Scheduling Multi-Server Jobs with Sublinear Regrets via Online Learning

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Abstract—Nowadays, multi-server jobs, which request multiple computing devices and hold onto them during their execution, dominate modern computing clusters. When allocating computing devices to them, it is difficult to make the tradeoff between the parallel computation gains and the internal communication overheads. Firstly, the computing gain does not increase linearly with computing devices. Secondly, the device type which dominates the communication overhead is various to different job types. To achieve a better gain-overhead tradeoff, we formulate an accumulative reward maximization program and design an online algorithm, i.e., OgaSched, to schedule multi-server jobs. The reward of a job is formulated as the parallel computation gain aggregated over the allocated computing devices minus the penalty on the dominant communication overhead. OgaSched allocates computing devices to each arrived job in the ascending direction of the reward gradients. OgaSched has a best-so-far regret with concave rewards, which grows sublinearly with the number of job types and the time slot length. OgaSched has several parallel sub-procedures to accelerate its computation, which greatly reduces the complexity. We conduct extensive trace-driven simulations to validate the performance of OgaSched. The results demonstrate that OgaSched outperforms widely used heuristics by 11.33%, 7.75%, 13.89%, and 13.44%, respectively.

Index Terms—Multi-server job, online gradient ascent, online scheduling, regret analysis.

1 Introduction

In today's computing clusters, many jobs request multiple computing devices (CPUs, GPUs, etc) simultaneously and hold onto them during their executions. Typical jobs are large-scale graph computations and distributed DNN model trainings [1]. These jobs are referred as *multi-server jobs* [2], [3]. Multi-server jobs of diverse device requirements, along with the other jobs, arrive to the cluster online, which puts great pressure to current schedulers to achieve a high system efficiency.

For multi-server jobs, when allocating multiple computing devices to them, it is difficult to make the tradeoff between *the parallel computation gains* and *the internal communication overheads*. For each multi-server job, the parallel computation gain is modeled as the speedup on the completion time with multiple devices, which could be fitted with a utility function [4]. Correspondingly, the internal communication overhead is modeled as the cost or latency caused by data synchronization and related operations between these devices. To make a better tradeoff, we need to fully take the following features of multi-server jobs into consideration.

- *The marginal effect of the computation gains decreases.* For instance, in the distributed training of DNNs, adding Parameter Servers (PSs) or workers (which request more computing devices) does not improve the training speed linearly. This is because the averaging of local gradients also takes more time to finish in each epoch [1], [4]. As a result, in the cluster of limited resources, it is challenging to allocate an appropriate number of computing devices to each job to maximize the overall gains of all jobs.
- *The type of device which dominates the communication overhead is various to different job types.* For example, in Spark, the dominant communication overhead of the Big Query jobs, which are generally organized as workflows of tasks, lies in the internal input-output data transferring between the interdependent CPU- and memory-intensive tasks [5]. However, the dominant overhead of the distributed training of DNNs lies in the data averaging and synchronizing between the GPU-intensive workers [6]. This variety greatly complicates the analysis on the gain-overhead tradeoff formally.

Despite the vast literature on the online scheduling algorithms and policies [1], [4], [6], [7], [8], [9], [10], [11], their model formulation and theoretical analysis which place emphasis on the gain-overhead tradeoff is limited. To fill the theoretical gap, in this paper, we propose an online scheduling algorithm, termed as OgaSched, to *learn* to allocate computing devices to multi-server jobs to maximize

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the overall system efficiency, i.e., *the resource utilization per computing device*. We try to analyze the tradeoff in a generic way. The generality is embodied in the following points. First of all, different from the specific works on deep learning jobs [4], [6], [1] or query jobs [5], we allow different types of multi-server jobs to *co-locate* in the cluster which consists of heterogeneous computing instances. Different job types can have different computing device requirements while different computing instances can be equipped with diverse quantities and types of computing devices. Secondly, we adopt general zero-startup non-decreasing utility functions to model the computation gains in terms of the completion times. Compared to existing literature, we allow the utilities to be diverse in their *level of concavity*. Specifically, we provide both analysis and experiments on linear, polynomial, logarithmic, and reciprocal utilities. Thirdly, we makes no assumptions on the arrival patterns of multi-server jobs. OGASCHED requests no knowledge on the job arrival distributions but tries to learn them to make better scheduling decisions.

In our model formulation, the overall system efficiency is expressed by the accumulative reward. Time is slotted, and the accumulative reward is obtained by summing up the rewards of each time, where a single-time reward is a linear aggregation of each job's reward. Further, a job's reward at each time is designed as the achieved parallel computation gain aggregated over the allocated computing devices minus the penalty on the dominant communication overhead. At each time, OGASCHED allocates computing devices to each arrived job in the direction that *makes the gradient of the reward increase*. OGASCHED is capable of handling high dimensional inputs in stochastic scenarios with unpredictable behaviors. We adopt regret, i.e., the gap on the accumulative reward between the proposed online algorithm and the offline optimum achieved by an oracle [12], to analyze the performance lower bound of OGASCHED. We prove that, OGASCHED has a State-of-the-Art (SOTA) regret, which is sublinear with the time slot length and the number of job types. This work fulfills one of the key deficiencies of the past works in the modeling and analysis of the gain-overhead tradeoff for multi-server jobs. The contributions are summarized as follows.

- For the online scheduling of multi-server jobs, we propose an algorithm, i.e., OGASCHED, to learn to strike the balance between the computation gain and the communication overhead. OGASCHED has no assumptions on the job arrival patterns. With a nice setup (defined in Sec. 3.1), OGASCHED achieves a SOTA regret $\mathcal{O}\big(\sqrt{|\mathcal{L}|T}\big)$ for general concave non-linear rewards, where T is the time slot length, and $\mathcal{L}$ is the set of job types. To the best of our knowledge, this is the first work that provides a regret which grows sublinearly with the number of job types.
- OGASCHED is accelerated by well designed parallel sub-procedures. The parallelism helps yield a complexity of $\mathcal{O}\big(\log(K)\big)$, where K is the number of device types.
- We conduct extensive trace-driven simulations to validate the performance of OGASCHED. The simulation results show that OGASCHED outperforms widely used heuristics including DRF [13], FAIRNESS, BINPACKING, and SPREADING by 11.33%, 7.75%, 13.89%, and 13.44%, respectively. We also provide large-scale validations.

The rest of this paper is organized as follows. We formulate the online scheduling problem for multi-server jobs in Sec. 2. We then present the design details of OGASCHED with regret analysis and discuss its extensions in Sec. 3. We demonstrate the experimental results in Sec. 4, and discuss related works in Sec. 5. Finally, we conclude this paper in Sec. 6.

2 BIPARTITE SCHEDULING WITH REGRETS

We focus on a cluster of heterogenous computing instances serving several types of multi-server jobs. Different computing instances are configurated with different types and quantities of computing devices, including GPUs, NPUs, TPUs, FPGA acceleration cards, etc. Jobs of different types have different demands on the computing devices.

2.1 Online Bipartite Scheduling

We use a bipartite graph $\mathcal{G} = (\mathcal{L}, \mathcal{R}, \mathcal{E})$ to model the job-server constraints, as shown in Fig. 1. In graph $\mathcal{G}$, $\mathcal{L}$ is the set of job types and indexed by l while $\mathcal{R}$ is the set of computing instances and indexed by r. The connections between the job types and the computing instances are recorded in $\mathcal{E}$. Because of the job-server constraints, type-l job may only be served by a subset of $\mathcal{R}$. We denote the subset by $\mathcal{R}_l = \{r \in \mathcal{R} \mid (l,r) \in \mathcal{E}\}$. Similarly, we use $\mathcal{L}_r = \{l \in \mathcal{L} \mid (l,r) \in \mathcal{E}\}$ to represent the set of job types that connect to computing instance r. We designate each job type $l \in \mathcal{L}$ as *port* and each connection $(l,r) \in \mathcal{E}$ as *channel*. $\mathcal{G}$ is called right d-regular *iff* the indegree of each right vertex is d, i.e., $\forall r \in \mathcal{R}, |\mathcal{L}_r| = d$.

