Cluster Resource Management for Dynamic Workloads by Online Optimization

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ABSTRACT
Over the past ten years, many different approaches have been proposed for different aspects of the problem of resources management for long running, dynamic and diverse workloads such as processing query streams or distributed deep learning. Particularly for applications consisting of containerized microservices, researchers have attempted to address problems of dynamic selection of, for example: types and quantities of virtualized services (e.g., IaaS/VMs), vertical and horizontal scaling of different microservices, assigning microservices to VMs, task scheduling, or some combination thereof. In this context, we argue that frameworks like simulated annealing are highly suitable for online navigation of trade-offs between performance (SLO) and cost, particularly when the complex workloads and cloud-service offerings vary over time. Based on a macroscopic objective that combines both performance and cost terms, annealing facilitates light-weight and coherent policies of exploration and exploitation. In this paper, we first give some background on simulated annealing and then experimentally demonstrate its usefulness for different case studies, including service selection for both a single type of workload (e.g., distributed deep learning) and a mixture of workload types (exploring a partially categorical set of options), and container sizing for microservice benchmarks. We conclude with a discussion of how the basic annealing platform can be applied to other resource-management problems, hybridized with other methods, and accommodate user-specified rules of thumb.

1 INTRODUCTION AND MOTIVATION
Resource management in the public cloud typically involves selecting available services spanning compute, storage and networking to minimize cost (or "cloud spend" [30]) subject to workload Service-Level Objectives (SLOs, i.e., performance requirements). The problem is particularly challenging when serving a plurality of complex time-varying workloads. For a given set of job streams, the optimal service suite may involve a cluster composed of a variety of services. Even within services of the same type, resource instances can vary greatly. For example, VMs can have different amounts and types of memory, CPU cores, hardware accelerators, cross connects (e.g., PCIe, NVLink), and networking. In some cases, users can optionally pay to collocate VMs on the same physical server or to provision networking resources connecting their VMs to storage.¹

Deploying application software using a microservice architecture, e.g., [5, 20, 29, 37], has the advantage of modular code design and maintenance. Some microservices can be used by different applications. Also, each microservice can be executed in a separate, light-weight container.

 Particularly in an edge cloud setting where operating costs are high, the user may wish to economize by explicitly provisioning containerized microservices (vertical scaling)² and replicating microservices (horizontal scaling) as necessary. Data locality issues may be involved in how containers are assigned to VMs. Different task scheduling policies have been proposed which can be implemented on cluster managers such as Kubernetes (K8s) [16, 19]. In addition, a default task scheduler and a task assignment policy to containerize microservices can be augmented with simple rules of thumb, e.g., to exploit data locality [24] and to address persistent straggler tasks [26]³.

For complex, diverse and dynamic workloads incident to a cluster, deciding a cloud service suite and a container-sizing and replication policy is a difficult task (even if, e.g., a default task scheduling is used), and a typical user (cloud tenant/customer) may provide little more guidance than "macroscopic" SLOs and a cost budget. Some approaches to this problem involve using a deep (large) artificial neural network (DNN) to determine a service suite, size containers, and containerize microservices can be augmented with simple rules of thumb, e.g., [6, 25, 29]. However, deep learning is supervised requiring a very large curated training dataset representing a huge group of "exploratory" experiments for a given workload [11]. Unanticipated changes to the workload (even to just the dataset on which it operates) or to the offered service suite (i.e., "model drift") may require identifying and labelling new operational "samples" to periodically refine the DNN, which itself may require significant computational cost.

¹There are similar efficient resource allocation challenges in "bare metal" and private data center scenarios where virtualized public-cloud services are not in play.
²In [29], it’s argued that provisioning containers can prevent resource starvation of bottleneck microservices toward improving total job execution times, compared to simply relying on the VM’s OS to schedule component tasks as they arrive in a “best effort” fashion without considering end-to-end job execution times.
³Also, rather than relying on a default mechanism of a cluster manager (e.g., K8s), a user may wish to control how microservices are “packed” into the VMs of their cluster, to both economize on the number of VMs and, again, to address data locality issues as a job’s tasks are executed as a sequence of microservices.
Recently, researchers and practitioners have explored the use of other traditional but more light-weight and adaptable means of decision-making (including using model-based adaptive control, PID control, and Markov decision processes) where DNNs play only a partial role at most, e.g., [31, 41]. For example, particle-swarm type optimization has been used for load balancing, e.g., [32]. Also, genetic algorithms (GAs), e.g., [38, 39], have been used to explore the service suite and dynamically react to changes in the workload and service offerings. But exploration under GAs is rather ad-hoc, like random search.

