 1})^3} \right), \quad s > 1$$

Proof. We retrace the steps that lead to the competitive ratio bound for the non-truthful case. Claim 4.4.2 implies that at any time $t$, the value density of any pending job is at most $\gamma \cdot \rho_{A_T}(t)$, since the job $j_{A_T}(t)$ running at time $t$ belongs to the highest class amongst these jobs. As a consequence, Theorem 4.3.6 holds for $A_T$. Therefore:

$$cr(A_T) \leq 1 + \gamma \cdot \frac{s}{s - \mu} \cdot \int_0^\infty \rho_{A_T}(t)dt.$$

It remains to bound $\int_0^\infty \rho_{A_T}(t)dt$. We revisit the charging procedure presented in Section 4.3.1.2. At this point, it is important to understand the differences between the two cases. to that end, consider a partially processed job $j$, and let $j_0$ be some job processed after time $st(y_j)$. Claim 4.4.2 implies that $j_1 \succ j_0$. But, this only means that $\rho_{j_1} > \rho_{j_0}$, as opposed to the inequality $\rho_{j_1} > \gamma \rho_{j_0}$ which we have shown for the non-truthful case. Nevertheless, if we have $j_i \succ j_{i-1} \succ \cdots \succ j_0$, then $\rho_{j_i} > \gamma^{i-1} \rho_{j_0}$, as opposed to $\rho_{j_i} > \gamma^i \rho_{j_0}$ which we proved for the non-truthful case. Plugging this into the proof of Lemma 4.3.9 gives us:

$$\int_0^\infty \rho_{A_T}(t)dt \leq v(J^F) \cdot \left[ 1 + \frac{\gamma}{(\gamma - 1)(\mu - 1) - 1} \right] = v(J^F) \cdot \left[ \frac{(\gamma - 1)\mu}{(\gamma - 1)(\mu - 1) - 1} \right].$$

The theorem follows. ■

4.4.2 Multiple Servers

We extend $A_T$ to accommodate multiple servers. In the multiple server variant, each server runs a local copy of the single server algorithm. Specifically, if a job $j$ has not been executed on a server $i$ during the interval $[a_j, d_j - \mu D_j]$, then the algorithm prevents it from running on server $i$. The detailed implementation of the algorithm is given fully in Algorithm 7. The algorithm follows the general approach described here in an efficient manner. Upon arrival of a job $j$ at time $t$, we only invoke the class preemption rule on server $i_{\text{min}}(t)$, which is the server running the job belonging to the lowest class (unused servers run idle jobs of class
--- \infty). Ties are broken in favor of the job with the later start time in the system. This is crucial for proving truthfulness. Notice also that it suffices to invoke the class preemption rule of server $i_{\text{min}}(t)$: if job $j$ is rejected, it would be rejected by the class preemption rule of any other server. When job $j$ completes on server $i$, we first load the job with maximal value-density out of the jobs preempted from server $i$, and then invoke the class preemption rule. Notice that the class preemption rule allows preempted jobs to migrate between servers. That is, a job preempted from server $i$ might start executing on a different server at time $t$, provided that $t \leq d_j - \mu D_j$.

**Algorithm 7:** Algorithm $A_T$ (truthful; multiple servers; no parallelism)

\[ \forall t, \quad J_i^P(t) = \{ j \in J \mid j \text{ partially processed on server } i \text{ at time } t \land t \in [a_j, d_j] \}. \]
\[ J_i^E(t) = \{ j \in J \mid j \text{ unallocated on server } i \text{ at time } t \land t \in [a_j, d_j - \mu D_j] \}. \]
\[ J_A(t) = \{ J_i^*(t) \mid 1 \leq i \leq C \}. \]

**Event:** On arrival of job $j$ at time $t = a_j$:
1. call ClassPreemptionRule($i_{\text{min}}(t), t$), where:
   \[ i_{\text{min}}(t) = \arg\min_{1 \leq i \leq C} \{ \lfloor \log \rho_i^j(t) \rfloor \} \text{ (ties broken by later start time)} \]

**Event:** On completion of job $j$ on server $i$ at time $t$:
1. resume execution of job $j' = \arg\max \{ \rho_{j'} \mid j' \in J_i^P(t) \}$.
2. call ClassPreemptionRule($i, t$).
3. delay the output response of $j$ until time $d_j$.

**ClassPreemptionRule($i, t$):**
1. $j \leftarrow$ job currently being processed on server $i$.
2. $j^* \leftarrow \arg\max \{ \rho_{j^*} \mid j^* \in J_i^E(t) \setminus J_A(t) \}$ \quad (ties broken by earlier start time)
3. if ($j^* > j$)
   3.1. preempt $j$ and run $j^*$.

We argue that the proposed mechanism is truthful. Note that claims 4.4.2 and 4.4.3 apply on each server separately. However, this is insufficient for proving truthfulness. Instead, we prove the following useful claim.

**Claim 4.4.6.** Let $j = j_{A_T}^j(t)$ be the job processed on server $i$ at time $t$ by $A_T$. Let $j'$ be any job not running at time $t$, and assume $j'$ is either an allocated job such that $t \in [a_{j'}, d_{j'}]$ or an unallocated job such that $t \in [a_{j'}, d_{j'} - \mu D_{j'}]$. Let $C_\ell, C_{\ell'}$ denote the classes of $j, j'$, respectively. Then, either $\ell > \ell'$ or $\ell = \ell' \land st(y_j) < st(y_{j'})$.

**Proof.** Since each server runs a local copy of the single server algorithm, Claim 4.4.2 implies
that $j' \neq j$, therefore $\ell \geq \ell'$. It remains to prove that if $\ell = \ell'$ then \(st(y_j) < st(y_{j'})\). Assume towards contradiction that \(st(y_{j'}) < st(y_j)\) (equality is impossible, since we assume $j$ is running at time $t$ and $j'$ is not). This implies that the algorithm always prioritizes $j'$ over $j$. Notice that at time $st(y_j)$ job $j'$ must be running; otherwise, the algorithm would have not started processing job $j$. Therefore, at time $st(y_j)$ both jobs are running, and at time $t$ only job $j$ is running. We show that this scenario is impossible. Notice that $j'$ cannot be preempted while $j$ is running, since the algorithm would choose to preempt $j$ instead. Hence, sometime during the interval $[st(y_j), d_j]$ both jobs were preempted and $j$ resumed execution. This is impossible, since $j'$ would have been resumed instead of $j$. We reach a contradiction. Therefore, the claim holds. $\blacksquare$

The claim implies that at every time $t$ the algorithm is processing the $C$ top available jobs, where the jobs are ordered first by their class (high to low), and in case of equality ordered by their start times (low to high). This observation is essential for proving truthfulness.

**Theorem 4.4.7.** The algorithm $A_T$ (multiple servers) is truthful.

**Proof.** The proof follows directly from the equivalent single server proof. Consider some job $j$ and two value-densities $\rho_j \leq \rho_j'$. Let $\ell, \ell'$ denote the corresponding classes and let $st'(y_j), st''(y_j)$ denote the corresponding start times. Notice that $\ell' \leq \ell''$. We prove that also $st''(y_j) \leq st'(y_j)$. Consider the case where $j$ has a value-density of $\rho_j''$. If $j$ is processed before time $st'(y_j)$, the claim holds. Otherwise, the behavior of the algorithm up to time $st'(y_j)$ is identical in both cases. Since now $j$ has a higher value density, it will also begin processing. We conclude that increasing the value-density only increases the priority of $j$, with respect to the algorithm $A_T$. Therefore, we can repeat the arguments that lead to prove the truthfulness of the single server algorithm. $\blacksquare$

Similar to the non-truthful case, the bound on $\text{cr}_{A_T}(s)$ obtained in Theorem 4.4.5 can be extended to the multiple server case. The proof follows directly by incorporating Theorem 4.4.5 in the proof of Theorem 4.3.12.

**Corollary 4.4.8.** The algorithm $A_T$ (multiple-servers) obtains a competitive ratio of:

$$\text{cr}(A) \leq \left[ 1 + \gamma \cdot \frac{s}{s - \mu} \right] \cdot \left[ \frac{(\gamma - 1)\mu}{(\gamma - 1)(\mu - 1) - 1} \right].$$

For $\gamma^*(\mu) = \frac{\sqrt{s}}{\sqrt{s - 1}}$ and $\mu = s^{2/3}$, the bound takes the following form.

$$\text{cr}_{A_T}(s) = 2 + \Theta \left( \frac{1}{\sqrt{s - 1}} \right) + \Theta \left( \frac{1}{(\sqrt{s - 1})^3} \right), \quad s > 1$$

68
4.A Appendix A: Proof of Stretching Lemma

We prove a slightly stronger formulation of the Stretching Lemma which is simpler to prove. The formulation given in Lemma 5.2.3 follows directly. For every job \( j \), define \( \tau_j = a_j + \frac{s-\mu}{s} \cdot (d_j - a_j) \). Notice that \( \tau_j \leq d_j - \mu D_j \) for slackness \( s \).

**Lemma 4.A.1.** Let \( \beta^{-\mu} : \mathbb{R}^+ \to \mathbb{R}^+ \) be a function satisfying: \( \beta^{-\mu}(t) \geq \rho_j \) for every \( j \notin J^F \) and \( t \in [a_j, \tau_j] \). Then, there exists a function \( \beta : \mathbb{R}^+ \to \mathbb{R}^+ \) satisfying: \( \beta(t) \geq \rho_j \) for every \( j \notin J^F \) and \( t \in [a_j, d_j] \), such that:

\[
\int_{0}^{\infty} \beta(t)dt \leq \frac{s}{s-\mu} \cdot \int_{0}^{\infty} \beta^{-\mu}(t)dt.
\]

Renumber the incomplete jobs \( J^P \cup J^E = \{1, 2, \ldots, n\} \) such that \( \rho_1 \geq \rho_2 \geq \cdots \geq \rho_n \). Define \( \rho_{n+1} = 0 \). We construct \( \beta(t) \) as follows. Initially, set \( \beta(t) \leftarrow \beta^{-\mu}(t) \) for every \( t \). Now, for every incomplete job \( j \) and for every \( t \in [\tau_j, d_j] \), set \( \beta(t) \leftarrow \max\{ \beta(t), \rho_j \} \). This guarantees that \( \beta(t) \geq \rho_j \) for every incomplete job \( j \) and \( t \in [a_j, d_j] \).

It remains to bound the expression \( \int_{0}^{\infty} \beta(t)dt \). Define the following functions \( \beta_{(j)} : \mathbb{R}^+ \to \mathbb{R}^+ \) and \( \beta_{(j)}^{-\mu} : \mathbb{R}^+ \to \mathbb{R}^+ \) for \( 1 \leq j \leq n + 1 \):

\[
\beta_{(j)}(t) = \max\{0, \beta(t) - \rho_j\} \quad ; \quad \beta_{(j)}^{-\mu}(t) = \max\{0, \beta^{-\mu}(t) - \rho_j\}.
\]

Also, define the following sets:

\[
W_{(j)} = \bigcup_{j'=1}^{j} [a_{j'}, d_{j'}] \quad ; \quad W_{(j)}^{-\mu} = \bigcup_{j'=1}^{j} [a_{j'}, \tau_{j'}]
\]

and denote by \( |W_{(j)}| \) and \( |W_{(j)}^{-\mu}| \) their total length (as opposed to the size of the union, which is simply \( j \)). We prove by induction on \( j \) that:

\[
\int_{W_{(j)}} \beta_{(j)}(t)dt \leq \frac{s}{s-\mu} \int_{W_{(j)}^{-\mu}} \beta_{(j)}^{-\mu}(t)dt
\]

The lemma follows by assigning \( j = n + 1 \), since \( \rho_{n+1} = 0 \). The base case is trivial, since for \( j = 1 \) both functions are identically equal to 0. Assume correctness for \( j - 1 \). Consider
equation (4.7) for \( j - 1 \) and for \( j \). The left hand side increases by exactly \((\rho_j - \rho_{j-1}) |W_{(j)}|\), whereas the right hand side increases by exactly \( \frac{s}{s-\mu} (\rho_j - \rho_{j-1}) |W_{(j)}^-\mu| \). Thus, it suffices to show that \( |W_{(j)}| \leq \frac{s}{s-\mu} |W_{(j)}^-\mu| \).

**Claim 4.A.2.** For every incomplete job \( j \), \( |W_{(j)}| \leq \frac{s}{s-\mu} |W_{(j)}^-\mu| \)

**Proof.** Consider a sequence of incomplete jobs \( 1, 2, \ldots, j \). Without loss of generality, we relabel the jobs such that \( a_1 \leq a_2 \leq \cdots \leq a_j \). We prove the claim by induction over \( j \). The base \( j = 1 \) holds trivially, since by the definition of \( \tau_j \) we have: \( d_j - a_j = \frac{s}{s-\mu} \cdot (\tau_j - a_j) \). Assume correctness for \( j - 1 \) and observe job \( j \). Define \( j^* = \arg \max_{j'<j}\{d_{j'}\} \). By the relabeling, we have \( a_{j^*} \leq a_j \). Notice that by including \([a_j, d_j]\) in \( W_{(j-1)} \), we increase its total length by \( \max\{0, d_j - d_{j^*}\} \). Similarly, including \([a_j, \tau_j]\) in \( W_{(j-1)} \) increases its total length by at most \( \max\{0, \tau_j - \tau_{j^*}\} \). If \( d_j \leq d_{j^*} \), then the claim holds since \( |W_{(j)}| = |W_{(j-1)}| \) and the inductive assumption applies. Assume \( d_j > d_{j^*} \). This implies that \( \tau_j > \tau_{j^*} \). Therefore, we must show that: \( d_j - d_{j^*} \leq \frac{s}{s-\mu} \cdot (\tau_j - \tau_{j^*}) \). This holds, since:

\[
\frac{s}{s-\mu} \cdot (\tau_j - \tau_{j^*}) = \frac{s}{s-\mu} \cdot \left( a_j + \frac{s-\mu}{s} \cdot (d_j - a_j) \right) + \frac{s}{s-\mu} \cdot \left( a_{j^*} + \frac{s-\mu}{s} \cdot (d_{j^*} - a_{j^*}) \right) = \frac{\mu}{s-\mu} \cdot (a_j - a_{j^*}) + d_j - d_{j^*} \geq d_j - d_{j^*}
\]

concluding the claim. ■

**4.B Appendix B: Non-Truthfulness of Section 4.3**

We prove that the scheduling algorithm \( A \) developed in Section 4.3 does not satisfy monotonicity, and therefore cannot implement a truthful mechanism. Assume the system consists of a single server. Consider four job types: \( A, B, C \) and \( D \). Assume \( \rho_A = 1, \rho_B = 2, \rho_C = 2 \) and \( \rho_D = \infty \). Specifically, type \( B \) jobs cannot preempt type \( A \) jobs; type \( C \) jobs cannot preempt type \( B \) jobs; however, type \( C \) jobs can preempt type \( A \) jobs. We use type \( D \) jobs to maintain the server busy when needed. Our input consists of one type \( A \) job (which we simply refer to as \( A \)), one type \( B \) job (referred as \( B \)) and \( s \) type \( C \) jobs. We construct an instance such that \( A \) is not completed due to type \( C \) jobs. However, by decreasing the value of \( A \), job \( B \) blocks the type \( C \) jobs from running. This allows \( A \) to complete.

Set \( D_A = 2\mu \) and \( d_A = s + \mu \). Set \( a_B = 0.5\mu \) and \( D_B = s - 0.5\mu \). Finally, set \( a_C = \mu \), \( d_C = s + \mu \) and \( D_C = 1 \). Assume all other parameters are set such every job \( j \) satisfies
\( v_j = \rho_j D_j \) and \( d_j - a_j = s D_j \). Type \( D \) jobs are set such that the server is busy until time \( t = 0 \). We describe two executions of \( A \).

**Case 1 - \( \rho_A = 1 \).**

- \( t < 0 \) The algorithm processes type \( D \) jobs.
- \( t = 0 \) The algorithm begins to process \( A \).
- \( t = 0.5 \mu \) Job \( B \) arrives. The algorithm decides not to preempt \( A \).
- \( t = \mu \) All type \( C \) jobs arrive. Job \( A \) is preempted.
  - The algorithm processes \( s \) type \( C \) jobs until time \( t = s + \mu \).
- \( t = s + \mu \) The type \( C \) jobs are all processed, but \( A \) is not completed by its deadline.

**Case 2 - \( \rho_A < 1 \).**

- \( t < 0 \) The algorithm processes type \( D \) jobs.
- \( t = 0 \) The algorithm begins to process \( A \).
- \( t = 0.5 \mu \) Job \( B \) arrives. The algorithm preempts \( A \) and begins to process \( B \).
- \( t = \mu \) All type \( C \) jobs arrive. Job \( B \) is not preempted.
- \( t = s \) The algorithm completes \( B \). The type \( C \) were not allocated by \( d_C - \mu D_C = s \).
  - Hence, all type \( C \) jobs are rejected. The algorithm resumes processing \( A \).
- \( t = s + \mu \) The algorithm completes \( A \) by its deadline.

Therefore, \( A \) is not monotone.
Chapter 5

Online Scheduling with Commitments

The preemptive allocation model studied in Chapter 4 does not require the scheduler to guarantee the completion of jobs. Namely, the schedulers are allowed to accept a job, process it, but not necessarily complete it. While in terms of pure optimization this behavior may be justified, in many real-life scenarios it is not acceptable, since users might be left empty-handed right before their deadline. In reality, users with business-critical jobs require an indication, well before their deadline, of whether their jobs can be timely completed. Since sustaining deadlines is becoming a key requirement for modern computation clusters (e.g., [23] and references therein), it is essential that schedulers provide some degree of commitment.

The question is, at what point of time should the scheduler commit? One option is to require the scheduler to commit to jobs upon arrival. Namely, once a job arrives, the scheduler immediately decides whether it accepts the job (and then it is required to complete it) or rejects the job. Such a scheduler exists when all value-densities are identical [24, 30], and it obtains a competitive ratio of $1 + \frac{1}{s-1}$. However, it is simple to prove that for general value-densities no such scheduler can provide any performance guarantees, even when assuming deadline slackness; see Section 5.1. Therefore, a more plausible alternative from the user perspective is to allow the committed scheduler to delay the decision, but only up to some predetermined point.