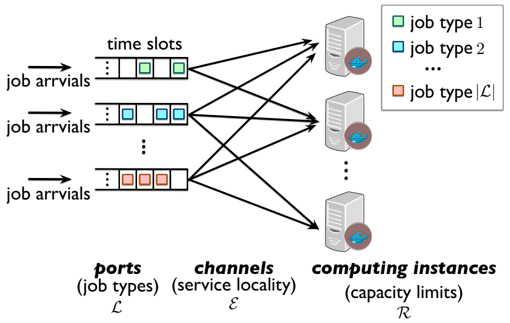

Fig. 1. The bipartite graph model for online job scheduling.

Time is discretized, and at each time $t \in \mathcal{T} \triangleq \{1, ..., T\}$, from each port, at most one job yields. Let us use

$$\boldsymbol{x}(t) = \Big[x_l(t)\Big]_{l\in\mathcal{L}} \in \{0,1\}^{|\mathcal{L}|} \tag{1}$$

to describe the job arrival status at time t. The cluster has K types of computing devices, and computing instance r has c_r^k type-k devices, where $k \in \mathcal{K} \triangleq \{1, 2, .., K\}$. For each type-$l$ job, we denote its requirements on each device by $\boldsymbol{a}_l = [a_l^k]_{k\in\mathcal{K}} \in \mathbb{N}^{|\mathcal{K}|}$. At time t, we use

$$\boldsymbol{y}(t) = \Big[y_{(l,r)}^k(t)\Big]_{l\in\mathcal{L}, r\in\mathcal{R}_l, k\in\mathcal{K}} \in \mathbb{R}^{\sum_{l\in\mathcal{L}}|\mathcal{R}_l|\times K} \tag{2}$$

to represent the scheduling decision. Here we allow $y^k_{(l,r)}(t)$ to be fractional[1], which can be implemented with time-sharing and checkpoint techniques [15], [16], [14].

The first constraint $\boldsymbol{y}(t)$ should satisfy is that, on each computing instance, a job should not be allocated with computing devices more than it requires. Formally, we have

$$0 \leq y^k_{(l,r)}(t) \leq a^k_l, \forall l, r, k, t. \tag{3}$$

The second constraint $\boldsymbol{y}(t)$ should satisfy is that, the computing devices allocated out from a computing instance should not more than it has:

$$\sum_{l \in \mathcal{L}_r} y^k_{(l,r)}(t) \leq c^k_r, \forall r, k, t. \tag{4}$$

Let us use $\mathcal{Y} \triangleq \{\boldsymbol{y} \in \mathbb{R}^{\sum_{l\in\mathcal{L}} |\mathcal{R}_l| \times K} \mid (3) \text{ and } (4) \text{ hold}\}$ to represent the solution space.

2.2 Regret Minimizing

The performance metric we use for online bipartite scheduling is the gain obtained by the parallel computations minus the penalty introduced by the dominant communication overheads. Specifically, we denote by $q_l\big(\boldsymbol{x}(t), \boldsymbol{y}(t)\big)$ the reward of port l at time t , and it is formulated as

$$q_l\big(\boldsymbol{x}(t), \boldsymbol{y}(t)\big) = x_l(t)\Big[\sum_{k\in\mathcal{K}} f_k\Big(\sum_{r\in\mathcal{R}_l} y^k_{(l,r)}(t)\Big) - \max_{k\in\mathcal{K}}\Big\{\beta_k \sum_{r\in\mathcal{R}_l} y^k_{(l,r)}(t)\Big\}\Big]. \tag{5}$$

In this formulation, the first part, $\sum_{k\in\mathcal{K}} f_k(\sum_{r\in\mathcal{R}_l} y^k_{(l,r)}(t))$, is the parallel computation gain, which is linearly aggregated over each type of computing devices. $f_k(\cdot)$ is the gain achieved by $\sum_{r\in\mathcal{R}_l} y^k_{(l,r)}(t)$ type-k computing devices collaboratively, where $f_k(\cdot)$ is a zero-startup concave utility defined in $\mathbb{R}_+$. Note that $\sum_{r\in\mathcal{R}_l} y^k_{(l,r)}(t)$ is the quota of the type-k computing devices allocated to the port-l job. As we have analyzed before, $\{f_k(\cdot)\}_{k\in\mathcal{K}}$ are concavity because the marginal effect of parallel computation decreases successively when increasing participated computing devices [17], [18]. We expect $\{f_k(\cdot)\}_{k\in\mathcal{K}}$ to be *continuously differentiable* because the property helps design a policy that yields a nice lower bound of the reward. The details will be demonstrated in Sec. 3.3. If $\{f_k(\cdot)\}_{k\in\mathcal{K}}$ are not differentiable everywhere, we can apply subgradient ascent related techniques in the policy design. The second part in (5) is $\max_{k\in\mathcal{K}}\{\beta_k \sum_{r\in\mathcal{R}_l} y^k_{(l,r)}(t)\}$, which reflects the dominant weighted communication overheads over different types of computing devices. Take the distributed training of DNNs as an example, the dominant communication overhead lies in the averaging and synchronizing of gradients over GPUs [19], [20]. $\{\beta_k\}_{k\in\mathcal{K}}$ are the coefficients to balance the gain and the overhead. W.L.O.G., we set each $\beta_k \in [0, 1]$. Theoretically, the second part of (5) is actually a penalty, the minimization of which guides the scheduling decisions to balance the communication overheads of different device types. Our reward design encourages each job to be served with the balance between the computation gain and the communication overhead being striked.

1. Currently, Machine-Learning-as-a-Service (MLaaS) platform, such as Alibaba PAI, supports GPU sharing in a space- and time-multiplexed manner by intercepting CUDA APIs [14].

We define the overall reward at time t as the linear aggregation over each port: $q\big(\boldsymbol{x}(t), \boldsymbol{y}(t)\big) = \sum_{l\in\mathcal{L}} q_l\big(\boldsymbol{x}(t), \boldsymbol{y}(t)\big)$. Based on this, the accumulative reward of scheduling policy π over the time horizon $\mathcal{T}$ is obtained by summing up the rewards obtained at each time until T: $Q^\pi\big(\{\boldsymbol{x}(t)\}_1^T, \{\boldsymbol{y}(t)\}_1^T\big) = \sum_{t\in\mathcal{T}} q\big(\boldsymbol{x}(t), \boldsymbol{y}(t)\big)$, where the scheduling decisions $\{\boldsymbol{y}(t)\}_1^T$ are made under the guidance of policy π. In the following, we just use Q and drop the superscript π for simplification.

We do not make any assumption on the distribution of the job arrival trajectory $\{\boldsymbol{x}(t)\}_1^T$. To obtain a non-trivial performance measure, we cast the multi-server bipartite scheduling problem into the framework of online learning, which prompts us to compare the performance of the online policy π with the best offline stationary policy π^* [21], [22]. Let us denote by $\boldsymbol{y}^*$ the optimal offline stationary resource allocation decision guided by policy π^*, i.e., $\boldsymbol{y}^* = \arg\sup_{\boldsymbol{y}\in\mathcal{Y}} Q\big(\{\boldsymbol{x}(t)\}_1^T, \boldsymbol{y}\big)$. Physically, $\boldsymbol{y}^*$ is the optimal stationary resource reservation decisions for each port whatever the actual job arrival status $\boldsymbol{x}(t)$ is. Formally, we define the regret $R_T^\pi\big(\{\boldsymbol{x}(t)\}_1^T\big)$ for the job arrival trajectory $\{\boldsymbol{x}(t)\}_1^T$ as

$$R_T^\pi\Big(\{\boldsymbol{x}(t)\}_1^T\Big) \triangleq Q\Big(\{\boldsymbol{x}(t)\}_1^T, \boldsymbol{y}^*\Big) - Q\Big(\{\boldsymbol{x}(t)\}_1^T, \{\boldsymbol{y}(t)\}_1^T\Big).$$

The final regret of policy π is further defined as the maximum regret achieved over every possible job arrival trajectory:

$$R_T^\pi \triangleq \sup_{\forall\{\boldsymbol{x}(t)\}_1^T} R_T^\pi\Big(\{\boldsymbol{x}(t)\}_1^T\Big). \tag{6}$$

Our goal is to find a policy π, under which a sequence of bipartite scheduling decisions $\{\boldsymbol{y}(t)\}_1^T$ is yielded, to minimize R_T^π.

