Prediction-Based Admission Control for IaaS Clouds with Multiple Service Classes

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***Abstract*—There is a growing adoption of cloud computing services, attracting users with different requirements and budgets to run their applications in cloud infrastructures. In order to match users' needs, cloud providers can offer multiple service classes with different pricing and Service Level Objective (SLO) guarantees. Admission control mechanisms can help providers to meet target SLOs by limiting the demand at peak periods. This paper proposes a prediction-based admission control model for IaaS clouds with multiple service classes, aiming to maximize request admission rates while fulfilling availability SLOs defined for each class. We evaluate our approach with trace-driven simulations fed with data from production systems. Our results show that admission control can reduce SLO violations significantly, specially in underprovisioned scenarios. Moreover, our predictive heuristics are less sensitive to different capacity planning and SLO decisions, as they fulfill availability SLOs for more than 91% of requests even in the worst case scenario, for which only 56% of SLOs are fulfilled by a simpler greedy heuristic and as little as 0.2% when admission control is not used.**

I. Introduction

Infrastructure-as-a-Service (IaaS) is a cloud computing model that enables users to access computational resources when needed, typically bundled as virtual machines (VMs). Users pay for what they use, instead of acquiring and maintaining their own hardware. A large variety of users are migrating to this model, typically having different budgets and Quality of Service (QoS) requirements for applications.

IaaS providers can offer multiple service classes (referred just as "classes" herefrom) to match a variety of user needs, with different pricing and Service Level Objectives (SLOs) defined for each class. Unfortunately, current cloud Service Level Agreements (SLAs) are very limited and usually contain only generic and simple SLOs. For example, Amazon EC2 [1] and Google Compute Engine [2] SLAs currently define a service uptime of 99.95% or higher as the only SLO, with a penalty for the provider (as a financial credit for affected users) if this SLO is violated. As the cloud market becomes more competitive, providers differentiate themselves by offering a wider range of classes, with combinations of pricing and SLOs that can attract more users and increase profits.

A challenge for providers is how to make efficient resource management decisions and meet SLOs for different classes. Appropriate capacity planning, admission control and scheduling of VMs are required for this task; capacity planning decides on the minimum capacity needed to accommodate the future demand, admission control decides on the minimum set of requests to reject so that SLOs of admitted requests are met, while scheduling decides in which physical machines should VMs be allocated [3]. The inherently high variation of cloud workloads and machine availability (e.g. due to failures and maintenance) makes these decisions even more challenging [4]. If resources are not overprovisioned, there may not be enough capacity available to allocate all VM requests at some periods; this would cause VMs to wait, resulting in lower availability and potential SLO violations.

In this paper we focus our attention on admission control mechanisms. These mechanisms can reduce availability SLO violations by rejecting incoming requests during peak periods. It is assumed that the rejection of incoming requests is less harmful than the violation of SLOs for requests already admitted – which is reasonable because SLO violations usually incur in penalties and affect the provider's reputation. An additional challenge is posed when multiple classes are offered, as admission decisions may have different consequences depending on the classes affected.

In this context, an important problem for IaaS providers is how to make efficient admission control decisions for multiple classes. In this paper we propose a prediction-based model to address this problem, aiming to maximize request admission rates while meeting VM availability SLOs for each class. We use forecasting methods to predict the future capacity available for each class by using historical observations. Based on the predictions, we dynamically define quotas for each class to limit the amount of resources that can be requested, such that new requests are rejected if the quota is exceeded.

The main contributions of this paper are: (1) A formal definition of part of the cloud resource management problem. (2) A novel prediction-based admission control model for IaaS clouds with multiple classes. (3) An evaluation of the proposed model by instantiating it with different forecasting methods, and trace-based simulations using data from production systems. (4) A demonstration that predictive admission control heuristics are less sensitive to diverse cloud environments, and achieve high SLO fulfillment rates even in high-contention scenarios in which simple greedy heuristics presented significantly more SLO violations.

This paper is organized as follows. Section II describes our system model and formulates the problem. Section III presents the prediction-based admission control model. Section IV describes how we instantiate it and defines the evaluated simulation scenarios. Section V evaluates our model comparing to other heuristics. Section VI discusses related work. Finally, Section VII presents our conclusions.

II. Problem Statement

This section describes the system model and formulates the multiclass admission control problem.

A. System Model

We consider an IaaS cloud *provider* that owns a set of physical *machines*. Each machine has a certain *capacity* for each type of *resource*, such as CPU, memory and disk. The *nominal cloud capacity* is the total amount of resources aggregated over all machines owned by the provider. The *available cloud capacity* accounts only for machines that are available for users, and may vary over time (e.g., due to machine failures). Different *instance types* are offered, which represent a combination of the capacities to be allocated for each resource type (e.g., 2 CPU-cores, 8GB memory, and 32GB disk), typically bundled as VMs.

