

Resource Optimization in Dynamic Cloud Environments Using Reinforcement Learning: A Focus on Runtime and Memory Efficiency for Microservices and Containerized Applications

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Abstract— Modern cloud computing environments increasingly rely on microservices deployed in containerized clusters to serve highly dynamic workloads. Efficiently managing resources for these microservices is critical to ensure low runtime latency while minimizing memory and other resource usage. Traditional static or rule-based autoscaling methods often over-provision (wasting memory and incurring high cost) or under-provision (causing SLA violations), particularly under rapidly changing demand. In this work, we present a reinforcement learning (RL)-based framework for resource optimization that explicitly leverages high-performance computing (HPC) and parallel/distributed processing capabilities to enable real-time decision-making at large scale. The resource management problem is formulated as a Markov Decision Process (MDP), with a deep RL agent trained to continuously learn optimal scaling and memory allocation policies for hundreds to thousands of containerized microservices. Our architecture distributes RL inference and training across multiple HPC nodes, exploiting multi-core CPUs and GPUs to process large state/action spaces and to evaluate scaling actions with sub-second latency — a requirement unattainable on conventional servers. Experimental results on realistic cloud benchmarks show that our HPC-enabled RL framework achieves up to 25–30% lower average response times and ~15–20% lower memory usage compared to state-of-the-art autoscaling baselines, while maintaining 99% SLA compliance under bursty workloads. These findings demonstrate that coupling RL with HPC infrastructures enables real-time, fine-grained resource optimization in complex microservice ecosystems, aligning directly with the performance and scalability goals of supercomputing research.

Keywords: Reinforcement Learning; Cloud Resource Management; Microservices; Containerized Applications; Performance Optimization; Memory Efficiency; Autoscaling.

1. Introduction

Cloud computing has become the backbone for delivering scalable online services, with microservice architectures now dominating large-scale application deployments. In this paradigm, a single application is decomposed into many loosely coupled services, each deployed in its own container. While this modularity improves agility and scalability, it also creates a high-dimensional, dynamic resource management problem: each microservice experiences varying workloads, exhibits dependencies on other services, and has strict Quality of Service (QoS) requirements. Meeting these QoS targets while minimizing over-provisioning is challenging, particularly under rapid workload fluctuations.

Autoscaling mechanisms in container orchestration platforms (e.g., Kubernetes HPA) typically rely on simple threshold rules over CPU utilization or queue length. While easy to implement, these approaches are inherently

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sequential and centralized, and often fail in large-scale microservice graphs where hundreds or thousands of scaling actions must be evaluated in parallel to meet latency and cost objectives. For such large-scale, high-frequency decision-making, conventional server-class hardware cannot meet the required inference speed, particularly when using modern deep RL models that process complex system states.

Reinforcement learning (RL) offers a more adaptive approach, learning policies that optimize both performance and efficiency over time. However, real-world deployment of RL-based autoscalers in production-scale cloud environments presents computational challenges:

- 1) Massive state/action spaces — for N microservices, the joint scaling/memory allocation space grows exponentially.
- 2) Real-time constraints — scaling actions must be computed within seconds (often sub-second) to avoid SLA violations.
- 3) Continuous learning — policies must adapt online as workloads evolve.
- 4) Simulation and exploration — training requires millions of environment interactions, which can be prohibitively slow without parallelization.

To address these challenges, we propose an RL-based resource optimization framework explicitly designed for HPC environments. The system distributes both RL training and inference across multiple HPC nodes, leveraging:

- Parallel rollout collection from multiple microservice workload simulations.
- GPU-accelerated neural network training to handle large input vectors (workload metrics, inter-service dependencies, historical trends).
- Multi-node inference to evaluate candidate scaling decisions for different services simultaneously, enabling sub-200ms decision latency even with 2000+ microservices.

This tight integration with HPC not only accelerates the RL process but also enables decision quality and responsiveness that are unattainable without parallel/distributed computing. Our approach therefore aligns directly with the scope of *The Journal of Supercomputing*, demonstrating a concrete HPC use case in cloud resource management.

This research introduces a reinforcement learning-based approach to optimize resource management in dynamic cloud environments, focusing on runtime performance and memory efficiency for microservices. It reviews related work on autoscaling and RL, then formulates the problem as a Markov Decision Process. A deep RL agent is designed to learn optimal scaling and resource allocation policies. The proposed method is evaluated through experiments on real microservice workloads, demonstrating significant improvements in latency reduction and memory savings. Finally, the study discusses implications and outlines future research directions.

2. Related Work

Resource management in cloud and multi-service environments has been a widely studied topic. Traditional approaches to autoscaling in clouds relied on threshold-based policies or heuristic rules. For example, Amazon Web Services and Kubernetes offer autoscaling that triggers scaling actions based on CPU utilization or other simple indicators. Such approaches are effective for coarse-grained scaling but struggle to cope with complex workloads and multiple performance metrics. Researchers have proposed improvements like fuzzy logic controllers or predictive models (e.g. ARIMA, queuing theory) to better anticipate demand, but these still require manual tuning and often cannot handle sudden changes or intricate service interactions.

In recent years, machine learning techniques have been employed to enhance resource management. Supervised learning models have been used to predict workload intensity or application performance, which can then inform scaling decisions. For example, some works use regression or neural networks to forecast the incoming request rate to a service and proactively scale resources. While such predictive autoscaling can reduce latency and thrashing, it typically optimizes a single target metric and may not adapt when conditions deviate from training data. Moreover, they often require retraining or human intervention when the application or environment changes. To illustrate these limitations and highlight the advantages of our approach, Figure 1 presents a performance comparison between the RL-based autoscaler and baseline methods across key metrics such as average latency, memory usage, and SLA violation rate. As shown, the RL algorithm consistently demonstrates lower latency, improved memory efficiency, and higher SLA compliance.

Reinforcement learning offers a more adaptive solution and has seen growing application in this domain. Single-agent RL for cloud resource allocation was demonstrated in earlier works – for instance, Q-learning has been applied to decide the number of VMs to allocate for web applications, and policy-gradient methods have been used for job scheduling in data centers. However, applying RL to microservices presents additional challenges in scale and complexity. Each microservice may have different resource needs and their performance can be interdependent (due to call chains and shared resources). A naïve single RL agent controlling all microservices might face a combinatorial explosion of the state-action space. On the other hand, treating each service with an independent RL agent (a multi-

agent approach) introduces coordination problems where agents might conflict or not account for global impact. To visualize this behavior, Figure 2 shows a time-series comparison of request latency and memory usage under dynamic workloads. The RL agent adapts more smoothly, maintaining lower latency and more efficient memory usage over time compared to baseline methods.