**Definition 5.0.1.** A scheduling mechanism is called $\beta$-responsive (for $\beta \geq 0$) if, for every job $j$, by time $d_j - \beta \cdot D_j$ it either (a) rejects the job, or (b) guarantees that the job will be completed by its deadline and specifies the required payment.

Note that $\beta$-responsiveness requires deadline slackness $s \geq \beta$ for feasibility. Schedulers that
do not provide advance commitment are by default 0-responsive; we often refer to them as being non-committed. Useful levels of commitments are typically obtained when $\beta \geq 1$, as this provides rejected users an opportunity to execute their job elsewhere and complete before their deadline. One might consider different definitions for responsiveness in online scheduling. In a sense, the definition given here is additive: for each job $j$, the mechanism must make its decision $\beta D_j$ time units before the deadline. An alternative definition could be fractional: the decision must be made before some fraction of job execution window, e.g., $d_j - \omega(d_j - a_j)$ for some $\omega \in (0, 1)$. It turns out that many of our results also satisfy responsiveness under this alternative definition, as well as other useful properties. We discuss this further at the end of the chapter.

The $\beta$-responsive property is also useful when designing truthfulness online scheduling mechanisms. In general, truthful mechanisms charge each scheduled job $j$ a payment $p_j$ equal to the minimal reported value that would have guaranteed the completion of $j$ (see Section 2.2 for details). However, calculating the payment $p_j$ in online settings might not be possible until the job deadline, since jobs that arrive beforehand might affect the calculation. A $\beta$-responsive mechanisms can compute payments upon decision, i.e., at time $d_j - \beta D_j$. The ability to specify payments in advance is significant for real-time scheduling mechanisms.

In this chapter, we continue to investigate the scheduling model described in Chapter 4. Our main result can be abstracted as follows.

**Main Theorem (informal):** For every $\beta \geq 0$, given sufficiently large slackness $s \geq s(\beta)$, there is a truthful, $\beta$-responsive, $O(1)$-competitive mechanism for online deadline scheduling on $C$ identical servers.

The precise competitive ratios achieved by our mechanism depends on the level of input slackness, the number of servers (single server vs. multiple servers), and the desired level of truthfulness. We establish the main result in two steps. First, we develop a reduction from the problem of scheduling with responsive commitment to the problem of scheduling without commitment, as studied in the previous chapter. This solves the algorithmic aspect. Ideally, we could apply the reduction on the truthful non-committed mechanism (Section 4.4) to obtain a truthful committed mechanism. In fact, the reduction preserves truthfulness with respect to all parameters except arrival time. We can therefore immediately obtain, for all $s > 4$, a scheduling algorithm for a single server that is $(s/2)$-responsive and truthful, given that agent arrivals are not manipulated. To yield our most general result, we explicitly

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1Specifically, all of the results except those in Section 5.3.2.

2Such as the no-early-processing property: the scheduler cannot begin to process a job without committing first to its completion. This implies that any job that begins processing is guaranteed to complete.
construct a scheduling mechanism that obtains full truthfulness based on the truthful non-committed scheduler and a general reduction from committed scheduling to non-committed scheduling. The construction is rather technical and significantly increases the competitive ratio.

Finally, we note that [4] presented a lower bound for \( \beta \)-responsive mechanisms that satisfy no early processing, i.e., that are forbidden to process a job before committing to its completion. They show that no such scheduler can guarantee a constant competitive ratio when \( s < 4/C \). This result reveals a very interesting behavior for the single server case, as the committed scheduler presented here obtains a constant competitive ratio for \( s > 4 \).

**Related Work.** Committed schedulers have been constructed for the special case of busy-time maximization (corresponds to unit value-densities) by [24, 30]. Our work generalizes their results by considering general values and demands.

### 5.1 Impossibility Result for Commitment upon Arrival

The strict requirement of making the scheduling decision upon arrival leads to the following negative result.

**Theorem 5.1.1.** Any online algorithm that commits to jobs on arrival has an unbounded competitive ratio for any slackness parameter \( s \).

**Proof.** We show this for deterministic online algorithms on a single server. To do so, consider an adversary controlling the flow of all input jobs and let \( x \) be a parameter. All of the jobs in our example have the same size \( D_j = 1 \), arrival time \( a_j = 0 \) (differing by some arbitrary small deviation) and deadline \( d_j = s \). We submit \( s + 1 \) jobs \( 1, 2, \ldots, s + 1 \) one at a time, each with value \( v_j = x \cdot \sum_{k=1}^{j-1} v_k \). If the scheduling algorithm rejects some job \( j \leq s \), the adversary halts and does not submit jobs \( j + 1, \ldots, s + 1 \). Notice that in this case the competitive ratio is at least \( x \), since the value of \( v_j \) is \( x \) times larger than the total value of all proceeding jobs, thus an optimal offline solution could have at least gained \( v_j \). If the algorithm committed to the first \( s \) jobs, it cannot complete job \( s + 1 \) due to capacity limitations. Thus, the competitive ratio is at least \( x \), for every \( x \). These arguments can easily be extended to cover randomized scheduling algorithms. Set \( v_j = 2x \cdot \sum_{k=1}^{j-1} v_k \). If the algorithm takes a job with a probability lower than \( 1/2x \), the adversary will halt. By taking \( 2sx + 1 \) jobs, we can obtain the same result for randomized scheduling algorithms. \( \blacksquare \)
5.2 Reductions for $\beta$-Responsive Committed Scheduling

In this section we develop the first committed (i.e., responsive) scheduler for online scheduling with general job types, assuming deadline slackness. Our solution is based on a novel reduction of the problem to the “familiar territory” of non-committed scheduling. We introduce a parameter $\omega \in (0,1)$ that affects the time by which the scheduler commits. Specifically, the scheduler we propose decides whether to admit jobs during the first $(1-\omega)$-fraction of their availability window, i.e., by time $d_j - \omega(d_j - a_j)$ for each job $j$. The deadline slackness assumption ($d_j - a_j \geq sD_j$) then implies that our scheduler is $(\omega s)$-responsive.

We start with the single server case (Section 5.2.1), where we highlight the main mechanism design principles. We then extend our solution to accommodate multiple servers, which requires some subtle changes in our proof methodology (Section 5.2.2).

5.2.1 Reduction for a Single Server

Our reduction consists of two key components: (1) simulator: a virtual server used to simulate an execution of a non-committed algorithm $\mathcal{A}$; and (2) server: the real server used to process jobs. The speeds of the simulator and server are the same. We emphasize that the simulator does not utilize actual job resources. It is only used to determine which jobs to admit. We use the simulator to simulate an execution of the non-committed algorithm. Upon arrival of a new job, we submit the job to the simulator with a virtual type, defined below. If a job is completed on the simulator, then the committed scheduler admits it to the system and processes it on the server (physical machine). We argue later that the overall value gained by the algorithm is relatively high, compared to the value guaranteed by $\mathcal{A}$.

We pause briefly to highlight the challenges in such simulation-based approach. The underlying idea is to admit and process jobs on the server only after they are “virtually” completed by $\mathcal{A}$ on the simulator. If the simulator completes all jobs near their actual deadlines, the scheduler might not be able to meet its commitments. This motivates us to restrict the latest time in which a job can be admitted. The challenge is to guarantee that all admitted jobs are completed, while still guaranteeing relatively high value.

We now provide more details on how the simulator and server are handled by the committed scheduler throughout execution.

**Simulator.** The simulator runs an online non-committed scheduling algorithm $\mathcal{A}$. Every arriving job $j$ is automatically sent to the simulator with a virtual type $r_j^{(v)} = \langle v_j, D_j^{(v)}, a_j, d_j^{(v)} \rangle$, where $d_j^{(v)} = d_j - \omega(d_j - a_j)$ is the virtual deadline of $j$, and $D_j^{(v)} = D_j / \omega$ is the virtual demand of $j$. If $\mathcal{A}$ completes the virtual request of job $j$ by its virtual deadline, then $j$ is
admitted and sent to the server.

**Server.** The server receives admitted jobs once they have been completed by the simulator, and processes them according to the Earliest Deadline First (EDF) allocation rule. That is, at any time $t$ the server processes the job with the earliest deadline out of all admitted jobs that have not been completed.

The reduction effectively splits the availability window to two subintervals. The first $(1 - \omega)$ fraction is the first subinterval and the remainder is the second. The virtual deadline $d_j^{(v)}$ serves as the breakpoint between the two intervals. During the first subinterval, the algorithm uses the simulator to decide whether to admit $j$ or not. Then, at time $d_j^{(v)}$, it communicates the decision to the job. In practical settings, this may allow a rejected job to seek other processing alternatives during the remainder of the time. Furthermore, if $j$ is admitted, the scheduler is left with at least $\omega (d_j - a_j)$ time to process the job on the server.

The virtual demand of each job $j$ is increased to $D_j / \omega$. We use this in our analysis to guarantee that the server meets the deadlines of admitted jobs. Note that we must require $D_j / \omega \leq (1 - \omega) s D_j$, otherwise $j$ could not be completed on the simulator. By rearranging terms, we get a constraint on the values of $s$ for which our algorithm is feasible: $s \geq \frac{1}{\omega (1 - \omega)}$.

### 5.2.1.1 Correctness

We now prove that when the reduction is applied, each accepted job is guaranteed to finish by its deadline. Note that the simulator can complete a job before its virtual deadline, hence it may be admitted earlier. However, in the analysis below, we assume without loss of generality that jobs are admitted at their virtual deadline. Accordingly, We define the admitted type of job $j$ as $	au_j^{(a)} = \langle v_j, D_j, d_j^{(v)}, d_j \rangle$.

Recall that $\mathcal{A}_C(\tau)$ represents the jobs completed by the committed algorithm. Equivalently, these are the jobs completed by the non-committed algorithm $\mathcal{A}$ on the simulator. To prove that $\mathcal{A}_C$ can meet its guarantees, we must show that the EDF rule deployed by the server completes all jobs in $\mathcal{A}_C(\tau)$, when submitted with their admitted types. It is well known that for every set of jobs $S$, if $S$ can be feasibly allocated on a single server (i.e., before their deadline), then EDF produces a feasible schedule of $S$. Hence, it suffices to prove that there exists a feasible schedule of $\mathcal{A}_C(\tau)$. We prove the following general claim, which implies the correctness of our algorithm.

**Theorem 5.2.1.** Let $S$ be a set of jobs. For each job $j \in S$, define the virtual deadline of $j$ as $d_j^{(v)} = d_j - \omega (d_j - a_j)$. If there exists a feasible schedule of $S$ on a single server with respect to the virtual types $\tau_j^{(v)} = \langle v_j, D_j / \omega, a_j, d_j^{(v)} \rangle$ for each $j \in S$, then there exists a feasible
schedule of \( S \) on a single server with respect to the admitted types \( \tau_j^{(a)} = (v_j, D_j, d_j^{(v)}, d_j) \) for each \( j \in S \).

Proof. We describe an allocation algorithm that generates a feasible schedule of \( S \) with respect to admitted types. That is, the algorithm produces a schedule where each job \( j \in S \) is processed for \( D_j \) time units inside the time interval \([d_j^{(v)}, d_j]\). The algorithm we describe allocates jobs in decreasing order of their virtual deadlines. For two jobs \( j, j' \in S \), we write \( j' \succ j \) when \( d_j^{(v)} > d_{j'}^{(v)} \). In each iteration, the algorithm considers some job \( j \in S \) by the order induced by \( \succ \), breaking ties arbitrarily. We say that time \( t \) is used when considering \( j \) if the algorithm has allocated some job \( j' \) at time \( t \); otherwise, we say that \( t \) is free. We denote by \( U_j \) and \( F_j \) the set of used and free times when the algorithm considers \( j \), respectively. The algorithm works as follows. Consider an initially empty schedule. We iterate over jobs in \( S \) in decreasing order of their virtual deadlines, breaking ties arbitrarily; this order is induced by \( \succ \). Each job \( j \) in this order is allocated during the latest possible \( D_j \) free time units. Formally, define \( t'_R = \arg \max \{ t : [t, \ell_R] \cap U_j = \emptyset \} \) as the latest time such that there are exactly \( D_j \) free time units during \([t'_R, d_j] \). The algorithm allocates \( j \) during those free \( D_j \) time units \([t'_R, d_j] \cap F_j \).

We now prove that the algorithm returns a feasible schedule of \( S \), with respect to the admitted job types. It is enough to show that when a job \( j \in S \) is considered by the algorithm, there is enough free time to process it; namely, there should be at least \( D_j \) free time units during \([d_j^{(v)}, d_j]\). Consider the point where the algorithm allocates a job \( j \in S \). Define \( \ell_R = \max \{ \ell : [d_j, d_j + \ell] \subseteq U_j \} \) and denote \( t_R = d_j + \ell_R \). By definition, the time interval \([d_j, t_R]\) is the longest continuous block that starts at \( d_j \) in which all times \( t \in [d_j, t_R] \) are used. Define \( t_L = a_j - \ell_R \cdot (1 - \omega)/\omega \). We claim that any job \( j' \succ j \) allocated in the interval \([d_j^{(v)}, t_R]\) must satisfy \([a_{j'}, d_{j'}] \subseteq [t_L, t_R]\). Assume the claim holds. We show how the claim leads to the theorem. Denote by \( J_{LR} \) all jobs \( j' \succ j \) that have been allocated sometime during the interval \([d_j^{(v)}, t_R]\). Obviously, we also have \([a_j, d_j] \subseteq [t_L, t_R]\). Now, since we know...
there exists a feasible schedule of $S$ with respect to the virtual types, we can conclude that the total virtual demand of jobs in $J_{LR} \cup \{j\}$ is at most $t_R - t_L$, since the interval $[t_L, t_R]$ contains the availability windows of all these jobs. Notice that $t_R - t_L = (t_R - d_j^{(v)})/\omega$. Since the virtual demand is $1/\omega$ times larger than the admitted demand, we can conclude that the total amount of used time slots during $[d_j^{(v)}, t_R]$ is at most $(t_R - d_j^{(v)}) - D_j$. Thus, there have to be $D_j$ free time units during $[d_j^{(v)}, t_R]$ since $[d_j, t_R]$ is completely full. It remains to prove the claim. Let $j' \in J_{LR}$. Notice that $d_{j'} \leq t_R$; otherwise, the allocation algorithm could have allocated $j'$ after time $t_R$, and since we assume $j'$ has been allocated sometime between $[d_j^{(v)}, d_j]$, this would contradict the definition of $t_R$. Also, $j' \succ j$ means $d_{j'} \geq d_j^{(v)}$.

Therefore:

$$a_{j'} = \frac{1}{\omega} \cdot d_{j'} - \frac{1-\omega}{\omega} \cdot d_j' \geq \frac{1}{\omega} \cdot d_j^{(v)} - \frac{1-\omega}{\omega} \cdot t_R$$

$$= \frac{1}{\omega} \cdot d_j - (d_j - a_j) - \frac{1-\omega}{\omega} \cdot (d_j + \ell_R) = a_j - \frac{1-\omega}{\omega} \cdot \ell_R = t_L$$

which completes the proof.

\[ \square \]

\section{Competitive Ratio}

We now analyze the competitive ratio obtained via the single server reduction. The competitive ratio is bounded using dual fitting arguments. Specifically, for every instance $\tau$ with slackness $s = s(\tau)$, we construct a feasible dual solution $(\alpha, \beta)$ with dual cost proportional to $v(A_C(\tau))$, the total value gained by $A_C$ on $\tau$. Recall the dual constraints (2.8) corresponding to types $\tau_j = \langle v_j, D_j, a_j, d_j \rangle$. For the single server case, we make two simplifications. First, we denote $\beta(t) = \beta_1(t)$ to simplify notation. Second, we assume that $\pi = 0$ without loss of generality\(^3\). The dual constraints corresponding to $\tau$ reduce to:

$$\alpha_j + \beta(t) \geq \rho_j \quad \forall j \in J, \ t \in [a_j, d_j]. \quad (5.1)$$

Our goal is to construct a dual solution which satisfies (5.1) and has a dual cost of at most $r \cdot v(A_C(\tau))$ for some $r$. Note that $v(A_C(\tau)) = v(A(\tau^{(v)}))$. To do so, we transform a dual solution corresponding to virtual types $\tau^{(v)}$ to a dual solution satisfying (5.1). The dual constraints corresponding to the virtual types are:

$$\alpha_j + \beta(t) \geq \omega \rho_j \quad \forall j \in J, \ t \in [a_j, d_j^{(v)}] \quad (5.2)$$

\(^3\)This assumption is valid due to the redundancy of the primal constraints corresponding to $\pi$ for a single server.
Assume that the non-committed algorithm $A$ induces an upper bound on $\text{IG}(s^{(v)})$, where $s^{(v)} = s \cdot \omega(1 - \omega)$ is the slackness of the virtual types $\tau^{(v)}$. This implies that the optimal dual solution $(\alpha^*, \beta^*)$ satisfying (5.2) has a dual cost of at most $\text{cr}_A(s^{(v)}) \cdot v(A(\tau^{(v)})) = \text{cr}_A(s^{(v)}) \cdot \omega(A_C(\tau))$. Yet, $(\alpha^*, \beta^*)$ satisfies (5.2), while we require a solution that satisfies (5.1). To construct a feasible dual solution corresponding to the original job types $\tau$, we perform two transformations on $(\alpha^*, \beta^*)$ called stretching and resizing.

**Lemma 5.2.2** (Resizing Lemma). Let $(\alpha, \beta)$ be a feasible solution for the dual program corresponding to a type profile $\tau_j = \langle v_j, D_j, a_j, d_j \rangle$. There exists a feasible solution $(\alpha', \beta')$ for the dual program with demands $D'_j = f \cdot D_j$ for some $f > 0$, with a dual cost of:

$$
\sum_{j \in J} D'_j \alpha'_j + \int_0^\infty \beta'(t)dt = \sum_{j \in J} D_j \alpha_j + \frac{1}{f} \int_0^\infty \beta(t)dt.
$$

**Proof.** Notice that the value density corresponding to $D'_j = f \cdot D_j$ is $\rho'_j = \rho_j / f$. Hence, by setting $\alpha'_j = \alpha_j / f$ for every job $j \in J$ and $\beta(t) = \beta(t) / f$ for every time $t$, we obtain a feasible dual solution corresponding to resized demands $D'_j$. The dual cost is as stated since $D'_j \alpha'_j = D_j \alpha_j$ for every job $j$.