Users *request* VMs and their associated instance types to the provider. Figure 1 shows the possible states of a VM request and the transitions between them. New requests are either *admitted* or *rejected* in the admission control phase. An admitted request moves to the scheduling phase, where it can be either in the *running* or in the *pending* state. A pending request changes to the *running* state when its associated VM is *allocated* in one of the available machines; this can only happen if the requested instance type fits in the machine capacity remaining from other allocations. A VM whose associated request is in the running state can be interrupted due to machine failures or preemption by higher-priority requests, taking the request back to the pending state. A request moves to the *released* state when the required service demand (i.e., execution time) of its associated VM is satisfied.

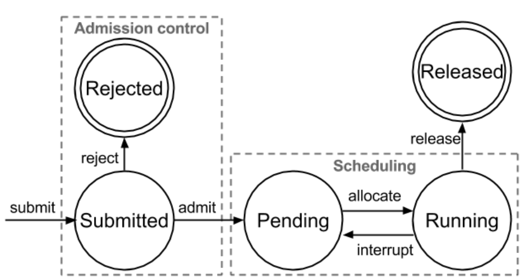


Figure 1. VM request state diagram in our IaaS cloud model.

For the sake of simplicity, we only consider CPU capacity (in number of cores) when allocating VMs to available machines, as CPU was shown to be the bottleneck resource in cloud workload analysis [4], [5]. Nevertheless, other resource types (e.g., memory and disk) could be easily considered by allocating a VM iff there is enough capacity for all of its required resource types.

The provider offers multiple *classes*, with different pricing and expected QoS. Each class has an SLA, which is a contract that defines SLOs the provider promises to meet, and penalties the provider pays in case an SLO is violated (i.e., the promise is not fulfilled). An important QoS metric in our model is the *VM availability*, defined as the percentage of time a VM request was running, since its submission until its release. We consider that the SLA of each class contains a VM availability SLO – i.e., the minimum VM availability accepted for VM requests admitted in a class, such that lower values result in SLO violations.

The assessment of cloud resource management decisions is made during an *observation period*, which is divided into time slots of finite duration called *epochs* [6]. The beginning of a new epoch occurs when at least one of these events happens: (1) the arrival of new VM requests; (2) the release of running requests; or (3) the change on the available cloud capacity. Let $E_1, \cdots, E_i, \cdots, E_N$ denote the epochs in an observation period, where N is the number of epochs in that period. Let $b(E_i)$ and $e(E_i)$ be the begin and end times of epoch E_i, respectively. Therefore, we define the observation period as the time interval $[b(E_1), e(E_N)]$. Let $\Delta_i = e(E_i) - b(E_i)$ be the duration of epoch E_i, and $\Delta = e(E_N) - b(E_1)$ be the duration of the observation period in time units.

We also use the following notation throughout the paper:

- M: number of machines owned by the provider. Let m denote the m-th machine ($1 \leq m \leq M,\ m \in \mathbb{N}$).
- K: number of classes offered by the provider. Let k denote the k-th class ($1 \leq k \leq K,\ k \in \mathbb{N}$).
- $W_k = \{V_{1k}, \cdots, V_{jk}, \cdots, V_{|W_k|k}\}$: workload stream for class k during the observation period, where V_{jk} denotes the j-th VM request for class k.
- S_{jk}: resource capacity in CPU-cores requested for the j-th VM request of class k.
- D_{jk}: service demand in time units (i.e., required execution time) for the j-th VM request of class k.
- $s(V_{jk})$: submission time of the j-th VM request of class k.
- $r(V_{jk})$: release time of the j-th VM request of class k.
- C_m: capacity of machine m in CPU-cores.
- $A_{im} \in \{0, 1\}$: availability of machine m at epoch i; indicates whether it is available (1) or unavailable (0).
- $x_{jk} \in \{0, 1\}$: admission of the j-th VM request of class k; indicates whether it is admitted (1) or rejected (0).
- $y_{ijkm} \in \{0, 1\}$: allocation of the j-th VM request of class k in machine m at epoch i; indicates whether it is allocated in the machine (1) or not (0).

- g_{jk}: revenue (economic gain) per time unit obtained by the provider for running the j-th VM request of class k.
- p_{jk}: penalty (economic loss) to the provider incurred in violating SLOs for the j-th VM request of class k.
- α_{jk}: VM availability observed for the j-th request of class k. Let α_k^{min} be the the VM availability SLO for class k – i.e., the minimum VM availability accepted for class k.
- θ_k: SLO fulfillment rate for class k, defined as the percentage of requests of class k for which the VM availability SLO was not violated (i.e., $\alpha_{jk} \geq \alpha_k^{min}$). Let θ_k^{min} be the minimum SLO fulfillment rate accepted for class k.

B. Problem Formulation

This paper addresses the admission control problem, which is part of the cloud resource management process. Figure 2 illustrates how admission control interacts with the capacity planning and scheduling phases in this process.

