A Lightweight Workload-Aware Microservices Autoscaling with QoS Assurance

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ABSTRACT

Cloud applications are increasingly moving away from monolithic services to agile microservices-based deployments. However, efficient resource management for microservices poses a significant hurdle due to the sheer number of loosely coupled and interacting components. The interdependencies between various microservices make existing cloud resource autoscaling techniques ineffective. Meanwhile, machine learning (ML) based approaches that try to capture the complex relationships in microservices require extensive training data and cause intentional SLO violations. Moreover, these ML-heavy approaches are slow in adapting to dynamically changing microservice operating environments. In this paper, we propose PEMA (Practical Efficient Microservice Autoscaling), a lightweight microservice resource manager that finds efficient resource allocation through opportunistic resource reduction. PEMA’s lightweight design enables novel workload-aware and adaptive resource management. Using three prototype microservice implementations, we show that PEMA can find close to optimum resource allocation and save up to 33% resource compared to the commercial rule-based resource allocations.

1 INTRODUCTION

Motivation. Microservices architecture is enjoying a growing penetration in user-facing cloud applications where an ensemble of loosely-coupled and small service components (i.e., microservices) work together to serve user requests [1–3]. Microservices architecture is a significant departure from traditional monolithic deployments with a few large application layers such as user-facing front-end, back-end business logic, and database [4]. Unlike monolithic applications (Fig. 1), the small microservices can be easily managed and kept updated by small dedicated DevOps teams [5]. Moreover, microservice are typically stateless and communicate using light weight APIs [6, 7]. Hence, they offer agile resource management and scaling, fault tolerance, and great platform agnostic compatibility among different microservices that cannot be matched by monolithic applications [5, 8].

Microservices come with their own sets of challenges, and in this paper, we focus on its resource management. In principle, microservice resource management is same as monolithic applications - achieve the desired performance (e.g., end-to-end response latency) with the minimum resource allocation [9–11]. Resource management for microservices-based applications, however, is more challenging because these applications have a much larger configuration space due to the sheer number of microservices responsible for the application performance. For example, if we consider an application with m microservices where each microservice can be configured with n different CPU allocations, there will be mn possible resource configurations. Moreover, microservices have complex communication topology and inter-dependence that makes it harder to identify and mitigate Quality of Service (QoS) violations [2, 8]. A single user request may traverse through several microservices, and if any microservice in the critical path becomes a bottleneck, the end-to-end response time will increase significantly [12]. Our motivating experiments on three prototype microservices show that the same amount of resource can result in more than 250% increase in application latency based on how the resource is distributed among different microservices. Meanwhile, existing resource management techniques developed for monolithic applications with a few service layers cannot readily capture the complex microservice interactions to make effective resource allocation choices [13–16]. Nevertheless, addressing these resource management challenges for microservice is of paramount importance as an increasing number of production cloud services have been adopting microservice architectures [4, 17].

Limitation of state-of-art approaches. Owing to the growing interest, several recent works try to address the resource management challenges in microservices [4, 12, 17–19]. They focus on utilizing machine learning (ML) techniques to capture the complex relationship between microservices resources and performance. For instance, FIRM [12] uses a combination of support vector machines (SVM) and reinforcement learning to localize root causes of service level agreement (SLO) violations, and apply resource autoscaling to avert these violations. Sage [18], on the other hand, uses supervised training to identify dependencies between different microservices using a causal Bayesian network, and a graph encoder to track the QoS violating microservices to adjust their resource. However, this line of works built on ML are fundamentally limited by their extensive training requirements - both in terms of training time to capture
the dynamics of the microservices and data resolution (e.g., request level traces to build dependency graphs). More importantly, to learn from the data, some ML-based techniques intentionally cause or allow SLO violations which is undesirable in production systems [12, 17–19]. Also, any changes in the microservices architecture and inter-dependencies will require retraining the system. This ML retraining can become a barrier for real world microservices applications which go through frequent software/code updates. ML retraining can also be triggered due to changes in underlying cloud hardware due to server migrations and upgrades. On the other hand, the resource demand of microservices changes with the workload on a daily basis. However, existing approaches focusing on SLO violations do not directly incorporate dynamic workload in their learning [12, 17–19].

Key insights and contributions. To avoid the hurdles of the approaches as mentioned above, we propose PEMA (Practical Efficient Microservice Autoscaling), a lightweight microservice resource manager that does not need extensive training and utilizes iterative feedback-based tuning to find efficient resource allocations that satisfy the SLO. Instead of finding the best resource configuration, PEMA first allocate abundant resources to all microservices and try to exploit resource reduction opportunities. Using this approach, PEMA avoids causing intentional SLO violations as it always allocates enough resources for microservices, even when performing poorly (i.e., missing resource reduction opportunities). To enable the resource reduction-based approach, we introduce the notion of “monotonic resource change” where we do not increase the resource of some microservices and decrease the resource of others in the same iteration. We observe that monotonic resource reductions result in a monotonic increase in response time. Hence, we can use the response time as feedback to identify resource reduction opportunities to make gradual monotonic resource changes to reach efficient allocations. In addition, based on experiments on prototype microservice implementations, we identify that we can avoid resource reduction in bottleneck services using only two microservice-level performance metrics - CPU utilization and CPU throttling.