3 Online Gradient Ascent

To minimize the regret R_T^π, we resort to an online variant of the gradient-based methods, online gradient ascent (OGA) [23]. A series of recent works have prove that OGA achieves the best possible regret for online caching problems in different network settings when the rewards are linear [22], [24], [25], [26]. In this paper, we extend OGA to the online bipartite scheduling problem for multi-server jobs with non-linear rewards. Before demonstrating the design details, we firstly give some preliminary definitions and analysis.

3.1 Preliminaries

Definition 1. Nice Setup. *If all the utilities $\{f_k\}_{k\in\mathcal{K}}$ are (i) linearly separable over computing instances, i.e.,*

$$f_k\Big(\sum_{r\in\mathcal{R}_l} y^k_{(l,r)}\Big) = \sum_{r\in\mathcal{R}_l} f_r^k\Big(y^k_{(l,r)}\Big), \tag{7}$$

and each concave utility $f_r^k(\cdot)$ is (ii) continuously differentiable in $\mathbb{R}_+$, and (iii) there exist $\varpi_r^k > 0$ such that

$$(f_r^k)'(0) \leq \varpi_r^k, \forall r, k, \tag{8}$$

we say this is a nice setup.

The following proposition shows the convexity of the regret minimization problem.

Algorithm 1: OGASCHED

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Input: Graph $\mathcal{G}$, requirements $\boldsymbol{a}$, and capacities $\boldsymbol{c}$
Output: Scheduling decisions $\{\boldsymbol{y}(t)\}_{t\in\mathcal{T}}$
1  Initialize $\boldsymbol{y}(1) \in \mathcal{Y}$ and $\eta_0$
2  for $t$ from $1$ to $T$ do
3      Observe the job arrival status $\boldsymbol{x}(t)$
4      Calculate the gradient $\nabla q(\boldsymbol{x}(t), \boldsymbol{y}(t))$ with (9)
5      $\boldsymbol{z}(t+1) \leftarrow \boldsymbol{y}(t) + \eta_t \nabla q(\boldsymbol{x}(t), \boldsymbol{y}(t))$
6      for each $(r,k)$ in zip$(\mathcal{R},\mathcal{K})$ do in parallel
7          Sort the elements of $\boldsymbol{z}^k_{(:,r)}(t+1)$ in descending order
8          first $\leftarrow$ True
9          while True do
10             $\mathcal{B}^2_{rk} \leftarrow \varnothing$
11             if first then
12                 $\mathcal{B}^1_{rk} \leftarrow \varnothing, \mathcal{B}^3_{rk} \leftarrow \mathcal{L}_r, \hat{\boldsymbol{y}} \leftarrow \boldsymbol{0}$
13             else
14                 if $\hat{y}^k_{(1,r)} > a^k_1$ then
15                     $\mathcal{B}^1_{rk} \leftarrow \{1\}, \mathcal{B}^3_{rk} \leftarrow \mathcal{L}_r \backslash \{1\}$
16                 else
17                     break
               /* Repeat loop                                    */
18             repeat
19                 Calculate $\rho^k_r$ with (13)
20                 for $l \in \mathcal{L}_r$ do
21                     if $l \in \mathcal{B}^1_{rk}$ then
22                         $\hat{y}^k_{(l,r)} \leftarrow a^k_l$
23                     else if $l \in \mathcal{B}^3_{rk}$ then
24                         $\hat{y}^k_{(l,r)} \leftarrow z^k_{(l,r)}(t+1) - \rho^k_r/2$
25                         if $\hat{y}^k_{(l,r)} < 0$ then
26                             $\mathcal{S}_{rk} \leftarrow \{l, l+1, ..., |\mathcal{L}_r|\}$
27                             break
28                 $B^3_{rk} \leftarrow B^3_{rk} \backslash \mathcal{S}_{rk}, B^2_{rk} \leftarrow \mathcal{B}^2_{rk} \cup \mathcal{S}_{rk}$
29             until $\mathcal{S}_{rk} = \varnothing$;
30             first $\leftarrow$ False
31     $\boldsymbol{y}(t+1) \leftarrow \hat{\boldsymbol{y}}$
32     Update $\eta_{t+1}$ from $\eta_t$
33 return the sequence of decisions $\{\boldsymbol{y}(t)\}_{t\in\mathcal{T}}$
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Proposition 1. CONVEXITY. *(i) The feasible solution space $\mathcal{Y}$ is convex. (ii) With a nice setup, at each time t, the single-slot reward function $q(\boldsymbol{x}(t), \boldsymbol{y}(t))$ is a concave function of $\boldsymbol{y}(t)$.*

As a continuously differentiable concave function of $\boldsymbol{y}(t)$, the derivative of $q(\cdot)$ at time t is

$$\frac{\partial q(\boldsymbol{x}(t), \boldsymbol{y}(t))}{\partial y^k_{(l,r)}(t)} = \begin{cases} x_l(t)\Big((f^k_r)'(y^k_{(l,r)}(t)) - \beta_k\Big) & k = k^* \\ x_l(t)(f^k_r)'(y^k_{(l,r)}(t)) & \text{o.w.,} \end{cases} \tag{9}$$

where k^* is defined as

$$k^* = \underset{k\in\mathcal{K}}{\operatorname{argmax}} \Big\{\beta_k \sum_{r\in\mathcal{R}_l} y^k_{(l,r)}\Big\}. \tag{10}$$

3.2 Online Gradient Ascent

In this section, we give the design details of the OGA-based bipartite scheduling policy.

Definition 2. THE OGA POLICY. *With any feasible initial bipartite scheduling decision $\boldsymbol{y}(1) \in \mathcal{Y}$, at each time $t \in \mathcal{T}$, the OGA policy gets $\boldsymbol{y}(t+1)$ in the direction of ascending the gradient of $q(\boldsymbol{x}(t), \boldsymbol{y}(t))$:*

$$\boldsymbol{y}(t+1) = \Pi_{\mathcal{Y}}\Big(\boldsymbol{y}(t) + \eta_t \nabla q(\boldsymbol{x}(t), \boldsymbol{y}(t))\Big), \tag{11}$$

where η_t is the step size, and $\Pi_{\mathcal{Y}}(\boldsymbol{z}) = \operatorname{argmin}_{\hat{\boldsymbol{y}}\in\mathcal{Y}} \|\hat{\boldsymbol{y}} - \boldsymbol{z}\|^2_2$ is the Euclidean projection of $\boldsymbol{z}$ onto $\mathcal{Y}$.

To implement the projection for large-scale scenarios with low complexity, we propose OGASCHED. Before demonstrating the design details, we firstly introduce the KKT conditions of the projection:

$$\forall l, r, k : \begin{cases} 2(\hat{y}^k_{(l,r)} - z^k_{(l,r)}) + \rho^k_r = 0 \\ \sum_{l\in\mathcal{L}_r} \hat{y}^k_{(l,r)} = c^k_r \ \& \ \rho^k_r > 0 \\ \hat{y}^k_{(l,r)} = a^k_l \ \& \ \mu^k_{l,r} > 0 \\ \hat{y}^k_{(l,r)} = 0 \ \& \ \lambda^k_{l,r} > 0. \end{cases} \tag{12}$$

where $\boldsymbol{\rho}$ is the dual variable for (4), $\boldsymbol{\mu}$ is the dual variable for $\boldsymbol{y}(t) \le \boldsymbol{a}$, and $\boldsymbol{\lambda}$ is the dual variable for $\boldsymbol{y}(t) \ge \boldsymbol{0}$.