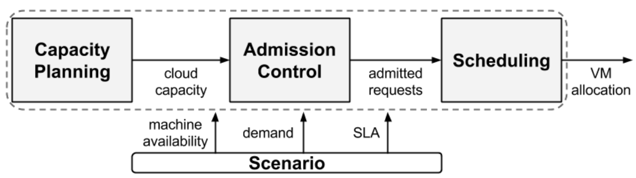


Figure 2. Cloud resource management process.

In the capacity planning phase, the provider defines which nominal cloud capacity is needed to execute an expected workload; in the admission control, it decides which requests to reject in order to meet SLOs of admitted ones; and in the scheduling, it chooses the VMs that will be running at each epoch, and in which machines they will be allocated.

We define the admission control and scheduling problems as an optimization model. We assume the capacity planning is performed separately, giving the set of M machines that comprise the cloud, where each machine m ($1 \leq m \leq M$) has a resource capacity C_m and an availability A_{im} for each epoch i ($1 \leq i \leq N$). The objective is to maximize the provider's profit, subject to VM availability SLOs for each class and the available cloud capacity. The decision variables for the admission control phase are the admission variables x_{jk} for each j-th VM request of class k; and for the scheduling phase are the allocation variables y_{ijkm} for each j-th VM request of class k in machine m at epoch i.

A *decision scenario* represents the set of input data used to assess a cloud resource management solution, given as:

$$\Phi = \langle N, M, K, W_k, S_{jk}, D_{jk}, C_m, A_{im} \rangle$$

Therefore, we formulate the optimization problem as:

Given Φ,

maximize

$$\mathcal{P} = \sum_{k=1}^{K} \sum_{j=1}^{|W_k|} \left(\sum_{m=1}^{M} \sum_{i=1}^{N} x_{jk} \cdot y_{ijkm} \cdot g_{jk} \cdot \Delta_i - p_{jk} \right) \quad (1)$$

s.t.

$$\sum_{k=1}^{K} \sum_{j=1}^{|W_k|} y_{ijkm} \cdot S_{jk} \leq C_m \cdot A_{im}, \quad \forall i, m \quad (2)$$

$$y_{ijkm} \leq x_{jk}, \quad \forall i, j, k, m \quad (3)$$

$$\theta_k \geq \theta_k^{min}, \quad \forall k \quad (4)$$

The objective function (Equation 1) to be maximized is the provider's profit $\mathcal{P}$, calculated as the revenue obtained by running VMs in each epoch, subtracted by the penalties for violating VM availability SLOs during the observation period.

The capacity constraint (Equation 2) states that the capacity allocated for all VMs in a machine must not be higher than the machine capacity, and that unavailable machines must not have allocations. The admission constraint (Equation 3) means that a VM request can be allocated iff it has been admitted. Finally, the SLA constraint (Equation 4) states that SLO fulfillment rates must not be lower than the minimum accepted rate defined for each class.

Unfortunately, this optimization problem is an example of a 0-1 integer linear programming problem and is known to be NP-complete. Additionally, its solution would require knowledge of future demands and machine availability values by the provider, which is unrealistic. Therefore, we propose predictive heuristics to address the multiclass admission control problem, and use this optimization model in our evaluation.

III. Prediction-Based Admission Control

We adopt a quota-based approach in our admission control model, in which the provider dynamically defines a *quota* to limit the amount of resources that can be allocated to a class. New requests are rejected if the total capacity requested by VMs in a class exceeds its quota. A similar strategy is used by Google's Borg system [7] and by Amazon EC2 cloud [8].

Priorities are assigned to classes with k = 1 being the highest priority and k = K the lowest. A provider can explicitly define priorities or they can be defined proportionally to VM availability SLOs. Our admission control model assumes a preemptive priority scheduling policy that allocates VMs of higher-priority classes first, similarly to Borg [7].

We assign quotas for a class based on the capacity available for the class and its VM availability SLO. The capacity available for a class depends not only on the available cloud capacity, but also on the demand from higher priority classes – the highest priority class is the only one for which the available capacity depends solely on the available machines.

Thus, the *available class capacity* for class k at epoch i is defined as

$$c_{ik} = \sum_{m=1}^{M} A_{im} \cdot C_m - \sum_{k'=1}^{k-1} \sum_{j=1}^{|W_{k'}|} x_{jk'} \cdot y_{ijk'm} \cdot S_{jk'}. \quad (5)$$

Let the *VM availability* for the j-th VM of class k be

$$\alpha_{jk} = \frac{\sum_{i=1}^{N} \sum_{m=1}^{M} y_{ijkm} \cdot \Delta_i}{r(V_{jk}) - s(V_{jk})} \cdot 100\%. \quad (6)$$

where $r(V_{jk})$ is the release time of the j-th VM request of class k – if the request is not released before the observation period finishes, we assume $r(V_{jk})$ to be the observation period end time $e(E_N)$.