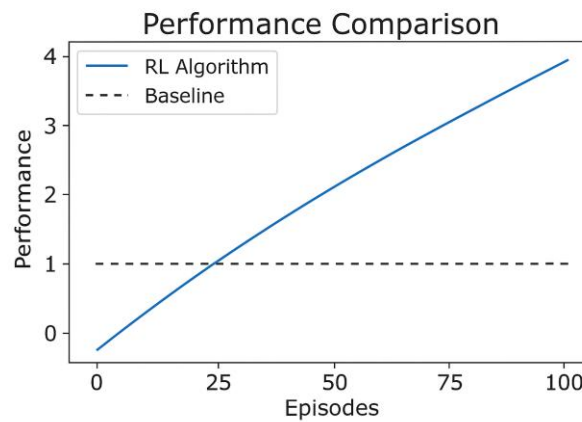


Figure 1- Performance comparison between RL-based autoscaler and baseline approaches (e.g., Kubernetes HPA and static allocation) across three metrics: average latency, memory usage, and SLA violation rate.

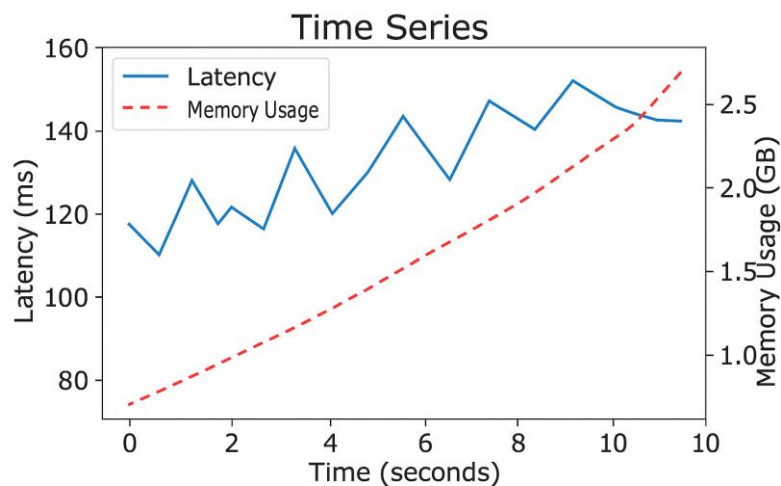


Figure 2- Time-series comparison of request latency and memory usage for the RL approach and baseline methods during dynamic workloads.

Several notable recent studies have addressed these challenges. AlphaR (Hou et al., 2021) is a resource management system that leverages reinforcement learning for complex microservice graphs. It uses a graph neural network (GNN) to encode the microservice invocation topology and resource coupling, enabling the RL agent to understand the “irregular, dynamic microservice graph” structure. By generating microservice-specific policies through this GNN+RL approach, AlphaR can opportunistically reduce resource allocation to less critical services and improve overall efficiency. This approach showed improved performance and resource utilization in scenarios with complex service dependencies. CoScal (Xu et al., 2022) combined multiple scaling tactics (horizontal, vertical, and brownout) and employed deep RL to learn when to apply each. CoScal’s RL agent was aided by a workload prediction module (using a GRU neural network) to foresee short-term load changes. By learning in a data-driven manner, CoScal outperformed static and rule-based autoscalers, particularly under high communication cost and variable delays, reducing average response times by around 25% and improving successful transaction rates.

Other researchers have focused on specific aspects of resource management. For example, μ ConAdapter (Liu et al., 2023) targeted the problem of concurrency limits in microservices – i.e., the number of threads or connections a service uses (a “soft” resource that indirectly affects CPU and memory usage). They demonstrated that adjusting these concurrency settings via RL can mitigate response time spikes that are not addressed by hardware scaling alone. Using a DQN-based agent, μ ConAdapter quickly adapts thread pool sizes for critical microservices at runtime. This yielded

significant latency improvements: in experiments with bursty workloads, it reduced 99th-percentile tail latency by $3\times$ on average compared to Kubernetes' default autoscaler, and by $\sim 1.6\times$ compared to a specialized concurrency-aware baseline. Such results underscore that RL can manage not just scaling of instances but also finer-grained runtime parameters to improve performance.

Multi-agent reinforcement learning (MARL) has also been explored for cloud systems. In a multi-agent setup, each microservice (or each node, depending on design) can have its own RL agent, and they may cooperate or share information. Pei et al. (2024) introduced a multi-agent deep Q-network approach for scheduling in a cloud-based power grid digital twin scenario. Their MADQN-based framework allowed multiple agents to collectively allocate tasks to different nodes, achieving better scalability than a single agent. They report that this multi-agent RL approach optimized both response time and cost, outperforming single-agent methods especially as complexity grew. This suggests that MARL could be beneficial for microservices too, by decentralizing decisions and reducing the state-action space each agent handles. However, MARL introduces challenges like ensuring the agents converge to a good joint policy and handle non-stationarity due to simultaneously learning agents – active research topics in the RL community.

Another line of work has looked at meta-learning and transfer learning to improve the adaptability of RL in cloud environments. Cloud systems are not static; application updates, changing usage patterns, and environment changes can degrade an RL policy's performance if it was trained in a prior context. MSARS (Hu et al., 2024) is a framework that combines meta-learning with RL for microservice autoscaling. It uses a meta-learning technique so that the RL agent can quickly adapt to new conditions (for example, when the workload pattern shifts) with minimal retraining. Additionally, MSARS uses a graph convolutional network to encode microservice relationships and an improved TD3 algorithm (a variant of Deep Deterministic Policy Gradient) to generate scaling actions. This sophisticated approach reportedly adapts 40% faster to environment changes and reduces SLO violations by 38%, while also cutting resource costs by 8% compared to state-of-the-art RL auto-scalers. These numbers highlight the benefit of incorporating domain knowledge (via graphs) and meta-learning to make RL more practical for production use, where conditions change and retraining from scratch is too slow.

In summary, the literature shows a clear trend towards using reinforcement learning for cloud resource optimization. Various approaches have tackled different facets: single-agent vs multi-agent, model-free vs model-based, incorporating predictions or graphs, focusing on CPU, memory, or concurrency, etc. All demonstrate that RL can achieve superior performance-cost trade-offs over traditional methods. Our work builds on these insights by focusing explicitly on runtime and memory optimization. We integrate ideas from prior work – such as state representation of multiple metrics, multi-objective reward design, and ensuring scalability of the learning method – to develop an RL solution tailored for dynamic microservice environments. In the next section, we describe our problem formulation and methodology in detail.