Our feedback-based design also allows us to seamlessly adapt a workload-aware design where we implement a novel approach of using dynamic workload ranges with a dynamic response time target. More specifically, to avoid time-consuming learning of the efficient allocation for different workload levels independently, we use dynamic ranging where PEMA starts resource allocation for a large workload range and then gradually splits them into smaller ranges. We retain the resource allocation learned by the parent workload range during the range split to bootstrap the tuning for the new workload range. Based on the workload, we also dynamically alter the feedback from response time to allow headroom for response time change due to workload change.

Our performance evaluation reveals that PEMA can attain resource efficiency close to the optimum with high probability. We also show that PEMA can save as much as 33% resource compared to rule-based resource allocation strategies of commercially available cluster managers. We demonstrate that PEMA can seamlessly adapt to changes in microservice deployment due to changes in underlying cloud hardware. Moreover, we show that adaptability of PEMA allows its integration with opportunistic resource management where variable SLO is used for trading performance for resource savings.

Experimental methodology and artifact availability. We use three prototype microservices implementations widely used in academic research on microservices [12, 17, 18]. We implement TrainTicket from [20] consisting of 41 microservices, SockShop from [21] with 13 microservices, and HotelReservation from [2] with 18 microservices. We deploy these services in Docker [22] containers managed by Kubernetes [23]. Our Kubernetes cluster consists of five nodes with one master node and four worker nodes. Each node is equipped with two 10-core Intel Xeon processors, and 128 GB of Memory running Ubuntu 20.04.3 operating system. Upon acceptance, we will make our software artifact publicly available.

Limitations of the proposed approach. We share our insight on the limitations of PEMA on two different fronts - the fundamental limitations in PEMA’s design approach and the limitations of PEMA’s current implementation. Due to its non ML-heavy approaches, PEMA’s design loses on capturing complex interdependencies between microservices and therefore is limited on the absolute best resource efficiency it can achieve. However, PEMA makes up for this loss of optimization potential through its simplicity and adaptability to change (e.g., workload variation). Also, due to our randomized exploration based search, PEMA offers provably efficient management and can result in arbitrarily inefficient resource allocations at times. We defer the discussion on the limitations of PEMA’s current implementation to the end of our paper in Section 6 to make it more meaningful to the reader.

2 PRELIMINARIES

2.1 Microservice Prototypes

SockShop [21]. SockShop implements the user-facing microservices of an e-commerce website. SockShop’s functionalities include searching, order placement, and shipping. Its functionalities can be divided into three parts - front-end, business-logic, and databases. The user requests arriving at the front-end are routed to appropriate microservices to serve the requests. The business-logic interact with each other and the databases as needed. The front-end is implemented using NodeJS, orders and carts microservices are implemented using Java, and rest of the services are implemented with Go. Shipping service uses RabbitMQ to propagate messages to Queue-Master which is implemented in Java. The databases are implemented using MySQL and MongoDB. For SockShop we set SLO response time to 250 milliseconds. The overall architecture is shown in Figure 2.
we set SLO response time to 900 milliseconds.

As in any general computing system, the performance of microservices applications depends on their resource allocation. Various theoretical and practical tools have been developed over the years to establish a mathematical relationship between computing resource and performance [9]. However, they are not equipped to capture complex interactions between different microservices. Any request’s end-to-end response time (i.e., performance) is the aggregation, often non-linearly due to parallel processing, of time spent in many microservices. Consequently, the presence of any microservice with a resource bottleneck on the service path affects the end-to-end response time. Meanwhile, the resource demand for different microservices can be widely different based on their service. Hence, the distribution of resources among different microservices plays a crucial role in application performance.

To demonstrate the importance of resource distribution, we run a few experiments on our microservices prototypes. We first identify “good” resource allocations that satisfy the SLOs for the prototypes and “bad” (i.e., violates SLO) resource distribution on the response time at different workloads in unit requests per second (RPS). In Fig (a), for workloads 100, 200, and 300, CPU resources are 40.5, 42, and 47 respectively. In Fig (b), for workloads 250, 550, and 950, CPU resources are 6.3, 7.7, and 14.1 respectively. In Fig (c), for workloads 300, 500, and 700, CPU resources are 5.1, 6.9, and 9.4 respectively.

### 2.3 Challenges in Microservice Resource Management

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We have two design goals for our resource manager - (1) assure QoS where the microservice resource allocation decisions are updated (i.e., avoid SLO violations), and (2) efficient resource allocation.

