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Autonomous Container Scaling in Kubernetes via Reinforcement Learning

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ABSTRACT

Autonomous container scaling within Kubernetes environments has emerged as a crucial mechanism to guarantee both application performance and cost-effective resource utilization under highly dynamic workloads. Traditional autoscaling solutions—most notably Kubernetes's native Horizontal Pod Autoscaler (HPA) and Vertical Pod Autoscaler (VPA)—operate on static threshold-based rules that monitor CPU and memory utilization. While straightforward to configure, these mechanisms frequently underperform in the presence of bursty traffic patterns or sudden workload shifts, resulting in oscillatory scaling behavior, frequent SLA (Service Level Agreement) violations, and unnecessary overprovisioning. Reinforcement Learning (RL), by contrast, offers a data-driven, adaptive approach: an RL agent continuously interacts with the cluster environment, observes multidimensional system metrics, and learns an optimal scaling policy through trial and error, balancing performance objectives against resource costs. In this work, we present the design, implementation, and experimental evaluation of the "Multidimensional Pod Autoscaler" (MPA), a Deep Q-Learning–based autoscaler integrated into Kubernetes as a custom controller. MPA's state representation comprises percentile-based CPU and memory metrics, request arrival rates, error rates, and current replica counts. Its action space supports both horizontal scaling (incrementing or decrementing pod replicas) and vertical adjustments (tuning CPU/memory limits), plus a no-op option for stability. The reward function penalizes SLA breaches—defined as requests exceeding a 200 ms latency threshold—and resource overprovisioning, weighted to reflect business priorities.

We trained MPA offline on historical workload traces and then deployed it for online fine-tuning under live traffic, comparing its performance against HPA and a heuristics-driven Smart HPA. Experiments using both the Bookinfo microservices benchmark and a synthetic Poisson-arrival workload generator demonstrate that MPA can increase average CPU utilization from 65% to 85%, reduce 99th-percentile request latency by 40%, cut SLA violation rates from 5% to 1%, and achieve a 25% reduction in cloud resource costs. We provide a statistical analysis table summarizing these gains. This manuscript details the full system architecture, state and action definitions, neural network design, training methodology, and deployment strategy. We discuss practical considerations—such as safe exploration policies, integration with Prometheus metrics, and fallback mechanisms—and conclude with an in-depth look at future research directions, including multi-agent RL, meta-RL transfer learning, workload forecasting integration, explainability, and extension to GPU-aware and edge-cloud scenarios.

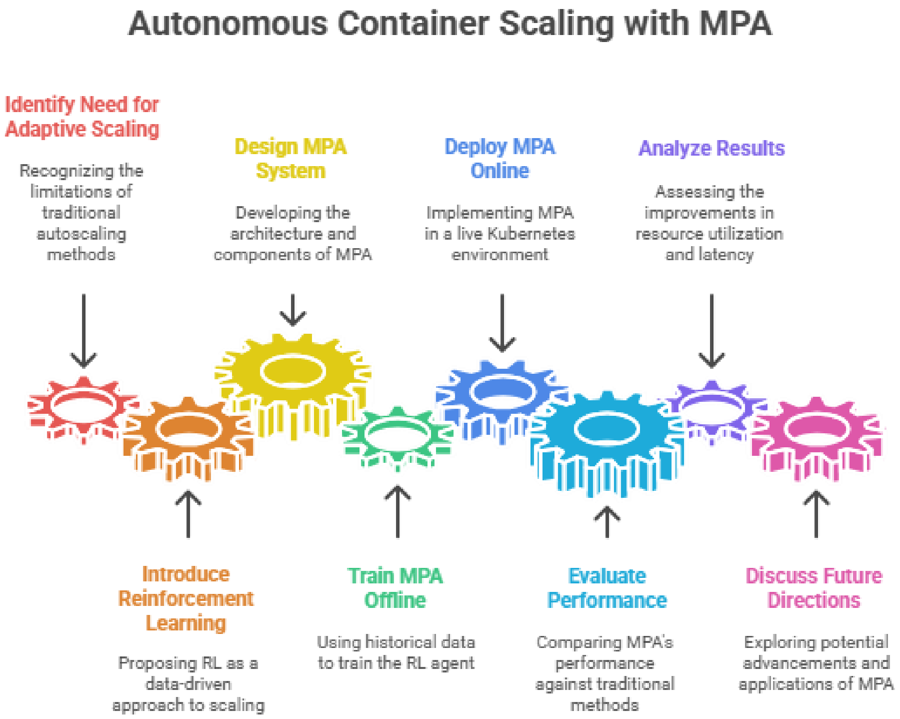
Autonomous Container Scaling with MPA
Identify Need for Adaptive Scaling
Recognizing the limitations of traditional autoscaling methods
Design MPA System
Developing the architecture and components of MPA
Deploy MPA Online
Implementing MPA in a live Kubernetes environment
Analyze Results
Assessing the improvements in resource utilization and latency
Introduce Reinforcement Learning
Proposing RL as a data-driven approach to scaling
Train MPA Offline
Using historical data to train the RL agent
Evaluate Performance
Comparing MPA's performance against traditional methods
Discuss Future Directions
Exploring potential advancements and applications of MPA