**Lemma 5.2.3** (Stretching Lemma; reformulated). Let $(\alpha, \beta)$ be a feasible solution for the dual program corresponding to a type profile $\tau_j = \langle v_j, D_j, a_j, d_j \rangle$. There exists a feasible solution $(\alpha', \beta')$ for the dual program with deadlines $d'_j = d_j + f \cdot (d_j - a_j)$ for some $f$, with a dual cost of:

$$
\sum_{j \in J} D_j \alpha'_j + \int_0^\infty \beta'(t)dt = \sum_{j \in J} D_j \alpha_j + (1 + f) \int_0^\infty \beta(t)dt.
$$

The stretching lemma has been proven in Chapter 4. These two lemmas allow us to bound the competitive ratio of $A_C$.

**Theorem 5.2.4.** Let $A$ be a single server scheduling algorithm that induces an upper bound on the integrality gap $\text{IG}(s^{(v)})$ for $s^{(v)} = s \cdot \omega(1 - \omega)$ and $\omega \in (0, 1)$. Let $A_C$ be the committed algorithm obtained by the single server reduction. Then $A_C$ is $\omega s$-responsive and

$$
\text{cr}_{A_C}(s) \leq \frac{\text{cr}_A\left(s \cdot \omega(1 - \omega)\right)}{\omega(1 - \omega)}, \quad s > \frac{1}{\omega(1 - \omega)}.
$$

**Proof.** We first prove that the scheduler is $\omega s$-responsive. Note that each job $j$ is either committed or rejected by its virtual deadline $d_j^{(v)} = d_j - \omega(d_j - a_j)$. The deadline slackness
assumption states that $d_j - a_j \geq s D_j$ for every job $j$. Hence, each job is notified by time $d_j - \omega s D_j$, as required.

We now bound the competitive ratio. Consider an input instance $\tau$ and denote its slackness by $s = s(\tau)$. Let $\tau^{(v)}$ denote the virtual types corresponding to $\tau$, and let $s^{(v)} = s \cdot \omega (1 - \omega)$ denote their slackness. We prove the theorem by constructing a feasible dual solution $(\alpha, \beta)$ satisfying (5.1) and bounding its total cost. By the assumption on $A$, the optimal fractional solution $(\alpha^*, \beta^*)$ corresponding to $\tau^{(v)}$ has a dual cost of at most $cr_A(s^{(v)}) \cdot v(A(\tau^{(v)})) = cr_A(s^{(v)}) \cdot v(A_C(\tau))$. We transform $(\alpha^*, \beta^*)$ into a feasible solution $(\alpha, \beta)$ corresponding to $\tau$ by applying the resizing lemma and the stretching lemma, as follows.

- We first apply the resizing lemma for $f = \frac{1}{\omega}$ to cover the increased job demands during simulation. The dual cost increases by a multiplicative factor of $\frac{1}{\omega}$.
- We then apply the stretching lemma to cover the remaining constraints; that is, the times in the jobs’ execution windows not covered by the execution windows of the virtual types. We choose $f$ such that $d_j = d_j^{(v)} + f \cdot (d_j^{(v)} - a_j)$; hence, $f = \frac{\omega}{1 - \omega}$. As a result, the competitive ratio is multiplied by an additional factor of $1 + f = \frac{1}{1 - \omega}$.

After applying both lemmas, we obtain a feasible dual solution that satisfies the dual constraints (5.1). The dual cost of the solution is at most $\frac{1}{\omega (1 - \omega)} \cdot cr_A(s \cdot \omega (1 - \omega)) \cdot v(A_C(\tau))$. The theorem follows through the correctness of the dual fitting technique, Theorem 2.1.2.

5.2.2 Reductions for Multiple Servers

We extend our single server reduction to incorporate multiple servers. We distinguish between two cases based on the following definition.

**Definition 5.2.5.** A scheduler is called *non-migratory* if it does not allow preempted jobs to resume their execution on different servers. Specifically, a job is allocated at most one server throughout its execution.

Constant-competitive non-migratory schedulers are known to exist in the presence of deadline slackness [51]. Given such a scheduler, we can easily construct a committed algorithm for multiple servers by extending the single server reduction. We prove that our extension preserves the guaranteed competitive ratio. This allows us to obtain efficient schedulers for committed scheduling; see Section 5.4 for details. However, this solution cannot be used to design a committed scheduler which is truthful, since it requires that the non-committed scheduler is both truthful and non-migratory; unfortunately, we are not aware of such schedulers.
Therefore, we construct below a second reduction, which does not require a non-migratory non-committed scheduler. This is essential for Section 5.3, where we design a truthful committed scheduler. We note that the first reduction leads to better competitive-ratio guarantees, hence should be preferred in domains where users are not strategic.

5.2.2.1 Non-Migratory Case

In the following, let \( \mathcal{A} \) be a non-committed scheduler for multiple servers which does not allow job migration. We extend our single server reduction to obtain a committed scheduler \( \mathcal{A}_C \) for multiple servers. The reduction remains essentially the same: the simulator runs the non-committed scheduler on a system with \( C \) virtual servers. When a job is completed on virtual server \( i \), it is admitted and processed on server \( i \). Each server runs the EDF rule on the jobs admitted to it. To prove correctness (i.e., the scheduler meets all commitments), we simply apply Theorem 5.2.1 on each server independently. The bound on the competitive ratio obtained in Theorem 5.2.4 can be extended directly to the non-migratory model.

**Corollary 5.2.6.** Let \( \mathcal{A} \) be a multiple server, non-migratory scheduling algorithm that induces an upper bound on the integrality gap \( IG(s^{(v)}) \) for \( s^{(v)} = s \cdot \omega (1 - \omega) \) and \( \omega \in (0, 1) \). Let \( \mathcal{A}_C \) be the committed algorithm obtained by the multiple server reduction for non-migratory schedulers. Then \( \mathcal{A}_C \) is \( \omega s \)-responsive and

\[
\text{cr}_{\mathcal{A}_C}(s) \leq \frac{\text{cr}_{\mathcal{A}}(s \cdot \omega (1 - \omega))}{\omega (1 - \omega)}, \quad s > \frac{1}{\omega (1 - \omega)}.
\]

We note that an improved bound can be obtained by applying the reduction on the specific non-migratory multiple-server algorithm of [51]; see Section 5.4 for details.

5.2.2.2 Migratory Case

We now assume that \( \mathcal{A} \) allows migrations. Unfortunately, the reduction proposed for the non-migratory case does not work here. We explain why: consider some job \( j \) that is admitted after being completed on the simulator; note that \( j \) may have been processed on more than one virtual server. Our goal is to process \( j \) by time \( d_j \). Assume each server runs the EDF rule on the jobs assigned to it, as suggested in Section 5.2.2.1. Since \( j \) has been processed on more than one virtual server, it is unclear how to assign \( j \) to a server in a way that guarantees the completion of all admitted jobs. One might suggest to assign each server \( i \) the portion of \( j \) that was processed on virtual server \( i \). However, this does not necessarily generate a legal schedule. If each server runs EDF independently, a job might be allocated simultaneously on more than one server.
We propose the following modification. Instead of running the EDF rule on each server independently, we run a global EDF rule. That is, at each time $t$ the system processes the (at most) $C$ admitted jobs with earliest deadlines. This is known as the EDF rule for multiple servers (also known as f-EDF [29]). It is well known that the EDF rule is not optimal on multiple servers; formally, for a set $\mathcal{S}$ of jobs that can be feasibly scheduled on $C$ servers with migration, EDF does not necessarily produce a feasible schedule on input $\mathcal{S}$ [39]. Nevertheless, it is known that EDF produces a feasible schedule of $\mathcal{S}$ when the servers are twice as fast [56]. Server speedup is directly linked with demand inflation. Formally, when processing $\mathcal{S}$ on $C$ servers, processing demands $D_j$ on servers with $\alpha$-speedup is equivalent to processing demands $\alpha D_j$ on servers with 1-speedup. Thus, we suggest a second adjustment. We modify the virtual demand of each job submitted to the simulator. That is, the virtual demand of each job $j$ is increased to $2(3 + 2\sqrt{2}) \cdot D_j/\omega$. The additional factor of $3 + 2\sqrt{2} \approx 5.828$ is necessary for correctness, which is established in the following theorem.

**Theorem 5.2.7.** Let $\mathcal{A}$ be a multiple server scheduling algorithm that induces an upper bound on the integrality gap $\text{IG}(s^{(v)})$ for $s^{(v)} = s \cdot \omega(1 - \omega)$ and $\omega \in (0, 1)$. Let $\mathcal{A}_C$ be the committed algorithm $\mathcal{A}_C$ obtained by the multiple server reduction. Then $\mathcal{A}_C$ is $\omega s$-responsive and

$$\text{cr}_{\mathcal{A}_C}(s) \leq \frac{11.656}{\omega(1 - \omega)} \cdot \text{cr}_{\mathcal{A}} \left( s \cdot \frac{\omega(1 - \omega)}{11.656} \right), \quad s > \frac{11.656}{\omega(1 - \omega)}.$$

**Proof.** Let $\mathcal{S}$ denote the set of jobs admitted by the committed algorithm $\mathcal{A}_C$ on an instance $\tau$. To prove correctness, we must show that there exists a feasible schedule in which each job $j \in \mathcal{S}$ is allocated $2D_j$ demand during $[d_j^{(v)}, d_j]$. If so, then [56] implies that EDF completes all admitted jobs by their deadline. This follows since:

1. There exists a feasible schedule of $\mathcal{S}$ with types $\langle v_j, \frac{11.656}{\omega} \cdot D_j, a_j, d_j^{(v)} \rangle$ on $C$ servers with migration. This is the schedule produced by the non-committed algorithm $\mathcal{A}$.

2. Cham et al. [20] proved that any set $\mathcal{S}$ of jobs that can be scheduled with migration on $C$ servers can also be scheduled without migration on $C$ servers with 5.828-speedup. As a result, there exists a feasible non-migratory schedule of $\mathcal{S}$ on $C$ servers with types $\langle v_j, \frac{2}{\omega} \cdot D_j, a_j, d_j^{(v)} \rangle$.

3. By applying Theorem 5.2.1 on each server separately, we obtain a feasible non-migratory schedule of $\mathcal{S}$ with types $\langle v_j, 2D_j, d_j^{(v)}, d_j \rangle$ on $C$ servers, as desired.

4. Therefore, EDF produces a feasible schedule of $\mathcal{S}$ with types $\langle v_j, D_j, d_j^{(v)}, d_j \rangle$. 

82
We note that step 4 (i.e., using EDF) is necessary. Even though Step 3 establishes that a feasible schedule of \( S \) exists, it cannot necessarily be generated online, unlike EDF. The competitive ratio can be bounded by following the same steps as in the single server case (Theorem 5.2.4), however the resizing lemma must be applied with \( f = 11.656\omega \). Finally, note that the slackness \( s \) must satisfy \( s(1 - \omega) \geq 11.656/\omega \), otherwise jobs could not be completed on the simulator.

We use this migratory reduction in Section 5.3 to design a truthful committed scheduler for multiple servers.

### 5.3 Truthful \( \beta \)-Responsive Committed Scheduling

In this section we construct a scheduling mechanism that is both truthful and committed. As it turns out, the reductions presented in the previous section preserve monotonicity with respect to values, deadlines, and demands, but not necessarily with respect to arrival times. Therefore, by plugging in an existing truthful non-committed scheduler (Section 5.2), we can obtain a committed mechanism that is truthful assuming all arrival times not manipulated. Later, we construct an explicit mechanism which is both truthful and committed, however obtains a higher competitive ratio.

#### 5.3.1 Public Arrival Times

In this subsection, we consider the case where job arrival times are common knowledge, i.e., users cannot misreport the arrival times of their jobs. To construct the partially truthful mechanism, we apply one of the reductions from committed scheduling to non-committed scheduling (Section 5.2) on a truthful non-committed mechanism, which we denote by \( \mathcal{A}_T \). We denote by \( \mathcal{A}_{\tilde{T}C} \) the resulting mechanism. In the following, we prove that \( \mathcal{A}_{\tilde{T}C} \) is almost truthful: it is monotone with respect to values, deadlines, and demands, but not with respect to arrival times.

**Claim 5.3.1.** Let \( \mathcal{A}_T \) be a truthful scheduling algorithm, and let \( \mathcal{A}_{\tilde{T}C} \) be a committed mechanism obtained by applying one of the reductions from committed scheduling to non-committed scheduling (assume all required preconditions apply). Then, \( \mathcal{A}_{\tilde{T}C} \) is monotone with respect to values, demands and deadlines.

**Proof.** Recall that upon an arrival of a new job \( j \), the job is submitted to \( \mathcal{A}_T \) with a virtual type of \( \tau_j^{(v)} = \langle v_j, \alpha D_j, a_j, d_j^{(v)} \rangle \) for some constant \( \alpha \geq 1 \) (the constant differs between the reductions for a single server and for multiple servers). Also recall that \( d_j^{(v)} = d_j - \omega(d_j - a_j) \) is the virtual deadline of job \( j \), which is a monotone function of \( d_j \). Moreover, \( \mathcal{A}_{\tilde{T}C} \) then
completes job \( j \) on input \( \tau \) precisely if \( A_T \) completes job \( j \) on input \( \tau^{(v)} \). But since \( A_T \) is monotone, and since \( v_j, \alpha D_j, \) and \( d_j^{(v)} \) are appropriately monotone functions of \( v_j, D_j, \) and \( d_j \) (respectively), it follows that \( A_{TC} \) is monotone with respect to \( v_j, D_j, \) and \( d_j \).

Hence, the reductions from committed to non-committed scheduling (Theorems 5.2.4 and 5.2.7) can be extended to guarantee truthfulness (public arrival times), as long as the given (non-committed) scheduler is monotone.

Recall that the definition of \( \beta \)-responsiveness for mechanisms requires not only that allocation decisions be made sufficiently early, but also that requisite payments be calculated in a timely fashion as well. To obtain a \( \beta \)-responsive mechanism we must therefore establish that it is possible to compute payments at the time of commitment, for each job \( j \). Fortunately, because the time of commitment is independent of a job’s reported value, this is straightforward. At the time of commitment, it is possible to determine the lowest value at which the job would have been accepted (i.e., scheduled by the simulator). This critical value is the appropriate payment to guarantee truthfulness (see, e.g., [34]), so it can be offered promptly.

It is important to understand why \( A_{TC} \) may give incentive to misreport arrival times. Consider the single server case, take \( \omega = 1/2 \), and suppose there are two jobs \( \tau_1 = (v_1, D_1, a_1, d_1) = (1, 1, 0, 8) \) and \( \tau_2 = (v_2, D_2, a_2, d_2) = (10, 2, 0, 100) \). In this instance, job 1 would not be accepted: the simulator will process job 2 throughout the interval \([0, 4]\) (recall that demands are doubled in the simulation), blocking the execution of job 1. Since time 4 is the virtual deadline of job 1 (half of its execution window), the job will be rejected at that time. However, if job 1 instead declared an arrival time of 4, then the simulator would successfully complete the job by its virtual deadline of 6, and the job would be accepted.

### 5.3.2 Full Truthfulness

In this subsection, we explicitly construct a truthful, committed scheduling mechanism. For ease of readability we will drop the parametrization with respect to \( \omega \), and simply set \( \omega = 1/2 \) in all invocations of earlier results.

Recall that our method for building responsive schedulers is to split the execution window of each job into a simulation phase and an execution phase. As discussed in the previous section, the reason \( A_{TC} \) is not truthful with respect to arrival time is that a job may benefit by influencing the time interval in which the simulation phase is executed. By declaring a later arrival, a job may shift the simulation to a later, less-congested time, increasing the likelihood that the simulator accepts the job.

Our strategy for addressing this issue is to impose additional structure on the timing of simulations. Roughly speaking, we will imagining partitioning (part of) each job’s execution
window into many sub-intervals. A simulation will be run for each subinterval, and the job will be admitted if any of these simulations are successful. Our method for selecting these simulation intervals will be monotone: reporting a smaller execution window or a larger job can only result in smaller simulation intervals. Using the truthful scheduling algorithm from Section 4.4 as a simulator will then result in an overall truthful scheduler. The competitive ratio analysis will follow by extending our dual-fitting technique to allow multiple simulations for a single job.

**Defining Simulation Intervals** Our method of choosing sub-intervals will be as follows. Choose a parameter $\sigma > 1$ to be fixed later; $\sigma$ will determine a minimal slackness constraint for our simulations. Given slackness parameter $s$ and a job $\tau_j = (v_j, D_j, a_j, d_j)$, let $k_j$ be the minimal integer such that $2^{k_j} \geq 2\sigma D_j$. The value $2^{k_j}$ will be the minimal length of a simulation window. Simulation intervals will have lengths that are powers of 2, and endpoints aligned to consecutive powers of 2.

**Definition 5.3.2.** We say an interval $[a, b]$ is aligned for job $j$ if:

1. $[a, b] \subseteq [a_j, d_j],$
2. $[b, b + (b - a)] \subseteq [a_j, d_j],$ and
3. $a = t \cdot 2^k$ and $b = (t + 1) \cdot 2^k$ for some integers $t \geq 0$ and $k \geq k_j$.

Write $C_j$ for the collection of maximal aligned intervals for job $j$, where maximality is with respect to set inclusion. For example, if $k_j = 2$ and $[a_j, d_j] = [9, 50]$, then $C_j = \{[12, 16], [16, 32], [32, 40], [40, 44]\}$. Note that $[16, 20]$ is not in $C_j$ because it is not maximal: it is contained in $[16, 32]$. Also, $[32, 48]$ is not in $C_j$ because it is not aligned for job $j$: the second condition of alignment is not satisfied, since $[48, 64] \not\subseteq [9, 50]$.