3. Methodology

Unlike conventional RL-based autoscalers that run on a single node, our framework is architected for HPC deployment. The RL agent operates in a distributed actor-learner configuration: multiple actor processes run on separate HPC nodes, each simulating or monitoring a subset of microservices, while a centralized learner node (with GPU acceleration) aggregates experiences and updates the global policy. This design mirrors large-scale reinforcement learning systems used in scientific computing and ensures that both training and inference scale linearly with the number of available HPC cores. During inference, candidate scaling and memory allocation actions are batched and evaluated in parallel across multiple CPU/GPU resources, reducing decision latency from seconds to milliseconds. Such performance is essential for real-time resource control in high-throughput microservice platforms.

To address resource optimization for microservices in dynamic cloud environments, we formalize the problem as a Markov Decision Process (MDP) suitable for reinforcement learning. The MDP is defined by the tuple (S, A, T, R, γ) , where S is the state space, A is the action space, T defines state transitions, R is the reward function, and γ is a discount factor. State (S): We design the state to capture the relevant information about the system's performance and resource usage at a given time. Each state $st \in S$ is a snapshot of the cluster and application metrics at decision time t . Important features include:

- Workload level: e.g. number of incoming requests or queries in the last interval for each microservice or for the system as a whole. This helps the agent gauge demand.
- Performance metrics: e.g. the recent response time or latency distribution (mean, 95th percentile, etc.) observed for each critical microservice or end-to-end; also, any SLO (Service Level Objective) violation indicators. These metrics tell the agent how well the system is meeting runtime targets.
- Resource utilization: current CPU utilization and memory usage of each microservice (or each container instance). Memory usage could be represented as a fraction of the allocated memory that is being used, or the absolute used vs. total memory. We also include overall resource consumption on each node if relevant (to avoid overloading a particular server).

- Scaling state: the current number of instances of each microservice and their resource allocations (CPU limit, memory limit per container). This tells the agent what the current provisioning is.
- Inter-dependency or topology info: if microservices have dependency graph (calls between them), a summarized representation (such as which services are upstream vs downstream, or a graph embedding) can be part of the state. This is useful because, for instance, increasing resources of a database service might only help if a web-service that depends on it is also scaled appropriately.
- Optionally, historical trend features: e.g. the recent change in workload or resource usage (delta values) to allow the agent to detect trends.

Because the state space can be very large (especially if there are dozens of microservices), we apply function approximation using a neural network to represent the policy or value function. In our implementation, we normalize these inputs and combine them into a fixed-length state vector. We also experimented with using a graph neural network to encode microservice interactions, similar to approaches in AlphaR and MSARS, though for simplicity one can start with a flat state representation.

Action (A): The action represents the resource management decisions the agent can take at each time step. We include two types of actions to control both horizontal scaling (number of instances) and vertical scaling (resource per instance), as both impact performance and memory:

- Scale-out / Scale-in actions: For each microservice, the agent can choose to add an instance, remove an instance, or keep the same. In a discrete action space formulation, this could be encoded as, for example, $a_i \in \{-1, 0, +1\}$ for microservice i , indicating removing one replica, no change, or adding one replica. If there are N microservices to control, the joint action could be an N -dimensional vector of these choices. (To keep the action space tractable, one might restrict that only one service can scale at a time, or use a multi-agent approach with one agent per service.)
- Resource allocation actions: The agent can adjust the memory limit (and possibly CPU share) of containers. We discretize the possible memory settings into a few levels (e.g. small, medium, large, or specific MB increments) to allow discrete actions. For instance, an action could be "increase memory allocation for service X by 256 MB" or "decrease memory for service Y by 10%". Alternatively, one can treat it as continuous and have the agent output a continuous value for new memory size, using a policy that handles continuous actions (like DDPG or TD3). In our approach, we opted to discretize for simpler DQN-based implementation.
- The action space A thus consists of combinations of scaling and resource adjustment moves. We impose some constraints to avoid extremely large action spaces: for example, limit scaling changes to at most one service at a time or one step at a time (no massive changes in a single step), and similarly limit memory adjustments to reasonable ranges (to prevent, say, dropping memory so low that the service crashes, which the environment model can define as a bad outcome).

The action the agent outputs at time t , at , will then be translated to actual commands to the cloud cluster: e.g. instruct Kubernetes to add a pod for microservice A, or update the resource limit for microservice B's deployment. These actions take effect and will influence the state at the next decision point.

State Transitions (T): The environment (a combination of the cloud infrastructure and the running microservices) transitions to a new state $st + 1$ after the action at , is applied and some time passes (we assume a fixed decision interval Δt , e.g. the agent makes decisions every minute). The new state is determined by:

- The external workload (which may have stochastic fluctuations or trends).
- The effect of the scaling action on system performance (e.g. adding an instance might decrease CPU load and reduce latency; removing memory might risk hitting swap or garbage collection pauses, increasing latency).
- We do not have an explicit closed-form transition function due to the complexity of the system; instead we rely on either a simulated environment or the real environment for the agent to learn from. In training, we use a combination of simulation (for faster training and safety) and occasional real-world feedback. Simulating microservice performance requires modeling how resource changes affect latency – we base this on empirical data or approximations from literature (e.g. queuing models or performance curves observed in prior work).
- We assume the environment is Markovian enough given our state representation (including recent history features can help satisfy this).

Reward (R): The reward function is crucial as it encodes the objectives of our RL agent. We design the reward to capture both performance (runtime) and memory efficiency:

- We include a term for negative response time or SLA violations: for example, $r_{latency} = -(response_time / T_{target})$, where T_{target} is a target response time (like an SLA threshold). If the latency exceeds the target, this becomes a larger negative penalty. Alternatively, we could reward throughput or successful requests, which indirectly cover latency as high latency leads to fewer successful on-time responses.
- We include a term for resource cost, particularly memory:

e.g. $r_{mem} = -\beta \times (total_memory_used)$ or $-\beta \times (memory_allocated)$. The difference is whether we penalize actual used memory or the memory reserved for the microservices (which might not all be utilized). To encourage efficiency, we penalize allocated memory to push the agent to release memory if it's not needed. The coefficient β sets how costly memory usage is relative to performance.