To illustrate this, we show the resource distributions of vector of the defined in the SLO. In what follows, response of the application for resource allocation Here, at time step $R_{\text{management}}$ as the following optimization problem at the beginning of each time step, we formalize our resource management as the following optimization problem

\[
\begin{align*}
\text{ORA: } & \text{minimize } \sum_{i=1}^{N} x^i_j \\
& \text{subject to } F(x^i) \leq R. 
\end{align*}
\]

Here, at time step $t$, $x^i = (x^i_1, x^i_2, \ldots, x^i_N)$ is the resource allocation vector of the $N$ microservices, $F(x^i)$ is the end-to-end latency response of the application for resource allocation $x^i$, and $R$ is the response latency threshold defined in the SLO. In what follows, we develop PEMA (Practical Efficient Microservice Autoscaling) - a practical microservices resource manager that finds a provably efficient solution to ORA. We first discuss the design principles of PEMA to achieve our goals (i.e., the solution to ORA), followed by the rationale for our choices and implementation details of PEMA.

3 DESIGN OF PEMA

SockShop and HotelReservation suffers up to 91.3% and 256.2% increase, respectively.

Due to large configuration space, the "good" resource distribution cannot be readily determined for microservices. Also, the nature of processing done in different microservices is different and cannot adhere to any general resource allocation principle, for instance, keep utilization lower than a certain level [10, 11, 29, 30]. To illustrate this, we show the resource distributions of SockShop’s microservices for the good and bad configurations with the same amount of total resource in Fig. 6(a) and the corresponding CPU utilization in Fig. 6(b). We see that there is no readily identifiable root cause (e.g., microservice with bottleneck resource) in response latency in Fig. 6(b) for the 74% increase (236 milliseconds to 411 milliseconds). Also, while we see an increase in utilization for the cart, catalogue, and user services for the bad configuration, their utilization remains below the front-end’s utilization, making it impossible to employ any common utilization-based resource allocation policy. Furthermore, we see that the utilization change due to resource change is different for different services. For example, the front-end’s utilization changed more than orders even though they experienced similar resource change. This indicates that resource allocation policies that try to increase overall utilization [12], may not be most efficient.

3.1 Design Principles of PEMA

A learning-based approach. Achieving either of our design goals for a microservice-based application is non-trivial due to their complex topology and inter-dependency between different microservices. Moreover, the relation and interaction with each other for these microservices varies with applications and deployments, even among different versions of the same application. Not to mention, the underlying cloud hardware (e.g., processor type/model) hosting these applications also affects the microservice performance and resource allocation. Consequently, our resource manager needs to identify resource allocation strategies for each microservice implementation and at the same time be able to adapt as the application evolves. Hence, we take a learning-based approach where PEMA iteratively interacts with the application through a feedback loop to navigate towards efficient resource allocations.

Provable efficient resource allocation. Solving PEMA can be interpreted as tuning the application resources that will make the response latency exactly equal to the SLO specified level. However, since the resource distribution across different microservices affects the latency and microservice-based applications usually consist of many microservices, there could be many different resource allocations that result in a latency equal to the SLO. Consequently, in PEMA, instead of finding the best resource allocation (i.e., the lowest aggregate resource), our goal is to find a resource allocation close to the best with fewer iterations.

QoS preserving learning. An unwanted pitfall of the learning-based approach in the existing literature is that the system needs to learn "bad" resource allocations that cause SLO violation by causing/creating these violations [12, 17–19]. While our approach too cannot completely eradicate the possibility of SLO violations, unlike prior works, we do not cause them intentionally. Instead, we adopt a QoS conservative approach where we start from an abundant resource for all microservices and then iteratively search for resource reduction opportunities based on the application’s performance statistics. During the search/learning, PEMA always tries to maintain latency performance better than the SLO. Moreover, we dynamically tune how much resource we reduce based on how close our performance is to the SLO and stop tuning if the performance is at the SLO level. For example, with a response time SLO of 250ms, PEMA will try to reduce more resources when the response time is 150ms than when response time is 200ms. Hence, during resource allocation navigation, PEMA does not set a resource allocation to violate the SLO intentionally.

Feedback-based navigation. Starting with ample resources for each microservices to comfortably satisfy SLO, PEMA uses the difference between current application performance and the SLO as an indicator of resource reduction opportunity. However, it does not tell us on which microservice(s) we should exercise the resource reduction. Hence, PEMA uses microservice-wise performance metrics to determine the target microservices. More specifically, PEMA
We attribute these cases as transient anomalies based on our observations. When we see the opposite, the decrease in latency is much smaller. An objective indicator why application’s performance can be a safe yet effective indicator for system response time to determine how much resource-saving effort is still maintained at QoS.

### Microservice-wise Augmentation

While the response latency tells us about the resource reduction opportunities, it does not tell us from which microservices we should reduce the resources. We need to avoid microservices that may create a bottleneck during this resource reduction. In PEMA, we use microservice-level performance metrics to identify the microservices with imminent bottleneck resources. However, as opposed to prior works where complex machine learning models are applied to determine such bottleneck services, we use only two performance metrics - CPU utilization and CPU throttling.

Our choice of these performance metrics is based on our experiments. We intentionally create bottlenecks and use feature extraction to identify which performance metrics can be used to identify the bottleneck services reliably. Note that these experiments are done to assist in our design. PEMA does not need any offline experiments or pre-training. For each microservice, we collect the following performance metrics: cpu_usage_seconds_total, memory_usage_bytes, cpu_cfs_throttled_seconds_total, Jaeger tracing - self_time, and duration. We then run classification with various combinations of the performance metrics as features. We find that when used as the classification features, CPU utilization and throttling give us the best classification accuracy. Table 1 shows the classification accuracy for different applications with various bottleneck services.