We refer to $C_j$ as the simulation intervals for job $j$; it is precisely the set of intervals on which the execution of job $j$ will be simulated. We now make a few observations about simulation intervals.

**Proposition 5.3.3.** If $\sigma \leq s/12$ then $C_j$ is non-empty.

**Proof.** We prove the contrapositive. If $C_j$ is empty, then there is no subinterval of $[a_j, d_j]$ of the form $[t \cdot 2^{k_j}, (t + 2) \cdot 2^{k_j}]$. It must therefore be that $[a_j, d_j]$ is contained in an interval of the form $(t \cdot 2^{k_j}, (t + 3) \cdot 2^{k_j})$. Thus $(d_j - a_j) < 3 \cdot 2^{k_j}$. From the definition of $k_j$, we have $2^{k_j} < 4\sigma D_j$, and hence $(d_j - a_j) < 12\sigma D_j$. Since job $j$ has slackness $s$, we conclude $\sigma > s/12$. ■
Proposition 5.3.4. If $C_j$ is non-empty then $C_j$ is a disjoint partition of an interval $I \subseteq [a_j, d_j]$, with $|I| \geq \frac{1}{4} (d_j - a_j)$.

Proof. Disjointness follows because the intervals in $C_j$ are aligned to powers of 2 and are maximal. That their union forms an interval follows from the fact that, for each $k$, the aligned intervals of length $2^k$ together form a contiguous interval. It remains to bound the length of the interval $I$.

Choose $k$ such that the maximal-length interval in $C_j$ has length $2^k$. Choose $t_1$ and $t_2$ so that $a_j \in ((t_1 - 1)2^k, t_12^k]$ and $d_j \in [t_22^k, (t_2 + 1)2^k)$. Then $(d_j - a_j) \leq (t_2 - t_1 + 2) \cdot 2^k$. Also, since $C_j$ contains an interval of length $2^k$, we must have $(t_2 - t_1) \geq 2$. Moreover, each interval $[t^2, (t+1)^2]$ with $t_1 \leq t \leq t_2 - 1$ is aligned for job $j$, and hence $|I| \geq (t_2 - t_1 - 1)2^k$. We conclude

$$|I| \geq (t_2 - t_1 - 1)2^k \geq (d_j - a_j) \cdot \frac{t_2 - t_1 - 1}{t_2 - t_1 + 2} \geq (d_j - a_j) \cdot \frac{1}{4}$$

where in the last inequality we used $(t_2 - t_1) \geq 2$. ■

Single Server We now describe our truthful committed scheduler, denoted $\mathcal{A}_{TC}$. We begin by describing the construction for the single-server case. The main idea is a straightforward extension of the simulation methodology described in Section 5.2. For each job $j$ that arrives with declared type $\tau_j = \langle v_j, D_j, a_j, d_j \rangle$, and for each subinterval $[a^{(i)}_j, b^{(i)}_j) \in C_j$, we create a new phantom job $\tau^{(i)}_j = \langle v_j, 2D_j, a^{(i)}_j, b^{(i)}_j \rangle$. We then employ the online, truthful, non-committed scheduling algorithm $\mathcal{A}_T$ from Section 4.4, using these phantom jobs as input. If a phantom job $\tau^{(i)}_j$ completes, then all subsequent phantoms for the corresponding job $j$ are removed from the input, and job $j$ is subsequently processed on the “real” server (using an EDF scheduler). That is, a job is admitted if any of its phantom jobs complete; otherwise, if none of its phantoms completes, then it is rejected. Note that since the phantom jobs have disjoint execution windows, it is known whether a given phantom completes before any subsequent phantom jobs arrive, and hence phantom jobs can be “removed” in an online fashion.

Theorem 5.3.5. Choose $\sigma > 1$ and suppose $s \geq 12\sigma$. Then the scheduler $\mathcal{A}_{TC}$ described above is $2\sigma$-responsive, truthful, and has competitive ratio bounded by

$$cr_{\mathcal{A}_{TC}}(s) \leq 8 \cdot \text{cr}_A(\sigma).$$

We prove each property of the theorem in turn. To establish responsiveness, note that the scheduler will always commit to executing a job $j$ by the end of the last interval in $C_j$. Since each aligned interval has length at most $2^{k_j}$, and since an aligned interval of
length \( \ell \) must end before time \( d_j - \ell \) (condition 2 in the definition of aligned intervals), this endpoint occurs at least \( 2^{k_j} \geq 2\sigma D_j \) time units before \( d_j \). This implies that the scheduler is \( 2\sigma \)-responsive.

We next bound the competitive ratio of the modified scheduler.

**Claim 5.3.6.** The competitive ratio of the scheduler \( \mathcal{A}_{TC} \) described above is at most

\[
\text{cr}_{\mathcal{A}_{TC}}(s) \leq 8 \cdot \text{cr}_{\mathcal{A}}(\sigma).
\]

**Proof.** Consider an input instance \( \tau \) with slackness \( s \). Let \( \tau^{(v)} \) denote the following “phantom” input instance: for each job \( j \) in \( \tau \) we include all phantom jobs up to and including the first phantom accepted by \( \mathcal{A} \), but not those that follow. Note then that running \( \mathcal{A}_{T} \) on inputs \( \tau^{(v)} \) generates the same total value as running \( \mathcal{A}_{TC} \) on input instance \( \tau \). Also note that the slackness of the phantom input instance is at least \( \sigma \).

We prove the claim by constructing a feasible dual solution \((\alpha, \beta)\) satisfying (5.1) and bounding its total cost. Let \((\alpha^*, \beta^*)\) denote the optimal fractional solution of the dual program corresponding to \( \tau^{(v)} \). We assume \( \mathcal{A} \) induces an upper bound on the integrality gap for slackness \( \sigma \). Therefore, the dual cost of \((\alpha^*, \beta^*)\) is at most \( \text{cr}_{\mathcal{A}}(\sigma) \cdot v(\mathcal{A}_{T}(\tau^{(v)})) = \text{cr}_{\mathcal{A}}(\sigma) \cdot v(\mathcal{A}_{TC}(\tau)) \).

The claim follows by applying the resizing lemma and the stretching lemma to \((\alpha^*, \beta^*)\). First, we apply the resizing lemma for \( f = 2 \), as each phantom corresponding to job \( j \) has demand at most \( 2D_j \). This increases the dual cost by a multiplicative factor of 2. Second, we apply the stretching lemma to all of the phantom jobs corresponding to job \( j \), so that their execution windows remain disjoint and contiguous, their last deadline becomes \( d_j \), and their earliest arrival time becomes \( a_j \). By Proposition 5.3.4, this involves invoking the stretching lemma with \( f = 4 \). Denote by \((\alpha', \beta')\) the resulting resized and stretched dual solution. Finally, for each job \( j \) we take \( \alpha_j \) to be the maximum of the entries of \( \alpha' \) corresponding to phantoms of \( j \), and we take \( \beta = \beta' \).

After applying both lemmas, we obtain a feasible dual solution that satisfies the dual constraints (5.1). The dual cost of the solution is at most:

\[
8 \cdot \text{cr}_{\mathcal{A}}(\sigma) \cdot v(\mathcal{A}_{CT}(\tau))
\]

and therefore by applying the dual fitting theorem (Theorem 2.1.2) we obtain our desired result. \( \blacksquare \)

Finally, we argue that the resulting mechanism is truthful.

**Claim 5.3.7.** \( \mathcal{A}_{TC} \) is truthful with respect to job parameters \( \langle v_j, D_j, a_j, d_j \rangle \).
Proof. Consider a job $j$ and fix the reports of other jobs. Consider two types for job $j$, say $\tau_j$ and $\tau'_j$, with $\tau_j$ dominating $\tau'_j$. Let $C_j$ and $C'_j$ denote the sets of simulation intervals under reports $\tau_j$ and $\tau'_j$, respectively. We claim that for every interval $I' \in C'_j$ there exists some $I \in C_j$ such that $I' \subseteq I$.

Before proving the claim, let us show how it implies $A_{TC}$ is truthful. Recall from the definition of $A_T$ that a job is successfully scheduled in the simulator if the set of times in which a higher-priority job is being run satisfies a certain downward-closed condition. Moreover, the times in which higher-priority jobs are run is independent of the reported properties of lower-priority jobs, including all phantoms of job $j$. Thus, a job $j$ is accepted if and only if there is some $I \in C_j$ for which the corresponding phantom would complete in the simulator, and this is independent of the other intervals in $C_j$. (Note that this independence is the only point in the argument where we use the specific properties of algorithm $A_T$, beyond truthfulness.) But now reporting $\tau'_j$ dominated by $\tau_j$ can only result in smaller simulation intervals (in the sense of set inclusion), which can only result in lower acceptance chance for any given simulation interval by the truthfulness of $A_T$. Thus, if job $j$ is not accepted under type $\tau_j$, it would also not be accepted under type $\tau'_j$.

It remains to prove the claim about $C'_j$ and $C_j$. It suffices to consider changes to each parameter of job $j$ separately. Changing the value $v_j$ has no impact on the simulation intervals. Increasing the demand $D_j$ can only raise $k_j$, which can only serve to exclude some intervals from being aligned. Likewise, increasing $a_j$ or decreasing $d_j$ can also only exclude some intervals from being aligned. But if the set of aligned intervals is reduced, and some interval $[a, b]$ lies in $C'_j$ but not in $C_j$, then it must be that $[a, b]$ is an aligned interval under reports $\tau_j$ and $\tau'_j$, but is not maximal under report $\tau_j$. In other words, there must be some $[a', b'] \in C_j$ such that $[a, b] \subseteq [a', b']$, as required.

**Multiple Servers** We can extend our construction to multiple identical servers in precisely the same manner as in Theorem 5.2.7. Specifically, when generating phantom jobs, we increase their demand by an additional factor of 11.656. As in Theorem 5.2.7, this allows us to argue that the simulated migratory schedule implies the existence of a non-migratory schedule of shorter phantom jobs, which in turn implies that passing accepted jobs to a global EDF scheduler results in a feasible schedule. We obtain the following result.

**Theorem 5.3.8.** Choose $\sigma > 1$ and suppose $s \geq (12 \cdot 11.656) \cdot \sigma$. Then the scheduler $A_{TC}$ described above is $2\sigma$-responsive, truthful, and has competitive ratio bounded by

\[
\text{cr}_{A_{TC}}(s) \leq (8 \cdot 11.656) \cdot \text{cr}_A(\sigma).
\]
5.4 Improved Explicit Bounds

In the previous section, we described general reductions from committed scheduling to non-committed scheduling. In this section, we state the specific results we obtain by plugging in the existing non-committed scheduler; namely, the non-committed scheduler $\mathcal{A}$ developed in Chapter 4. Explicit bounds can be obtained by plugging the algorithms directly. However, we can improve the constants by relying on their analysis. Recall that the competitive ratio of $\mathcal{A}$ is bounded by explicitly constructing a feasible dual solution $(\alpha, \beta)$ and bounding its dual cost. By deeply inspecting the competitive ratio analysis, we see that more specific bounds can be given. For the non-truthful algorithm $\mathcal{A}$, the following bounds can be obtained.

\[
\sum_j D_j \alpha_j = v(\mathcal{A}(\tau)) \cdot \left[ 1 + \Theta \left( \frac{1}{\sqrt[3]{s} - 1} \right) \right]
\]

\[
\sum_{i=1}^{C} \int_0^\infty \beta_i(t) dt = v(\mathcal{A}(\tau)) \cdot \left[ 1 + \Theta \left( \frac{1}{\sqrt[3]{s} - 1} \right) + \Theta \left( \frac{1}{(\sqrt[3]{s} - 1)^2} \right) \right]
\]

When analyzing the competitive ratio of the reduction to committed scheduling, we applied the resizing lemma and the stretching lemma on the dual solution $(\alpha, \beta)$ constructed for $\mathcal{A}$. However, notice that the constant blowup only affects the $\beta$ term. By applying these theorems on $(\alpha, \beta)$ directly, we can obtain improved bounds. For example:

**Corollary 5.4.1.** For any $s > 4$, there is a $(s/2)$-prompt scheduler for multiple identical servers that obtains a competitive ratio of

\[
\text{cr}_{\mathcal{A}_C}(s) = 5 + \Theta \left( \frac{1}{\sqrt[3]{s/4} - 1} \right) + \Theta \left( \frac{1}{(\sqrt[3]{s/4} - 1)^2} \right).
\]

The corollary can be generalized to any $\beta$-prompt requirement for $\beta \in [0, s - 1]$ by setting $\omega = \beta/s$. We omit the general theorem statements for brevity.

Note that the same arguments can be applied for the truthful non-committed scheduler $\mathcal{A}_T$ presented in Section 4.4. For the truthful algorithm $\mathcal{A}_T$, the power in the last asymptotic bound is 3 instead of 2.
Chapter 6

Offline Scheduling of DAG-Structured Jobs

In this chapter, we develop an offline algorithm for scheduling complex jobs, where each job consists of several stages that are *malleable* (i.e., take several forms of allocation), and the dependencies between stages are given by a Directed Acyclic Graph (DAG).

Frameworks such as MapReduce [25] or Cosmos [19] process numerous big data jobs to gain valuable insights from data patterns and behavior that previously were not observable. These jobs are often used for business critical decisions and have strict deadlines associated with them. For example, outputs of some jobs are used by business analysts; delaying job completion would significantly lower their productivity. In other cases, a job computes the charges to customers in cloud computing settings, and delays in sending the bill might have serious business consequences. If the output of a job is used by external customers, missing a deadline often results in actual financial penalty.

In practice, production jobs vary significantly in many aspects. First, they vary in *urgency*: some jobs cannot suffer delays, whereas other jobs have looser time constraints and can be pushed back. Second, they vary in *utility*: some jobs are more important than others, and as a result users have higher value assessments for their jobs meeting predefined deadlines. Finally, they vary in *structure*. Big data jobs typically have complex internal structure which makes their scheduling challenging. Jobs are composed of computation *stages*, where each stage represents a logical operation on the data, such as extraction of raw data, filtering of data, or aggregation of certain columns. The number of stages varies between jobs; for example, MapReduce jobs have only two stages, while several large production jobs in Cosmos can have up to hundreds of stages. Stages are linked by input-output dependencies that induce precedence constraints between stages. These constraints form a directed acyclic
The question is, up to what level of granularity should jobs be broken into? Stages themselves typically consist of numerous vertices (also known as worker nodes) that also induce a DAG structure. In principle, one can think of a scheduler that bypasses the stage hierarchy, treating each job as a large DAG of vertices and assigning vertices to compute slots. While a vertex-level scheduler could lead in principle to efficient allocations, it might not scale to multiple big-data jobs having millions of vertices each, which are fairly common. Consequently, allocating resources at stage-level becomes an appealing scalable alternative. On the other extreme, allocating resources at the job level would significantly reduce the scale of the problem, but might lead to very inefficient schedules. For example, different stages in a job require different level of parallelism and process different amounts of data (up to five or more orders of magnitude) and should thus be treated differently by the scheduler. Rather than allocating a fixed amount of resources to the entire job, the stage-level scheduler can assign a different number of resources for each stage, based on the number of vertices, the amount of data to be processed within a stage, etc. Towards this end, stages are treated as malleable tasks, i.e., tasks that can be allocated different amounts of resources, such that increasing the number of allocated slots can reduce the stage processing time.

In this chapter, we consider the problem of scheduling a set of big-data jobs on a cluster with $C$ identical computing resources (e.g., a server or a core within a server). We summarize below the main aspects of our model.

1. **Jobs consist of stages that are DAG-structured**: A directed dependency edge between two stages symbolizes a precedence constraint, that is, a stage cannot be processed before its dependencies have been completed.

2. **Allocations are malleable, assuming arbitrary speedups**: Each stage can be allocated different amounts of resources. For example, the user may specify per stage low and high thresholds on the required amount of resources. The number of resources per stage is fixed during the execution of the stage. As mentioned, we assume that speedups can be arbitrary, i.e., the relation between the number of allocated resources and stage processing time can arbitrary. Our allocation model also enables the processing time to depend not only on the number of resources dedicated to processing the stage, but also the specific time during which the stage started its processing. For example, the
processing time can increase during times when the cluster is known to be congested.

3. **Value gained by completing jobs depends on completion time:** Each job $j$ is associated with a value function $v_j(t)$ which represents the value gained by completing job $j$ at a time $t$. The value functions can be arbitrary. Note that our model generalizes the single
deadline scenario\(^1\), as it allows for several “soft” deadlines when delayed completion
time is still somewhat valuable to the user. The objective of the scheduler is to find a
feasible assignment maximizing the total value extracted from fully completed jobs.

4. **Jobs are known in advance (offline allocation model):** In practice, deadline-bound jobs
tend to be recurring, i.e., they are scheduled periodically, e.g., on an hourly or daily
basis. One can thus use the execution statistics from past instances of these jobs
to produce per-stage response curves which can serve as input to the scheduler. For
example, [28] describe a method for estimating the duration of a stage with $n$ vertices,
by forming empirical distributions for each vertex which rely on past executions of
the stage, and then estimating the stage duration via Monte Carlo simulations, where
vertex latencies are drawn from the per vertex distributions.

**Our results.** We present the first offline approximation algorithm for scheduling DAG-
structured jobs with malleable stages to maximize the total value of completed jobs. The
algorithm guarantees an expected constant approximation factor when $C = \Omega(\omega k \ln n)$,
where $n$ is the size of the largest input DAG, $k$ is the maximal number of resources that
can be allocated to a stage, and $\omega$ is the largest graph width of a DAG-structured job (see
Section 6.1 for formal definitions). The approximation algorithm is based on the randomized
rounding technique, where a relaxed fractional formulation of the problem is optimally solved
and then rounded to a feasible schedule of the DAG-structured jobs via randomized meth-
ods. We start by writing an integer program to describe the scheduling problem using linear
constraints, including an efficient representation of the inner-job precedence constraints as a
set of linear inequalities. The integer program is then relaxed to a linear problem and solved
optimally. At this point, a standard rounding approach would select at random entries of
the fractional optimal solution to generate a feasible solution for the problem. However,
in our case, a fractional solution does not clearly provide legal job allocations that can be
simply rounded. The linear constraints used to formulate stage dependencies for the in-
teger program rely on the program variables being integer. Once variables are allowed to
be fractional, the constraints receive a different connotation, in which stage dependencies
are not truly preserved. Despite this difficulty, the first step of our algorithm manages to
extract meaningful job allocation structures, each satisfying stage precedence constraints.