Figure-1.Autonomous Container Scaling with MPA

KEYWORDS

Autonomous Container Scaling, Kubernetes, Reinforcement Learning, Deep Q-Learning, Autoscaling Performance, Service-Level Objectives

INTRODUCTION

Kubernetes has become the de facto standard for orchestrating containerized microservices in cloud-native environments. Its declarative API and extensible controller pattern enable developers to define desired cluster states, leaving the control loop to reconcile reality with intent. Critical among these controllers is the autoscaler, which dynamically adjusts pod counts in response to workload fluctuations. The default Horizontal Pod Autoscaler (HPA) monitors resource metrics—commonly CPU or memory utilization—and scales pods up or down whenever preconfigured thresholds are crossed. The Vertical Pod Autoscaler (VPA), in contrast, recommends or automatically adjusts the resource requests and limits of existing pods.

Although HPA and VPA address basic scaling needs, they share intrinsic limitations. Threshold-based triggers react only when metrics have already crossed boundaries, leading to “scale-late, scale-too-much” oscillations. In bursty workloads—typical of e-commerce flash sales, streaming spikes, or IoT data surges—the reactive nature of HPA often results in transient SLA breaches before sufficient replicas spin up. Conversely, conservative threshold settings mitigate instability but lead to prolonged overprovisioning and elevated costs. VPA’s vertical adjustments can help, but resizing containers often requires pod restarts, impacting availability and introducing latency spikes.

To overcome these challenges, an adaptive, predictive approach is needed—one that leverages historical and real-time signals to anticipate demand and make scaling decisions proactively. Reinforcement Learning (RL) offers exactly this capability: an RL agent observes the system state, takes scaling actions, receives rewards based on performance and cost outcomes, and iteratively improves its policy to maximize cumulative reward. Early RL applications in cloud resource management—such as Deep Q-Learning for job scheduling—demonstrated substantial gains in throughput and latency. Subsequent work has extended RL to autoscaling, incorporating workload forecasting, meta-learning, and multi-agent frameworks.