For each $r \in \mathcal{R}$ and each $k \in \mathcal{K}$, we divide the ports $l \in \mathcal{L}$ into three disjoint sets:

$$\mathcal{B}^1_{rk} = \Big\{l \in \mathcal{L}_r \mid \forall(l,r,k) : \hat{y}^k_{(l,r)} = a^k_l\Big\}$$
$$\mathcal{B}^2_{rk} = \Big\{l \in \mathcal{L}_r \mid \forall(l,r,k) : \hat{y}^k_{(l,r)} = 0\Big\}$$
$$\mathcal{B}^3_{rk} = \Big\{l \in \mathcal{L}_r \mid \forall(l,r,k) : 2(\hat{y}^k_{(l,r)} - z^k_{(l,r)}) + \rho^k_r = 0\Big\},$$

where

$$\rho^k_r = \frac{2}{|\mathcal{B}^3_{rk}|}\Big(\sum_{l\in\mathcal{B}^3_{rk}} z^k_{(l,r)} - c^k_r + \sum_{l\in\mathcal{B}^1_{rk}} a^k_l\Big), \forall r, k. \tag{13}$$

Our algorithm, termed as OGASCHED, works by solving the equation system (12) iteratively. The number of projections is linearly propotional to the size of the solution's dimensions, i.e., $\sum_{l\in\mathcal{L}} |\mathcal{R}_l| \times K$. Nevertheless, we can do the projections for different combinations of r and k in parallel because they are not interwoven. Thus, the time complexity of OGASCHED is of $\mathcal{O}(|\mathcal{L}| \times \log(K \sum_{l\in\mathcal{L}} |\mathcal{R}_l|))$ in each time slot, where the $\log(\cdot)$ operator comes form the sorting operation (step 7). The multiplier $|\mathcal{L}|$ outside $\log(\cdot)$ comes from the repeat loop (step 18 $\sim$ step 29). In our experiments, the repeat loop's execution count is significantly less than the number of job types $|\mathcal{L}|$.

3.3 Regret Analysis

In this section, we discuss the regret of OGASCHED. The main result is summarized in Theorem 1.

Theorem 1. REGRET UPPER BOUND. *With a nice setup, the regret of OGASCHED is upper bounded by*

$$R^{\text{OGASCHED}}_T \le \sqrt{2T \sum_{k\in\mathcal{K}} \sum_{r\in\mathcal{R}} \bar{a}^k c^k_r} \times \sqrt{\sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \Big((\beta^*)^2 + K(\varpi^*_r)^2\Big)}, \tag{14}$$

where $\bar{a}^k = \max_{l\in\mathcal{L}} a_l^k$*,* $\beta^* = \max_{k\in\mathcal{K}} \beta_k$*, and* $\varpi_r^* = \max_{k\in\mathcal{K}} \varpi_r^k$.

Proof. The result is based on the non-expansiveness property of Euclidean projection and the concavity of $\{f_r^k(\cdot)\}_{r,k}$. Our proof has two parts. The first part gives the general form of the upper bound while the second part gives the specific upper bounds of involved variables.

At each time $t > 1$, for the $\boldsymbol{y}(t)$ yielded by OGASCHED, we have

$$\begin{aligned}\|\boldsymbol{y}(t) - \boldsymbol{y}^*\|^2 &= \left\|\Pi_{\mathcal{Y}}\big(\boldsymbol{y}(t-1) + \eta_t \nabla q(t-1)\big) - \boldsymbol{y}^*\right\|^2 \\ &\overset{(i)}{\leq} \|\boldsymbol{y}(t-1) - \boldsymbol{y}^*\|^2 + \eta_t^2 \|\nabla q(t-1)\|^2 \\ &\quad + 2\eta_t \nabla q\big(\boldsymbol{y}(t-1)\big)^{\mathrm{T}}\big(\boldsymbol{y}(t-1) - \boldsymbol{y}^*\big), \end{aligned} \tag{15}$$

where $\nabla q\big(\boldsymbol{y}(t-1)\big)$ is a shorthand for $\nabla q(\boldsymbol{x}(t-1), \boldsymbol{y}(t-1))$. (i) is because the non-expansiveness property of the Euclidean projection. By moving $\|\boldsymbol{y}(t-1) - \boldsymbol{y}^*\|^2$ to the LHS of (15) and summing the inequality telescopically over $\mathcal{T}$, we have

$$\begin{aligned}&\sum_{t=2}^{T+1} \nabla q\big(\boldsymbol{y}(t-1)\big)^{\mathrm{T}}\big(\boldsymbol{y}^* - \boldsymbol{y}(t-1)\big) \\ &\overset{(i)}{\leq} \frac{\eta \sum_{t=1}^{T} \|\nabla q(\boldsymbol{y}(t))\|^2}{2} + \frac{\|\boldsymbol{y}(1) - \boldsymbol{y}^*\|^2 - \|\boldsymbol{y}(T) - \boldsymbol{y}^*\|^2}{2\eta} \\ &\overset{(ii)}{\leq} \frac{\eta T (\max\|\nabla q\|)^2}{2} + \frac{diam(\mathcal{Y})^2}{2\eta}. \end{aligned} \tag{16}$$

Inequality (i) is because $\forall t \in \mathcal{T}$ we set $\eta_t \equiv \eta$. In (ii), we use the fact that $\|\boldsymbol{y}(T) - \boldsymbol{y}^*\| \geq 0$. In (15), $\max\|\nabla q\|$ is the maximum Euclidean norm of the gradient of $q(\boldsymbol{x}(t), \boldsymbol{y}(t))$ over every possible $\boldsymbol{y}(t)$, and $diam(\mathcal{Y})$ is the largest Euclidean distance between any two elements of $\mathcal{Y}$. Because $q(\cdot)$ is a concave function of $\boldsymbol{y}(t)$, we have

$$\begin{aligned} R_T^{\text{OGASCHED}} &= \sup_{\forall \{\boldsymbol{x}(t)\}_1^T} \sum_{t=1}^{T} \Big(q\big(\boldsymbol{x}(t), \boldsymbol{y}^*\big) - q\big(\boldsymbol{x}(t), \boldsymbol{y}(t)\big)\Big) \\ &\leq \sup_{\forall \{\boldsymbol{x}(t)\}_1^T} \sum_{t=1}^{T} \nabla q\big(\boldsymbol{y}(t)\big)^{\mathrm{T}}\big(\boldsymbol{y}^* - \boldsymbol{y}(t)\big) \quad \triangleright (15) \\ &\leq \frac{diam(\mathcal{Y})^2}{2\eta} + \frac{\eta T (\max\|\nabla q\|)^2}{2}. \end{aligned} \tag{17}$$

In the following, we give the upper bound of $\max\|\nabla q\|$ and $diam(\mathcal{Y})$, respectively.

1) *The upper bound of* $\max\|\nabla q\|$. With the result of (9), we have

$$\begin{aligned} \|\nabla q\|^2 &= \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \left[x_l(t)^2 \Big((f_r^{k^*})'\big(y_{(l,r)}^{k^*}(t)\big) - \beta_{k^*}\Big)^2\right] \\ &\quad + \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \sum_{k\neq k^*} x_l(t)^2 (f_r^k)'\Big(y_{(l,r)}^k(t)\Big)^2 \\ &= \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} x_l(t)^2 \Bigg[\sum_{k\in\mathcal{K}} \Big((f_r^k)'\big(y_{(l,r)}^k(t)\big)\Big)^2 \\ &\quad - 2\beta_{k^*} (f_r^{k^*})'\big(y_{(l,r)}^{k^*}(t)\big)\Bigg] + \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} x_l(t)^2 \beta_{k^*}^2. \end{aligned} \tag{18}$$

where k^* is defined in (10). The second part of (18) can be upper bounded by

$$\sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} x_l(t)^2 \beta_{k^*}^2 \leq \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} (\beta^*)^2, \tag{19}$$

where $\beta^* = \max_{k\in\mathcal{K}} \beta_k$. If $\mathcal{G}$ is right d-regular, the bound reduces to $d|\mathcal{L}|(\beta^*)^2$. For the first part of (18), we use $(f_r^{k^*})'$ to replace $(f_r^{k^*})'(y_{(l,r)}^{k^*}(t))$ for simplification. Then we have

$$\begin{aligned} &\sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} x_l(t)^2 \Big[\sum_{k\in\mathcal{K}} \big((f_r^k)'\big)^2 - 2\beta_{k^*} (f_r^{k^*})'\Big] \\ &\leq \underbrace{\sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \sum_{k\neq k^*} \big((f_r^k)'\big)^2}_{\text{PART-A}} + \underbrace{\sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} (f_r^{k^*})'\big((f_r^{k^*})' - 2\beta_{k^*}\big)}_{\text{PART-B}}. \end{aligned}$$