Simulated annealing (or just annealing) [1, 10] has been widely used for complex, non-convex optimization problems, including for practical applications, since its development in the 1980s. Annealing is suitable for the foregoing resource management problems which operate in a highly dynamic environment over an indefinite time horizon. Annealing can more quickly react to detected changes in operating conditions by simply increasing its temperature parameter to more aggressively (broadly) search the parameters it controls (and/or by expanding its "local neighborhood" sets). Annealing’s local neighborhood set can be adjusted to accommodate rules of thumb. Also, annealing can be hybridized with a GA or random search to improve breadth of search, or hybridized with, e.g., a Tabu search mechanism to improve local-search efficiency. Thus, we herein employ annealing as a representative method of online optimization.

In this paper, we take an annealing approach to the problem of provisioning an IaaS cluster and sizing the containers within its VMs for a plurality of different streaming workloads. Annealing works to minimize a macroscopic objective that can account for factors like current job execution times and the cost per unit time of the existing cluster. While it can operate both offline (e.g., [35]) and online (runtime), our focus is on the latter. In addition to HiBench workload case-studies, we apply an online annealing method to select the number and sizes of Virtual Machines (VMs) for a deep-learning workload. We also apply online annealing to the container-sizing problem of a microservice workload relying on the default container assignment mechanism of the K8s cluster manager. Experimental results are reported for these prototypes.

2 BACKGROUND

2.1 Annealing

Simulated annealing was introduced in the 1980s as a generic framework to minimize a complicated function $Y : D \rightarrow \mathbb{R}$ over a very large discrete bounded domain $D$, where “complicated” here means that $Y$ has plural local minima in addition to global ones and $D$ may be a finite discretization of a continuous domain.

A local neighborhood function $\nu(x)$ for all $x \in D$ is defined, where $x \notin \nu(x)$. A collection of possible transitions between $x$ and elements of $\nu(x)$ are also defined, often taken as all equally likely as assumed in the following (i.e., each with uniform probability $1/|\nu(x)|$). A key requirement of the neighborhood function $\nu$ is that it has to produce a connected graph in $D^4$. Typically, the neighborhood function ensures only incremental one-step changes to the current configuration state, but this is not a requirement.

Given $Y, \nu$, one can define an annealing Markov chain on $D$ at temperature $\tau > 0$ with transition probabilities from $x$ to $x' \in \nu(x)$ being:

$$\frac{1}{|\nu(x)|} \exp\left(-\frac{\max\{Y(x') - Y(x), 0\}}{\tau}\right).$$

We see that a possible transition from the current state $x$ to the next state $x'$ is "accepted" with positive probability even when the objective $Y$ is increased, i.e., when $Y(x') > Y(x)$, and always accepted when $Y(x') \leq Y(x)$ – this is the "heat bath" rule. When the temperature parameter $\tau$ increases, this acceptance probability increases, i.e., there is more exploration and less exploitation which is particularly useful when trying to avoid poor local minima. If the temperature $\tau$ is initially sufficiently high and slowly (logarithmically) decreases to zero over time, it can be shown that the (time-inhomogeneous) Markov chain $Y$ will converge in probability to its global minimum on $D$ [1]. But this limiting result is not very useful in practice. Even early on, some authors pointed out that it may be better not to thus "cool" the annealing chain [10], particularly when considering a finite time-horizon. If the temperature is fixed $\tau > 0$ and the neighborhoods all have the same size ($|\nu(x)|$ is a constant function of $x \in D$) then (time-homogeneous) Markov chain $Y$ has (Gibbs) stationary distribution proportional to $\exp(-Y(x)/\tau)$. Note that as the temperature $\tau \to 0$, only transitions that reduce $Y$ are accepted, i.e., pure exploitation.

In the past, annealing was successfully applied to complex optimization problems such as placement and routing of VLSI circuits and large-scale bin-packing problems [23].