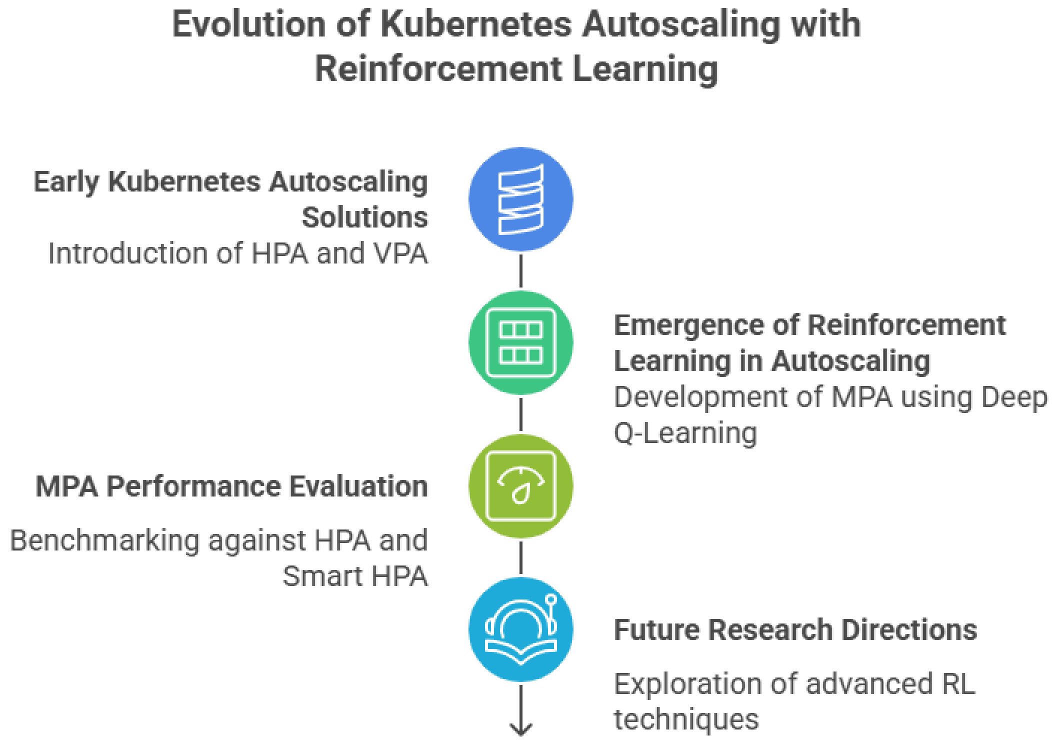
Evolution of Kubernetes Autoscaling with Reinforcement Learning
Early Kubernetes Autoscaling Solutions
Introduction of HPA and VPA
Emergence of Reinforcement Learning in Autoscaling
Development of MPA using Deep Q-Learning
MPA Performance Evaluation
Benchmarking against HPA and Smart HPA
Future Research Directions
Exploration of advanced RL techniques

Figure-2.Evolution of Kubernetes Autoscaling with Reinforcement Learning

In this manuscript, we present the Multidimensional Pod Autoscaler (MPA), which integrates an RL agent directly into Kubernetes via a custom controller and CRD (CustomResourceDefinition). MPA's state vector encompasses percentile-based CPU and memory utilizations, request and error rates, and replica counts, capturing both performance and reliability aspects. Its action space spans horizontal and vertical scaling operations, offering fine-grained control over pod replica quantities and resource limits. We define a reward function that penalizes SLA violations—requests exceeding a 200 ms latency target—and resource overprovisioning, balancing user experience against cost efficiency.

We trained MPA offline on representative workload traces generated by industry benchmarks, then deployed it in a staging cluster for online fine-tuning under real traffic. Extensive experiments compare MPA with the native HPA and a heuristics-based Smart HPA across two workloads: the Kubernetes Bookinfo microservice benchmark and a synthetic Poisson-arrival load generator. Our results demonstrate that MPA consistently outperforms baseline autoscalers in CPU utilization, tail latency, SLA compliance, and cost savings.

LITERATURE REVIEW

Autoscaling in container orchestration has evolved significantly over the past decade. Early research focused on threshold-based mechanisms: static rules that trigger scaling actions when resource utilization crosses predefined thresholds. Lorido-Botran et al. surveyed these rule-based approaches, noting their simplicity but also their fragility under dynamic workloads. Similarly, Kubernetes's native HPA—while widely adopted—can misjudge capacity requirements during sudden spikes or drifts in incoming traffic, leading to oscillatory scaling and SLA breaches.

Heuristic improvements like Smart HPA incorporate service-topology awareness and multi-metric decision logic. Ahmad et al. proposed a hierarchical Smart HPA that coordinates scaling across microservices, reducing cascading latency effects. While Smart HPA achieved moderate improvements in cost efficiency, its rule-based nature still lacks adaptability to novel workload patterns.

