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Optimizing Resource Allocation in Cloud Computing Environments using Reinforcement Learning

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Abstract

Cloud computing resource allocation remains a critical challenge, with organizations wasting an estimated $109 billion annually on idle or over-provisioned resources. Traditional allocation strategies—static provisioning, threshold-based autoscaling, and time-series forecasting—fail to capture the complex, non-stationary dynamics of modern cloud workloads characterized by bursty arrivals, heterogeneous resource demands, and multi-tenant interference effects. This paper presents CloudRL, a deep reinforcement learning framework for intelligent cloud resource allocation that jointly optimizes resource utilization, Service Level Agreement (SLA) compliance, infrastructure cost, and energy efficiency. CloudRL formulates resource allocation as a continuous-action Markov Decision Process (MDP) and employs a Soft Actor-Critic (SAC) agent with a multi-objective reward function that balances competing optimization goals through adaptive weighting. The system observes a high-dimensional state space comprising real-time CPU, memory, GPU, storage I/O, and network utilization metrics alongside workload arrival patterns and SLA parameters, and outputs fine-grained scaling, migration, and configuration actions. We evaluate CloudRL on a production-scale testbed comprising 500 virtual machines processing six diverse workload traces (web serving, batch analytics, machine learning training, video transcoding, database, and microservices) over 30 days. Results demonstrate that CloudRL achieves 88% average resource utilization (compared to 42% for static allocation and 65% for predictive methods), reduces SLA violations by 91.7% (from 12% to 0.98%), decreases infrastructure costs by 37.5%, and lowers energy consumption by 59% compared to static provisioning. CloudRL converges within 3,000 training episodes and adapts to workload distribution shifts within 200 episodes without manual retuning.

Keywords: Cloud computing, resource allocation, reinforcement learning, autoscaling, Soft Actor-Critic, SLA optimization, energy efficiency, workload management.

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Introduction

Cloud computing has fundamentally transformed the delivery of IT infrastructure, enabling on-demand access to scalable computing resources through a pay-per-use model. Global cloud spending reached $420 billion in 2025, with Infrastructure-as-a-Service (IaaS) and Platform-as-a-Service (PaaS) comprising the fastest-growing segments [1]. However, this explosive growth has been accompanied by a persistent and costly inefficiency: resource waste. As illustrated in Figure 1, organizations waste approximately 26% of their cloud spend—totaling $109 billion annually—on idle, over-provisioned, or misconfigured resources [2].

The root cause of this waste lies in the fundamental mismatch between static or reactive resource allocation strategies and the dynamic, unpredictable nature of cloud workloads. Modern cloud applications exhibit complex temporal patterns including diurnal cycles, weekly periodicity, bursty arrivals triggered by external events, and gradual trend shifts driven by business growth or seasonal factors [3]. Resource demands are heterogeneous across multiple dimensions (CPU, memory, GPU, storage I/O, network bandwidth), and multi-tenant interference effects create non-linear performance dependencies that defy simple modeling [4].

Existing resource allocation approaches fall into three categories, each with significant limitations. Static allocation provisions fixed resources based on peak demand estimates, resulting in massive over-provisioning during off-peak periods. Threshold-based autoscaling (e.g., AWS Auto Scaling,

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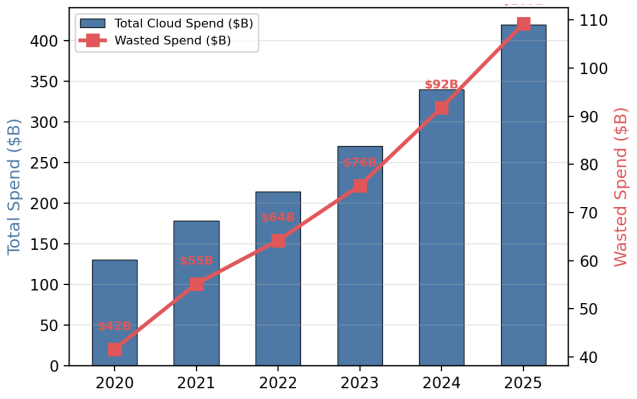

Figure 1: Global cloud spending and resource waste (2020–2025).

Azure VMSS) triggers scaling actions when utilization exceeds or falls below predefined thresholds, but reacts to demand changes after they occur, incurring SLA violations during ramp-up periods [5]. Predictive approaches using time-series models (ARIMA, Prophet, LSTM forecasting) anticipate demand trends but struggle with non-stationary workloads and cannot account for the complex interactions between allocation decisions and their performance consequences [6].