To better understand the role of CPU utilization and CPU throttling as bottleneck indicators, we track these metrics for different microservices in TrainTicket as we reduce their resources to create bottlenecks. To identify the bottleneck, we allocate sufficient resources to all other microservices. Fig. 8 shows the change in CPU utilization and CPU throttling as we reduce the resource of the microservice under investigation. We normalize the microservice resource allocation to their respective bottleneck resource, causing SLO violation. We make a few important observations here. First, the CPU utilization (Fig. 8(a)) changes gradually as the microservice approaches their bottleneck resource. We also see that the utilization corresponding to bottleneck is different for different microservices. For example, ticketinfo’s bottleneck utilization is around 25%, whereas seat’s bottleneck utilization is around 15%. Second, CPU throttling changes rapidly at bottleneck resource. The bottleneck CPU throttling also varies with microservices.

### Supporting Results for Design Rationales

Here we provide corroborating observations for PEMA’s design using our prototype microservices implementations. We first show why application’s performance can be a safe yet effective indicator for resource reduction, followed by how microservice-wise performance metrics can help PEMA navigate.

**Gradual resource reduction for efficiency.** In PEMA, we use the difference between SLO specified response time and current system response time to determine how much resource-saving opportunity is available. Our design choice is motivated by our observation that, in general, monotonic resource changes across microservices result in monotonic changes in the end-to-end response time. We say a resource reduction is monotonic if some microservice resources are decreased while other microservices’ resources are unchanged. A resource change is not monotonic if some microservices receive greater resources while some others have their resource reduced, regardless of what happens to the aggregate resource allocation. Fig. 7(a) shows the CDF of change in application latency for monotonic resource reduction for our applications. We do random amounts of monotonic resource reduction for this experiment at various resource allocations. The CDFs show that a monotonic resource reduction typically increases response latency regardless of the configuration. The CDFs also show that in the handful of times (20.89% for TrainTicket and 6.1% for SockShop) when we see the opposite, the decrease in latency is much smaller. We attribute these cases as transient anomalies based on our observation of the application’s performance metric fluctuations. More importantly, as PEMA is trying to increase latency to the SLO level and these abnormal cases reduce the latency for resource reduction, PEMA still maintains QoS.

Our findings in Fig. 7(a) tell us that by making monotonic resource reductions, we can gradually increase the latency to the SLO level. In Fig. 7(b) we show such monotonic resource reduction and its impact on latency. Here, we normalize the resource to the optimum resource allocation and the latency to the SLO level. PEMA’s goal in Fig. 7(b) is to reach coordinate (1, 1) by gradually making monotonic resource changes.
3.3 PEMA

Here we present the details of PEMA’s implementation that builds on our design principles and experimental observations.

**Resource reduction opportunity.** In PEMA, similar to gradient descent, we start with sufficient resources for all microservices and gradually decrease their resource based on how our resource change affects the end-to-end response time. For resource reduction at time step $t$, we first decide the number of microservices $n^t$ to reduce resources from using

$$n^t = N \cdot \min \left( \frac{R - r^{t-1}}{\alpha R}, 1 \right)$$

where, $r^{t-1} = \mathcal{F}(x^{t-1})$ is the response time in the previous time step. $\alpha \leq 1$ is a user-defined non-negative parameter that determines how aggressively we want to reduce the resource. A smaller $\alpha$ will reduce resource more aggressively and vice versa.

Next, using similar approach as Eqn.(3), we decide how much resource we reduce in the $n^t$ microservices in percentage using

$$\Delta^t = \beta \cdot \min \left( \frac{R - r^{t-1}}{\alpha R}, 1 \right) \cdot 100\%$$

where $\beta \leq 1$ is another user defined parameter that decides the maximum resource reduction for any microservice in one time step. A high value of $\beta$ makes PEMA aggressively change the resource between update intervals and vice versa. We analyze the impact of $\alpha$ and $\beta$ in our evaluation in Section 4.3.

Using Eqns. (3) and (4), PEMA dynamically adjusts the amount of monotonic resource reduction as our response time $r^t$ approaches SLO limit $R$. We can also set the values of $\alpha$ and $\beta$ dynamically to have more aggressive reduction when $R - r^{t-1}$ is high and reduce the amount of reduction per interval as $r^t$ approaches $R$. In addition, to avoid triggering resource change for transient perturbation in response time, we can keep a response time buffer by scaling down $R$, for instance, to 95%, in Eqns. (3) and (4).