According to Little's law [3], we can define the mean number of VM requests in a system as

$$L = R \cdot \lambda = \frac{S}{\alpha} \cdot \frac{c}{S} = \frac{c}{\alpha} \quad (7)$$

where R is the mean VM sojourn time, λ the mean throughput in finished VMs per unit time, S the mean service demand, α the mean VM availability, and c the mean available class capacity. Equation (7) tells us that a higher number L of admitted requests implies in lower VM availability. Thus, we consider L to be a good estimator of the maximum number of requests that can be admitted aiming at a VM availability α, given an estimated available class capacity c.

Therefore, we define the quota l_{ik} at epoch i for class k aiming at achieving a VM availability α_k as

$$l_{ik} = \frac{\mathcal{F}(b(E_i), k, h)}{\alpha_k} \quad (8)$$

where $\mathcal{F}(.)$ is a prediction function applied at the beginning of epoch E_i to estimate the minimum available class capacity for class k in the following h time units.

The available class capacity can be overestimated due to its variation over time, which may cause SLO violations. To deal with this, we calculate confidence intervals for predictions, and make conservative estimates by using the lower-bounds of prediction intervals as the predicted values.

Let $f(\vec{c}_{tk}, h)$ denote a forecasting method that uses as input the data vector $\vec{c}_{tk}$ of available capacities for class k observed until time t to make a prediction for h time units ahead. Thus, we calculate the lower bound for the one-sided prediction interval with unknown variance [9] as

$$\mathcal{F}(t, k, h) = f(\vec{c}_{tk}, h) - z_\gamma \cdot \sigma \cdot \sqrt{1 + \frac{1}{n}} \quad (9)$$

where z_γ is the γ-percentile of the Student t-distribution with $n - 1$ degrees of freedom; γ is the confidence level; σ is the standard deviation and n the size of the historical data sample.

By applying this prediction-based model, a cloud provider can define quotas for each class over time. Any forecasting method (or a combination of methods [10]) can be used. In the next section, we instantiate the model with two different forecasting techniques to evaluate its efficacy.

IV. Evaluation Methodology

This section describes the specifics of the admission control heuristics, the metrics used to evaluate them, and the scenarios used in the trace-based simulations.

A. Admission Control Heuristics

We instantiate our model with two predictive heuristics and a greedy one. We also compare them with a heuristic oblivious to admission control. The heuristics evaluated are:

- *pred-cmean*: predictive heuristic that uses our model to assign a quota to each class using the Conservative Mean forecasting method.
- *pred-ets*: predictive heuristic that uses our model to assign a quota to each class using the Exponential Smoothing (ETS) forecasting method.
- *greedy-quota*: greedy heuristic that uses our model to assign a quota to each class based only on the current available capacity for a class – i.e., the estimated available class capacity is equal to the last value observed.
- *no-adm-control*: simple heuristic that does not use admission control, admitting all requests for every class.

The forecasting methods used by *pred-cmean* and *pred-ets* heuristics are described as follows:

- *Conservative Mean*: we compute simple arithmetic means for three different input data samples: the *last hour mean* uses data from the previous hour to capture short-term changes; the *last day mean* uses data from the previous 24 hours to capture mid-term changes; and the *seasonal daily mean* uses historical values from the same clock-time as the time being predicted (e.g., every 9am), but for previous days to capture daily patterns. The minimum value of the three means is used as a conservative prediction; this way, it quickly reacts to sudden observed capacity decays, but slowly increases predictions for capacity growth spikes.
- *Exponential Smoothing (ETS)*: a forecasting method that combines models based on the weighted averages of input values, with the weights exponentially decaying for older values. The ETS model has three components: Error correction (E), Trend (T), and Seasonal (S). Each component can be of a certain type: None, Additive, Multiplicative, and other variations. The different combinations of component types result in different ETS methods, where each method has a set of parameters to be estimated [11]. We used Akaike's Information Criterion (AIC) [12] to pick a good ETS model: it estimates the probability of the data arising from each model by using a maximum likelihood estimator, and penalizes models with a large number of parameters [13]. Similarly to our previous

work [5], we used the ETS implementation from the R *forecasting* package [14].

We used a confidence level of $\gamma = 95\%$ to calculate prediction confidence intervals – this can be adjusted by providers for more/less conservative predictions [5]. The historical data used as input for predictions accumulates over time, so the sample size n grows over the simulation. This presented no problem for the observation periods we evaluate (29 days); but, for longer periods it would be preferable to adopt a sliding window approach to avoid performance problems.

At the beginning of an observation period, the sample size for the first predictions will be very small, which affects the predictive strategies. To overcome this problem, we adopted a conservative approach during the first simulated hour by defining the quota for a class equal to the available class capacity at the moment – it means that no VM request will be pending at the time of admission, although they can be interrupted later on due to machine failures or preemption.