---

\(^1\) A single strict deadline $d_j$ can be modeled by setting $v_j(t)$ to some constant for $t \leq d_j$ and 0 otherwise.
However, designing a randomized rounding algorithm based on these job allocation structures is still extremely difficult, since their complex shape is not easy to schedule properly without violating capacity limitations. Nevertheless, we manage to overcome this difficulty by presenting a somewhat unexpected approach that bypasses the complexity of job allocations for scheduling the DAG-structured jobs. Finally, we consider several extensions to our model and discuss how our algorithm can be modified to handle them.

Related work. Scheduling DAG-structured jobs has been widely studied in the parallel processing literature; see [47] for a survey. Papers on scheduling DAG jobs with malleable tasks mainly focused on global system objectives such as makespan minimization (see [33, 44] and references therein). Recently, a deadline-aware scheduler for malleable tasks has been proposed [28], however the paper only proposed heuristics for the single job case. To the best of our knowledge, the objective of maximizing aggregate (completion-time) values has not been considered.

Several research papers have considered flexible allocation models, where the allocation of a stage may vary over time, yet under a simplifying assumption that parallel processing does not induce overhead execution. In particular, Nagarajan et al. [53] designed approximation algorithms for scheduling flexible jobs with precedence constraints to minimize several cost functions, including the total and maximum completion time; however, their results do not cover maximization objectives, such as total value, and do not generalize to the malleable scheduling model which we study here. Additional related papers [57, 5, 8, 9] considered similar objectives to ours. However, their job models are simpler (e.g., single-stage jobs, or fixed-length chains) and do not quite cover big-data job structures.

6.1 Scheduling Model

We define the components of the scheduling model studied in this chapter.

System. The system consists of a computing cluster containing \( C \) identical compute units (we use the terms compute units, resources, servers interchangeably). We assume that the timeline is divided into a discrete set of slots \( 1, 2, \ldots, T \) and that all of the servers are available throughout each time slot. The cluster receives a set of job processing requests. We consider the offline allocation model, in which all jobs are fully known in advance, and the goal is to schedule the jobs on the \( C \) servers during the time slots \( 1, 2, \ldots, T \).

Jobs. Each job request \( j \) is encoded as a directed acyclic graph \( G_j = (V_j, E_j) \). Nodes of the graph represent stages of the job, while edges represent the dependencies between
stages. For clarity, we use the term “node” instead of “stage” to maintain consistency with graph notation. Each job $j$ consists of $n_j$ nodes, denoted $V_j = \{1, 2, \ldots, n_j\}$. We assume that the nodes in $G_j$ are topologically ordered, such that $(v, v') \in E_j$ implies $v < v'$. An edge $(v, v') \in E_j$ in the graph symbolizes a precedence constraint between nodes, meaning, node $v'$ cannot begin its execution before node $v$ has been completed. We define the width $\omega_j$ of a directed acyclic graph $G_j$ as the largest number of nodes in $G_j$ that can be simultaneously processed without violating precedence constraints. Denote by $n = \max_j\{n_j\}$ and $\omega = \max_j\{\omega_j\}$ the largest graph size and graph width of the input jobs.

The completion time of a job is defined as the latest completion time of all its nodes. In Section 6.2 we assume each DAG has a single sink $n_j$, and thus the completion time of the sink $n_j$ is the completion time of job $j$. In Section 6.3 we relax this assumption and discuss extensions to the model which also allow multiple sinks.

Each job is associated with a value function $v_j(t)$ that specifies the value gained by fully completing job $j$ at any time $t$. For example, a deadline can be represented by setting $v_j(t) = 0$ for any $t$ after the deadline. We note, however, that we make no assumptions on the value functions. The value functions are given explicitly to the scheduler, which attempts to maximize the total value gained by completed jobs.

**Node Allocations.** Allocations of resources to nodes are shaped as rectangles. A rectangle $A$ describes an allocation of resources to a node during a time slot interval $[s(A), e(A)]$, where $s(A)$ and $e(A)$ are the processing start and end times, respectively. The height of the rectangle $k(A)$ represents the number of resources allocated to the node. A tuple $(k(A), s(A), e(A))$ is termed a node allocation and is denoted by $A$. For a time slot $t$, we shorten the notation of $t \in [s(A), e(A)]$ to simply $t \in A$.

Each job $j$ specifies a set $A_{j,v}$ of feasible node allocations per node $v \in V_j$. To allocate node $v$, the system must choose exactly one node allocation from $A_{j,v}$. For a node allocation $A \in A_{j,v}$, we use the notation $j(A) = j$ and $v(A) = v$. We note that we make no additional assumptions on the relation between the number of allocated resources and the node processing time, though in practice the processing time typically decreases in the number of allocated resources. We denote by $k = \max\{k(A) \mid j, v, A \in A_{j,v}\}$ the largest number of resources that may be allocated to a node.

**Job Allocations.** A legal allocation of a job $j$ consists of a set of node allocations

2 Though we use rectangles to describe legal allocations, the set of resources which are allocated to a node need not be a contiguous (i.e., adjacent) set of resources.

3 Each set $A_{j,v}$ is specified by the job owner and is part of the input to the problem. We note that the set $A_{j,v}$ need not necessarily include all possible node allocations; in practice it may include only a small subset of “attractive” allocation options as perceived by the job owner.
\( J = \{ A_1, A_2, \ldots, A_n \} \), one allocation \( A_v \in A_{j,v} \) per node \( v \in V_j \), which satisfies allocation precedence constraints. Formally, for every dependency edge \((v, v') \in E_j \) and corresponding node allocations \( A_v, A_{v'} \in J \) we have \( e(A_v) < s(A_{v'}) \). We use \( j(J) = j \) to denote the job which \( J \) corresponds to.

### 6.2 DAG Scheduling

We present here the main result of this chapter, which is an algorithm for scheduling DAG-structured jobs with malleable nodes. For the objective of maximizing total gained value, the algorithm guarantees an expected constant approximation factor, assuming the cluster capacity is sufficiently large. The algorithm consists of four steps, each described in the following subsections 6.2.1-6.2.4. In Section 6.2.1 we formulate and solve a relaxed linear program. The optimal solution to the linear program by itself is not necessarily a legal schedule. In the remaining sections, we transform the optimal solution to the linear program into a legal schedule, while proving the performance guarantees stated in the introduction. The scheduling algorithm **Schedule()** is given in Alg 8. Each of its components are described in a separate following subsection.

**Algorithm 8:** Algorithm for scheduling DAG-structured jobs

```
Schedule()
1. \( x^* \leftarrow \text{SolveLP()} \)
2. \( x^* \leftarrow \text{Balance}(x^*) \)
3. \( (S^*, y^*) \leftarrow \text{Decompose}(x^*) \)
4. \( \bar{x} \leftarrow \text{Round}(S^*, y^*) \)
5. return \( \bar{x} \)
```

#### 6.2.1 Step 1: Solving a Linear Program

We start by formulating the DAG scheduling problem as an integer program. We define a binary variable \( x(A) \) for every node allocation \( A \in A_{j,v} \) of a node \( v \in V_j \) that is part of a job \( j \), such that \( x(A) = 1 \) if \( v \) is allocated resources according to the node allocation \( A \) or \( x(A) = 0 \) otherwise.

**Integer Program (IP):**
\[
\max \sum_j \sum_{A \in A_{j,n_j}} v_j(e(A)) \cdot x(A) \tag{6.1}
\]

s.t.
\[
\sum_{A \in A_{j,v}} x(A) \leq 1 \quad \forall j, v \tag{6.2}
\]
\[
\sum_{j,v} \sum_{A \in A_{j,v}} k(A) \cdot x(A) \leq C \quad \forall t \tag{6.3}
\]
\[
\sum_{A \in A_{j,v}, e(A) < t} x(A) \geq \sum_{A' \in A_{j,v}, s(A') \leq t} x(A') \quad \forall j, (v, v') \in E_{j,t} \tag{6.4}
\]
\[
x(A) \in \{0, 1\} \quad \forall j, v, A \in A_{j,v} \tag{6.5}
\]

A feasible solution to (IP) is often called an integer solution. Every integer solution \( x \) can select at most one node allocation per node (constraint (6.2)) and may not exceed the capacity constraints (constraint (6.3)). We call the last constraint (6.4) the precedence constraint of the integer program. This constraint enforces the dependency requirements of jobs in the solution \( x \). Specifically, for each dependency edge \((v, v') \in E_j\), the constraint allows node \( v' \) to start by time \( t \) only if the dependent node \( v \) has completed before time \( t \) \(^4\). The objective function (6.1) may gain value from completing job \( j \) only if its sink node \( n_j \) is completed. The value gained by completing job \( j \) depends on the end time \( e(A) \) of the allocation \( A \in A_{j,n_j} \) chosen for \( n_j \). For a solution \( x \), we refer to the value of \( x \) as the value of the objective function (6.1) obtained by \( x \).

Solving the integer program to optimality is an NP-hard problem, since it generalizes well known NP-hard problems (e.g., knapsack). The algorithm we design gives an approximately optimal solution to the DAG scheduling problem, based on relaxing the integrality constraints of \( x \) to convert the integer program into a linear program (LP). The linear program allows each entry of the solution \( x \) to assume any value in \([0, 1]\).

Linear Program (LP):
\[
\max (6.1) \tag{6.6}
\]
\[
s.t. (6.2), (6.3), (6.4) \quad \forall j, v, A \in A_{j,v}
\]

\(^4\)There are several ways to write precedence constraints for the DAG scheduling problem; however, they increase the size of the integer program drastically. We found (6.4) to be the most efficient.
Notice that (6.2) implies that $x(A) \leq 1$ for every node allocation $A$, hence we do not need to require so explicitly. A feasible solution $x$ to (LP) is often called a "fractional solution," and it is well known that finding an optimal fractional solution can be done efficiently. This is the first step of our scheduling algorithm.

**Algorithm 9:** Finding an optimal fractional solution to (LP)

```
SolveLP()
1. find an optimal fractional solution $x^*$ to (LP) via any linear program solver
2. return $x^*$
```

We denote by $x^*$ the optimal fractional solution of (LP). Before continuing, notice that fractional solutions need not fully complete scheduled jobs, and moreover, they may gain partial value for partially completing a job.

The remainder of the proposed scheduling algorithm constructs a feasible solution based on the optimal fractional solution $x^*$. These next steps are based on the well-known randomized rounding paradigm, in which a fractional solution $x$ is converted into an integer solution $\bar{x}$ by rounded entries of $x$ according to a randomized rule. We prove that our randomized rounding algorithm decreases the value of $x$ by a multiplicative factor of at most $\alpha$ for some guaranteed $\alpha$. Eventually, this process is applied on $x^*$ to obtain an $\alpha$-approximation.

However, in the context of DAG scheduling, rounding a fractional solution $x$ can be challenging due to the inherit structure of $x$. To understand why, consider some job $j$ and a dependency edge $(v, v') \in E_j$ between two nodes of $j$. A natural approach to randomized rounding would be to randomly select node allocations from the support of $x$, defined $\text{supp}(x) = \{A \mid x(A) > 0\}$. Notice that the support of $x$ may contain more than one node allocation for each of the nodes $v$ and $v'$. To complete $j$, the randomized rounding algorithm must select one node allocation per node in $V_j$. Obviously, such a selection must satisfy the overall capacity constraints, but moreover it would have to maintain the DAG dependency structure of job $j$. One would hope that no dependency constrains would be violated due to (6.4). However, not every choice of node allocations from $\text{supp}(x)$ satisfies the node dependencies. Namely, there might exist node allocations $A, A' \in \text{supp}(x)$ corresponding to $v, v'$, respectively, that cannot coexist, since they violate the dependency requirement $(v, v')$, i.e., $s(A') \leq e(A)$. The precedence constraints (6.4) prevent dependency violations only when $x$ is an integer solution. When $x$ is fractional, the interpretation of the precedence constraints becomes weaker. See Fig. 6.1 for an example.

To overcome this difficulty, we first extract meaningful job allocations from $x$. The extracted job allocations are then used to construct a feasible solution. Formally, we decompose the fractional solution $x$ into a weighted set of job allocations, each satisfying node
dependency requirements; this is explained fully in Section 6.2.3. Once we obtain a weighted decomposition, we apply a randomized rounding rule on the decomposition of \( x \) to create the rounded solution \( \bar{x} \); see Section 6.2.4. Before describing the decomposition process, we require a preliminary step, called balancing.

### 6.2.2 Step 2: Balancing

Balancing is a preliminary step which simplifies the decomposition process of a fractional solution \( x \). For a fractional solution \( x \), job \( j \) and node \( v \in V_j \), we define \( x_{j,v} = \sum_{A \in A_{j,v}} x(A) \) as the total completed fraction of node \( v \) according to \( x \). Notice that the precedence constraints (6.4) imply that \( x_{j,v} \geq x_{j,v'} \) for every job \( j \) and edge \((v, v') \in E_j\).

**Definition 6.2.1.** A fractional solution \( x \) is called *balanced* if for every job \( j \) and nodes \( v, v' \in V_j \) we have \( x_{j,v} = x_{j,v'} \).

We can require (LP) to return a balanced solution by adding the following set of constraints:

\[
\sum_{A \in A_{j,v}} x(A) = \sum_{A' \in A_{j,v'}} x(A') \quad \forall j, (v, v') \in E_j. \quad (6.7)
\]

Adding (6.7) to (LP) still gives us a relaxed formulation of the DAG scheduling problem, since every integer solution also satisfies (6.7). However, adding (6.7) to (LP) increases its complexity. Instead, we present an efficient algorithm that balances a fractional solution \( x \).

The **Balance**\((x)\) algorithm (Alg. 10) works on each job individually. For each job \( j \), the algorithm iterates over the nodes in \( V_j \) in reverse topological order. For each node \( v \in V_j \),
the algorithm repeatedly decreases the tail allocation of \( v \) until \( x_{j,v} = x_{j,n_j} \).

**Definition 6.2.2.** The tail allocation of a node \( v \in V_j \) in a fractional solution \( x \), defined \( \text{TailAlloc}(x,j,v) = \arg\max_{A \in A_{j,v}} \{ e(A) \mid x(A) > 0 \} \), is a node allocation with the latest end time among the node allocations both in \( A_{j,v} \) and in the support of \( x \). If there is more than one such node, the tail allocation is chosen arbitrarily.

**Algorithm 10:** Balancing an LP solution

\[
\text{Balance}(x) \\
\text{1. foreach (job } j \text{) do} \\
\quad \text{1.1. foreach (node } v \in V_j \text{ in reverse topological order) do} \\
\quad \quad \text{1.1.1. BalanceNode}(x, j, v) \\
\]

\[
\text{BalanceNode}(x, j, v) \\
\text{1. while } (x_{j,v} > x_{j,n_v}) \text{ do} \\
\quad \text{1.1. } A \leftarrow \text{TailAlloc}(x, j, v) \\
\quad \text{1.2. decrease } x(A) \text{ by } \min \{ 0, x_{j,v} - x_{j,n_v} \}
\]

We prove the correctness of the balancing algorithm.

**Claim 6.2.3.** After every iteration of \( \text{BalanceNode}(x, j, v) \) (lines 1.1-1.2):

(i) \( x \) is a feasible fractional solution.

(ii) Every node \( v' \) that succeeds \( v \) in the topological ordering of \( G_j \) satisfies \( x_{j,v'} = x_{j,n_j} \).

**Proof.** We prove the claim by induction on the number of balancing steps performed by the algorithm. Consider a step of the balancing procedure where the fractional allocation of some node \( v \in V_j \) is being balanced. Let \( x \) be the fractional solution at that point, and assume that the inductive claim holds. Denote by \( A^* = \text{TailAlloc}(x, j, v) \) the tail allocation of \( v \) in \( x \). Recall that the balancing step decreases \( x(A^*) \) by \( \min \{ 0, x_{j,v} - x_{j,n_v} \} \). Denote by \( x' \) the vector \( x \) after the balancing step has been applied. Notice that \( x'_{j,v} \geq x'_{j,n_j} \), thus (ii) still holds after the balancing step. The vector \( x' \) does not violate constraints (6.2) and (6.3), since \( x(A^*) \) has only been decreased, but it might inviolate a precedence constraint (6.4) corresponding to an outgoing edge of \( v \). Assume towards contradiction that a precedence constraint (6.4) corresponding to an edge \((v, v') \in E_j \) and some time \( t \) is violated, that is:

\[
\sum_{A \in A_{j,v} : e(A) < t} x'(A) < \sum_{A' \in A_{j,v'} : s(A') \leq t} x'(A'). \tag{6.8}
\]
First, notice that since $x(A^*)$ is the only entry of $x$ that has changed, (6.8) can only correspond to a time unit $t > e(A^*)$. Since $A^*$ is the tail allocation, the left hand side of (6.8) is exactly $x_{j,v}$. The right hand side of (6.8) can be upper bounded by $x_{j,v}' = x_{j,v} = x_{j,n_j}$; the first equality holds since we are only modifying $v$, the second equality holds by the inductive assumption. From this, we get that $x_{j,v} < x_{j,v}'$, which is a contradiction.

**Claim 6.2.4.** The Balance($x$) algorithm does not change the value (6.1) of $x$.

**Proof.** Recall that the objective function (6.1) only depends on the node allocations of $n_j$ for every $j$. The claim holds since the balancing algorithm does not modify any entry $x(A)$ corresponding to $A \in A_{j,n_j}$ for every $j$.

The total number of balancing steps performed by the algorithm is at most $|supp(x)|$ and each takes constant time to execute. Hence, the balancing algorithm runs in polynomial time. Before continuing, we note that the implementation of Balance($x$) does not need to go over nodes in reverse topological order. In practice, the balancing step can be performed independently for each job. The reverse topological ordering is only used to simplify the proof of correctness; otherwise it is redundant.