For PART-A we have PART-A $\leq (K-1)\sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} (\varpi_r^*)^2$, where $\varpi_r^* = \max_{k\in\mathcal{K}} \varpi_r^k$. If $\mathcal{G}$ is right d-regular, the bound reduces to $d|\mathcal{L}|(K-1)(\varpi_r^*)^2$. To analyze the upper bound of PART-B, we need to partition the computing instances into two disjoint sets:

$$\mathcal{R}_1 = \Big\{r \in \mathcal{R} : \varpi_r^{k^*} \leq 2\beta_{k^*}\Big\}$$
$$\mathcal{R}_2 = \Big\{r \in \mathcal{R} : \varpi_r^{k^*} > 2\beta_{k^*}\Big\}.$$

$\forall r \in \mathcal{R}_1$, the maximum of $(f_r^{k^*})'\big((f_r^{k^*})' - 2\beta_{k^*}\big)$ is 0 since $(f_r^{k^*})' \geq 0$ holds. $\forall r \in \mathcal{R}_2$, the maximum is $(\varpi_r^{k^*})^2 - 2\beta_{k^*}\varpi_r^{k^*}$. Thus,

$$\text{PART-B} \leq \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l \cap \mathcal{R}_2} \Big((\varpi_r^{k^*})^2 - 2\beta_{k^*}\varpi_r^{k^*}\Big). \tag{20}$$

Recall that in (20) $\mathcal{R}_l$ is the set of computing instances that connects to port l. Because $\beta_k \in [0,1]$ holds for each $k \in \mathcal{K}$, $\forall l \in \mathcal{L}, r \in \mathcal{R}_l \cap \mathcal{R}_2$, we have

$$(\varpi_r^{k^*})^2 - 2\beta_{k^*}\varpi_r^{k^*} \leq (\varpi_r^*)^2 - 2\beta_{k^*}\varpi_r^* \leq (\varpi_r^*)^2, \tag{21}$$

Finally, we can get

$$\|\nabla q\|^2 \leq \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \Big((\beta^*)^2 + K(\varpi_r^*)^2\Big). \tag{22}$$

For the upper bound in (22), all the computing instances $r \in \mathcal{R}_l$ fall into the set $\mathcal{R}_2$.

2) *The upper bound of diam*$(\mathcal{Y})$. By definition we have

$$diam(\mathcal{Y}) = \sup_{\boldsymbol{y},\boldsymbol{z}\in\mathcal{Y}} \|\boldsymbol{y} - \boldsymbol{z}\|. \tag{23}$$

To find the upper bound of $\|\boldsymbol{y} - \boldsymbol{z}\|$, we can get

$$\begin{aligned} \|\boldsymbol{y} - \boldsymbol{z}\|^2 &= \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \sum_{k\in\mathcal{K}} \Big(y_{(l,r)}^k - z_{(l,r)}^k\Big)^2 \\ &\overset{(i)}{\leq} \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \sum_{k\in\mathcal{K}} |y_{(l,r)}^k - z_{(l,r)}^k| \cdot a_l^k \\ &\leq \sum_{l\in\mathcal{L}} \sum_{r\in\mathcal{R}_l} \sum_{k\in\mathcal{K}} a_l^k \Big(y_{(l,r)}^k + z_{(l,r)}^k\Big) \\ &= \sum_{k\in\mathcal{K}} \bar{a}^k \sum_{r\in\mathcal{R}} \Big(\sum_{l\in\mathcal{L}_r} y_{(l,r)}^k(t) + \sum_{l\in\mathcal{L}_r} z_{(l,r)}^k(t)\Big) \\ &\overset{(ii)}{\leq} 2\sum_{k\in\mathcal{K}} \bar{a}^k \sum_{r\in\mathcal{R}} c_r^k, \end{aligned} \tag{24}$$

where $\bar{a}^k = \max_{l\in\mathcal{L}} a_l^k$. In (24), (i) is because the constraint (3). In (ii), we use the capacity constraint (4). As a result, we have

$$diam(\mathcal{Y}) \leq \sqrt{2\sum_{k\in\mathcal{K}} \bar{a}^k \sum_{r\in\mathcal{R}} c_r^k}. \tag{25}$$

Combing the result (22) and (25), and set η as $\frac{diam(\mathcal{Y})}{\|\nabla q\|\sqrt{T}}$, we finally get the result. $\square$

The theorem indicates that the suboptimality gap between OGASCHED and the offline optimal is of $\Theta(\mathcal{H}_{\mathcal{G}} \times \sqrt{T})$, where $\mathcal{H}_{\mathcal{G}}$ is a factor characterized the scale of the bipartite graph $\mathcal{G}$. In addition, we can find that the regret grows sublinearly with the number of job types $|\mathcal{L}|$. To the best of our knowledge, this is the best regret for the online bipartite scheduling problem with non-linear rewards. The proof also indicates that, to achieve a not-too-bad accumulative reward, at each time t, the learning rate η_t should be set as

$$\eta_t = \frac{diam(\mathcal{Y})}{\|\nabla q(\boldsymbol{x}(t), \boldsymbol{y}(t))\| \sqrt{T}}. \tag{26}$$

3.4 Extending to Multiple Job Arrivals

OGASCHED can be applied to the scenarios where multiple jobs are yielded from each port in each time slot. In this case, the job arrival status $\boldsymbol{x}(t)$ is re-formulated as $\boldsymbol{x}(t) = \left[x_l(t)\right]_{l\in\mathcal{L}} \in \mathbb{N}^{|\mathcal{L}|}$, where $x_l(t)$ indicates the number of jobs arrive at port l at time t. Further, the scheduling decisions at time t is re-formulated as

$$\boldsymbol{y}(t) = \left[y_{(l,r)}^{j,k}\right]_{l,j,r,k} \in \mathbb{R}^{\sum_{l\in\mathcal{L}} J_l \times |\mathcal{R}_l| \times K},$$

where J_l is the maximum number of the type-l jobs arrive during each time slot, i.e. $J_l = \max_{t\in\mathcal{T}} x_l(t)$. Correspondingly, the port-l reward is re-formulated as

$$q_l(\boldsymbol{x}(t), \boldsymbol{y}(t)) = \sum_{j=1}^{J_l} \mathbb{1}\{j \le x_l(t)\} \Big[\sum_{k\in\mathcal{K}} f_k\Big(\sum_{r\in\mathcal{R}_l} y_{(l,r)}^{j,k}(t)\Big) - \max_{k\in\mathcal{K}} \Big\{ \beta_k \sum_{r\in\mathcal{R}_l} y_{(l,r)}^{j,k}(t) \Big\} \Big],$$

where $\mathbb{1}\{p\}$ is the indicator function: $\mathbb{1}\{p\}$ is 1 if the predicate p is true, otherwise 0. The new formulated problem can be solved by native OGASCHED after transformations.

3.5 Extending to Gang Scheduling

OGASCHED can be extended to the Gang Scheduling scenarios, where the scheduling decisions for the task instances of a job follows the ALL-OR-NOTHING property. In other words, only when *all* tasks[2] of a job are successfully scheduled, the job could be launched.