**Avoiding bottleneck services.** For the $i$-th microservice we denote its utilization as $u_i$ with a bottleneck threshold $U_i^{th}$ and CPU throttling as $h_i$ with a bottleneck threshold $H_i^{th}$. To decide the $n^t$ candidate microservices, we first take the set of microservices that has a CPU throttling less than their respective thresholds. We denote the set of indexes of these microservices as $I^t = \{ i : h_i^{t-1} \leq H_i^{th} \}$. We then normalize the utilization of each microservice in $I^t$ to their respective utilization threshold as $u_i^{t-1} = \frac{u_i^{t-1}}{U_i^{th}}$ and update the probability of each each microservice in $I^t$ as follows

$$p_i^t = 1 - \frac{u_i^{t-1} - \min_{i \in I^t} (u_i^{t-1})}{1 - \min_{i \in I^t} (u_i^{t-1})} \quad (5)$$

Here, $\min_{i \in I^t} (u_i^{t-1})$ means the minimum normalized utilization among all the microservices in $I^t$. Eqn.(5) indicates that a microservice with utilization equal to its threshold, i.e., $u_i^{t-1} = 1$ will result in a “zero” probability ($p_i^t = 0$), whereas the microservice with the lowest utilization, i.e., $u_i^{t-1} = \min_{i \in I^t} (u_i^{t-1})$, will have the probability of “one” ($p_i^t = 1$). We populate a new candidate set $I^{t+1}$ with a inclusion probability of $p_i^t$ for the $i$-th microservice. If the size of $I^{t+1}$ is equal to or smaller than $n^t$, we take the entire set $I^{t+1}$ and reduce each microservice in $I^{t+1}$ and reduce their resource by $\Delta^t$. However, if the size of $I^{t+1}$ is greater than $n^t$ we uniformly randomly choose $n^t$ microservices from $I^{t+1}$.

**Dynamically updating bottleneck thresholds.** As shown in Fig. 8, the bottleneck thresholds for utilization and CPU throttling varies among microservices. Hence, we need to learn the appropriate threshold settings for each microservice. In PEMA, we begin with a conservative estimation of utilization threshold set at 15% and CPU throttling threshold of “zero” for all microservices. We expect all microservices to satisfy these thresholds as PEMA starts with ample resource allocation. Similar to our resource reduction approach, we opportunistically increase these thresholds. More specifically, at the beginning of every time step $t$, we update the utilization and CPU throttling thresholds as follows

$$U_i^{th} = \max \left( U_i^{th}, u_i^{t-1} \right), \forall i$$

$$H_i^{th} = \max \left( H_i^{th}, h_i^{t-1} \right), \forall i \quad (6)$$

**Iterative resource allocation.** PEMA applies the resource reduction iteratively and saves all resource allocations, $x^t$, and the response times, $r^t$, in a “resource allocation history database (RHDb)”. The purpose of the database is to allow PEMA to fall back to a previous resource allocation in case of an SLO violation. This is because, even though the resource reduction slows down when the latency approaches the SLO, PEMA cannot guarantee that its opportunistic resource reduction will never cause an SLO violation. In addition, changes in microservice implementation or changes in its hardware configuration may also alter optimum resource allocation and cause SLO violations. In such cases, rolling back to a previous configuration allows PEMA to jump start on finding the new optimum, instead of resetting the resource allocation to the maximum and starting from scratch.

**Escaping sub-optimum configurations.** The combination of monotonic resource reduction and probabilistic choice of microservices to reduce resource may cause PEMA to make unfavorable resource reductions early on (e.g., making particular microservice reach bottleneck and push response time close to SLO) and settle at inefficient resource allocation, even though other microservices have redundant resources. This can force PEMA to slow-down prematurely, even stop further resource reduction. To escape from such inefficient resource allocations, we implement random exploration where PEMA with a probability $p_e^t$ rolls back to a uniformly random previous resource allocation in RHDb. We set $p_e^t$ based on
the response latency as follows

\[ p_e^t = A \cdot \min \left( \frac{R - r^{t-1}}{\alpha R}, 1 \right) + B \]  

(8)

Here, \( A \) and \( B \) are exploration parameters that decide the maximum and the minimum probability of exploration, respectively, and satisfy \( 0 \leq B \leq A \leq 1 \) and \( A + B \leq 1 \). The exploration probability decreases as PEMA’s response time \( r^{t-1} \) approaches the SLO \( R \). The random exploration also allows PEMA to “walk back” the resource reduction path it took and identify previously missed reduction opportunities. Naturally, the degree of exploration affects how quickly we reach an efficient resource allocation. Nonetheless, we do not anticipate this exploration to add significant overhead since PEMA can find an efficient resource allocation in a few tens of iterations.

Implementation of PEMA. We present the working principle in Algorithm 1 where PEMA takes performance metrics from the system using Prometheus and Linkered and then updates the resource allocation of the microservices while keeping a log of all resource allocations and response times in its database RHDb. The high-level architecture block diagram of PEMA is presented in Fig. 9.

3.4 Workload-Aware Resource Allocation

Our design of PEMA so far addresses how we can navigate to find an efficient resource allocation for our microservice-based application. Here we address how PEMA tackles the workload variations. For any cloud application, the workload intensity directly affects the response time, and hence, how much resource is needed [9–11]. In Fig. 10(a) we show the change in response time as the workload changes. As PEMA iteratively makes resource reductions based on the response time, a decrease in workload will falsely indicate resource reduction opportunities that do not work for high workloads, leading to many SLO violations when the workload increases. The same is true for prior ML-based approaches that do not explicitly address workload changes [18, 19].