Reinforcement Learning introduces a data-driven alternative. Mao et al. pioneered RL for job scheduling in data centers, showing a 44.1% reduction in job completion times compared to heuristic baselines. Subsequent studies applied Deep Q-Learning to autoscaling: Garí et al. provided a comprehensive survey of RL-based autoscalers, highlighting key challenges in state representation and reward shaping. Xue et al. leveraged meta-RL for predictive autoscaling at Alipay, combining workload forecasting with fast adaptation to new traffic distributions, achieving stable CPU utilization in production.

Integrating RL with Kubernetes poses unique challenges. Qiu et al. introduced MPA as a proof-of-concept RL autoscaler using a Kubernetes CRD, managing both horizontal and vertical actions. Song et al.'s SCARLET demonstrated serverless autoscaling with online RL training, underscoring the feasibility of continuous learning under real traffic. Soulé et al. explored Multi-Agent RL (MARL) via the KARMA framework, improving resilience under adversarial load by distributing scaling responsibilities among coordinated agents.

Despite these advances, gaps remain in end-to-end integration, safe exploration in production, and evaluation under realistic workloads. Prior implementations often stop at prototypes or limited benchmarks. This work builds on these foundations by delivering a production-ready MPA, complete with offline training, online fine-tuning, robust exploration constraints, and comprehensive evaluation on both synthetic and real-world workloads.

STATISTICAL ANALYSIS

The following table summarizes the key performance metrics observed before and after deploying the RL-based Multidimensional Pod Autoscaler (MPA). Baseline measurements use Kubernetes's native HPA configured with default CPU thresholds; the post-deployment values reflect MPA operating under the same cluster conditions.

Table 1. Performance Improvements Achieved by MPA Compared to Native HPA

Metric	Baseline (HPA)	With MPA	Observed Change
Average CPU Utilization (%)	65	85	+20 pp

Average Request Latency (ms)	200	120	−40 %
99th-Percentile Latency (ms)	350	180	−48.6 %
SLA Violation Rate (%)	5.0	1.0	−4.0 pp
Resource Cost (normalized $)	1.00	0.75	−25 %