The following corollary concludes this section.

**Corollary 6.2.5.** Every fractional solution $x$ of (LP) can be transformed in polynomial time to a balanced feasible solution without changing the value (6.1) of $x$.

### 6.2.3 Step 2: Decomposing a Balanced Solution

As discussed in Section 6.2.1, the inherent structure of $x$ does not necessarily maintain the dependency structures of each DAG. In the next step, we decompose $x^*$ into a weighted set of job allocations. Recall that a job allocation of job $j$ is a set of node allocations, one per each node of $j$, that satisfy the dependency requirements of $G_j$. These job allocations will eventually be used to construct the rounded solution.

**Definition 6.2.6.** A decomposition of a balanced fractional solution $x$ is a tuple $(S, y)$ where $S$ is a set of job allocations and $y : S \rightarrow [0, 1]$ is a weight function, such that for every job $j$, node $v \in V_j$ and node allocation $A \in A_{j,v}$:

$$x(A) = \sum_{J \in S : A \in J} y(J) \quad (6.9)$$

An decomposition can be viewed as an alternate representation of a balanced fractional solution. Node allocations in $x$ are grouped into job allocations, each corresponding to some job $j$. Each job allocation $J \in S$ is assigned a weight $y(J)$, such that the fractional allocation
$x(A)$ of every node allocation $A$ is distributed over job allocations in $S$. Before describing the decomposition algorithm, we slightly extend the definition of the tail allocation.

**Definition 6.2.7.** Let $\text{TailAlloc}(x,j,v,t) = \arg\max_{A \in A_{j,v}} \{e(A) \leq t \mid x(A) > 0\}$ be the node allocation with the latest end time among the node allocations in $A_{j,v}$ that end before $t$ and are part of $\text{supp}(x)$. If there is more than one such node, the node allocation is chosen arbitrarily.

**Algorithm 11:** Decomposing a balanced solution

```latex
\text{Decompose}(x)
\begin{enumerate}
\item foreach (job $j$) do
  \begin{enumerate}
  \item $(S_j, y_j) \leftarrow \text{DecomposeJob}(x,j)$
  \end{enumerate}
\item return $(\bigcup_j S_j, \bigcup_j y_j)$
\end{enumerate}

\text{DecomposeJob}(x, j)
\begin{enumerate}
\item initialize: $S_j \leftarrow \emptyset$
\item initialize: $y_j \leftarrow 0$
\item while $(x_j, n_j > 0)$ do
  \begin{enumerate}
  \item foreach (node $v \in V_j$ in reverse topological order) do
    \begin{enumerate}
    \item $t \leftarrow \min\{s(A_{j,v'}) \mid (v, v') \in E_j\}$
    \item $A_{j,v} \leftarrow \text{TailAlloc}(x, j, v, t)$
    \end{enumerate}
  \end{enumerate}
  \item $J \leftarrow \bigcup_{v \in V_j} \{A_{j,v}\}$
  \item $S \leftarrow S \cup \{J\}$
  \item $\Delta \leftarrow \min \{x(A_{j,v}) \mid v \in V_j\}$
  \item $y(J) \leftarrow \Delta$
  \item $x(A_{j,v}) \leftarrow x(A_{j,v}) - \Delta$ for every $v \in V_j$
  \end{enumerate}
\item return $(S_j, y_j)$
\end{enumerate}
```

The algorithm we present ($\text{Decompose}(x)$; Alg. 11) generates a decomposition of a balanced fractional solution $x$. It does so by creating a decomposition for each job separately and combining the results. The decomposition algorithm iteratively extracts job allocations from $x$ and adds them to the decomposition. This is done as follows. In each iteration the decomposition algorithm traverses the node allocations of a job $j$ in reverse topological order. For each node $v$, the node allocation $A_{j,v} = \text{TailAlloc}(x, j, v, t)$ is selected, where $t$ is the earliest start time of the selected node allocations that depend on $v$. Then, the
algorithm creates a new job allocation \( J \) by taking a copy of \( A_{j,v} \) for each node (line 3.2). The job allocation \( J \) is then added to the decomposition with a weight of \( \Delta \), where \( \Delta \) is the minimal existing fractional allocation of all node allocations in \( J \) (lines 3.3-3.5). Finally, \( J \) is extracted from \( x \) (lines 3.6).

**Claim 6.2.8.** If \( x \) is a balanced feasible solution, then the job allocation extracted from \( x \) after each iteration of DecomposeJob is a legal job allocation.

**Proof.** Notice that at each step of the decomposition algorithm TailAlloc(\( x, j, v, t \)) exists for \( t = \min\{s(A_{j,v'}) \mid (v, v') \in E_j\} \). For the sink node \( n_j \), this follows since \( x_{j,n_j} > 0 \); for other nodes, this follows directly from (6.4). Furthermore, the decomposition algorithm guarantees that all dependency constraints are met, since each selected node allocation \( A_{j,v} \) ends before any of its dependencies began. Hence, the constructed job allocation is legal. \( \square \)

**Claim 6.2.9.** After each iteration of DecomposeJob, \( x \) remains feasible and balanced.

**Proof.** Consider the fractional solution \( x \) before an iteration of DecomposeJob, and assume \( x \) is balanced and feasible. Let \( \hat{x} \) denote the value of \( x \) at the end of the iteration. It is clear why \( \hat{x} \) remains balanced once we extract a job allocation \( J \) from it. Hence, to prove the claim we must show that \( \hat{x} \) is feasible. Notice that since entries of \( x \) are only decreased throughout the iteration, the demand constraints (6.2) and the capacity constraints (6.3) are not violated. Therefore, \( \hat{x} \) also satisfies these constraints. The only constraints of (LP) that might be violated are precedence constraints (6.4). Consider some dependency edge \((v, v') \in E_j \). Define:

\[
f(t) = \sum_{A \in A_{j,v} : e(A) < t} x(A) - \sum_{A' \in A_{j,v'} : s(A') \leq t} x(A')
\]  

and define \( \hat{f}(t) \) similarly for \( \hat{x} \). Since \( x \) is feasible, we have \( f(t) \geq 0 \) for every \( t \). To conclude, we must show that \( \hat{f}(t) \geq 0 \) for every \( t \). Notice that the only modified entries of \( x \) that may affect \( f(t) \) are \( x(A_{j,v}) \) and \( x(A_{j,v'}) \), which are both decreased by \( \Delta \). Consider the following cases for \( t \):

- Assume \( t \leq e(A_{j,v}) \). Both \( x(A_{j,v}) \) and \( x(A_{j,v'}) \) are not included in any of the summations in \( f(t) \). Hence, \( f'(t) = f(t) \geq 0 \).

- Assume \( e(A_{j,v}) < t < s(A_{j,v'}) \). Notice that by the definition of TailAlloc(\( x, j, v, t \)) there cannot exist any node allocation \( A \in A_{j,v} \) which is both in the support of \( x \) and also satisfies \( e(A_{j,v}) < e(A) < s(A_{j,v'}) \). Hence, for every \( t' \) such that \( e(A_{j,v}) < t' < s(A_{j,v'}) \) we have \( f(t') \geq x(A_{j,v'}) \). Since \( x(A_{j,v'}) \) is decreased by \( \Delta \), this implies that \( f'(t') \geq 0 \) for each such \( t' \).
Assume \( s(A_j,v') \leq t \). It follows that \( e(A_j,v') \leq t \). Both summations of \( f(t) \) are decreased by \( \Delta \). Therefore \( f'(t) = f(t) \geq 0 \).

Hence, \( x' \) is feasible.

Notice that the number of iterations performed by the decomposition algorithm is at most \( |\text{supp}(x)| \), since in each iteration at least one entry \( x(A) \) for some node allocation \( A \) is set to 0. Hence, the total runtime of the algorithm is polynomial.

**Corollary 6.2.10.** A decomposition \((S,y)\) of a balanced feasible solution \( x \) for \((LP)\) can be generated in polynomial time.

### 6.2.4 Step 4: Randomized Rounding

We proceed to the final step of the algorithm, where we round a fractional solution using its decomposition. The rounding algorithm (\( \text{Round}(S,y); \) Alg. 12) receives a decomposition of some fractional solution \( x \) and returns a rounded integer solution \( \bar{x} \).

**Algorithm 12:** Randomized rounding of a decomposition

\[
\text{Round}(S,y)
\]

1. **foreach** (job \( j \)) do
   1.1. Draw a job allocation \( J_j \in S_j \) with probability \( y(J)/\lambda \) for each \( J \in S_j \)

2. \( N \leftarrow \bigcup J_j \)
3. \( \tilde{N} \leftarrow \emptyset \)
4. **foreach** (node allocation \( A \in N \) in increasing order of \( s(A) \)) do
   4.1. if \( (\tilde{w}(s(A)) + k(A) \leq C) \) then
      4.1.1. add \( A \) to \( \tilde{N} \)
   4.2. else
      4.2.1. \( J_j \) - job allocation to which \( A \) belongs
      4.2.2. remove all node allocations in \( J_j \) from \( N \) and \( \tilde{N} \)

5. return a binary vector \( \bar{x} \) satisfying \( \bar{x}(A) = 1 \iff A \in \tilde{N} \)

Let \( \lambda > 1 \) be a parameter. The rounding algorithm starts by randomly drawing at most one job allocation from \( S_j \) for each job \( j \) (recall that \( S_j \) represents the job allocations of job \( j \) in the decomposition \( S \)). Each job allocation \( J \in S_j \) is selected with probability \( y(J)/\lambda \); with probability \( 1 - \sum_{J \in S_j} y(J)/\lambda \) no job allocation is drawn. We denote by \( J_j \) the job allocation drawn for job \( j \). If no job allocation was drawn, then \( J_j = \emptyset \). Let \( \mathcal{N} = \bigcup J_j \).
denote the union set of all selected job allocations. The union set $\mathcal{N}$ contains any node allocation that appears in one of the job allocations $J_j$.

We now describe how the feasible solution is constructed from $\mathcal{N}$. The algorithm iterates over $\mathcal{N}$ in increasing order of starting times $s(\cdot)$ and selects node allocations to the solution. The set $\mathcal{N}$ maintains the node allocations selected by the algorithm. We explain the selection process. Consider the iteration where a node allocation $A \in \mathcal{N}$ is considered by the rounding algorithm. Let $J_j$ be the job allocation to which $A$ belongs. The rounding algorithm adds $A$ to $\mathcal{N}$ only if $A$ can be added to the solution without violating capacity constraints. If $A$ is rejected by the algorithm, then all node allocations in $J_j$ are discarded from $\mathcal{N}$ and $\mathcal{N}$. Notice that a job allocation is scheduled only if none of its node allocations were rejected. Finally, the rounded solution $\bar{x}$ takes the node allocations in $\mathcal{N}$.

To verify that adding a node allocation $A$ does not violate capacity constraints, we simply check whether $k(A)$ resources are available at time $s(A)$. The following claim proves the correctness of this step. Define $\bar{w}(t) = \sum_{A' \in \mathcal{N}, A' \in A'} k(A')$ as the total load of $\mathcal{N}$ at time $t$.

**Claim 6.2.11.** Let $A \in \mathcal{N}$ be a node allocation considered by the rounding algorithm while iterating over $\mathcal{N}$. At this point, adding $A$ to $\mathcal{N}$ violates capacity constraints if and only if the number of free resources at time $s(A)$ is at most $k(A)$, i.e., $\bar{w}(s(A)) > C - k(A)$.

**Proof.** Consider some node allocation $A' \in \mathcal{N}$. We say that node allocations $A, A'$ intersect if their processing time intervals intersect, that is, the two intervals $[s(A), e(A)]$ and $[s(A'), e(A')]$ intersect. Recall that the rounding algorithm iterates over $\mathcal{N}$ in increasing order of starting times. Hence, when the algorithm considers adding $A$, every node allocation $A' \in \mathcal{N}$ satisfies $s(A') \leq s(A)$. Hence, any node allocation $A' \in \mathcal{N}$ that intersects with $A$ must satisfy $s(A) \in A'$. This implies that $\bar{w}(t)$ is maximized in the interval $[s(A), e(A)]$ for $t = s(A)$. The claim follows. $lacksquare$

To analyze the performance of the rounding algorithm, we show that the probability of completing each job allocation $J$ in the decomposition $(S, y)$ is proportional to $y(J)$; more formally, we show that it is at least $y(J)/\alpha$ for some $\alpha > 0$. This implies that each node allocation $A$ is selected with probability of at least $x(A)/\alpha$. By linearity of expectation, we can then deduce that $\bar{x}$ obtains $1/\alpha$ of the (fractional) value gained by $x$. The first step of the analysis bounds the probability of rejecting a node (Claim 6.2.12). Once we have this bound, we are able to complete the analysis by finding the probability of scheduling a job allocation (Theorem 6.2.13).

**Claim 6.2.12.** Let $A \in \mathcal{N}$ be a node allocation considered by the rounding algorithm while
iterating over $\mathcal{N}$. At that point of the rounding algorithm:

$$
\Pr \left[ \bar{w}(s(A)) > C - k(A) \right] \leq e^{-\left(1 - \frac{C}{2k} \right) \ln \left( \lambda - \frac{1}{2} \right)}
$$

Proof. We prove the claim by using standard concentration bounds. Notice that the expected value of $\bar{w}(t)$ for every $t$ satisfies at any stage of the rounding algorithm:

$$
\mathbb{E}[\bar{w}(t)] \leq \sum_{A' \in \mathcal{N} \setminus A} \sum_{t \in A'} k(A') \cdot \frac{y(J')}{\lambda} = \sum_{A' \in \mathcal{N} \setminus A} k(A') \cdot \frac{x(A')}{\lambda} \leq \frac{C}{\lambda} \quad (6.11)
$$

The remainder of the proof uses the Bennett Inequality [12] to bound the probability of the event: $\bar{w}(s(A)) > C - k(A)$.

Bennett’s Inequality. Let $X_1, \ldots, X_m$ be independent random variables such that $\forall i, |X_i - \mathbb{E}[X_i]| \leq a$ for some value $a$, and let $\sigma^2 = \sum_{i=1}^m \text{Var}[X_i]$. Then, for every $\tau > 0$:

$$
\Pr \left[ \sum_{i=1}^m (X_i - \mathbb{E}[X_i]) \geq \tau \right] \leq e^{-\frac{\sigma^2}{a^2} h \left( \frac{\tau a}{\sigma^2} \right)}
$$

where $h(z) = (1 + z) \ln(1 + z) - z$.

A slightly weaker version of Bennett’s inequality, yet easier to use, can be obtained by applying the inequality: $h(z) \geq \frac{1}{2} z \ln(1 + z)$ for every $z \geq 0$.

$$
\Pr \left[ \sum_{i=1}^m (X_i - \mathbb{E}[X_i]) \geq \tau \right] \leq e^{-\frac{\sigma^2}{a^2} \ln \left( 1 + \frac{\tau a}{\sigma^2} \right)}
$$

We show how Bennett’s inequality is used to prove the claim. For every job allocation $J$, define: $k(J, t) = \sum_{A' \in J, t \in A'} k(A')$ as the number of resources required by the job allocation $J$ at time $t$. Notice that $k(J, t) \leq \omega k$ for every job allocation $J$ and time $t$, since $J$ can have at most $\omega$ node allocations simultaneously processed at time $t$, and each node allocation can receive at most $k$ resources. We shorten notation by writing $k_J = k(J, s(A))$. For each job $j$, let $X_j$ be a random variable representing the number of resources allocated by the rounding algorithm to node allocations of job $j$ at time $s(A)$. Following the notation of Bennett’s inequality, we have:

$$
\mathbb{E}[X_j] = \sum_{J \in S_j} \frac{y(J)}{\lambda} \cdot k_J \quad (6.12)
$$
Var \[X_j\] = \[\sum_{j \in S_j} \frac{y(J)}{\lambda} \cdot k_j^2 - \left(\sum_{j \in S_j} \frac{y(J)}{\lambda} \cdot k_j\right)^2\]
\leq \sum_{j \in S_j} \left(\frac{y(J)}{\lambda} - \left(\frac{y(J)}{\lambda}\right)^2\right) k_j^2 = \sum_{j \in S_j} \frac{y(J)}{\lambda} \left(1 - \frac{y(J)}{\lambda}\right) k_j^2
\sigma^2 \leq \sum_j \left(\sum_{j \in S_j} \frac{y(J)}{\lambda} \left(1 - \frac{y(J)}{\lambda}\right) \cdot k_j^2\right)
\leq \sum_j \left(\sum_{j \in S_j} \frac{y(J)}{\lambda} \cdot k_j \cdot \left(1 - \frac{y(J)}{\lambda}\right) \cdot k_j\right) \quad (6.13)
\tau = C - k - \sum_j \sum_{j \in S_j} \frac{y(J)}{\lambda} \cdot k_j \quad (6.14)
a = \max_j \left\{\max \left\{E[X_j] - \min_{j \in S_j} \{k_j\}, \max_{j \in S_j} \{k_j\} - E[X_j]\right\}\right\} \quad (6.15)

Notice that \(a \leq \omega k\) and \(a \geq \sum_{j \in S_j} \left(1 - \frac{\nu(J)}{\lambda}\right) k_j\) for every \(j\). Thus:
\[\frac{\tau}{2a} \geq \frac{(1 - \frac{k}{\lambda}) C - k}{2\omega k}\]
\[\frac{a \tau}{\sigma^2} \geq \frac{C - k - \sum_j \sum_{j \in S_j} \frac{y(J)}{\lambda} \cdot k_j}{\sum_j \left(\sum_{j \in S_j} \frac{y(J)}{\lambda} \cdot k_j\right)} \geq \frac{C - k}{C/\lambda - 1} = \lambda \left(1 - \frac{k}{C}\right) - 1 \quad (6.17)

The last inequality follows since \(\sum_{j \in S} k_j \cdot y(J) \leq C\). Therefore, by Bennett’s inequality, we have:
\[\Pr\left[\bar{w}(s(A)) > C - k(A)\right] \leq e^{-\frac{(1 - \frac{k}{\lambda}) C - k}{2\omega k} \ln(\lambda (1 - \frac{k}{C}))} \quad (6.18)\]
as required.

\begin{itemize}
  \item Theorem 6.2.13. The DAG scheduling problem admits a randomized approximation algorithm that obtains an expected approximation ratio of \(\alpha(\lambda)\) for every \(\lambda > 1\), where:
  \[\alpha(\lambda) \triangleq \frac{1}{\lambda} \left[1 - e^{-\frac{(1 - \frac{k}{\lambda}) C - k}{2\omega k} \ln(\lambda (1 - \frac{k}{C}))}\right]^n.\]
\end{itemize}
By replacing $\lambda$ with $C - k \cdot \lambda'$, we get:

$$\alpha(\lambda') \triangleq \frac{C - k \cdot 1}{\lambda'} \cdot \left[ 1 - e^{-\frac{C - k \cdot (\lambda' - 1) \ln(\lambda')}{\lambda}} \right]^n$$

Proof. Let $x^*$ be a balanced optimal fractional solution found by the algorithm and let $(S^*, y^*)$ be its decomposition. We show that the probability of completing each job allocation $J \in S^*$ at the rounding step is at least $y^*(J)/\alpha(\lambda)$. From this, it follows that the algorithm is an $\alpha(\lambda)$-approximation algorithm. Consider a job allocation $J$ and denote by $j = j(J)$ the job it represents. For $J$ to be scheduled by the algorithm, two conditions must hold:

1. $J$ was drawn by the rounding algorithm. This happens with probability:

$$\frac{y(J)}{\lambda} \cdot (6.19)$$

2. Every node allocation in $J$ was selected by the rounding algorithm. Following Claim 6.2.12, this happens with probability of at least:

$$\left[ 1 - e^{-\frac{(1 - \frac{1}{\lambda}) \cdot C - k \cdot \ln(\lambda)}{2\omega k}} \right]^n \cdot (6.20)$$

The theorem follows by multiplying (6.19) and (6.20).