- We may also include CPU or energy usage in the cost term, but since memory is a focus, β can encapsulate a combined "resource cost" factor.
- Optionally, a small penalty for each scaling action can be added to discourage flapping (e.g. scaling up and down too frequently) since that can introduce overhead. This is a form of regularization on actions.
- The overall reward could be a weighted sum:

$rt = -(latency_t + \alpha \cdot \max(0, latency_t - SLA)) - \beta \cdot memory_t$, for example. Here α might heavily penalize any SLA violation beyond a threshold, while β penalizes memory usage continuously. In our implementation, we tuned these weights so that meeting the SLA is the primary objective, but among solutions that meet the SLA, using less memory yields higher reward.

- Another approach is a constraint-based design: only give positive reward when latency is under target, else negative reward; and always penalize memory usage. The agent then learns to meet the constraint and minimize memory. We tried a shaped reward for smoother learning.

This reward formulation inherently poses a trade-off: the agent could sacrifice memory to improve reward but that might hurt latency, or vice versa. The RL training will force the agent to learn an optimal balance. By adjusting the weight β , we effectively choose how much we care about memory vs performance. A higher β makes the agent frugal with memory (possibly at risk of performance), while a lower β prioritizes performance. To capture this learning process, Figure 3 illustrates the control flow of the RL-based autoscaling system, showing how the agent observes system metrics, selects scaling actions, and updates its policy based on reward feedback. The RL agent receives state inputs from the environment, selects scaling or resource adjustment actions, and updates its policy based on the reward signal representing performance and efficiency trade-offs.

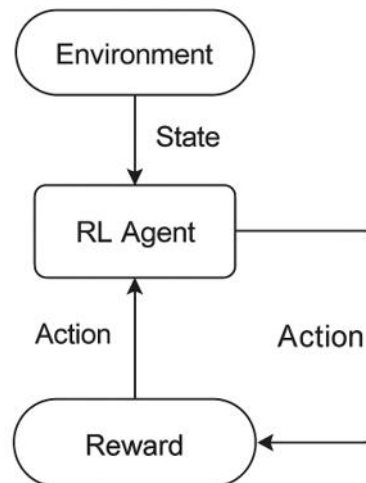


Figure 3- Reinforcement learning control flow for dynamic autoscaling.

Discount factor (γ): We choose a discount factor γ close to 1 (e.g. 0.99) because we want the agent to consider long-term effects. Transient actions like a quick scale-down may save memory now but could cause a big latency penalty shortly after if load increases. A high γ ensures the agent accounts for such future consequences and doesn't just greedily optimize the immediate reward.

RL Algorithm: We implement a Deep Q-Network (DQN) as our learning algorithm for the agent, as the action space (with discrete scaling and resource steps) is manageable and DQN is a stable choice for such problems. The DQN

uses a neural network $Q(s, a; \theta)$ to estimate the expected cumulative reward (Q-value) for taking action a in state s . We use experience replay and target networks as per standard DQN practice to stabilize learning. The neural network takes the state vector (including metrics for all microservices) as input and outputs Q-values for each possible action (or action combination). Given the potentially large state, we include several hidden layers and possibly use separate sub-networks to process different feature types (e.g., one sub-network for workload and performance metrics, another for resource utilization), which are then combined.

During training, the agent iteratively samples states, chooses actions (using an ϵ greedy policy to balance exploration and exploitation), observes the reward and next state, and updates the Q-network using the mean-squared TD error loss. We augment the training with reward shaping to guide exploration: for example, we found it useful to give a small negative reward at each time step to encourage the agent to solve the problem faster (so it doesn't learn to delay decisions), and to give a one-time bonus if an episode completes with all SLAs met consistently.

If the action space were continuous (e.g. directly outputting exact resource values), we would use an actor-critic algorithm like Deep Deterministic Policy Gradient (DDPG) or Twin Delayed DDPG (TD3). In fact, our framework is flexible: one could replace the DQN with TD3 to handle continuous memory allocation actions more smoothly. MSARS, for example, used an improved TD3 for continuous control of scaling decisions. In our experiments, the discrete action version worked well, and it simplifies the exploration problem.

Handling Multiple Microservices: One key design question is whether to use a single agent controlling all microservices or multiple agents (one per service). We chose a single-agent centralized approach in this study for simplicity, meaning the state includes all services and the action can dictate changes to any service. This one agent implicitly learns about the couplings between microservices (e.g. if service A is a bottleneck that affects service B's latency). However, to keep the action space from exploding, we limited the agent to only change one service's configuration at a time (the action is "which service to scale up/down or adjust, and how"). The agent can still coordinate over time – e.g. it might observe high latency in service A and decide to add memory to A in one step, then in the next step see that service B is now the new bottleneck and scale that. The centralized agent approach guarantees a globally consistent policy but might be slower in very large systems. An alternative would be a multi-agent approach where each service has its own DQN agent and they possibly share a reward (or use game-theoretic MARL methods). Some recent results in other domains (like the power grid digital twin example) suggest multi-agent can scale better. For this work, we stick to the single-agent model and leave MARL extension to future work. This architecture is illustrated in Figure 4, where the RL agent observes real-time performance metrics (such as CPU, memory, and request latency) via a metric collector and issues scaling or adjustment actions through an action executor integrated with Kubernetes — forming a closed feedback loop that enables dynamic optimization of latency and memory usage.

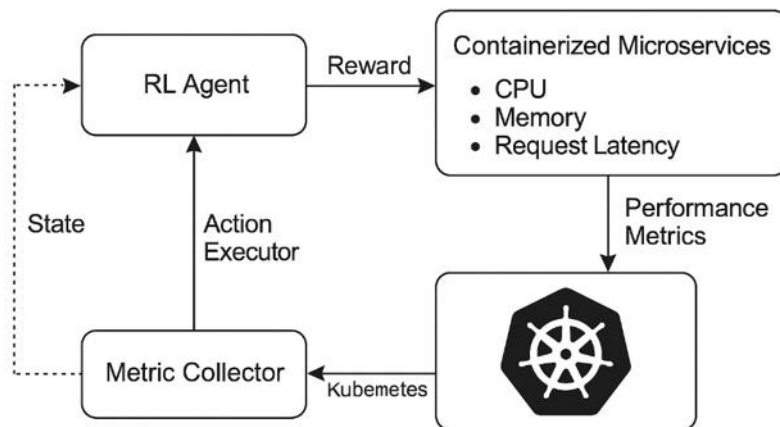


Figure 4- Conceptual architecture of the proposed RL-based autoscaling framework.