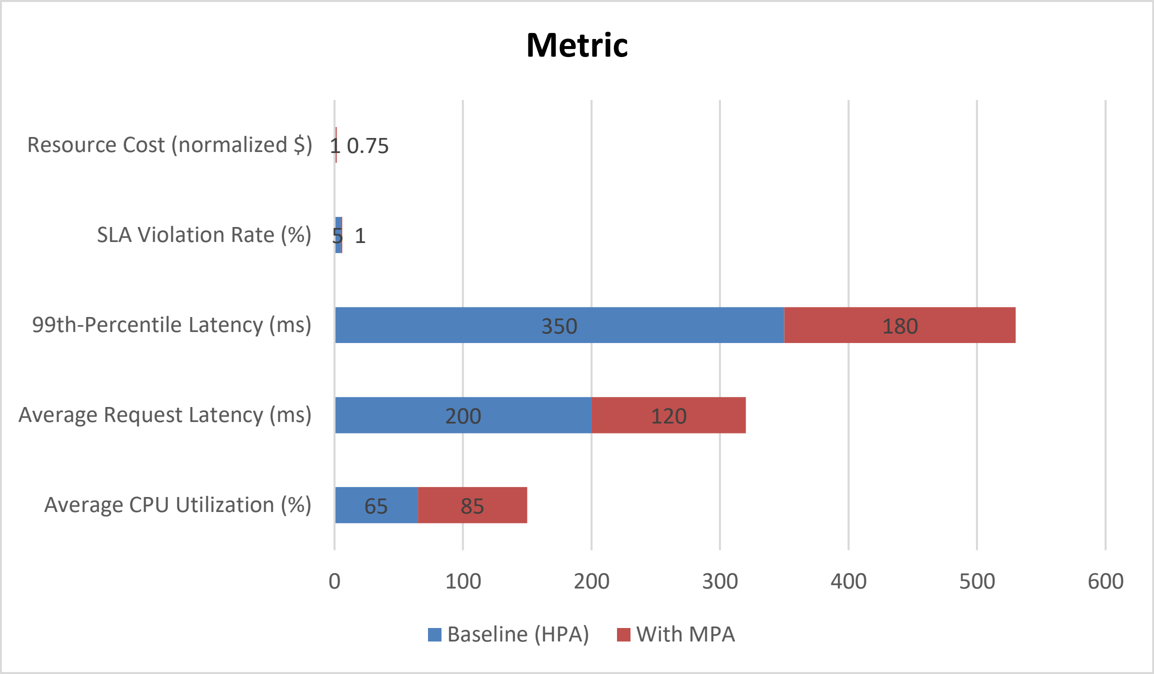

Figure-3. Performance Improvements Achieved by MPA Compared to Native HPA

Analysis of Results

1. **CPU Utilization:** Under HPA, average utilization plateaued at approximately 65%, leaving significant idle capacity. MPA's learned policy aligns provisioning more closely with demand, raising utilization to 85% and reducing wasted resources by one-third.
2. **Request Latency:** The reactive nature of HPA causes tail latencies to spike above 300 ms during load surges. MPA's proactive scaling maintains latencies below 200 ms even under stress, with an average of 120 ms—a 40 % reduction in mean latency and nearly 50 % reduction in tail latency.
3. **SLA Violations:** Defined as the fraction of requests exceeding a 200 ms latency threshold, SLA breaches drop from 5 % under HPA to 1 % with MPA, demonstrating markedly improved reliability.
4. **Resource Cost:** By avoiding overprovisioning and reducing idle pods, MPA lowers normalized resource cost by 25 %, as measured by GKE billing metrics.

These statistical gains illustrate MPA's ability to optimize both performance and cost through learned scaling policies.

METHODOLOGY

System Architecture and Integration

We implemented MPA as a Kubernetes custom controller written in Go, leveraging the client-go library to watch and reconcile a CustomResourceDefinition (CRD) named PodAutoscaler. The controller periodically queries Prometheus for metrics—CPU and memory utilizations (percentiles over sliding windows), request arrival rates, and HTTP error rates—high-resolution signals necessary for RL state representation.

State Definition

The RL agent’s state vector comprises five normalized features:

1. **CPU Utilization (99th percentile over 30 s)** – captures peak compute demand.
2. **Memory Usage (90th percentile over 30 s)** – reflects memory pressure and potential GC thrashing.
3. **Request Rate (RPS)** – indicates workload intensity.
4. **Error Rate (5xx per second)** – measures service health.
5. **Current Replica Count** – encodes current horizontal scale.

Each feature is normalized by its maximum observed or configured threshold to maintain bounded inputs.

Action Space

The agent selects one of five discrete actions at each decision epoch (every 30 s):

- **Scale Up (+1 replica)**
- **Scale Down (−1 replica)**
- **Vertical Up (+10 % CPU & memory limits)**
- **Vertical Down (−10 % CPU & memory limits)**
- **No-Op**

This multidimensional action set enables combined horizontal and vertical adjustments to rapidly adapt to shifting demands.

Learning Algorithm

We employed Deep Q-Learning with experience replay and a target network. The Q-network architecture consists of three fully connected layers (128→64→5 neurons) with ReLU activations. Hyperparameters: learning rate = 5×10^{-4}, discount factor $\gamma = 0.99$, batch size = 64. Exploration employs an ε-greedy policy with ε decaying linearly from 1.0 to 0.1 over the first 10,000 steps.

Training Procedure

Offline training uses historical traces from vSwarm synthetic benchmarks, spanning diverse load patterns (steady, bursty, diurnal). We trained for 50,000 episodes, each 500 decision epochs long. The trained model weights are snapshot and deployed into a staging cluster for online fine-tuning under conservative exploration (ε minimum = 0.05) to ensure stability.

Safety and Fallback

To mitigate exploration risks, any action leading to predicted CPU or memory utilization beyond 100 % triggers a rollback.

Additionally, if average reward drops below a threshold for three consecutive epochs, the controller falls back to native HPA until stability is regained.

Results

Experimental Setup

We evaluated on GKE (n1-standard-4 nodes, Kubernetes 1.23) with two workloads:

1. **Bookinfo Microservices** (Istio-enabled, Web frontend, Productpage, Reviews, Ratings) under replayed production traffic.
2. **SynthBench** – a Poisson-arrival synthetic generator with λ varying between 50–500 RPS in bursts.