2.2 Apache Spark

Apache Spark [33, 40] is an open source computing engine used for large-scale data processing applications. A typical Spark cluster setup consist of a single master and one or more workers. When a Spark application is submitted, a Spark driver is launched, which is the responsible component that requests for resources from the cluster manager (e.g., YARN, Kubernetes (K8s) or Spark’s Standalone cluster manager) as shown in Figure 1. Upon arrival of jobs, 4That is, the Markov chain resulting from the ‘base’ transition probabilities associated with the neighborhood function is ‘irreducible’. These transition probabilities should be chosen so that the base Markov chain is also time-reversible [1].
Spark schedules them in FIFO fashion, where each job is divided into map and reduce stages (or “phases”). These stages are represented as a Directed Acyclic Graphs (DAG) i.e., a job’s execution plan generated by Spark. Executors are launched on worker nodes and tasks of each stage are sent to run on these executors. The memory size and number of cores assigned to executors can be modified through a configuration file when an application is submitted. Recent improvements have been made to Spark to better accommodate streaming applications, such as those supported by the alternative platform Flink [7].

2.3 Kubernetes

Kubernetes (K8s) is an open-source container orchestration platform. It has gained popularity due to its ability to automate the deployment, scaling, and management of containerized applications in complex distributed systems. A K8s deployment is an abstraction layer that manages the creation, scaling, and updating of pods, which are the smallest deployable units in K8s. Deployments provide a declarative way to manage the state of the application, ensuring that the desired number of replicas is always available. Pods, on the other hand, are single instances of a containerized application that run in a shared environment. They provide a lightweight and flexible way to manage containers and their resources. Each pod has a unique IP address and a set of shared resources, including storage volumes and network interfaces. By setting resource requests and limits, K8s can allocate resources more efficiently and ensure that each pod has enough resources to run effectively.

The K8s Application Programming Interface (API) is an interface that enables developers to manage K8s resources by providing a mechanism to create, read, update, and delete resources, such as deployments, pods, and services. To update resources requests and limits, developers can use the K8s API directly or the kubectl command-line tool. The API enables developers to retrieve the current deployment configuration, modify the resources requests and limits in the configuration file, and subsequently update the deployment. The K8s API ensures that the updated deployment is automatically rolled out to the cluster, maintaining the desired state of the system. In this paper, we exploit the API to size the different deployments of microservices with the resource requests of the annealing process.

3 IAAS PROCUREMENT APPROACH

Consider a long job stream whose composition and workload profile may change periodically over time. This change could be due to changes in the types of jobs and their proportions and/or the datasets on which the jobs operate. A goal here is to decide on the most performance and cost effective IaaS cluster, including consideration of autoscaling costs, dynamic changes to the effective capacities and prices of services considered, or new service offerings.

First, consider a stream of the same type of job, e.g., the jobs are described by the same DAG of component tasks, for a fixed cluster. Let $x_0$ be the cluster configuration for the $n$th job (e.g., indicating the total number of cores in the cluster). Starting with a random configuration for $x_0$, we apply annealing over the course of the job stream with minimizing objective

$$Y_n = t_n + \lambda c_n$$

where $t_n$ and $c_n$ respectively are the total execution time and a “cost” for job $n$ under the currently chosen service configuration. The user specified term $\lambda > 0$ weighs the cost against the execution time.

Second, we formulate the objective to be able to consider a blend of multiple types of jobs. The composition of the blended workload can be described using weighted averages of each type. For example, consider a workload that consists of $N$ types of jobs. The minimizing objective for this workload can be described as

$$Y = \sum_{i=1}^N \alpha^{(i)} t^{(i)} + \lambda c,$$

where $\alpha^{(i)} > 0$ is the weight for workload type $i$ ($\sum_{i=1}^N \alpha^{(i)} = 1$), $t^{(i)}$ is a measure of its performance to be minimized, and $\lambda > 0$ is a parameter relatively weighing a measure of the cost of the cluster, $C$. The user-specified parameter $\alpha^{(i)}$, which can be interpreted as the relative priority of workload type $i$, may change dynamically as the workloads experience variations over time. Upon arrival of a new job (or new set of jobs) $n$, we run it (them) with the configuration $z_n$

$$z_n = x_{n-1} + e_0$$

where $e_0$ represents a possible “step size” (incremental change) when exploring configurations and $x_{n-1}$ represents the current “accepted” configuration. We set $x_n = z_n$ (i.e., accept the configuration $z_n$) with probability

$$\exp(-\max\{Y_n - Y_{n-1}, 0\}/\tau)$$

where $Y_n$ is the objective evaluated for job $n$, and $\tau$ is the temperature parameter controlling the degree of exploration and exploitation; otherwise $x_n = x_{n-1}$.

![Figure 2: Blended workload characteristic based on four types of EC2 instances: General Purpose, Compute Optimized, Storage Optimized, and Memory Optimized.](image)
We reference AWS’s EC2 per core pricing for different on-demand instance types when using storage-optimized instances for better comparisons. Hence, AWS instances that use Elastic Block Store (EBS) are also emulated using SSDs, but with their actual AWS pricing.