In the following, we show briefly how Gang Scheduling can be modeled. To start with, for each job type $l \in \mathcal{L}$, we denote the corresponding set of task components by $\mathcal{Q}_l$ and indexed by q. Correspondingly, the job requests $\boldsymbol{a}_l$ is redefined as $\boldsymbol{a}_l = \left[a_l^{q,k}\right]_{l,q,k} \in \mathbb{R}^{\sum_{l\in\mathcal{L}} |\mathcal{Q}_l| \times K}$. Similarly, we redefine the scheduling decisions at time t as $\boldsymbol{y}(t) = \left[y_{(l,r)}^{q,k}\right]_{l,q,r,k} \in \mathbb{R}^{\sum_{l\in\mathcal{L}} |\mathcal{Q}_l| \times |\mathcal{R}_l| \times K}$. As a result, the solution space $\mathcal{Y}$ turns to

$$\mathcal{Y} = \Big\{ y_{(l,r)}^{q,k} \mid \sum_{q\in\mathcal{Q}_l} \mathbb{1}\{ \sum_{r\in\mathcal{R}_l} \sum_{k\in\mathcal{K}} y_{(l,r)}^{q,k} > 0\} \ge m_l(t), \forall l, \quad 0 \le y_{(l,r)}^{q,k}(t) \le a_l^{q,k}, \forall l, r, q, k, t, \quad \sum_{l\in\mathcal{L}_r} \sum_{q\in\mathcal{Q}_l} y_{(l,r)}^{q,k}(t) \le c_r^k, \forall r, k, t \Big\},$$

2. In practice, not all tasks of a job need to be scheduled. In Kubernetes, the job submitter can specify the minimum number of tasks that must be scheduled successfully. In the following, we use $m_l(t)$ to represent the minimum number of tasks that should be scheduled at time t of the type-l job.

where in the first inequality, $m_l(t)$ is the minimum number of task components that should be scheduled at time t of type-l job. The port-l reward at time t is re-formulated as

$$q_l(\boldsymbol{x}(t), \boldsymbol{y}(t)) = x_l(t) \Big[\sum_{k\in\mathcal{K}} f_k\Big(\sum_{q\in\mathcal{Q}_l} \sum_{r\in\mathcal{R}_l} y_{(l,r)}^{q,k}(t)\Big) - \max_{k\in\mathcal{K}} \Big\{ \beta_k \sum_{q\in\mathcal{Q}_l} \sum_{r\in\mathcal{R}_l} y_{(l,r)}^{q,k}(t) \Big\} \Big].$$

The new formulated problem is more difficult because $\mathcal{Y}$ is no longer a convex set and $q_l(\boldsymbol{x}(t), \boldsymbol{y}(t))$ is not differentiable everywhere. Nevertheless, we can still develop a similar online scheduling algorithm with the subgradient ascent and mirror ascent related techniques which retains a sublinear regret. The design detail is omitted due to space limits.

4 EXPERIMENTAL RESULTS

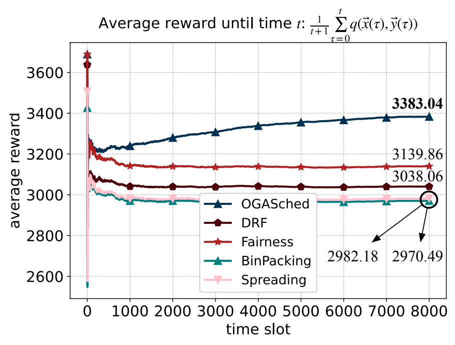
In this section, we conduct extensive experiments to validate the performance of OGASCHED. Based on the Alibaba cluster trace datasets [27], we firstly examine the theoretically guaranteed superiority of OGASCHED against several baselines on the accumulative and average rewards. Then, we analyze the generality and robustness of it under different cluster settings. At last, we validate the efficacy of OGASCHED in large-scale scenarios. The trace-driven simulation is conducted on a server with 48 Intel Xeon Silver 4214 CPUs, 256 GB memory, and 2 Tesla P100 GPUs. The code will be released after double-blind review.

Traces. We hybrid the traces from cluster-trace-v2018 and cluster-trace-gpu-v2020 of the Alibaba Cluster Trace Program. Specifically, we leverage the specifications of the machines, the arrival patterns and resource requirements of different kind of jobs to generate our simulation environment.

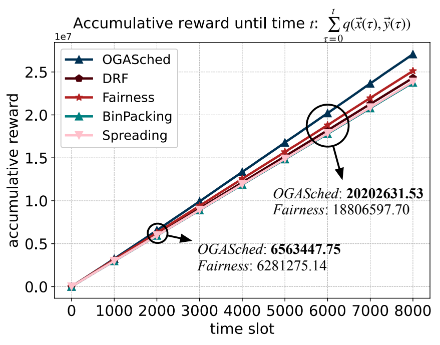
Baselines. The following widely used baselines are implemented to make comparisons with OGASCHED.

- DRF [13]. It is adopted by YARN [28] and Mesos [29]. In our scenario, DRF allocates resources to ports that yield jobs in the ascending order of their dominant resource shares. The dominant share s_l of port l is calculated as $s_l = \max_{k\in\mathcal{K}}\{a_l^k / \sum_{r\in\mathcal{R}_l} c_r^k\}$.
- FAIRNESS. We implement FAIRNESS in this way: at each time t, we allocate the type-k resource of each node r to each port l that yield a job according to the job's share $a_l^k / \sum_{l\in\mathcal{L}_r} a_l^k$.
- BINPACKING. It is optional in Kubernetes with the name of MOSTALLOCATED strategy and supported in Volcano as a configurable plugin [30]. Specifically, it scores the computing instances based on the utilization of resources, favoring the ones with higher allocation.
- SPREADING. It is similar to BINPACKING in procedures but with an opposite favor. The nodes with lower utilizations of resources have higher scores.

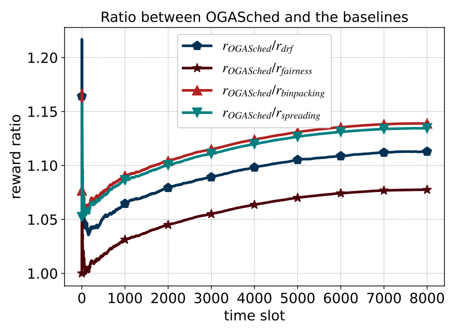
Default Settings. In default settings, our simulation environment has 128 computing instances, each equipped with 6 types of computing devices (CPUs, MEM, GPUs, NPUs, TPUs, and FPGAs), and 10 job types of different resource



(a) Average rewards.



(b) Accumulative rewards.



(c) Ratios between OGASCHED and baselines.

Fig. 2. Performance verification of OGASCHED. It takes one hour for OGASCHED to finish when $T = 8000$, $\beta \in [0.4, 0.6]$, and contention level is 11.

requirements. Large-scale validations will be demonstrated in Sec. 4.3. The computing instances and jobs are carefully selected from the trace to reflect heterogenity. We support 4 types of utilities:

$$f_r^k(y) = \begin{cases} \alpha y & \textit{linear} \\ \alpha \ln(y+1) & \textit{log} \\ \alpha^{-1} - (y+\alpha)^{-1} & \textit{reciprocal} \\ \alpha\sqrt{y+1} - \alpha & \textit{poly}, \end{cases} \tag{27}$$

The default settings of main parameters are listed in Tab. 1. In this table, the initial learning rate and the decay are used to tune the learning rate at each time t around the value (26). Job arrival probability ρ is adopted to adjust the job arrival status with Bernoulli Distributions. This parameter is applied on the basis of the actual arrival patterns from the trace to increase stochasticity. The contention level, located at the last cell of this table, is designed to tune the level of resource contention. The larger this value, the more fierce the contention. The effect of it will be analyzed in detail in Sec. 4.2.

TABLE 1
Default parameter settings.