B. Simulation Scenarios

The evaluation was performed through trace-based simulations. We used workloads from Google's cluster data publicly available [15]. The traces were collected during 29 days in May 2011 from a cluster with over 12k physical machines and over 25M task submissions recorded. (Analysis of these traces can be found in [4] and [16].)

The resource capacity data in the trace is normalized by the size of the largest machine in the cluster, which was not published; although we do not have absolute resource capacity values, we are still able to calculate relative values of requested capacity over the machines' capacities, as they are normalized by the same constant factor. This relative resource capacity information is enough for our simulations.

We consider each task submitted in the traces as a VM request. This is how we map traces' attributes to simulations:

- *VM request submission time* ($s(V_{jk})$): submission time of each task.
- *VM class* (k): priority range associated to each task. Based on the trace description [15], we assign three priority groups: "prod" to tasks with high priorities ($9 \leq priority \leq 11$); "batch" to tasks with middle priorities ($2 \leq priority \leq 8$); and "free" to tasks with low priorities ($0 \leq priority \leq 1$).
- *VM requested capacity* (S_{jk}): requested CPU capacity for each task. For tasks that update this value over time, we consider the maximum observed during the task lifetime.
- *VM service demand* (D_{jk}): total time each task was in the "running" state in time units.
- *Machine capacity* (C_m): CPU capacity of each physical machine in CPU-cores.
- *Machine availability* (A_{im}): actual time periods that each physical machine was available.

Because task and machine availability events occur very frequently in the traces, we aggregate events in fixed 5-minute intervals. This was done to reduce simulation time and make it feasible to evaluate the complete trace in many different scenarios. Thus, admission control and scheduling decisions are made at this time granularity, which makes every epoch E_i to have the same size ($\Delta_i = 5$ minutes, $\forall i$). If a machine became unavailable at any time within an epoch, we consider this machine was unavailable during the whole epoch period. VM request submission events within an epoch are anticipated to the beginning of the same epoch, and VM request release events are delayed to the beginning of the following epoch.

At each new epoch, the admission control mechanism can adjust the quotas defined for classes and reject incoming requests if a quota is exceeded. As we focus on admission control, VM placement is not simulated (i.e., VMs are not assigned to particular machines). The scheduler allocates requests based on their priorities, such that the total capacity allocated for VMs is not greater than the available cloud capacity. We use a preemptive priority scheduling policy (described in Section III). VM requests within the same priority are allocated in a First-Come-First-Served basis. We also use an aggressive backfilling approach [17], on which requests are skipped in the scheduling queue if they do not fit in the current available capacity; although skipped requests will become unavailable, they are reconsidered by the scheduler every next epoch, being able to preempt lower-priority requests.

We use simple linear functions to calculate the revenue and penalty, which are proportional to the VM requested capacity and availability SLO. The revenue per unit time obtained for running the j-th VM request of class k is defined as

$$g_{jk} = S_{jk} \cdot \alpha_k^{min}. \tag{10}$$

We consider the penalty paid by the provider is also proportional to the total time the VM was running or pending. Therefore, we define the penalty incurred in violating the VM availability SLO for the j-th VM request of class k as

$$p_{jk} = \begin{cases} 0, & \text{if } \alpha_{jk} \geq \alpha_k^{min} \\ S_{jk} \cdot \alpha_k^{min} \cdot \left(r(V_{jk}) - s(V_{jk})\right), & \text{otherwise.} \end{cases} \tag{11}$$

The admission control heuristics are assessed for different metrics, which are defined as follows:

- *Admission rate* – percentage of class-k requests admitted:
$$\frac{\sum_{j=1}^{|W_k|} x_{jk}}{|W_k|} \cdot 100\%. \tag{12}$$
- *SLO fulfillment* – percentage of class-k admitted VM requests for which the observed VM availability was at least equal to the VM availability SLO defined for that

class:

$$\theta_k = \frac{|\{V_{jk} \in W_k : \alpha_{jk} \geq \alpha_k^{min} \wedge x_{jk} = 1\}|}{|\{V_{jk} \in W_k : x_{jk} = 1\}|} \cdot 100\% \tag{13}$$

- *Mean cloud utilization* – percentage of the available cloud capacity that is allocated for VMs, averaged for each epoch:

$$\sum_{i=1}^{N} \left(\frac{\sum_{k=1}^{K} \sum_{j=1}^{|W_k|} \sum_{m=1}^{M} y_{ijkm}}{\sum_{m=1}^{M} C_m \cdot A_{im}} \cdot \frac{\Delta_i}{\Delta} \right) \cdot 100\%. \tag{14}$$

- *Profit efficiency* – profit obtained for heuristic h normalized by the highest profit of all heuristics in the same scenario:

$$\frac{\mathcal{P}_h}{\max(\mathcal{P}_1, \cdots, \mathcal{P}_H)} \cdot 100\% \tag{15}$$

  where H is the number of heuristics evaluated and P_h is the profit achieved by heuristic h. The best heuristic in a scenario will have profit efficiency equal to 100%.