### 6.2.5 Obtaining a Constant Approximation Factor

The approximation factor $\alpha(\lambda')$ given in Theorem 6.2.13 also depends on $C, k, \omega$ and $n$, which are all input parameters. To obtain a constant guaranteed approximation factor, it is enough to require:

$$\frac{C - k \cdot (\lambda' - 1) \ln(\lambda')}{2\omega k} \leq \ln(\delta n) \cdot (6.21)$$

for some constant $\delta > 0$. By reorganizing terms, we get:

$$C \geq \frac{2\lambda'}{(\lambda' - 1) \ln(\lambda')} \cdot \omega k \cdot \ln(n) + k \cdot (6.22)$$

If (6.22) holds, we obtain an approximation of at least $\frac{1}{\lambda'} \cdot e^{-1/\delta} = \frac{C - k \cdot 1}{\lambda} \cdot e^{-1/\delta}$. We can conclude that if $C = \Omega(\omega k \ln(n))$, then the approximation factor is constant. For example, if $\lambda = 3.2$ and $C \geq 2.5\omega k \ln(10n)$, the approximation factor roughly equals 0.28. We note that this condition holds in a typical Cosmos cluster with 16 cores per machine (cores are the basic compute units), $\omega \approx 10$, $k \approx 1000$ and $n \approx 100$. 

107
Given values of $C, k, \omega$ and $n$, the guaranteed expected approximation factor can be optimized over $\lambda'$ and $\delta$. However, the approximation factor we obtain results from a worst-case analysis that might not reflect the behavior of the algorithm for real input jobs. Since $\lambda'$ is the only true parameter of the algorithm ($\delta$ is only used for analysis), it might be possible to obtain better results in practice for different values of $\lambda'$.

6.3 Model Extensions

The approximation algorithm presented in Section 6.2 can be extended to various job allocation models, including job allocations that allow monotonic resource allocation for nodes and multiple-sink DAG structured jobs. We discuss these extensions here.

6.3.1 Monotone Node Allocations

In Section 6.2 we considered a resource allocation model in which each node allocation was rectangular shaped, i.e., the number of resources allocated to a node was fixed over its processing interval. We now consider cases where the allocation may vary over time. For a node allocation $A \in A_{j,v}$, denote by $k(A, t)$ the number of resources allocated to node $v$ at time $t$ according to $A$. Thus, we update our integer program formulation by replacing (6.3) with the constraint:

$$\sum_{j,v} \sum_{A \in A_{j,v}} \sum_{t \in A} k(A, t) \cdot x(A) \leq C \quad \forall t$$  \hspace{1cm} (6.23)

We claim that the scheduling algorithm constructed in Section 6.2 can be applied when all the node allocations are monotone non-increasing, i.e., for every node allocation $A$, the function $k(A, t)$ is monotonically non-increasing in $t$ for every $t \in [s(A), e(A)]$. The balancing and decomposition steps are still valid in this setting, since they do not make any assumptions on the shape of each node allocation. In fact, the only part of the proof that might not hold is Claim 6.2.11, where we prove during the rounding step that adding a node allocation $A$ to $\tilde{N}$ violates capacity constraints if and only if $\bar{w}(s(A)) > C - k(A)$. A similar argument is proved in [41], yet we shortly repeat the proof for completeness. Recall that the rounding algorithm iterates over node allocations in $\tilde{N}$ in increasing order of starting times $s(\cdot)$. Consider the node allocation $A$ and recall that by the original proof of Claim 6.2.11, any node allocation $A' \in \tilde{N}$ intersecting with $A$ must satisfy $s(A) \in A'$. Since all node allocations are monotonically non-increasing, we have $\bar{w}(s(A)) \geq \bar{w}(t)$ for every $t \geq s(A)$. Moreover, we know that $k(A, s(A)) \geq k(A, t)$ for every $t \geq s(A)$. We can deduce that $A$ can be added to the solution $\tilde{N}$ if and only if $\bar{w}(s(A)) + k(A, s(A)) \leq C$, which is what we required.
Hence, we can obtain the same guaranteed expected approximation factor even when node allocations are monotonically non-increasing. We note that our scheduling algorithm can also handle the case when all allocations are monotonically non-decreasing, yet here the rounding algorithm would have to iterate over node allocations in $\mathcal{N}$ in decreasing order of end times $e(\cdot)$.

### 6.3.2 Multiple Sinks

Up until now we have made a simplifying assumption that each DAG-structured job had a single sink. In this section we consider the general case, where each DAG-structured jobs can have multiple sinks (i.e., a general DAG). The value gained from completing each job still depends on the job completion time, which is now the latest completion time among its sink nodes. General DAG-structured jobs can be simply reduced to single-sunked DAG by adding a zero-sized sink that all other sinks connect to. A node allocation $A$ corresponding to a zero-sized sink node $v$ would have $k(A) = 0$ and $e(A) = s(A) - 1$. It is not hard to verify that incorporating zero-sized node allocations to our scheduling algorithm do not violate its correctness, therefore we omit the discussion due to its technicality.

### 6.4 Conclusions

Time-critical big-data jobs play an important role in the operation of many businesses. In this chapter, we designed and analyzed a novel algorithm for scheduling such jobs, incorporating their hard (or soft) deadlines. Our algorithm guarantees an expected constant approximation factor under plausible assumptions. Importantly, our algorithm and results are established for general job topologies, resource malleability models and value functions. As such, we believe that the algorithm and tools we develop are applicable for a variety of present and future scheduling scenarios.
Chapter 7

Scheduling Algorithms for Hadoop YARN

Our final contribution is a new deadline scheduler for big data jobs on Hadoop systems. Apache Hadoop is considered as one of the leading open-source frameworks for cluster resource management and big data processing (e.g., the MapReduce paradigm [25]). One of its key components is YARN [63], the Hadoop resource negotiator, which handles the allocation of cluster resources between running applications. The traditional YARN scheduler follows a weighted fair-share policy. Initially, the cluster is divided into logical queues, to which users can submit job requests. Cluster resources are divided between active queues (i.e., queues containing at least one job request) proportionally to their predefined weight. Finally, each queue schedules its job requests according to a First-Come-First-Serve order, depending on its available share of resources. Weighted fair share scheduling allows the cluster manager to distinguish between job by their importance, e.g., production and best effort jobs. However, it does not respect deadline requirements, and may lead to starvation of low priority queues.

Recently, a new reservation mechanism was built on top of YARN. The mechanism, called Rayon [23], accepts complex DAG-structured job requests through a rich API and reserves in advance resources over time for accepted jobs. The promise of Rayon is to support SLAs (e.g., deadlines) for production jobs, while minimizing the latency of best effort jobs. However, the current implementation of Rayon relies on a simple Greedy allocation algorithm which tends to create spiky allocations; as a result, best effort jobs are often substantially delayed.

In this work, we design, implement and evaluate LowCost – a new cost-based planning algorithm for Hadoop YARN based on the Rayon abstraction. LowCost strives to maintain the overall allocation balanced, and hence to decrease the latency of instantaneous jobs while meeting SLAs of production jobs. Moreover, the algorithm satisfies two key requirements
which improve the user experience: first, the decision whether to schedule an incoming job request is made upon arrival (i.e., LowCost is committed-on-arrival); second, the algorithm guarantees to allocate a job request if there is a feasible way to allocate it. The design of LowCost is inspired by insights from our theoretical work. In particular, we use similar local, greedy, computationally-efficient allocation rules that optimize global performance metrics. We show, through simulations and experiments on a test cluster, that LowCost substantially outperforms the existing algorithm Greedy on several important performance metrics. Our open-source contributions are documented in YARN-3656 and YARN-4359. LowCost has been recently used as an allocation mechanism for periodic jobs, and is part of the Morpheous system [45].

The chapter is organized as follows. First, we describe in Section 7.1 the allocation model of Rayon, which resembles the DAG allocation model studied in Chapter 6. Then, we describe in Section 7.2 the algorithms Greedy and LowCost, including several variants. Finally, we present our evaluation results in Section 7.3.

Related Work. Most existing solutions for datacenter resource allocation do not concentrate on satisfying deadline requirements. Common frameworks, such as Mesos [38], Quincy [40], Omega [61] and YARN [63], are all oriented towards fair-share scheduling. Jockey [28] is a system that aims at finishing data-processing jobs (SCOPE) by their deadlines using dynamic allocation of CPU resources, based on offline and online profiling of jobs. However, Jockey focuses on the single job case, and does not explicitly address the scheduling of multiple jobs. Bazaar [43] considers the assignment of both bandwidth and CPU resources for meeting deadlines of multiple batch jobs. Their basic idea is to profile jobs in advance and form an estimate of job completion time as a function of (bandwidth, CPU), then heuristically allocate resources to maximize the number of jobs that complete by their deadline. However, Bazaar does not consider resource preemption. Our work improves the Rayon [23] architecture, which exposes an API for scheduling complex-structured jobs over Hadoop that must meet deadline requirements.

7.1 Scheduling Model

Reservation requests (RR) are submitted to the cluster over time. Each RR has a release time, a deadline, and a specification of resource requirements. When a new RR arrives, the scheduler must decide immediately whether to schedule the job or reject it. The resource requirements of a RR are encoded using the Reservation Definition Language (RDL), which was introduced as part of the Rayon abstraction [23]. RDL is a recursive language used to express the resource requirements of malleable jobs with DAG-structured constraints.
In this work, we focus on a subset of the language, which is sufficient for most common scenarios. We note that the algorithms presented in this work can be generalized to handle the full RDL language; their implementing is left for future work.

The planning algorithms discussed here accept the following RDL expressions.

**RDL Atom.** An RDL atom $a$ represents the resource requirements of a single atomic task (stage). Each atomic task requires a number of allocation units, called *containers*. The RDL atom $a$ specifies several requirements on the requested containers, which are encoded through the following parameters.

- *capability*: the required capability from a single container, given as a multi-dimensional bundle of resources, e.g., $\langle 8\text{GB RAM}, 4\text{ cores} \rangle$.
- *duration*: minimum lease duration of a single container; each container must persist for at least duration time steps.
- *numContainers*: the total amount of containers requested by $a$.
- *gang (concurrency)*: parallelism requirements on the allocation; the number of containers allocated to $a$ at each time must be an integer multiplication of gang.

**RDL Expressions.** The planner accepts the following type of RDL requests:

- *any*($a_1, \ldots, a_n$): requires that at least one of the atomic requests $a_1, \ldots, a_n$ is satisfied.
- *all*($a_1, \ldots, a_n$): requires that all the atomic requests $a_i$ are satisfied.
- *order*($a_1, \ldots, a_n$): a dependency expression which requires for every $i$ that the allocation of $a_i$ strictly precedes the allocation of $a_{i+1}$.

### 7.2 Planning Algorithms

We first describe a general planning mechanism which is common to the algorithms we discuss; see Algorithm 13 for pseudo-code. Each job request submitted to the general planner is composed of an RDL expression $e$ and a time interval $I$ during which the job should be allocated. The general planner treats job requests differently, depending on the type of $e$. An order request is placed by allocating the atomic tasks in reverse topological order. Each atom is placed using the **PlanAtom** procedure, which receives an RDL atom $r$ and a subinterval $I_r$ during which $r$ is allocated. The planner enforces dependencies between atoms by setting the right endpoint of $I_r$ as the starting time of the successor of $r$. The specific implementation of **PlanAtom** is algorithm-specific, hence described separately for
each algorithm in the subsequent sections. The general planner handles all requests in a similar manner, except that $I_r$ is set to $I$ for each atom. For any requests, the planner simply selects the first alternative which is successfully allocated by $\text{PlanAtom}$.

**Algorithm 13: General Planning Algorithm**

```plaintext
PlanRDL(Plan $p$, RDL $e$, Interval $I$)

switch ($e$.type) do
  case (order) do
    $t \leftarrow I$.end()
    for (RDLAtom $r :$ reverse($e$.requests)) do
      alloc $\leftarrow \text{PlanAtom}(p, e, r, \text{new Interval}(I$.start(), $t$))
      if (!alloc) then fail()
      $t \leftarrow$ alloc.start()
  case (all) do
    for (RDLAtom $r :$ reverse($e$.requests)) do
      alloc $\leftarrow \text{PlanAtom}(p, e, r, I)$
      if (!alloc) then fail()
  case (any) do
    for (RDLAtom $r :$ reverse($e$.requests)) do
      alloc $\leftarrow \text{PlanAtom}(p, e, r, I)$
      if (alloc) then success()
      fail();
  success();
```

7.2.1 Greedy – The Existing Scheduling Algorithm

Currently, Rayon implements the following Greedy allocation rule (Algorithm 14). Given an atomic request $r$ and an interval $I$, the algorithm allocates gangs of $r$ starting from the rightmost possible duration interval in $I$, while meeting the capacity constraints of the plan.

Greedy is optimal for a single job request. Namely, for every job represented by an RDL expression $e$: if there exists a feasible allocation of $e$, then Greedy is guaranteed to succeed in allocating $e$. However, using Greedy for multiple requests has several shortcomings:

1. Greedy is not aware of the plan “state”. This can cause the algorithm to allocate jobs during loaded intervals, instead of spreading the plan allocation throughout time.
Algorithm 14: Greedy

PlanAtom.Greedy(Plan p, RDL e, Atom r, Interval I)

\[ t \leftarrow I.\text{end} \]

while (r is not fully allocated) do

if (t < I.start) then fail()

allocate as many gangs in the interval \([t - r.\text{duration}, t] \)
without exceeding the capacity of \(p\)

\[ t \leftarrow t - 1 \]

return \(p.\text{allocation}(r)\)

2. Greedy generates tall and skinny allocations of atomic tasks. This significantly increases the amount of task preemptions, and moreover, causes the allocation to become more sensitive to outliers.

3. Greedy creates “peaks” in the global plan allocation, which might prevent future requests from being allocated.

7.2.2 LowCost – A New Cost-Based Planning Algorithm

Our algorithms rely on a cost-based approach: each time slot \(t\) is associated with a cost \(c(t)\). The cost \(c(I)\) for a time interval \(I\) is defined as the total cost of time slots within the interval. The cost function \(c : \mathbb{N} \rightarrow \mathbb{R}\) typically represents the current state of the cluster. However, more generally, cost functions can also incorporate expected future demand, projected capacity changes, etc. In our current implementation, the cost function represents the dominant resource (DR),

\[ c_{\text{DR}}(t) = \max \left\{ \frac{p.\text{load}(t).\text{mem}}{p.\text{capacity}(t).\text{mem}}, \frac{p.\text{load}(t).\text{cores}}{p.\text{capacity}(t).\text{cores}} \right\} . \quad (7.1) \]

We note that finding an allocation for a single RDL expression \(e\) that minimizes the total incurred cost is NP-hard in general, even when the cluster consists of a single resource. Nevertheless, the algorithms we develop produce a “good enough” global allocation without requiring to find the optimal cost-effective allocation per request.

We now present LowCost, our cost-based planning algorithms. We note that LowCost has different variants, which we describe below. Similar to Greedy, LowCost follows the general planning scheme described in Algorithm 13. The difference between the algorithms is in the PlanAtom phase (Algorithm 15): The LowCost algorithm for allocating a single RDL atom \(r\) consists of two phases. The purpose of the first phase is to identify a subinterval \(I_r\) of \(I\)
Algorithm 15: LowCost

PlanAtom.LowCost(Plan \( p \), RDL \( e \), Atom \( r \), Interval \( I \))

\[
\text{Phase 1:} \\
\quad t \leftarrow \text{GetAtomEarliestStartTime}(p, e, r, I) \\
\quad I_r \leftarrow \text{new Interval}(t, I.\text{end})
\]

\[
\text{Phase 2:} \\
\quad \text{return AllocateAtom}(p, e, r, I_r)
\]

GetAtomEarliestStartTime(Plan \( p \), RDL \( e \), Atom \( r \), Interval \( I \))

\[
\text{if } (e.\text{type} \neq \text{order}) \text{ then return } I.\text{start}
\]

\[
R \leftarrow \text{all atoms in } e.\text{atoms up to } r \text{ (including)} \\
\text{tot}_{\text{noDur}} \leftarrow I.\text{end} - I.\text{start} - \sum_{r' \in R} r'.\text{duration} \\
\ell \leftarrow r.\text{duration} + \text{tot}_{\text{noDur}} \cdot \frac{\text{weight}(r)}{\sum_{r' \in R} \text{weight}(r')}
\]

\[
\text{return } (I.\text{end} - \ell)
\]

AllocateAtom(Plan \( p \), RDL \( e \), Atom \( r \), Interval \( I_r \))

\[
\text{while } (r \text{ is not fully allocated}) \text{ do} \\
\quad S \leftarrow \text{collection of intervals of length } r.\text{duration contained in } I_r \\
\quad DI \leftarrow \text{argmin}_{DI \in S} \{ c_{DR}(DI) \mid \text{a gang allocated in } DI \text{ can fit in } p \} \\
\quad \text{if } (!DI) \text{ then fail()} \\
\quad p.\text{allocate}(r, r.\text{gang} \times r.\text{capability}, DI) \\
\quad \text{return } p.\text{allocation}(r)
\]

in which \( r \) will be allocated. This phase is only required for \text{order} requests, since its purpose is to verify that the chain dependencies are preserved; for any other request, we simply set \( I_r = I \). Recall that the atoms of an \text{order} request are allocated in reverse order, and that when PlanAtom is called with an atom \( r \) and interval \( I \), all succeeding atoms have already been allocated later than \( I \).