PARAMETER	VALUE	PARAMETER	VALUE
job types num. $\lvert\mathcal{L}\rvert$	10	node num. $\lvert\mathcal{R}\rvert$	128
device type num. K	6	time slot num. T	2000
range of α	$[1.0, 1.5]$	range of β	$[0.3, 0.5]$
initial learning rate η_0	25	decay	0.9999
job arrival prob. ρ	0.7	contention level	10

4.1 Performance Verification

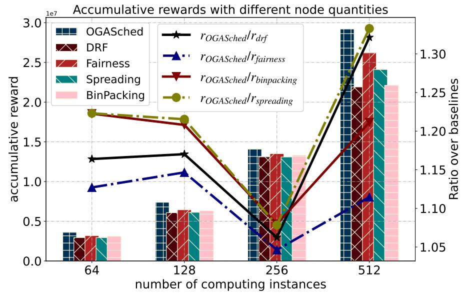
In this section, we compare the performance of OGASCHED with the baselines in terms of the achieved accumulative and average rewards.

In Fig. 2(a), the y-axis is the average reward unitl time t, i.e., $\frac{1}{t}\sum_{\tau=1}^{t} q\big(\boldsymbol{x}(\tau), \boldsymbol{y}(\tau)\big)$. Compared with the baselines, OGASCHED has a clear advantage on the performance (with the increases of 11.33%, 7.75%, 13.89%, and 13.44% compared with DRF, FARINESS, BINPACKING, and SPREADING, respectively). Besides, it shows that the performance of OGASCHED has a tendency to increase as the length of the time horizon increases. The curve of OGASCHED starts steep and later flattens. The reason is that, as a learning-powered algorithm, OGASCHED learns the underlying distribution of job arrival patterns and it can make better decision by adjusting the step directions. It is interesting to find that the rewards oscillate at the beginning time slots. One of the leading factors is that OGASCHED is boosted with a well designed initial solution. In our experiments, a 8000-time slot training only takes one hour. Thus, no surprisingly, the rewards achieved in the beginning can be easily surpassed when the time slot is sufficiently large.

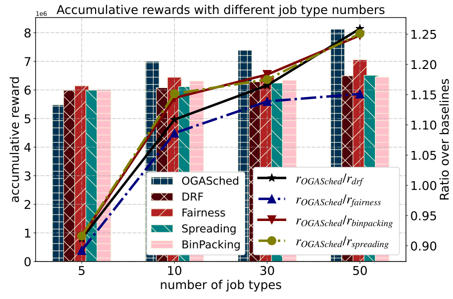
It is not a surprise that FAIRNESS achieves the best among the baselines. FAIRNESS adopts a proportional allocation strategy and allocates resources to each non-empty port *without bias*, which increases the computation gains adequately. When the contention is not fierce while the communication overhead is low, the advantages of FAIRNESS will be more steady. By contrast, the advantages of BINPACKING and SPREADING are respectively high resource utilization and job isolation, which do not contribute to the reward directly.

Fig. 2(b) shows that the accumulative rewards achieved by all the five algorithms. In the beginning, FAIRNESS and DRF have the slight edge, benefiting by the propotional allocation idea. Nevertheless, as the time slot increases, OGASCHED is able to surpass them without difficulty. Fig. 2(c) demonstrates the ratio on the achieved average rewards between OGASCHED and the baselines. Similarly, the ratios oscillate at the beginning. After that, they increase steeply and later flattens.

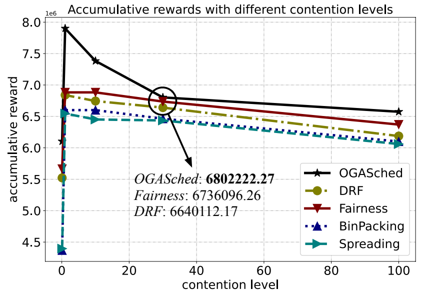
The hyper-parameters of OGASCHED, especially the initial learning rate η_0 and the decay, have a remarkable impact on its performance. From Fig. 4 we can find that, a wrong setting of these hyper-parameters could lead to a poor performance, even the decrease of the accumulative reward (which means, the reward is negative in many time slots). At the last of Sec. 3.3, we claim that, to achieve an accumulative reward with a lower bound guarantee, at each time t, the learning rate should be set around (26). Note that in (26), the learning rate is encouraged to be larger and larger as time moves, which is counterintuitive and it goes against the convergence to a local optimum. The curves in Fig. 4(b) also verify that, setting decay as 0.9999 is better than 1.0001. The best decay in practice does not follow the guidance of theory because the regret analysis only gives the *worst* case guarantee on the accumulative rewards. In our experiments, the best range for decay is $[0.995, 0.9999]$.



(a) Accumulative rewards vs. $|\mathcal{R}|$.



(b) Accumulative rewards vs. $|\mathcal{L}|$.

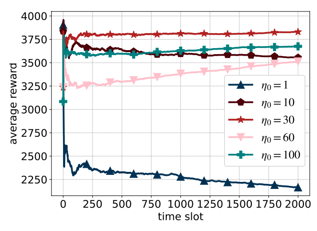


(c) Accumulative rewards vs. contention.

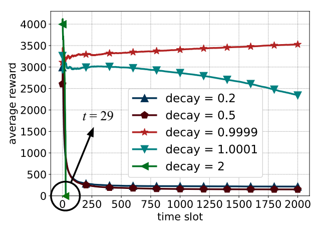
Fig. 3. Scalability verification of OGASCHED under different scales of the bipartite graph and the contention levels.

TABLE 2
Generality and Robustness validation under different scenario settings.

Avg. Reward	Time Horizon Length T				Job Arrival Probability ρ				Graph Dense		
	1000	2000	5000	10000	0.3	0.5	0.7	0.9	≈ 2	≈ 2.5	≈ 3
OGASCHED	**2578.53**	**2886.33**	**2911.37**	**3104.98**	**1904.87**	**2154.18**	**3117.29**	**2938.22**	**2816.18**	**2904.51**	**3127.47**
DRF	2422.47	2493.02	2449.23	**2497.85**	**1364.53**	**2086.59**	2503.01	2755.41	2417.08	2786.94	2795.42
FAIRNESS	**2532.24**	**2582.80**	**2552.41**	2436.22	1295.53	1997.19	**2628.02**	**2873.84**	**2501.54**	**2857.60**	**2918.98**
BINPACKING	2386.01	2449.15	2444.32	2365.13	1246.39	1897.79	2518.98	2740.19	2374.31	2757.71	2829.19
SPREADING	2382.01	2466.71	2436.60	2362.88	1250.67	1888.06	2519.37	2737.93	2382.87	2766.07	2836.37



(a) Impact of η_0.



(b) Impact of decay.

Fig. 4. The performance of OGASCHED with different hyper-parameters.

4.2 Scalability, Generality and Robustness Evaluations

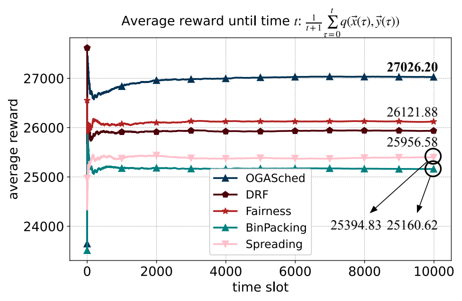
In this section, we evaluate the performance of OGASCHED under different scales of scenario settings. Fig. 3(a) and Fig. 3(b) demonstrate the impact of the scale of the bipartite graph $\mathcal{G}$. In these two figures, the left y-axis is the accumulative reward while the right y-axis is the ratio r_a/r_b, where r_a is the accumulative reward achieved by OGASCHED, and r_b is the baselines'. Firstly, we observe that, whatever the number of the computing instances is, OGASCHED takes the leading position. Besides, as $|\mathcal{R}|$ increases, all the algorithms obtain a larger accumulative reward. The result is evident because a large cluster can provide sufficient computing devices, which leads to jobs being fully served. It is also worth noting that, when $|\mathcal{R}|$ increases, the superiority of OGASCHED over the baselines firstly increases then decreases. It demonstrates that the resource contention is fierce when $|\mathcal{R}| \in [128, 256]$. In this case, it is necessary for OGASCHED to be trained with a larger time slot. Fig. 3(b) shows that the number of job types, i.e., $|\mathcal{L}|$, has a weaker impact than $|\mathcal{R}|$ to the performance of OGASCHED. The phenomenon verifies the conclusion we have concluded, i.e., the regret grows linearly with $|\mathcal{R}|$, but it is sublinear with $|\mathcal{L}|$.