Different cloud scenarios are evaluated by changing the following simulation parameters:

- *Capacity size factor*: a multiplicative factor applied to the capacity of each machine extracted from the original trace – e.g., a capacity size factor of 1.1 means that each machine has 10% more capacity than the original values in the traces.
- *SLO strength*: represent the quality level of VM availability SLOs offered in the scenario, as the combination of SLO values defined for each class – e.g., a medium-quality strength having $(100\%, 90\%, 50\%)$ SLOs defined for *prod*, *batch* and *free* classes, respectively.

V. Results

This section presents the evaluation results; first for a base scenario and then for sensitivity analysis that explores different capacity planning and VM availability SLO scenarios.

A. Base Scenario

The base scenario uses the demand and capacity data extracted from the traces without any modification (i.e., capacity size factor $= 1$) and the following base VM availability SLOs: *prod* $= 100\%$, *batch* $= 90\%$, *free* $= 50\%$.

Figure 3 shows the SLO fulfillment (top) and admission rate (bottom) of VM requests for each class for different admission control heuristics in the base scenario. The SLO fulfillments for the *prod* class was 100% under all heuristics, because there was enough capacity to allocate all requests even with no admission control. For the *batch* class, the predictive heuristics had the highest SLO fulfillments, while *greedy-quota* and *no-adm-ctrl* had slightly lower values. The difference was more significant for the *free* class; the predictive heuristics had more than twice the fulfillments of *greedy-quota* while *no-adm-ctrl* had almost no fulfillments.

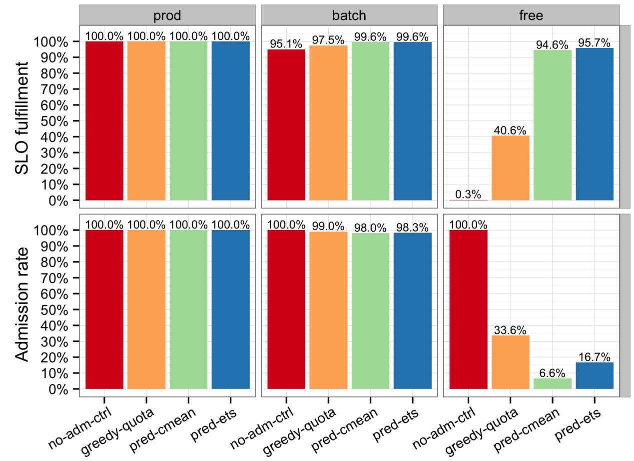


Figure 3. Percentage of requests with VM availability SLOs fulfilled (top graphs) and admitted (bottom graphs) per class in the base scenario.

Admission rates for *no-adm-ctrl* is always 100% as it is oblivious to admission control. For *prod* class, all heuristics admitted all requests because no rejection was needed to fulfill all SLOs. For *batch*, *greedy-quota* had slightly more admissions than predictive heuristics. For the *free* class, *greedy-quota* had more than twice the admissions of *pred-ets* and more than five times the admissions of *pred-cmean*.

The lower admission rates of prediction-based methods are required to achieve higher SLO fulfillments, our most important metric. Predictive heuristics had higher SLO fulfillments than *greedy-quota* because the greedy approach relies only on the current available class capacity, which can decrease in the future and cause SLO violations. The forecasting methods not only give better predictions on future available class capacities, but also handle high variations by calculating lower bounds for prediction intervals to reduce violations. Although both predictive approaches had similar SLO fulfillments, *pred-ets* had higher admission rates than *pred-cmean* because the latter is typically more conservative, as it uses the minimum value of arithmetic mean calculations for three different samples.

The results highlight the importance of admission control to meet VM availability SLOs, showing that SLO fulfillments can be very low when admission control is not used. The base scenario exhibits low resource contention for *prod* and *batch* classes, which presents high SLO fulfillments and high admission rates. On the other hand, the *free* class requires lower admission rates in order to achieve high SLO fulfillments. More contention scenarios are explored in the next section.

B. Capacity Planning Sensitivity Analysis

We now analyze the sensitivity of the heuristics to different capacity planning decisions by using these different capacity size factor values: $0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3$.

The base SLO strength values were used.

Figure 4 shows the SLO fulfillment (left) and the admission rate (right) aggregated for all service classes as a function of the capacity size factor. The SLO fulfillment is lower for smaller capacities for *no-adm-ctrl* and *greedy-quota*, which exhibit 0.2% and 56% SLO fulfillments in the worst case, respectively. On the other hand, the predictive heuristics are not significantly affected by capacity size variations, having in the worst case 91% of SLOs fulfilled.