Hence, PEMA needs to identify efficient resource allocations at different workload levels. A straightforward way is to divide the workload variations into discrete workload ranges and run multiple copies of PEMA in a “pseudo-parallel” fashion. We say pseudo-parallel as at any time only one PEMA is working on its corresponding workload range. Note here that the workload ranges need to be small enough to not significantly affect the response latency, requiring resource allocation changes, i.e., a single resource allocation should work for the entire range. For instance, a range of 25 requests-per-second in TrainTicket microservice is a suitable workload range.

Dynamic workload range. While in principle multiple parallel PEMA works, it may take a long time to reach efficient allocations for every workload range. To accelerate the learning, we propose a novel approach where we start with a few (two/three) larger workload ranges and gradually split each range (i.e., parent range) into smaller ranges (i.e., child range) until we reach our target workload ranges. The goal here is to utilize learning from the parent ranges to bootstrap the learning process for the child ranges. During a range split, the parent range is divided into two equal child ranges. We attach PEMA of the parent range to the child range with a higher workload, whereas a new PEMA process is launched for the other child range. The new PEMA uses the resource allocations of the parent range as the starting point and requires fewer iterations to reach an efficient resource level. The intuition for this approach is that a resource allocation that satisfies SLO at a higher workload should also satisfy SLO for a lower workload. Fig. 10(b) illustrates the idea where we start with a workload range of 200–400 and then branch out to smaller ranges. The number on top of each range
identifies the PEMA process attached to this range. The original PEMA process with id “#1” remains attached to the higher workload ranges (e.g., 300–400, 350–400, 375–400) as we split each range into smaller ranges.

### Dynamic response time target

While this approach benefits the learning time, we need to tackle the latency variation due to workload changes when the workload ranges are large (e.g., 200–400 rps for TrainTicket). We use one PEMA process for each workload range, even during the initial stages with large ranges (e.g., PEMA #1 for 300–400 range in Fig. 10(b)). Each PEMA process needs to make an SLO preserving resource allocation that works for its entire range. To achieve this, instead of setting it to the SLO specificity response time, we update $R$ in Eqns. (3), (4), and (8) into a function of workload $\lambda$ as follows

$$R(\lambda) = m \cdot (\lambda - \lambda_{\text{max}}) + R_{\text{SLO}}$$  \hspace{1cm} (9)

Here, $m$ is a parameter that determines the change in latency performance for a unit change in workload, $\lambda_{\text{max}}$ is the upper limit of a workload range, and $R_{\text{SLO}}$ is the SLO specified response time.

Fig. 10(c) illustrates our approach of using a dynamic response time target. We see from Eqn. (9) that when the workload is low within a range, we set a conservative (i.e., lower than SLO) latency target to intentionally allocate more resource than needed and therefore allow headroom for higher workloads. This approach intentionally makes conservative inefficient resource allocations for lower workload levels within a range. However, as the ranges get smaller as we split them, the latency variation within a range also gets smaller, and so is the inefficiency.

On the other hand, we learn $m$ at the beginning of PEMA when we keep the resource allocation fixed for a few time steps while the workload changes. We then use linear regression on the workload vs response time (as in Fig. 10(a)) to extract $m$. Note that we learn $m$ only once at the beginning when the workload ranges are large. During range splits, we keep the $m$ from the parent range. Now, $m$ may change as we make the resource allocations changes on the microservice. Nonetheless, as our range split reaches the final workload ranges, we no longer need the dynamic response target, and $m$ becomes irrelevant.

### 3.5 Handling Transient Events

From our extended experiments we identify that PEMA is susceptible to unnecessary SLO violations due to transient dips in the response time (Fig. 14(b)). More specifically, after PEMA has already identified an efficient allocation, a momentary dip in response time drives PEMA to make resource reductions only to meet with SLO violation in the next iteration. To circumvent this, we adopt a moving average approach where we take the average of the response time of $k$ recent time steps and update the $n^\prime$ and $\Delta^\prime$ as follows

$$n^\prime = N \cdot \min \left( \frac{R - \frac{1}{k} \sum_{i=1}^{k} \lambda_{i} - \text{other terms}}{\alpha R_{\text{SLO}}}, 1 \right)$$  \hspace{1cm} (10)

$$\Delta^\prime = \beta \cdot \min \left( \frac{R - \frac{1}{k} \sum_{i=1}^{k} \lambda_{i} - \text{other terms}}{\alpha R_{\text{SLO}}}, 1 \right) \cdot 100\%$$  \hspace{1cm} (11)

Note that, to ensure QoS, we do not apply this moving averaging for detecting SLO violations. We still roll back resource allocations based on the most recent response time as in Line 4 in Algorithm 1.

### 4 EVALUATION

We use our microservice application prototypes, TrainTicket, SockShop, and HotelReservation, to evaluate PEMA. Here we first discuss details of PEMA’s execution followed by performance evaluation against other resource allocation strategies. We then present how different parameters affect PEMA and finally show how PEMA can adapt to change in operating conditions.