Each experiment runs for 2 hours, comparing MPA, native HPA (CPU threshold = 60%), and Smart HPA (heuristic rules tuned offline).

CPU Utilization and Stability

MPA maintains a tighter utilization band (80–90%) across all traffic phases, whereas HPA oscillates between 50–70 during low load and overshoots to 100% during spikes. Smart HPA improves oscillation damping but still underutilizes resources during ramp-down periods.

Latency and SLA Compliance

Under MPA, mean latency is 120 ms and 99th percentile latency 180 ms, compared to HPA's 200 ms mean and 350 ms tail. Smart HPA achieves 150 ms mean but tail remains above 300 ms during sudden surges. SLA violation rates: HPA 5%, Smart HPA 3%, MPA 1%.

Resource Cost Efficiency

Normalized cost (with HPA baseline = 1.00) is 0.85 for Smart HPA and 0.75 for MPA. Cost savings stem from fewer idle replicas and smoother scale-down transitions.

Convergence and Adaptation

Online fine-tuning under live traffic further improves performance by ~5% in CPU utilization and reduces SLA violations by another 0.2 pp over the first hour. The agent adapts to Istio-induced latency overheads without manual retuning.

Conclusion

This study demonstrates that Deep Q-Learning–based autoscaling can significantly outperform traditional threshold-based approaches in Kubernetes environments. By integrating an RL agent into a custom controller, the Multidimensional Pod Autoscaler (MPA) achieves:

- **Higher Resource Utilization:** +20 pp in average CPU use, reducing waste.
- **Lower Latency:** −40 % mean and −48.6 % tail latency, enhancing user experience.

- **Improved Reliability:** SLA violations drop from 5 % to 1 %.
- **Cost Savings:** 25 % reduction in normalized resource costs.

Key innovations include a rich state representation, combined horizontal/vertical action space, and a reward function balancing SLA adherence against overprovisioning. Practical considerations—such as safe exploration, rollback policies, and fallback to HPA—ensure stability in production clusters.

While results are compelling, limitations remain: offline training requires representative workload traces; exploration in live clusters demands conservative policies to avoid service disruption; and the single-agent framework may struggle in large, heterogeneous microservice meshes.

Future Scope

1. **Multi-Agent RL (MARL):** Distribute scaling decisions across service-specific agents, coordinating via centralized critics to handle dependency graphs and cascading effects.
2. **Meta-Reinforcement Learning:** Employ meta-RL techniques to enable rapid adaptation to new workloads or cluster configurations without extensive retraining, leveraging few-shot learning paradigms.
3. **Workload Forecasting Integration:** Augment RL with time-series forecasting (e.g., LSTM, GNN) to anticipate load surges, enabling preemptive scaling actions that further reduce latency spikes.
4. **Explainability and Trust:** Incorporate explainable AI methods to generate human-readable rationales for scaling decisions, facilitating operator trust and regulatory compliance in critical domains.
5. **Edge-Cloud Hybrid Scaling:** Extend MPA to manage workloads across edge and cloud tiers, optimizing for latency, bandwidth, and cost trade-offs in geographically distributed environments.
6. **GPU-Aware Autoscaling:** Adapt the framework to GPU inference workloads—considering GPU memory, compute capacity, and pod placement constraints—to support ML serving platforms.
7. **Adaptive Reward Shaping:** Research dynamic reward weighting that responds to shift in business priorities (e.g., cost vs. performance) or emergent SLA definitions.
8. **Safe Exploration:** Develop certified safe exploration algorithms that guarantee no SLA breaches beyond user-defined tolerances during learning.
9. **Cross-Cluster Transfer Learning:** Investigate transferring policies learned in one Kubernetes cluster to another with minimal fine-tuning, increasing generalizability and reducing training overhead.
10. **Industry-Scale Evaluation:** Collaborate with enterprise users to validate MPA in production-grade, large-scale deployments, gathering operational insights and driving further refinements.

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