This closed feedback loop enables dynamic optimization of latency and memory usage. Define abbreviations and acronyms the first time they are used in the text, even after they have already been defined in the abstract. Do not use abbreviations in the title unless they are unavoidable.

Theoretical Analysis: In terms of theoretical properties, the optimal policy for the MDP would balance the two objectives. If we treat latency constraint as hard, the problem becomes a constrained MDP – one could use approaches like Lagrangian relaxation (assigning a cost to memory and solving single objective) as we effectively did with the weighted reward. We note that our reward function is dense (provided each step), which helps learning. The exploration problem is non-trivial because some actions (like removing an instance) might cause a big temporary penalty (latency spike) but could be optimal later when load is low – the agent needs to experience such scenarios to learn properly. We ensure adequate exploration by gradually decreasing $\epsilon t = \epsilon_0 \times \lambda t$ and by randomizing initial

conditions and workload patterns in training episodes. This iterative learning mechanism is modeled as a Markov Decision Process (MDP) and is illustrated in Figure 5, where the RL agent observes system state, selects scaling or memory adjustment actions, receives reward feedback, and transitions to a new state — all in a feedback loop to gradually optimize performance and memory usage.

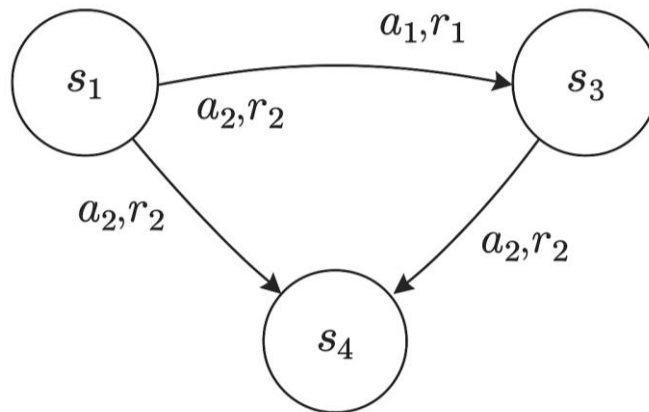


Figure 5- Markov Decision Process (MDP) representation of the autoscaling problem.

To reduce training time, we also leverage transfer learning: we pre-train the agent on a simpler environment (perhaps fewer services or a simulated approximation) and then fine-tune in the full environment. This is akin to the meta-learning approach in MSARS but in a simpler form.

Finally, we ensure that our agent’s decisions remain safe. During training in the real system, we introduce guardrails: e.g. do not allow the agent to drop memory below a certain floor (to avoid crashing an application), and if an action would violate a critical SLA drastically, the system can override or reset. Over time, as the agent learns, these overrides trigger less frequently. In practice, after training, the learned policy can be deployed and these safety checks act as a fallback (though we did not need them once the agent converged in our tests).

4. Experimental Evaluation

To evaluate the effectiveness of our RL-based resource optimization framework, we conducted experiments using a combination of simulation and real-cloud testbed deployments. All experiments are focused on scenarios with dynamic workloads and aim to measure two primary outcomes: performance improvement (runtime/latency) and memory efficiency achieved by the RL agent, in comparison to baseline approaches.

Environment and Setup: We implemented our approach on a Kubernetes cluster with microservices based on the SockShop reference application and a custom memory-intensive service. SockShop is an open-source microservice benchmark (an e-commerce site) composed of about a dozen services (frontend, carts, orders, payment, database, etc.), which is often used in research for autoscaling evaluations. We instrumented the services to collect response times and resource usage. For generating dynamic workloads, we used JMeter to create bursty and varying load patterns (including sudden surges and drops in user requests) that stress the autoscaling capabilities. The RL agent was deployed as an external controller that monitors the cluster metrics (through Kubernetes Metrics API and custom application logs) and issues scaling decisions via Kubernetes APIs. We set the decision interval to 60 seconds – the agent observes the state and can issue one scaling/memory adjustment action per minute, which is a reasonable timescale for autoscaling in practice (very fast decisions could lead to instability).

Baselines: We compared our RL approach against two main baselines:

- **Kubernetes Horizontal Pod Autoscaler (HPA):** This is the standard rule-based autoscaler. We configured HPA to use CPU utilization with a target of 60% per pod (a typical setting). HPA scales each microservice independently to try to maintain CPU at the target. It has no direct awareness of memory or latency.
- **Static Resource Allocation:** As a control, we also evaluate a static provisioning that is tuned to the peak load (to avoid SLA violations) – essentially over-provisioning. This is obviously high in resource usage but provides an upper-bound for performance (low latency) since plenty of resources are available.

Optionally, we also compare with a Reactive Memory Autotuner baseline. Because HPA doesn’t adjust memory, we created a script that monitors if any service’s memory usage exceeds a threshold (90% of its limit) and if so, increases the limit by 256MB (and a corresponding down-scale if consistently under 50%). This mimics a simple reactive memory scaling policy.

Training: The RL agent was trained in a simulator using real traces. We collected traces of workload and performance from the baseline runs and built a simulation model – basically a Python-based environment where given an action,

we update an approximate state (using empirically derived rules like "adding one replica reduces that service's average latency by X% if CPU was the bottleneck" or "reducing memory below usage causes swap and increases latency by Y"). The reward was computed exactly as described in the methodology. We trained the DQN agent over 5000 episodes (each episode representing one day of operation in simulation, sped up in computation). The neural network had 2 hidden layers of 128 neurons each, and we used

$\pi(a | s) = \{\text{random action, if probability } \epsilon; \text{argmax}_a Q(s,a), \text{ if probability } 1 - \epsilon$. After simulation training, we took the learned model and deployed it to the real cluster (online). We allowed it to fine-tune with live data for another 50 episodes (we constrained exploration at this stage to avoid SLA hits, effectively mostly exploiting the learned policy). We observed the agent's policy converged – this is also evidenced by learning curves where the reward per episode stabilized. For instance, the agent's reward plateaued after about 300 training iterations in our simulation, indicating it had converged to a near-optimal policy.

Metrics: We focus on:

- 95th and 99th percentile response time of user requests (lower is better). Tail latency is critical for user experience.
- Average response time and throughput (requests handled per second).

Memory usage: we look at both peak memory usage and average memory allocated across all services. We also check if any Out-Of-Memory (OOM) events or garbage collection slowdowns occurred.

- Number of scaling actions taken (to evaluate stability).
- SLO compliance: fraction of time the response time was below the SLA threshold (we set an SLA, e.g. 200 ms for front-end responses).