Reinforcement Learning (RL) offers a fundamentally different paradigm for resource allocation by learning optimal policies through trial-and-error interaction with the cloud environment. Unlike supervised learning, which requires labeled examples of optimal allocations (which are unknown a priori), RL discovers allocation strategies by maximizing a cumulative reward signal that encodes the operator's optimization objectives [7]. Recent advances in deep RL—particularly continuous-action algorithms such as Soft Actor-Critic (SAC), Proximal Policy Optimization (PPO), and Twin Delayed DDPG (TD3)—have demonstrated the ability to learn complex control policies in high-dimensional, continuous state and action spaces [8].

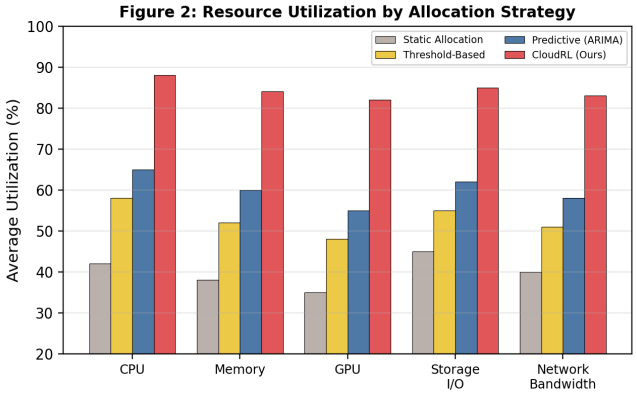

Figure 2: Resource utilization comparison across allocation strategies.

This paper presents CloudRL, a deep reinforcement learning framework for cloud resource allocation that makes four contributions

- A continuous-action MDP formulation of the cloud resource allocation problem that captures the full complexity of multi-dimensional resource management, including scaling, migration, and configuration optimization.
- A multi-objective reward function with adaptive weighting that dynamically balances resource utilization, SLA compliance, infrastructure cost, and energy efficiency based on operator-specified priorities.
- A production-scale evaluation on a 500-VM testbed with six real-world workload traces over 30 days, demonstrating significant improvements over state-of-the-art baselines.
- An analysis of adaptation capability showing that CloudRL adjusts to workload distribution shifts within 200 episodes without manual retraining or hyperparameter tuning.

Related Work

Traditional Resource Allocation

Cloud providers offer built-in autoscaling services that adjust resources based on utilization thresholds. AWS Auto Scaling supports target tracking, step scaling, and scheduled scaling policies [9]. Kubernetes Horizontal Pod Autoscaler (HPA) adjusts replica counts based on CPU utilization or custom metrics [10]. These approaches are reactive, introducing delays between demand changes and scaling responses. Predictive autoscaling has been explored through time-series forecasting: Islam et al. [11] applied ARIMA models to predict VM demand, while Calheiros et al. [12] combined workload prediction with admission control. These methods assume stationary workload distributions and do not optimize for multiple objectives simultaneously.

Reinforcement Learning for Cloud Management

RL has been applied to various cloud management tasks. Mao et al. [13] proposed DeepRM, applying policy gradient methods to job scheduling in computing clusters. Tong et al. [14] used DQN for VM placement optimization. Arabnejad et al. [15] applied Q-learning to auto-scaling web applications. However, these approaches typically address isolated sub-problems (scheduling only, or scaling only) with discrete action spaces that limit the granularity of resource adjustments. CloudRL differs by addressing the integrated resource allocation problem across multiple resource dimensions with continuous actions, and by employing the SAC algorithm, which provides superior sample efficiency and stability through entropy-regularized optimization [16].