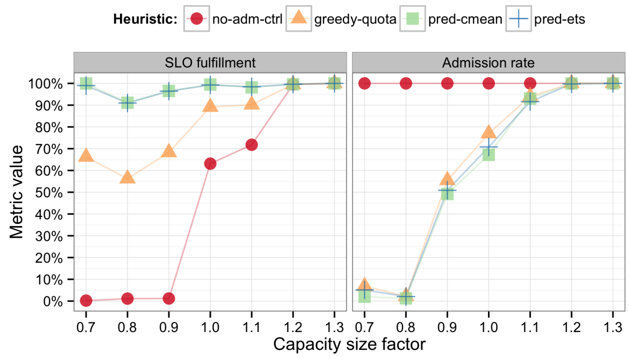
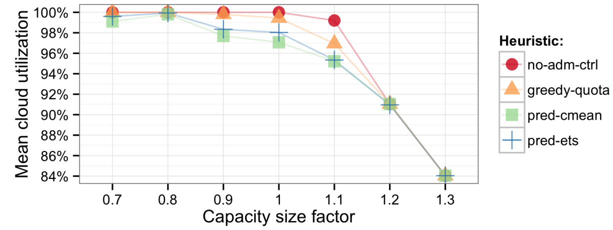


Figure 4. Percentage of requests with VM availability SLOs fulfilled (left), and admitted (right) when varying the cloud capacity size factor.

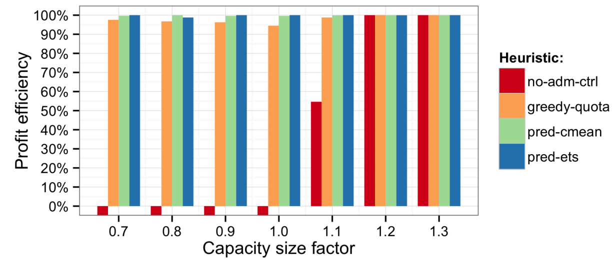
Again, the admission rate for *no-adm-ctrl* is always 100%, while for the other heuristics it tends to decrease as the capacity shrinks. Note that for quota-based heuristics the admission rate is lower for capacity factor 0.8 than for 0.7. This happened because in the former scenario, all *prod* requests are admitted while in the latter, $\approx 25\%$ of *prod* requests are rejected to meet SLOs. Since *prod* VMs require more capacity and have higher service demands than other classes on average, the rejection of a few *prod* VM requests generates enough spare capacity to allocate many low-demanding VMs from *batch* and *free* classes, which increases overall admission rates.

Although the greedy heuristic had higher admission rates than predictive ones, it had lower SLO fulfillment and higher sensitivity (variation) to different capacity planning scenarios. As explained, predictive heuristics can better estimate future available class capacity and handle high variations. SLO fulfillments for both predictive methods were very similar, although *pred-ets* had higher admission rates than *pred-cmean*, as the latter tends to be more conservative.

Figure 5a shows the mean cloud utilization for different capacity size factors. As expected, the cloud utilization decreases when the cloud capacity is increased. Predictive heuristics had lower utilizations in most scenarios due to the lower admission rates needed to achieve high SLO fulfillments. Note that the utilization, admission rates and SLO fulfillments were the same for all heuristics at a capacity size factor of 1.3, which is an overprovisioned scenario with low cloud utilization.



(a)



(b)

Figure 5. Results for (a) mean cloud utilization and (b) profit efficiency when varying the cloud capacity size factor.

Figure 5b shows the profit efficiency for different capacity size factors. For capacity factors lower than 1.1 the profits for *no-adm-ctrl* (only shown partially in the graph) are negative. All heuristics had similarly high profits when resources are overprovisioned (capacity factors 1.2 and 1.3). Predictive heuristics had the best profits overall, very similar to each other with a difference not higher than 1.3%. The *greedy-quota* also had high profits and a maximum difference with predictive heuristics of 5.5%.

Note that the profit mostly comes from *prod*-class VMs because they usually request more capacity, have higher service demands and generate more revenue. Because in most scenarios evaluated the cloud capacity is enough to allocate all *prod* VMs, all heuristics obtained high revenues from this class. Thus, we believe the difference in the profits of the various heuristics would be larger for scenarios where the *prod* class also experienced high resource contention.

C. Availability SLOs Sensitivity Analysis

We now examine the sensitivity of the heuristics to different VM availability SLOs. We vary SLO strengths by keeping the *prod*-class SLO at 100% and using the following SLO combinations for *batch* and *free* classes: very-low $(50\%, 10\%)$, low $(70\%, 30\%)$, middle $(90\%, 50\%)$, high $(99\%, 70\%)$, and very-high $(99.9\%, 90\%)$.

Figure 6 shows the SLO fulfillment (left) and admission rate (right) for different heuristics when varying the SLO strength. The quota-based heuristics tend to define more conservative quotas for higher SLOs, which resulted in higher SLO fulfillments. The worst-case scenario for each heuristic yield SLO fulfillments of 63.0% (*no-adm-ctrl*), 84.9% (*greedy-quota*), 94.9% (*pred-cmean*), and 93.2% (*pred-ets*). The admission rate decreases for predictive heuristics when

SLOs are stronger, because more rejections are required to fulfill them.