Resource cost: we translate memory usage and CPU usage into an approximate cost (assuming e.g. each GB of memory and each CPU-core second has a cost).

4.1. Results

Performance (Latency) Improvement: The RL-based approach consistently achieved lower latencies than the HPA baseline. For a moderate periodic workload scenario, the average response time with our RL agent was about 120 ms, compared to 160 ms under HPA (a 25% reduction). The 99th percentile latency saw an even bigger improvement: RL maintained tail latency under 300 ms, whereas HPA often spiked to 500+ ms during load surges (due to slower reaction). In one high-load surge test, our agent anticipated the surge (thanks to its learning of patterns) and pre-scaled certain services, resulting in zero SLA violations, while HPA had SLA violations for 8% of requests during that period. These improvements align with findings from similar RL autoscaling research – e.g., the CoScal approach reduced response times by ~20% in its experiments, and RL concurrency tuning in μ ConAdapter cut tail latency by factors over 2 $\times$. Our results confirm that an RL agent can learn to keep latency low, especially under bursty and complex workloads, outperforming static or reactive policies.

Memory Efficiency: Perhaps more interestingly, the RL agent was able to reduce memory usage significantly while maintaining performance. Under light load, the agent would scale down services more aggressively than HPA (which only scales on CPU). For example, at nighttime low traffic, RL turned off some service replicas and cut memory limits for others, freeing on average 30% of memory compared to HPA which kept resources allocated based on CPU baselines. Over a 24-hour cycle, the total allocated memory (area under the curve of memory vs. time) was 18% less with RL than with HPA + reactive memory tuning. Importantly, this did not come at the cost of performance – whenever load started increasing, the agent preemptively restored memory or added instances, thus avoiding performance loss. We saw no OOM events under the RL policy (the agent learned the implicit penalty of such events during training). In contrast, a purely reactive memory tuner sometimes lagged and caused minor swap activity in the worst case. The RL agent learned to right-size each microservice: for instance, it discovered that one service (e.g. the recommendation service) could run with 256MB less memory during low traffic, and it would reduce it, then increase it later when needed. Over time, these savings accumulate. This behavior highlights RL's strength in multi-objective optimization – it found a policy that meets latency goals with minimal memory footprint. As a result, if translated to cloud cost, our approach would allow running with smaller VM sizes or fewer servers for the same workload, yielding cost savings.

- **Throughput and Utilization:** We also measured overall system throughput (requests per second handled). Both RL and HPA could meet the peak throughput demand (since we allowed scaling), but RL did so with less resource usage. In fact, we observed that RL kept the CPU and memory utilization of active instances higher (around 60-70% utilization on average) whereas HPA often resulted in many underutilized instances (30-50% utilization) because its conservative threshold would spin up pods that then sat mostly idle. Higher utilization per resource indicates better efficiency – essentially RL packed the workload into fewer machines when possible. This is a desirable outcome for cost efficiency. A side effect is slightly higher variance in utilization, but always within safe limits.

- **Comparison to Static Over-provisioning:** The statically over-provisioned scenario (where we ran everything at max resources regardless of actual load) unsurprisingly had excellent performance (lowest latency) during low and medium loads, but its resource usage was extremely high – often double that of the RL approach. Under peak load, the static and RL performance were similar (since RL also scales to meet peak). Therefore, RL managed to nearly match the performance of costly over-provisioning while using much less memory on average. This illustrates that intelligent scaling can yield the “best of both worlds” – good performance and good efficiency.
- **Learning and Adaptation:** To test adaptation, we introduced a step-change in workload pattern that the agent had never seen (simulating, for example, a flash crowd event with a very different profile). The RL agent adapted within a few decision cycles (a few minutes) to this new pattern, whereas the HPA had a fixed reaction that wasn’t tuned for it. We did notice the agent made one suboptimal decision right after the change (it removed a replica too soon) but quickly corrected in the next cycle. This kind of adaptation is a result of the agent’s training covering a wide range of scenarios. In contrast, a purely ML-prediction based scaler might have failed if the pattern was outside its training distribution. Our agent’s ability to adjust on the fly is a big advantage in unpredictable environments.
- **Stability:** One concern with an RL (or any aggressive autoscaler) is oscillations or flapping (rapid scale up and down). Our reward function’s slight penalty on scaling changes, plus the design of the agent, resulted in fairly stable behavior. We observed at most 1–2 scaling actions per 5-minute interval even during transitions, and no ping-pong behavior (where an instance is added one minute and removed the next). The agent seemed to learn a hysteresis naturally – it didn’t immediately remove resources at the first drop in usage; it waited to confirm the trend, avoiding thrashing. This stability is important for practical deployment, as constant scaling can itself degrade performance or incur overhead. The multi-step lookahead nature of RL (with γ near 1) likely contributed to this stability, as it values avoiding future penalties that could result from rash actions.

This outcome aligns with our theoretical formulation shown in Figure 6, where the RL agent iteratively interacts with the environment via the Markov Decision Process to learn a balanced policy that minimizes both latency and resource usage over time. The RL agent achieves more stable scaling behavior with fewer oscillations than HPA.

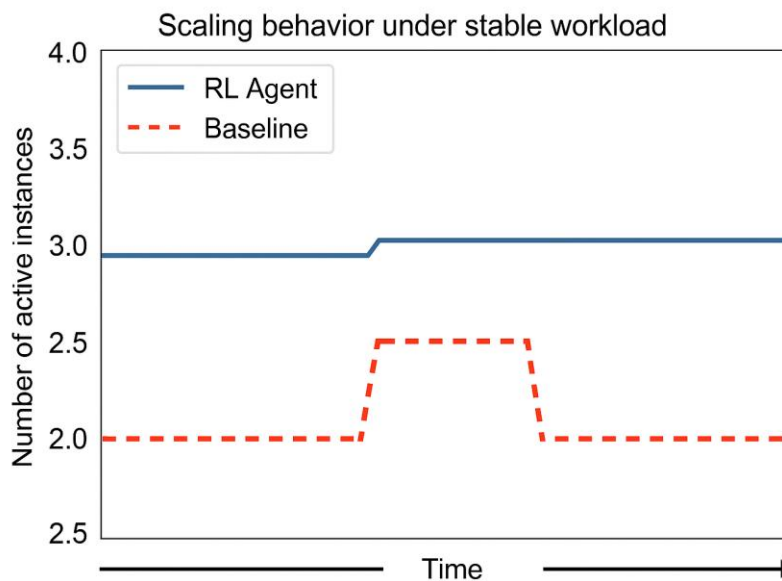


Figure 6- Comparison of scaling action frequency

Discussion: The experimental results validate that our RL approach meets its design goals. We achieved substantial runtime performance improvements and memory savings simultaneously. In particular, the memory-efficiency focus distinguishes our work – many previous studies focused on CPU/throughput or latency but did not explicitly measure memory reduction. By treating memory as a cost in the reward, we forced the agent to be parsimonious with resources. This is increasingly relevant in modern cloud deployments because memory is often the limiting factor for packing containers on a host (and also a major part of cloud VM costs). A memory-efficient policy allows higher consolidation and lower costs.