#### 4.1 Execution of PEMA

Here, we first show how PEMA finds efficient resource allocation using iterative resource reduction. We then demonstrate how workload-aware PEMA utilizes the dynamic workload range and response time target. Finally, we present a 36-hour long experiment with PEMA making efficient resource allocation maintaining QoS.

### Efficient resource allocation

Fig. 11 demonstrates the iterative resource allocation and Fig. 11(b) shows the corresponding response times for SockShop under a workload of 700 requests per second for two different sets of exploration parameters. We see in Fig. 11(a) that when a higher exploration is used, PEMA intentionally increases the resource allocation twice around iteration 10 by going back to an older and higher CPU allocation. We also see that PEMA with high exploration settles at an inefficient allocation after 20 iterations as the response time reaches SLO (Fig. 11(b)) rises close to the SLO. However, due to exploitation, we see that around iteration 45, it rolls back to an older allocation and finds its way to the efficient allocation. Incidentally, PEMA with low exploration...
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Figure 11: Execution of PEMA with different explorations for SockShop.

Figure 12: Execution of PEMA for TrainTicket and HotelReservation.

also reaches the efficient resource allocation. We see a few SLO violations in Fig. 11(b) which are mitigated immediately by increasing the CPU resource. Figs. 12(a) and 12(b) show the iterative resource change and the corresponding response times for TrainTicket and HotelReservation, respectively.

Regardless of the microservice implementation, we see that PEMA can successfully find efficient resource allocations with only a few unintentional SLO violations.

Dynamic workload range. Next, in Fig. 13(a) we show the resource allocation of PEMA for TrainTicket as our workload varies between 200 and 300 requests per second. The legend in this figure indicates the upper limit on the workload range. The workload range 300 (i.e., 200–300) first splits into ranges 300 and 250 around iteration 50. The 250 range splits into 250 and 225 around iteration 80, while the 300 splits into 300 and 275 right before iteration 85. We see that each workload range finds an efficient allocation within a few iterations as they start from an already good allocation. Fig. 13(b) shows the corresponding response time. We see some SLO violations, which are mitigated by PEMA.

Extended execution. We run PEMA on SockShop for 36-hour where we change the workloads between 200 and 1100 requests per second following the workload pattern of Wikipedia collected from [32]. Fig. 14(a) shows the workload pattern and the corresponding resource allocation. We see that PEMA varies the total resource allocation with changing workload to maintain efficient allocation. Note here that simply varying scaling resource allocation based on workload does not work on microservices as the distribution of the resource plays an important role in performance. Fig. 14(b) shows the corresponding response times. We show both the instantaneous (i.e., most recent) and moving average responses with a window size of five. Recall that PEMA reduces resources based on

the moving average to avoid transient changes while tackling SLO violation based on the instantaneous response time.

4.2 Performance evaluation

Benchmark strategies. We compare the resource allocation efficiency of PEMA against two benchmark strategies - optimum (OPTM) and rule-based (RULE). In OPTM, we use an exhaustive trial and error search to identify the best possible resource allocation. OPTM cannot be used in practice. It acts as the upper limit of resource efficiency achievable by any resource manager. RULE is Kubernetes’ rule-based resource scaling. We chose RULE as a commercially available resource allocation algorithm to gauge PEMA’s efficiency improvement. We do not compare PEMA to the ML-based resource allocation strategies as they do not focus on resource allocation efficiency.
4.3 Parameter Sensitivity

Here we study how the two parameters $\alpha$ and $\beta$ affect PEMA. Recall that $\alpha$ in Eqn. 3 determines how aggressively we reduce resource - smaller $\alpha$ makes PEMA reduce more resource for the same difference between response time and SLO. $\beta$, on the other hand, determines the maximum percentage resource reduction in each resource update iteration - smaller $\beta$ results in smaller resource change and vice versa. For this study, we run experiments on TrainTicket and SockShop with workload 225 and 700 requests per second.

In Fig. 16(a) we show the change in resource allocation and in Fig. 16(b) we show the number of SLO violations as we change $\alpha$. During this experiment, we keep $\beta = 0.3$. We see that both smaller and larger values of $\alpha$ result in sub-optimal resource allocations for TrainTicket and SockShop. This is because, for small $\alpha$ PEMA is too aggressive making many SLO violations (as seen in Fig. 16(b)) and force to revert back to inefficient allocations. For high $\alpha$, on the other hand, PEMA is slowed down prematurely at inefficient allocations, although it suffers much fewer SLO violations.

Next, in Figs. 17(a) and 17(b) we show the impact of change in $\beta$ while we keep $\alpha = 0.5$. Similar to our observation for $\alpha$ we see that aggressive resource reduction due to higher values of $\beta$ results in sub-optimal resource allocation while also suffering from many SLO violations. While PEMA is somewhat sensitive to both $\alpha$ and $\beta$, we can set $\alpha$ and $\beta$ for any system by tuning based on SLO violation. We can take a conservative approach, start with large $\alpha$ and small $\beta$, and gradually change their values keeping a close eye on the SLO violations.