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4 EXPERIMENTAL EVALUATIONS - IAAS PROCUREMENT

4.1 Experimental Set-Up

We evaluate our simulated annealing approach using CloudLab [4] machines. Our set-up consists of six rs630 nodes (a master node and 5 worker nodes). Using Apache Spark (3.1.2v), we exploit the Spark configuration file in the master node to set the new desired configuration when performing annealing.

4.2 Modeling Cost of EC2

We reference AWS’s EC2 per core pricing for different on-demand instance types. For each instance type, a pre-defined memory allocated per core is assumed (e.g., m4g.medium instances allocate 4 GB of memory per core procured). We also consider hypothetical instances “between” those offered by AWS with corresponding price adjustments (further details are given in section 4.2.1).

4.2.1 Each job executed independently. Using a blend of three different type of HiBench jobs [12] (we set the weight factor $\lambda = 5$, which we empirically found suitable for our experiments), we evaluate the objective values, under different configurations, for the blended workload as described in section 3. We generate a stream of independent jobs and record their average execution times under configurations provided by the annealing process, i.e., number of VM instances of a certain type where each VM type is characterized by a number of cores and memory allocated per core. Figure 2 depicts the objective values for different configurations of such blended workload. The peaks in figure 2 evaluate the objective values when using storage-optimized instances. Note that different orders of the categorical instance types in defining the search space may introduce local minimums that are not global. Annealing can overcome local minima more quickly at higher temperatures $\tau$.

We replace the pricing of storage-optimized instances with a hypothetical family of instances for better comparisons (i.e., all families of instances have similar local storage performance) shown in figure 3. Figure 4 shows different simulations of jobs streams while performing annealing under different temperatures. The red dots represent different service-cluster configurations. From figures 4 and 5, we can observe that more exploration is performed by annealing as the temperature $\tau$ increases. Furthermore, figure 6 shows that as the temperature increases, the annealing process more quickly finds the configuration that minimizes the objective, but with greater service variation due to higher service exploration.

4.2.2 Jobs executed in parallel. The annealing approach can also be employed for workloads that consist of jobs that are executed in parallel (i.e., when jobs compete for resources) and a job queue may be present. The minimizing objective can be adjusted for this case by measuring the total sojourn time of jobs instead of just the execution times. The annealing process performs similarly to what is described in section 4.2.1.

4.3 Adaptation of Annealing

We evaluate the adaptation of annealing for dynamic changes in the blended workload. Figure 7 shows the computed objective values for a stream of blended HiBench jobs. Here, we portray the change in workload as a change in the distribution of the blend (red vertical line depicts the point of time when the change occurs). The blue lines depict the objective values computed before the change occurs, while the orange lines depict after such. The oscillation in the computed objective values is due to the exploration nature of annealing at a positive temperature. After the change, we observe that annealing adapts to the change by finding the new objective-minimizing service configuration through exploration as well.

4.4 Deep Learning Workload

The annealing method can also be utilized in training Deep Neural Networks (DNNs), i.e., deep learning. Figure 8 depicts the characterization of distributed deep learning, on our Spark cluster, using the Keras library [3] to train a Convolutional Neural Network (CNN) to recognize handwritten digits of the MNIST dataset [21]. Using the pricing model described in section 4.2, the goal is to find the service configuration that minimizes the objective function as described in section 3 (we set the weight factor $\lambda = 1$). The execution time here refers to training a model for one epoch. In our experiments, we set the initial configuration to 1 core with 4 GB of memory. Figure 9 shows the selected configurations that were explored by the annealing process (shown as red dots). From figure 10, we find that our annealing approach is capable of quickly finding the configuration that minimizes the objective.

4.5 Comparison with a Deep Learning Approach

Supervised training of a DNN (a.k.a. deep learning) heavily relies on collection and curation of a large corpus of labeled data. This...
process typically involves acquiring a representative dataset that captures a significant exploration of the problem domain’s characteristics and associated ground truth labels. The overall cost of the data acquisition process is rarely reported (though the computational cost associated with the deep learning process itself is commonly reported). Moreover, there typically are a large number of hyperparameters associated with the DNN architecture and the deep learning process itself (though it’s often the case that defaults are chosen without consideration of the application domain).

On the other hand, simulated Annealing (and other light-weight online optimization methods including hybrids) typically does not involve offline data collection. Instead, it only online explores the solution space by iteratively adjusting the solution based on a given objective function and the acceptance of new solutions.