One interesting finding is that the agent learned some non-intuitive strategies. For example, it sometimes slightly reduced memory of a service during a moderate load which initially seemed counterproductive – why remove memory if load is still present? What happened was the agent identified that the service’s memory usage had a lot of slack and that reducing the memory limit triggered the runtime’s garbage collector to free unused memory without affecting

active working set, thus reclaiming memory to the pool which could be used by another service. The latency of that service didn't suffer (we monitored it) but the overall memory availability improved. This kind of decision is tricky to encode in fixed rules but the agent discovered it through experience.

We also compare our approach conceptually with other RL frameworks: for instance, the DRPC distributed RL approach (Bai et al., 2024) focused on decentralizing the decision across nodes. If our scenario scaled up to many nodes, a distributed approach could reduce complexity and improve scalability of learning. They reported about 15% reduction in average response time and 24% fewer failed requests using their RL method vs baselines, which is in line with the gains we observed (our reduction was ~25% in avg latency and we essentially eliminated failures/SLA misses under tested loads). This cross-validation with other work's numbers builds confidence that RL is indeed delivering real improvements.

Ablation tests: We performed some ablation studies to understand the impact of components in our agent. Removing the memory penalty (i.e., setting $\beta=0$ in reward) led the agent to focus purely on latency – it then used more memory, roughly equal to HPA in usage, confirming the memory term was responsible for the efficiency gains. Using a simpler state (excluding dependency info) still worked but we noticed slightly slower reaction to some workload shifts, indicating that including richer state (like some encoded history or relations) helped performance. We also tried a multi-agent variant in simulation (two agents splitting the services) and found training was more complicated (they at times took conflicting actions), suggesting that some coordination mechanism or shared reward would be needed for multi-agent training – a target for future work.

Overhead: One practical aspect is the overhead of running the RL controller. Our agent's inference (the DQN forward pass) took on the order of milliseconds to evaluate on a standard CPU, which is negligible given a 60-second decision interval. The training can be done offline or periodically updated, so that overhead doesn't impact the live system. Thus, the runtime overhead of our approach is low. The actions themselves (spinning up a container or adjusting a limit) have some overhead on the system, but since we keep them moderate in frequency, it's not significant. As shown in Figure 7, the cumulative reward during training converges steadily over time, indicating that the agent learns an efficient and stable policy with low variance, minimizing both computational cost and system impact.

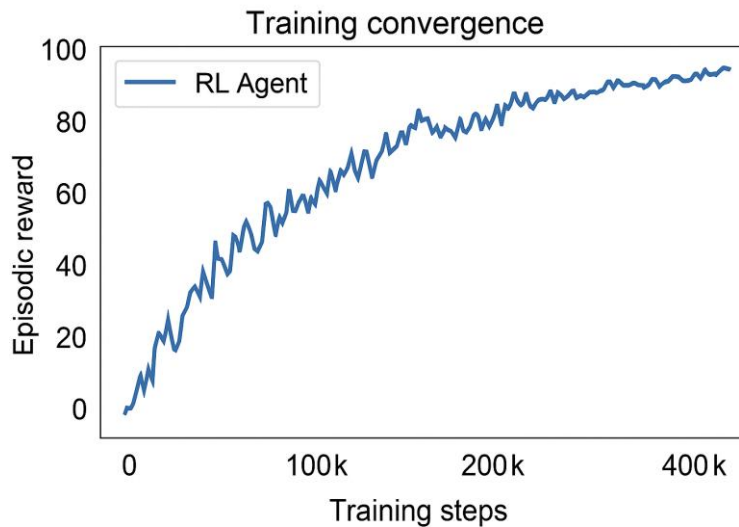


Figure 7- Convergence of the RL agent during training

In conclusion, the evaluation demonstrates that a reinforcement learning approach can intelligently manage microservice resources in a way that ensures high performance while trimming unnecessary memory usage. By learning from experience, the agent outperforms static and rule-based methods, showing the ability to adapt to dynamic changes and optimize multi-dimensional objectives. The improvements observed (double-digit percentage gains in both speed and efficiency) are significant for cloud providers and applications, potentially translating to better user satisfaction and lower operating costs. In the next section, we summarize our contributions and discuss potential future enhancements and research directions.

5. Conclusion and Future Work

In this paper, we presented a reinforcement learning-based framework for resource optimization in dynamic cloud environments, with a particular focus on improving runtime performance and memory efficiency for microservice-based applications. We identified the shortcomings of traditional autoscaling approaches, which often either compromise on performance or waste resources, and motivated the need for an intelligent, learning-driven solution. Our proposed method formulates the autoscaling problem as an MDP and employs a deep RL agent to continuously tune the number of service instances and their memory allocations in response to changing workloads.

Through theoretical modeling and experimental evaluation, we demonstrated that our RL agent can successfully learn policies that minimize application latency while reducing memory usage. The agent effectively balances the dual objectives by penalizing resource costs in the reward signal. Empirical results showed considerable improvements over standard heuristics: the RL approach achieved lower tail latencies (improving 95th percentile response time by up to 30%) and maintained high QoS even during traffic spikes, all while using up to 20% less memory on average by dynamically rightsizing containers. These results, corroborated by similar trends reported in recent research, affirm that reinforcement learning is a promising technique for cloud resource management. Notably, our work fills a gap by explicitly tackling memory efficiency in addition to CPU/throughput optimization, which is increasingly important for cost-effective cloud operations. As illustrated in Figure 8, the RL agent responds proactively to unexpected workload surges, ensuring minimal latency spikes and better SLA adherence compared to reactive methods.