Fig. 3(c) shows the impact of contention level. This parameter works as a multiplier to the resource requirements of jobs. We can observe that, when moving contention level from 0.1 to 1, all the achieved accumulative rewards increase. This is obvious because a larger resource requirement leads to a larger computation gain on the premise of low contention. However, increasing the multiplier further leads to the downgrade of performances and the reduction of the superiority of OGASCHED. Even so, OGASCHED always performs the best. Fig. 6 shows the average computation gain and communication overhead penalty of each time slot under different contention levels. We can find that the penalty increases with the contention level slowly.

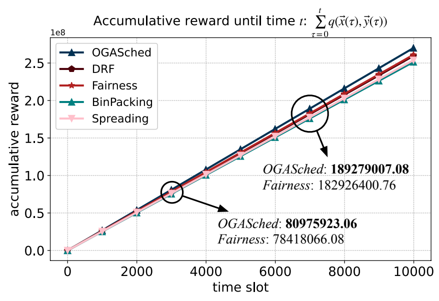
Fig. 7 demonstrates the accumulative rewards with different utilities. Because of the diminishing marginal effect, the rewards with *ploy*, *log*, and *reciprocal* utilities are significantly less than the rewards with *linear* utilities. Nevertheless, the diminishing marginal effect does not change the superiority of OGASCHED against the baselines. Even in the *all reciprocal* utility settings, for FAIRNESS, OGASCHED has its advantages.

In addition to the above evaluations, we also test the generality and robustness of OGASCHED under different settings of the following parameters: the time horizon length T, the job arrival probability ρ, and the dense of the bipartite graph. The graph dense is calculated as $\sum_{r\in\mathcal{R}} |\mathcal{L}_r|/|\mathcal{R}|$. The results are shown in Tab. 2. The two largest values in each column of the table are made bold. Besides, for each parameter and each algorithm, the setting which leads to the largest reward is marked with a light-grey background. We summarize the key findings as follows.

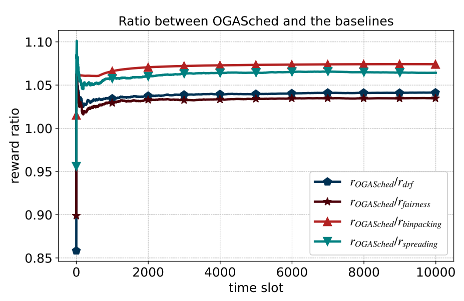
- Firstly, whatever the parameter settings, OGASCHED always performs the best, and its performance has a positive correlation with the time horizon length T. As we have analyzed, a large time horizon provides more chances for OGASCHED to learn the underlying distributions, thereby increasing the reward in the gradient ascent directions.



(a) Average rewards.



(b) Accumulative rewards.



(c) Ratios over the baselines.

Fig. 5. Large-scale validations. It takes 15 hours for OGASCHED to complete when $T = 10000$, $\beta \in [0.01, 0.015]$, and contention level is 5.

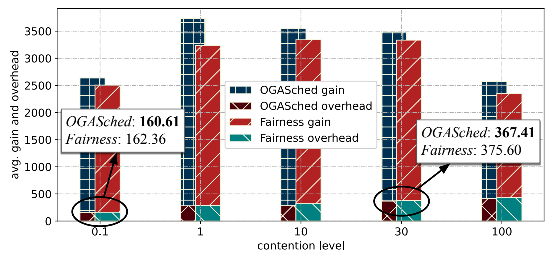


Fig. 6. Average computation gain and communication overhead of each time slot under different contention levels.

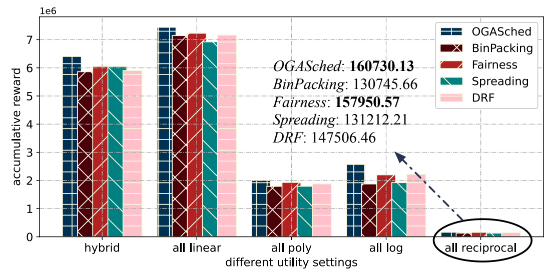


Fig. 7. Accumulative rewards with different utilities.

- Increasing the job arrival probability can lead to a high resource utilization, thereby increasing the rewards. However, a large job arrival probability also brings in a fierce resource contention. A direct consequence of it is that, for OGASCHED, many elements in the vector $\boldsymbol{y}(t)$ fall into the interior of $\mathcal{Y}$, rather than the boundaries, thereby leading to a reward reduction. The phenomenon can be observed when moving ρ from 0.7 to 0.9.
- Graph dense has a similar effect on the reward to the job arrival probability. Nevertheless, the reasons behind are distinct. A larger graph dense increases the opportunities for a job to be served with a large possible parallelism, thereby increasing the computation gain. By contrast, the communication overhead has a slow rate of growth.

4.3 Large-Scale Validations

To test the efficacy of OGASCHED in large-scale scenarios, we conduct the following experiments. In these experiments, the number of the job types is set as 100 while the quantity of the computing instances is 1024 in default. The results in Fig. 5 show that the superiority of OGASCHED is preserved even in large-scale scenarios.

5 Related Works

The design of online job scheduling algorithms that yield a nice theoretical bound is always the focus of attention from the research community. Existing online job scheduling algorithms can be organized in two categories.

In the first category, the online algorithms are elaborately designed for specific job types, such as DNN model training [19], [31], [18], [4], [11], [6], [32], big-data query & analytics [5], [33], multi-stage workflows [34], [10], etc. A typical work on DNN model training is [11], where the authors fully take the layered structure of DNNs into consideration and develop an efficient resource scheduling algorithm based on the sum-of-ratios multi-dimensional-knapsack decomposition method. The authors further prove that the proposed algorithm has a SOTA approximation ratio within a polynomial running time. [6] is another work that fully explores the Bulk Synchronous Parallel (BSP) property of the DNN training jobs. The authors develop an algorithm which is $\mathcal{O}(\ln|\mathcal{M}|)$-approximate with high probability, where $\mathcal{M}$ is the set of computing devices. These works are designed for specific job types, and they do not provide a general analysis on the gain-overhead tradeoff for multi-server jobs. This paper intends to fill the gap.

In the second category, the type of job are not specified, while the theoretical superiority is highlighted. The algorithms are designed with different theoretical basis, including online approximate algorithms [35], [8], [36], Online Convex Optimization (OCO) techniques [7], game-theoretical approaches [9], online learning and DRL-based algorithms [37], [38], etc. In these works, the performance of the proposed algorithms are usually analyzed with approximate ratio, competitive ratio, Price of Anarchy (PoA), and regret. A typical recent work is [7]. The authors develop an algorithm whose dynamic regret is upper bounded by $\mathcal{O}(\textsc{Opt}^{1-\beta})$, where $\beta \in [0,1)$. None of existing works analyze the gain-overhead tradeoff and provide a regret of $\mathcal{O}(\sqrt{|\mathcal{L}|T})$ as this paper demonstrates.

6 Conclusions

In this paper, we study the online scheduling of multi-server jobs in terms of the gain-overhead tradeoff. The problem is formulated as an accumulative reward maximization program. The reward of scheduling a job is designed as the difference between the computation gain and the penalty on the dominant communication overhead. We propose an algorithm, i.e. OGASCHED, to learn the best possible scheduling decision in the ascending direction of the reward gradients. OGASCHED is the first algorithm that has a sublinear regret with respect to the number of the job types and time slot length, which is a SOTA result for concave rewards. OGASCHED is well designed to be parallelized, which makes large-scale applications possible. The superiority of OGASCHED is also validated with extensive trace-driven simulations. Future extensions may include, i.e., more elaborate modeling and analysis on the intra-node and inter-node communication overheads.

ACKNOWLEDGMENTS

This work was supported in part by the National Key Research and Development Program of China under Grant 2022YFB4500100, the National Science Foundation of China under Grants 62125206 and U20A20173, and the Key Research Project of Zhejiang Province under Grant 2022C01145.

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