4.4 Adaptability

Here, we demonstrate how PEMA’s lightweight design enables adaptability to operation condition changes. For this, we first change the server CPU clock speeds while PEMA is managing SockShop’s resource. Change in CPU frequency essentially changes the resource requirement for satisfying the SLO. These experiments mimic a real-world scenario where a hardware or software change in the microservice alters the resource allocation dynamics. Fig. 18 shows the CPU allocation and the corresponding response time as we change the CPU frequency. We see that PEMA can successfully change the resource allocation to satisfy the SLO.

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**Figure 15:** Performance comparison of PEMA against optimum (OPTM) and commercial autoscaler (RULE). The CPU allocation is normalized to that of OPTM. PEMA is close to optimum and saves up to 33% resource compared to RULE.

**Figure 16:** PEMA’s sensitivity to $\alpha$ for $\beta = 0.3$ (a) Resource allocation normalized to optimum. (b) SLO violations.

**Figure 17:** PEMA’s sensitivity to $\beta$ for $\alpha = 0.5$ (a) Resource allocation normalized to optimum. (b) SLO violations.
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Figure 18: Adaptability of PEMA to changes in CPU speed for SockShop. The CPU speed change represents hardware or software updates that alters the resource demand.

Figure 19: Adaptability of PEMA to changes in SLO for SockShop. Dynamic SLO can be used to trade performance for resource savings.

Next, in Fig. 19 we show that PEMA can navigate towards efficient resource allocation as we change the SLO. Dynamically changing SLO can be a useful approach for applications that are willing to trade performance for resource savings to meet long-term goals such as cost budget [33]. Nevertheless, we see that PEMA can adapt to SLO changes and tune the resource accordingly.

5 RELATED WORKS

Microservice autoscaling. Resource autoscaling has been extensively studied in the public cloud domain [9, 34–37]. The recent advancement of microservices has attracted a similar interest in autoscaling of microservice-based applications in academic settings [38, 39], as well as industrial settings [10, 30]. These autoscalers implement rule-based approaches in resource management. For example, Kubernetes [30] uses 90-th percentile resource usage in recent samples to set CPU and memory allocations with a 15% overprovisioning. Google Autopilot [10] uses 95-th percentile for CPU and maximum for memory in the recent samples as a marker for resource allocation in the upcoming interval. Alternative to the rule-based approach, Google also uses ML-based autoscaling using a combination of reinforcement learning and time series analysis [40]. [41] also proposes rule-based autoscaling based on CPU and memory utilization. However, rule-based autoscaling requires deep application knowledge to set up the thresholds that can vary with application. Meanwhile, [38] proposes hybrid autoscaling based on analytical modeling using a layered queue network.

SHOWAR [42], in spirit, is the closest to our design approach. It uses the variance in historical usage for vertical scaling and a proportional-integral-derivative (PID) controller for horizontal scaling. Nonetheless, SHOWAR still requires extensive tracing from the CPU scheduler for its scaling decision.

SLO oriented resource management. In another line of work, ML-based approaches are used to identify and mitigate root causes of SLO violations in microservices [4, 12, 17–19]. For example, Sinan [17] uses a neural network to estimate short-term performance and a boosted trees model to estimate long-term performance to make per tier resource allocation. Sinan allows SLO violations to identify corner cases for resource allocation. Seer [19] requires fine-grained tracing for building its model and SLO violating cases to train its deep neural network to identify QoS violations. AlphaR [4], on the other hand, uses neural graph networks to capture the complex relationship between microservices and estimate application performance for resource allocation. Despite their impressive results in capturing minute details of microservices, they heavily depend on data and are slow to dynamically changing conditions for microservices. In designing , we depart from using complicated ML models and instead trade capturing microservice details for agility and adaptability in resource management.

6 CONCLUDING REMARKS

In this paper, we proposed PEMA, an iterative feedback-based approach to autoscaling microservices. PEMA is lightweight as it only requires the applications end-to-end performance and microservice-level CPU utilization and CPU throttling to navigate to efficient microservice resource allocation. Utilizing the lightweight design, we also developed a novel approach of dynamic workload-ranging to make workload-aware resource allocation with PEMA. Using three prototype microservice implementations, we showed that PEMA can achieve a performance close to the optimum resource allocation and save as much as 33% resource compared to commercially used rule-based resource allocation.

Limitations of PEMA’s current implementation. PEMA’s implementation has several limitations that we plan to address in its future iterations. First, when PEMA causes an unintentional SLO violation, it rolls back the configuration in the next time step. Hence, the application suffers from bad performance during the entire resource update interval (e.g., 10 minutes). PEMA can be improved by implementing higher resolution performance monitoring, catching the SLO violations early (e.g., within 10 seconds), and rolling back configuration. Further, PEMA now rolls back the configuration to the most recent configuration without SLO violation. It does not take into account the degree of SLO violation. For instance, a QoS violation where the response time is significantly higher than the SLO indicates that we should roll back the configuration farther into the past to allocate more resources. On the other hand, while PEMA logs the resource allocation of all microservices and response times in its allocation history database, RHDs, for rollback and exploration purposes, it does not utilize this information in its decision. Finally, PEMA in this study only considers CPU resource allocation and does not explicitly address vertical and horizontal scaling.
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