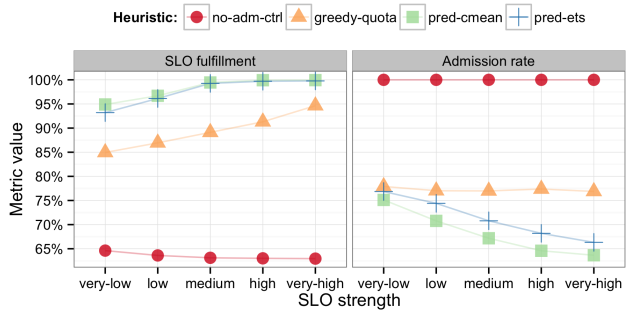


Figure 6. Percentage of requests with VM availability SLOs fulfilled (left), and admitted (right) when varying the SLO strength.

Figure 7 shows the mean cloud utilization when varying the SLO strength. The utilization decreases when the SLO strength increases for quota-based heuristics, caused by lower admission rates. Profit efficiency graphs are omitted on this analysis due to space limitation; nevertheless, predictive heuristics also had the best profits for all SLO strength scenarios.

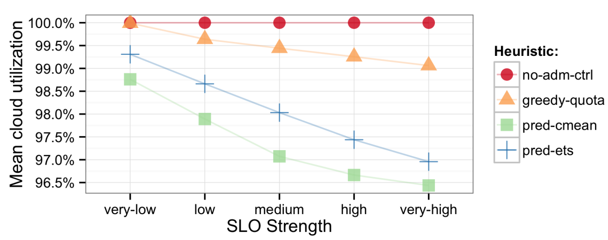


Figure 7. Mean cloud utilization when varying the SLO strength.

The predictive heuristics were not significantly affected when defining different VM availability SLOs for each class. Additionally, setting strict SLOs for all classes results in lower utilization, which suggests that instead of offering all classes with high SLO targets, it is preferable to have a wider range of SLOs to utilize the cloud capacity more efficiently.

VI. Related Work

Resource management in cloud environments has been extensively studied [18]. Most of previous work has covered problems from the cloud user's point of view [19]–[21]. This paper addresses the admission control problem from the perspective of an IaaS cloud provider.

From the provider's side, strategies have been proposed for the allocation and migration of VMs, aiming to improve cloud utilization and reduce SLO violations [22]–[24]. Although we have similar goals, we tackle a different problem in this paper. Thus, our admission control approach complements VM allocation and migration methods and could be combined to develop a complete cloud resource management solution.

In our previous work, we reclaim unused cloud capacity to offer a new *Economy* class with long-term availability SLOs, by predicting the minimum capacity to be available for this class in 6-month periods [5]. We extend this work by proposing an admission control model that handles short-term demand variation, in order to maximize admission rates while meeting VM availability SLOs for multiple classes.

Marshall et al. consider opportunistic leases (with no SLOs) to be combined with high-quality VM allocations to improve cloud utilization [25]. Similar best-effort services offered by public clouds are Amazon EC2 spot instances [1] and Google Cloud preemptible instances [26]. Our work not only combines multiple classes to achieve higher utilization, but also defines VM availability SLOs for each class and shows how to achieve high SLO fulfillments for them.

Unuvar et al. propose a stochastic admission control model with overbooking of cloud resources [27]. They fit observed VM usage data to a Beta distribution, and reject requests based on the probability of exceeding an utilization threshold. Cherkasova and Phaal propose a predictive admission control for e-commerce applications that adjusts an admission threshold based on average observed load [28]. Similarly, our prediction-based model defines admission quotas based on the estimated probability of violating SLOs. However, we use more sophisticated forecasting techniques that can capture seasonal patterns and short-term demand spikes observed in cloud workloads. Moreover, differently from these studies, our model considers multiple classes and SLOs. Although overbooking was not investigated in our evaluation, this could be easily considered in our quota-based model by predicting resource usage instead of allocated VM capacity.

VII. Conclusion

IaaS cloud providers can offer a wide range of service classes to increase their profits, by attracting users with different QoS requirements and budgets. Therefore, an important problem for providers is how to maximize their profits while meeting SLOs defined for the different classes. This paper proposed a prediction-based admission control model that addresses this problem. We dynamically define quotas to limit the admission of VM requests for different classes, by forecasting the expected capacity to be available for each class.

Our results show that admission control mechanisms are necessary to fulfill availability SLOs when the cloud capacity is not overprovisioned. Our prediction-based approach was not significantly affected by different capacity planning and SLO decisions, exhibiting consistently high SLO fulfillments and the highest profits for the different scenarios analyzed when compared to other heuristics. Moreover, the results suggest that it is important to offer a wide range of

SLOs in order to achieve high utilization, which could also attract more users.

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