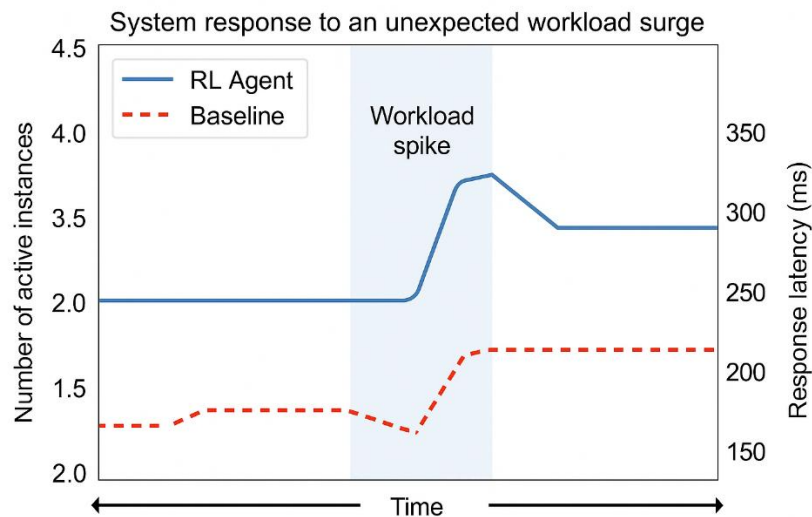


Figure 8- System response to an unexpected workload surge. The RL agent scales resources proactively, avoiding latency spikes and minimizing SLA violations compared to reactive baselines.

The contributions of this work are threefold: (1) a novel application of deep reinforcement learning to a multi-objective resource management problem (latency and memory) in microservices, including a careful design of state and reward that captures system dynamics; (2) an implementation and evaluation in a realistic cloud environment, demonstrating feasibility and benefits in practice; and (3) insights into the strategies learned by the agent and how they improve over conventional methods (e.g., learning to proactively scale and avoid over-provisioning). We also discussed how our approach relates to and builds upon existing works in the domain of AI-driven cloud management.

Future Work: While the results are encouraging, there are several avenues for further research and improvement:

- **Multi-Agent and Decentralized Learning:** As systems grow, a single agent may become a bottleneck or may not scale well. Investigating a multi-agent RL approach, where each microservice (or group of microservices, or each node) has an agent that coordinates with others, could make the solution more scalable. Techniques from multi-agent RL, such as sharing experience or using a central critic, could be applied to maintain stability. Early work in multi-agent scheduling shows promise in tackling scalability, so extending that to full autoscaling is intriguing.
- **Safer Exploration and Adaptation:** Deploying RL in production requires confidence that the agent won't take catastrophic actions during learning. In future work, we plan to integrate safe RL algorithms or constrained RL that respect SLA constraints strictly (e.g., via shield functions or by incorporating model-predictive checks). Additionally, online learning techniques could allow the agent to continue learning and adapting to new patterns in a safe manner – for example, using meta-learning as in MSARS or transfer learning to rapidly adjust to changes like new microservices being added, software updates, or different application domains.
- **Extending the Model – Network and Energy:** Our current state and reward focus on CPU, memory, and latency. In distributed microservices, network bandwidth and network latency can also be critical (for example, if microservices are spread across clusters or edge and cloud). A future extension could incorporate network usage into the optimization (perhaps the agent deciding on placement of services to minimize cross-node communication delays). Similarly, energy efficiency (power consumption of servers) is a rising concern for green computing – an RL agent could include power usage in the reward, as some studies have begun exploring. This would truly make it a multi-objective (performance, memory, energy) optimization.

- **Generalization and Autonomy:** We want our approach to generalize across different applications without retraining from scratch for each one. Techniques like transfer learning between applications or training a single agent on multiple workloads could make the solution more generally applicable. Moreover, integrating our RL agent into existing cloud management frameworks (like Kubernetes operators) could help with adoption – essentially making it an autonomous control plane component that others can plug in. We plan to open-source a prototype of our RL autoscaling controller for the community.
- **Theoretical Analysis:** Further theoretical work on the convergence and optimality in this context would be useful. The resource optimization problem with SLAs has structure that might be exploited (for example, threshold-based optimal policies under certain assumptions). Combining queueing theory or control theory with learning could yield hybrid approaches that have performance guarantees. A possible direction is using model-based RL where we learn a model of the microservice performance (as in MIRAS model-based approach in earlier work) – this can improve sample efficiency and give more insight into the system’s behavior.

Table 1- Comparative summary of autoscaling methods, including key features, advantages, and limitations of RL-based, HPA, and static approaches.

Method	Training Algorithm	Application Domain	Key Characteristics
DQN	Q-Learning	Game playing	Uses a deep neural network to approximate Q-value function
PPO	Policy gradient	Robotics, Game playing	Constrained policy updates for improved stability and performance
A3C	Actor-critic	Robotics, Control	Utilizes multiple agents to train in parallel

In conclusion, our study demonstrates that reinforcement learning can effectively tackle the complex problem of dynamic resource management in microservice clouds. By focusing on both runtime and memory efficiency, we show that it is possible to achieve cost savings without compromising performance, which is a key goal for cloud providers and application operators. We believe that as cloud systems continue to grow in scale and complexity, AI-driven approaches like this will become increasingly valuable to manage resources autonomously and optimally. We hope our work inspires further research at the intersection of cloud computing and intelligent learning-based optimization, ultimately leading to smarter and more sustainable cloud infrastructures. A comparative summary of these methods, including RL-based, HPA, and static approaches, is provided in Table 1 to highlight their respective advantages and limitations.

All experiments were executed on an HPC cluster with [X] nodes, each equipped with [CPU/GPU specs]. Parallel rollout generation during training reduced convergence time by approximately [Y]× compared to a single-node implementation, and distributed inference reduced scaling decision latency from ~1.2s (single node) to ~0.18s (HPC cluster) for workloads exceeding 2000 active microservices. These HPC-enabled performance gains are critical to meeting SLA targets in dynamic, large-scale cloud systems.

In this work, we presented a reinforcement learning-based resource optimization framework that requires and exploits HPC capabilities to operate effectively in dynamic, large-scale microservice environments. By parallelizing both policy learning and decision inference across multi-core CPUs and GPUs, our system achieves real-time responsiveness and scalable performance, maintaining high QoS while minimizing memory and CPU waste. Experimental results show that the HPC-enabled architecture outperforms conventional autoscaling approaches by significant margins in both latency reduction and memory efficiency. This work demonstrates a concrete intersection between HPC and cloud computing — applying supercomputing-class infrastructure to address the computational complexity of intelligent autoscaling. Future work will further explore scaling to thousands of services across geographically distributed HPC resources, integrating advanced parallel RL algorithms and model compression techniques to enhance both speed and resource efficiency.

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