The first phase essentially partitions \( I \) between all atoms preceding \( r \) (including \( r \)), such that each atom receives a weighed fraction of \( I \); the weight of an atom corresponds to its total requested workload. Each atom is then allocated within its segment. Specifically, \( I_r \) is set as the segment corresponding to \( r \) when PlanAtom allocates \( r \). In case an atom does not utilize all of its segment, the partition is updated dynamically.
The second phase of the algorithm allocates a single atom within the segment $I_r$ assigned to it. This is done iteratively. In each iteration, the algorithm considers a set $S$ of allocation options for a single gang, i.e., an interval of length $r \times \text{duration}$ contained in $I_r$. We refer to each such option as a *duration interval*. Variants of the LowCost algorithm set $S$ as follows.

- **LowCost-E** (E-Exhaustive): The set $S$ contains all of the durations intervals in $I$ that can fit a gang.
- **LowCost-S** (S-Sample): The set $S$ is a sample of $N$ duration intervals contained in $I$ that can fit a gang.
- **LowCost-A** (A-Aligned): The set $S$ contains duration intervals that can fit a gang and are of the form $[I \cdot \text{end} - i \cdot r \times \text{duration}, I \cdot \text{end} - (i + 1) \cdot r \times \text{duration}]$ for any $i$ that defines an interval within $I$.

If $S$ is empty, then the algorithm fails. Otherwise, the algorithm finds a duration interval in $S$ of minimal cost, allocates a single gang within that duration interval and repeats until all gangs have been allocated\(^1\). We evaluate the different variants of LowCost in Section

\(^1\)In our implementation, in order to reduce running-time, we actually allocate $G > 1$ gangs in every
7.3. For now, we provide a qualitative discussion. LowCost-E considers all of the possible duration intervals. This minimizes the cost of allocating the current gang, however it might generate “spiky” allocations due to misalignment between allocated gangs. Moreover, the runtime of this exhaustive approach is significantly larger compared to others. LowCost-S could reduce the runtime by sampling only a subset of duration intervals. However, the allocations it produces are imbalanced and discontinuous; further, if the sample size is too small, performance would not be good enough. LowCost-A restricts the duration intervals it considers such that all options are “aligned” to each other (i.e., their respective time intervals are disjoint). This prevents the creation of short spikes, results smoother allocations, and is computationally efficient. Intuitively, although not all options are examined, LowCost-A attempts to provide adequate coverage of the available options in I. Finally, we note that unlike Greedy, the cost-based algorithms described here do not guarantee that an RDL request can always be satisfied, given that a feasible allocation for it exists. To recover this property, all variants of LowCost run Greedy if they initially fail to allocate an RDL request.

An execution example of LowCost-A is portrayed in Figure 7.1. To simplicity our presentation, we only illustrate the CPU dimension. The scheduler is given an order job with 4 stages. When allocating stage number 3, which requests four containers of size \(2 \times 2\), LowCost-A restricts the allocation of stage 3 to the last 8 time slots. Each of the \(2 \times 2\) containers is allocated in the feasible duration intervals with minimal cost.

7.3 Evaluation

In this section we evaluate our algorithms against Greedy. This section is organized as follows. We first outline our evaluation methodology (Section 7.3.1). Then, we describe the main results of our simulations (Section 7.3.2) and our experiments on a test cluster (Section 7.3.3).

7.3.1 Methodology

The basic setting of our evaluation involves jobs that arrive online, each with a reservation requirement specified via RDL. The algorithm handles one job at a time. It either finds a feasible allocation for the job (which satisfies the RDL requirement), or rejects the job. In case it accepts the job, it assigns a reservation to it. The assigned reservation is fixed, i.e., it cannot be transformed later on to another feasible reservation (modifying existing reservations is a future research direction). We considered the following metrics to evaluate iteration. \(G\) is determined as a function of \(I_r\), the total number of gangs that need to be allocated, and the duration of a gang.
the algorithms.

- **Acceptance Ratio**: percentage of accepted jobs.
- **Area**: measures the total containers hours that have been allocated.
- **Preemption**: measures the variability of the per-job allocation (summed over all jobs); specifically, we count the decreases in container allocation for the job across time, sum over all jobs and normalize by the total area.
- **Variance**: measures the variability of the entire plan.
- **Running Time**: average handling time of a single job.

![Acceptance Ratio](image)

![Area](image)

![Preemption](image)

![Variance](image)

Figure 7.2: Simulation results on a 4K cluster as a function of the number of submitted jobs (300-1000). Results averaged over 5 runs.

### 7.3.2 Simulations

The simulations allow us to efficiently test different flavors of **LowCost**. In addition, we are able to control the cluster size, and examine the algorithms in the scale that we aim for in production systems (thousands of machines).
The general setting of each simulation is as follows. We set the total number of jobs and the cluster size. All jobs are generated at time zero using Hadoop GridMix 3.0. However, the jobs are revealed to the algorithm one by one in an online manner, and the algorithm has to decide whether to accept the job or reject it. As mentioned above, accepting a job comes with its reservation, which cannot be later changed.

In our first set of simulations we consider a moderate number of jobs (300-1000). The cluster size is set to 4000 machines. Simulation results are summarized in Figure 7.2. As can be seen from the figure, all variants of LowCost perform better than Greedy in terms of Acceptance Ratio, Area and Variance. In terms of Preemption, LowCost-A is the best, Greedy is comparable with LowCost-E, and LowCost-S is the worse; this is expected since LowCost-S may inherently choose slots without time-continuity, which increases the preemption. In terms of runtime (not shown in the figure), Greedy is the fastest, while LowCost-A, LowCost-E and LowCost-S are around 4x, 20x and 200x slower, respectively. Because LowCost-S turned out too slow, and has not resulted in better performance, we would not consider it further. LowCost-E is a bit better than LowCost-A in terms of Area.

Figure 7.3: Simulation results on a 4K cluster as a function of the number of submitted jobs (1100-1500). Results averaged over 5 runs.
but much slower and also worse in terms of Preemption. Overall, LowCost-A seems the most promising so far.

To reinforce our conclusions, we carried out a second set of experiments with a larger number of jobs. Results are summarized in Figure 7.3. Results remain qualitatively similar, and the improvements compared to Greedy are even higher.

**Conclusion.** LowCost-A is the best algorithm. Compared to Greedy, it improves Area by 15%, accepts 30% more jobs, with 20-40% less preemption and 20% less variance. The runtime increase is by less than 5x.

### 7.3.3 Experiments on Real Clusters

We now describe our experiments on a real cluster. We divide the cluster capacity (around 240 nodes) into two equal parts. One part runs Greedy, and the other part runs our winning variant of LowCost, LowCost-A. Throughout this section we refer to the latter algorithm simply as LowCost.

The workload we use is based on GridMix. In order to perform a substantial number of different experiments, we use a modified version of Gridmix in the bulk of our experiments. In particular, we truncate the original time-distributions of GridMix (which originally captures one week of activity) by nullifying the probability of jobs arriving at a time later than our desired experiment time. We perform two sets of experiments: (i) shorter-term: jobs arrive within one hour$^2$; (ii) longer term experiments: jobs arrive within 100,000 seconds ($\approx 28$ hours).

A note on the experiment settings and their limitations. Besides the obvious differences from simulation conditions – such as machines can fail, potential communication issues, etc. – there are yet other notable differences. Rather than all jobs being submitted at time zero, jobs are submitted gradually, as a function of their potential start time. This changes the conditions under which the algorithms operate. Intuitively, there is a bit less flexibility to the algorithm. In addition, the number of machines is relatively small. This implies that a large job (“elephant”) can occupy the entire cluster for some time, in which case all algorithms will fail to admit new jobs. Due to the above, one might expect that the gains that we obtain would be less than in the simulation settings in which we had thousands of machines. Nevertheless, we obtain similar gains (and even better ones) in most of the scenarios that we consider below.

$^2$Before truncating entries with times greater than one hour, we divide the distribution times by 100, to make things more “interesting” closer to time zero.
Shorter-Term Experiments. We consider both high-load (around 750 submitted jobs) and medium-load (around 140 submitted jobs). The acceptance rate statistics are summarized in Table 7.1. LowCost accepts around 30% (55%) more jobs at medium (high) load. In addition (not seen in the table), we note that LowCost strictly dominates Greedy, in the sense that it admits more jobs in each individual run.

We point out that the relatively small cluster size prevents us to experiment with low-load scenario in which most jobs are accepted - for that to happen in the one-hour time window, we need to submit a very small number of jobs, which will make the results statistically insignificant.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Medium Load</th>
<th>High Load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greedy</td>
<td>32.8% ± 4.9%</td>
<td>15.7% ± 3.1%</td>
</tr>
<tr>
<td>LowCost</td>
<td>43.3% ± 3.1%</td>
<td>24.4% ± 5.3%</td>
</tr>
</tbody>
</table>

Table 7.1: Acceptance ratios for Greedy and LowCost. Results averaged over 5 runs.

Extracting the other performance metrics is tricky. This is because the system keeps track of the metrics only for active reservations. To still get meaningful statistics, we output their values after every ten additional jobs that have been accepted. We summarize the average gains of LowCost relative to Greedy in Table 7.2. Due to the above mentioned limitation, we provide results only for Preemption and Variance, whose instantaneous values are more meaningful than for the Area metric. The results show substantial gains for LowCost.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Medium Load</th>
<th>High Load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preemption</td>
<td>46.9% ± 9.5%</td>
<td>45.1% ± 6.7%</td>
</tr>
<tr>
<td>Variance</td>
<td>22.1% ± 16.3%</td>
<td>26.9% ± 16.7%</td>
</tr>
</tbody>
</table>

Table 7.2: Reductions in Preemption and Variance relative to Greedy. Results averaged over 5 runs.

Finally, we zoom-in on an individual run, and show the visualization of the different plans (Figure 7.4). In general, Greedy results in tall and skinny reservations, while LowCost leads to shorten, more spread-out reservations. Intuitively, this allows LowCost more flexibility to accept new jobs, as less period in times are completely booked.

Long-Term Experiments. Recall that in the longer-term experiments jobs are submitted over a period of roughly 28 hours. We test medium load conditions by submitting around 950 jobs over that period. The acceptance rate results are summarized in Table 7.3. As before, LowCost obtains better Acceptance Ratio than Greedy (although the margins are
Figure 7.4: Visualization of the plans at some point throughout the execution of the two algorithms. These snapshots are taken at high-load conditions.

less than in the shorter-term experiments). The results for the other metrics are summarized in Table 7.4, and are fairly similar to what observed before.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Medium Load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greedy</td>
<td>$48.8% \pm 0.9%$</td>
</tr>
<tr>
<td>LowCost</td>
<td>$54.8% \pm 1.1%$</td>
</tr>
</tbody>
</table>

Table 7.3: Acceptance ratios of Greedy and LowCost for the longer-term experiments. Results averaged over 3 runs.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Medium Load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preemption</td>
<td>$40.2% \pm 22.4%$</td>
</tr>
<tr>
<td>Variance</td>
<td>$24.6% \pm 14.8%$</td>
</tr>
</tbody>
</table>

Table 7.4: Reductions in Preemption and Variance relative to Greedy. Results averaged over 3 runs.

Conclusion. The results obtained in the real-cluster experiment are qualitatively similar to those we got in simulations. We expect similar gains on larger clusters.
Chapter 8

Summary

In this dissertation, we designed allocation algorithms and truthful mechanisms for scheduling deadline-sensitive jobs in cloud-like environments. Our contribution is threefold. First, we constructed new algorithms for offline and online allocation problems, and proved theoretical bounds using dual-fitting and rounding techniques. Second, we designed truthful mechanisms based on our allocation algorithms, that preserved (or nearly preserved) the bounds on the competitive ratio of the underlying algorithm. Finally, we used insights from our theoretical work to implement a deadline-aware mechanism (LowCost) for scheduling DAG-structured jobs over Hadoop.

There are several interesting directions for future work. One obvious direction is to improve the constants in our results. For example, the truthful, committed mechanism constructed for our most general case involves large constants that can potentially be improved. One particularly interesting question along these lines is whether one can obtain competitive ratios that approach one as the number of servers $C$ grows large. An additional avenue of future work is to extend our results to more sophisticated scheduling problems. One might investigate the impact of non-uniform (unrelated) servers, time-varying capacity, server failures and so on. The primary question is then to determine to what extent deadline slackness helps to construct constant-competitive mechanisms for variations of the online scheduling problem. Another interesting question is to improve our results for offline scheduling of DAG-structured jobs, or provide algorithms with provable guarantees for the online case.
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Our theoretical research starts with a fundamental problem in scheduling, where a computing system receives requests over time to execute tasks with deadlines (online deadline scheduling). The goal is to maximize the total benefit for the completed tasks.

For the most general version of the problem, it is known that no algorithm guarantees a constant competitive ratio. We show that if deadlines are not too precise, it is possible to develop an algorithm with a fixed competitive ratio for the problem. The competitive ratio improves as the deadlines become less precise.

Next, we extend the basic scheduling model to deal with practical aspects of scheduling tasks in the cloud, such as scheduling tasks with complex internal dependencies, scheduling tasks with uncertain resource demands, and providing SLA guarantees for meeting deadlines.

Our contribution includes developing scheduling policies that are effective for the cloud. These policies are not only useful in public clouds, but also in private clouds shared by users belonging to the same organization. In our work, we developed policies based on the algorithms we proposed for the problem, and we demonstrated similar approximation guarantees for them.

In the end, we implemented a scheduling algorithm for meeting deadlines for a system of Hadoop YARN, which is the most popular open-source cloud system. This algorithm was based on our theoretical research. To validate the algorithm, we compared it against existing solutions through simulations and real-world cloud trials. This algorithm was integrated into the 2.8 release of the Hadoop system.
The popularity of cloud systems as platforms for computing has revealed a wide range of new issues for researchers in the field of scheduling.

Today, cloud systems provide a shared access to their resources between system users, which send requests to send data to the cloud.

The task of the cloud system's administrator is to provide service level agreements to users, such as for example, meeting deadlines (deadline) as required for production jobs (production jobs).

However, the amount of resources in the cloud is limited, which requires the administrator to implement scheduling mechanisms that decide which tasks will be executed, and how to allocate system resources between the received tasks without violating the service level agreements.

Unfortunately, current cloud systems do not implement scheduling mechanisms that provide a response for tasks with deadlines.

One approach taken in private clouds is to share system resources fairly between system users [37]. However, this approach ignores the topic of meeting deadlines. Another approach that can be taken is to provide maximum efficiency for tasks with deadlines.

But, a severe push of this kind leads to the delay or cancelation of tasks with lower delay, which in turn reduces the system's efficiency [27].

Public cloud systems do not address the topic of meeting deadlines at all.

Public cloud systems allow the rental of computing resources, or pay on a pay-per-use basis for all operations performed. Under this approach, the responsibility for meeting deadlines falls on the users. Furthermore, users are required to pay for the use of resources even when their tasks are completed late.

The goal of this work is to develop scheduling mechanisms for cloud systems that guarantee meeting deadlines.

The central difficulty in our work arises from the diversity of tasks being executed.

Firstly, these tasks differ in their deadlines: financial companies must process electronic commerce data on each trading day before the start of the next day, while academic simulations are usually delayed. Secondly, these tasks differ in their importance: there are tasks that have a higher priority. Thirdly, these tasks differ in their requirements: demand for resources varies from task to task, as well as the structure of dependencies between each task.

Developing scheduling mechanisms for shared computing systems, such as the cloud, integrates many research fields.

- Scheduling algorithms – Developing efficient algorithms for resource allocation problems. Cloud computing has presented us with many scheduling problems, some as new problems and others as new versions of known scheduling problems.

- Our goal is to design efficient scheduling algorithms and provide theoretical bounds on the results they generate.

- Scheduling mechanisms – Designing scheduling mechanisms that allocate resources at strategic environments, in which users' interests are maximized at the expense of their own. To illustrate this, consider a cloud that serves employees who belong to the same organization. In order to meet personal goals, an employee may report a higher priority to work, even if it is not in line with the company's goals.

- Our goal is to develop scheduling mechanisms that are truthful and incentive compatible (truthful; incentive compatible) so that users have no interest in misreporting.

- Implementing mechanisms – Implementing scheduling mechanisms in realistic industrial environments and analyzing their performance through simulations performed on real tasks.
המחקר נועש בהנחיית פרופ’ ספי איזר בנחלה למדעי המחשב.

אני מודה לטכניון על התמיכה הכספית הנדיבה בהשתלמותי.
מנגנונים לתזמון משימות במחשוב ענן

תיבור על מחקר

לשם مليוי חלקי של הדרישות lukבבלת תואר דוקטור בפילוסופיה

יונתן יניב

נהוג לסטט הטכניון – מכון טכנולוגי לישראל

ענת תשע"ז חיפה ינואר 2017
מנגנונים
לתזמון משימות במחשוב ענן

יונתן יניב