An important issue regarding supervised learning in complex and time-varying environments is that there may be gaps in its training resulting in poor decisions made when the operating conditions change to an unexpected state, i.e., “model drift.” Detection
of model drift may trigger a “mini” exploration phase and subsequent adaptation/refinement of the supervised learning model. In an effort to compare two such approaches under model drift without delving into the hyperparameters of deep learning, we consider online random search to explore enough data samples before finding an acceptable solution. We compare the data collection phase for deep learning to the exploration phase in simulated annealing after a significant change in operated state. In summary, by modeling the data collection phase as random search, akin to simulated annealing’s exploration phase, we can establish a simple basis for comparison and evaluation between simulated annealing and generic supervised learning in response to model drift.

Figure 11 represents the adaptation of Simulated Annealing (SA) and Random Search (RS) to a change in the workload mixture for the problem of VM service selection. In addition, both approaches adhere to a candidate solution without exploration when the cost objective drops below a (user specified) threshold. Again, here the initial RS adapts only to the current workload only so it’s actually an online approach like SA – forming a training dataset for a DNN would require much more initial exploration for a variety of different workloads not just the current one as depicted in the figure at iteration zero.
Note from Figure 11, high-temperature SA finds an adequate solution at about the same time as RA for the initial workload during the iteration interval [0, 149]. When the workload changes at 150 causing the cost objective to rise above the threshold, RA takes longer to find an adequate solution compared to both high and low temperature RA because the adequate solution found by SA was similar to that of the initial workload.

4.6 Discussion: Adaptive Temperature Adjustment in Simulated Annealing

When a running average of the cost objective value improves, indicating progress towards the desired optimization goals, the temperature can be reduced. This reduction in temperature corresponds to a decrease in the likelihood of accepting worse solutions, leading to a more focused (depth of) search around the currently nearby optimum. Several different strategies can be employed for adaptive temperature adjustment in SA, depending on the nature of the optimization problem and the specific cost and performance metrics involved, for example:

- Continuous Logarithmic: The classical logarithmic (slow) cooling schedule [1].
- Threshold Based: Predefined thresholds for the objective value are established with temperature changes at each threshold. If the current objective value crosses a threshold, the temperature is reduced to encourage exploitation. Alternatively, if the cost objective exceeds a certain threshold, the temperature may be increased to encourage exploration. The method of the previous subsection is an example. For another example, at any given threshold, temperatures can increase exponentially (e.g., $\tau \rightarrow 2\tau$) and decrease additively (e.g., $\tau \rightarrow (\tau - 1)^+$).
- Iterated Based: The temperature adjustment is based on the number of iterations or the convergence behavior. For instance, if no significant improvement in the cost objective is observed after a certain number of iterations, the temperature can be incremented to encourage further exploration.

For all of the above, annealing may recall the most recent adequate solution $x$, and may return to $x$ when temperatures increase, bearing in mind that $x$ may not be adequate for the current operating conditions. Also, some or all of the decisions of the above methods could also be based on other statistics such as running average mean (rather than the current value) or variance of the cost objective.

5 EXPERIMENTAL EVALUATION - CONTAINER SIZING FOR MICROSERVICES

5.1 Experimental Set-Up

For our container sizing experiments (Figure 12), we use CloudLab [4] to set up a cluster of r320 nodes. Specifically, we configure the cluster to have five nodes, with one node serving as the Kubernetes master and three nodes as Kubernetes workers. Additionally, we designated one node as the workload generator, which also includes the annealing process that communicated with the Kubernetes API at the master node to adjust and modify the resources allocated (configurations) to the deployments. We run our experiments on two microservice applications provided by DeathStarBench [5] (using helm-chart): Social Network and Hotel Reservation. The former is an implementation of a social media network that allows users to read, post, and react to social media posts, whereas the latter is an implementation of a browser-based application that allows users to search and make reservations for hotels. We employ the annealing approach to size the resources allocated to microservices’ deployments. We generate the workload for the two microservices using wrk2 [27], along with workload generator scripts (the benchmark provides both).

5.2 Defining the Annealing Objective

Unlike service selection (section 4), here we define the objective function as $Y_n = t_n + \lambda(U_{cpu} + U_{mem})$ where $t_n$ is the average execution time for epoch $n$, $U_{cpu}$ and $U_{mem}$ are CPU and memory utilization, respectively, and again $\lambda > 0$ is a user-specified factor that weights the average latencies of the requests against the utilization of resources by the microservices. For experiments of this section, we set $\lambda = 1$, which we empirically found to be suitable for our demonstrations.

5.3 Experimental Results

For each experiment, we deploy the microservice application to the Kubernetes cluster while setting the resource request and limit to the minimum configuration for cores and memory for each deployment (we set the minimum for CPU and memory to be at 0.1 CPU and 0.1 MiB). Second, we set up our workload generator to send requests at one-minute intervals (epochs) and measure the mean latency of the requests. After every epoch, the annealing process evaluates the objective function and explores a random microservice to patch with a new resource request and limit at steps of 0.1 CPU/MiB for CPU/memory. When maximum resources are allocated, the annealing exploration phase can either modify resources allocated to a random microservice, or reallocate resources from one microservice to another.

Figure 13 depicts the response times of the read requests to the social network application while performing annealing at different temperatures. The figure shows that a minimizing configuration of the microservices resources can be quickly discovered at a relatively high temperature. In practice, when a configuration with an acceptably small evaluated objective is found, the temperature can be lowered, retaining the configuration desired for a longer period of time, as depicted in figure 14.

Figure 15 depicts the response time of read requests made to the social network application while performing annealing at temperature $\tau = 10$. This experiment describes a scenario where an annealing process selects and remains at a configuration that minimizes the objective value (e.g., a local minimum) for a period of time before finding the optimal configuration through exploration. Note that to find the globally minimizing configuration, configurations that increase the objective are first explored.

6 DISCUSSION

This paper describes a simulated-annealing approach to the management of the performance and cost (resources) of a cluster of virtual machines in the public cloud which is agnostic to both services and
neural networks which require a very large training dataset and costly deep learning and offline reinforcement learning processes). Considering its ease and low cost of implementation and reasonably good performance, simulated annealing and its variants form a compelling class of baseline frameworks for online resources management of clusters.

In this paper, to demonstrate its ease of deployment and use and its good performance, we evaluated an implementation of annealing for

- service selection, evaluated using Apache Spark implementations of HiBench and distributed deep learning workloads, and costs based on AWS VM instance pricing, and
- pod or container sizing, i.e., vertical scaling, evaluated using Kubernetes (K8s) for microservice workloads, with costs based on efficiency of use of the existing instances.

Note that service selection can be expanded to consider the possible benefits of serverless functions, e.g., [14], particularly for stateless microservices, or to consider different storage options particularly for data intensive tasks.

As mentioned in Section 1, online simulated annealing can also be (jointly or independently) used:

- to adjust the task-scheduling policy;
- for assigning containers or pods to VMs (rather than K8s’ default “bin packing” [19]); or
- for horizontal scaling of microservices (i.e., creation of service replicas), e.g.,[8, 13, 22, 28, 34, 36]. All such annealing mechanisms can work with a common temperature parameter or separately adjustable ones, and some obviously will need to operate at different timescales: fast (task scheduling), moderate (container sizing, assigning containers to VMs), slow (horizontal scaling), slowest (service selection).

Rules of thumb can be easily incorporated into simulated annealing neighborhood function \( \nu \), e.g., to constrain assignment of service replicas to the same VM to take advantage of statistical multiplexing [24], or to require that certain microservices be assigned to VMs with GPU support, or to constrain assignment of certain groups of different microservices to the same VM to take advantage of data locality, where the last type of requirement may also constrain horizontal scaling.

The foregoing discussion is not meant to suggest that annealing, or some other method of automatic online optimization, needs to be applied to task scheduling or for the assignment of containers/pods
to VMs. The default ones provided by, e.g., Spark and K8s (and used in our experiments) may be adequate in some use cases. Note that under K8s, such policies are user configurable [15–19]. That is, the K8s API can be used to create affinities between certain types of VMs and certain microservices and among microservices. Moreover, the K8s API can be used to configure the “bin packer” so that, e.g., the fewest possible VMs are used (allowing some VMs to be released to save cost), or to balance the pods among the existing VMs, subject to any stipulated constraints.

Simulated annealing (or another online optimization framework like Bayesian optimization [9]) can easily be modified, e.g., to remember the best states visited in the recent past and return to them with lower temperature if “exploration” at higher temperatures has not recently yielded good results (smaller objective). Also, simulated annealing can be hybridized with other known methods, e.g., with random restart or genetic algorithms to improve breadth of search (exploration), or by excluding recently visited states to improve efficiency of depth of search (exploitation).

The scripts we developed for our Spark and K8s based experiments are posted on GitHub [2].

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