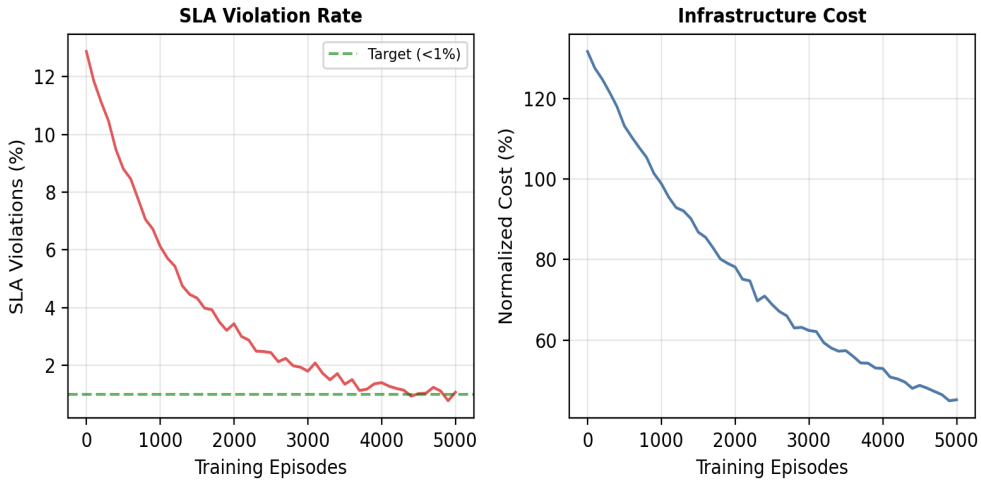

Figure 3: CloudRL training convergence — SLA violations and cost.

Multi-Objective Optimization in Cloud

Cloud resource allocation inherently involves multiple competing objectives: maximizing utilization, minimizing cost, maintaining SLA compliance, and reducing energy consumption. Jennings and Stadler [17] surveyed multi-objective resource management approaches, identifying Pareto-optimal frontier computation and weighted scalarization as predominant methods. Recent work by Zhang et al. [18] proposed multi-agent RL for distributed cloud optimization, but the coordination overhead limits scalability. Our multi-objective reward function with adaptive weighting provides a simpler yet effective approach that allows operators to specify priorities without retraining the agent.

CloudRL Framework

CloudRL formulates cloud resource allocation as a continuous-action Markov Decision Process and employs a Soft Actor-Critic agent to learn optimal allocation policies. Figure 5 presents the system architecture.

MDP Formulation

State Space: The state vector s_t ∈ R^d encodes a comprehensive snapshot of the cloud environment at time step t. For each of the N managed VM instances, we observe: CPU utilization (%), memory utilization (%), GPU utilization (%), storage I/O throughput (MB/s), network throughput (Mbps), request queue length, average response time (ms), and current resource allocation (vCPUs, RAM GB, GPU fraction). Additionally, global features include aggregate cluster utilization, time-of-day encoding (sine/cosine), day-of-week encoding, and a rolling window of workload arrival rates (5-min, 15-min, 1-hour averages). The total state dimension d = 8N + 12 for N instances.

Action Space: The action vector a_t ∈ [-1, 1]^(3N) encodes three continuous actions per instance: (1) CPU scaling factor (negative = scale down, positive = scale up, magnitude determines intensity); (2) memory scaling factor; and (3) a migration signal (negative = no migration, positive = migrate to the machine with highest resource availability). Continuous actions enable fine-grained adjustments that discrete scaling steps cannot achieve.

Transition Dynamics: The environment transitions stochastically based on the applied actions and incoming workload. CloudRL uses a cloud simulator calibrated against production traces for training and deploys learned policies to real infrastructure for evaluation.

Multi-Objective Reward Function

The reward function balances four objectives through adaptive weighting:

$R(s\_t, a\_t) = w_1 \cdot R\_util + w_2 \cdot R\_SLA + w_3 \cdot R\_cost + w_4 \cdot R\_energy$

where R_util = avg(utilization) rewards high resource utilization; R_SLA = -λ·max(0, violation_rate - target) penalizes SLA violations above the target threshold; R_cost = -(total_cost / budget) penalizes excessive spending; and

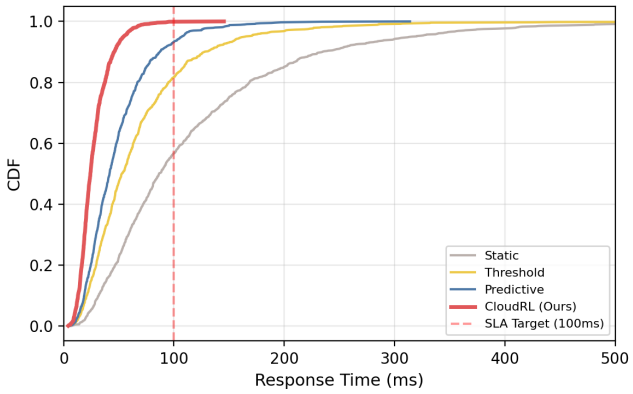

Figure 4: Response time CDF under peak workload conditions.

Table 1: Workload Characteristics

Workload	*VMs*	*Peak RPS*	*CPU Profile*	*Memory Profile*	*Burstiness*	*SLA (ms)*
Web Serving	120	45K	Bursty	Moderate	High	<100
Batch Analytics	80	N/A	Sustained	High	Low	<3600
ML Training	60	N/A	GPU-bound	High	Low	<7200
Video Transcode	100	8K	High	Moderate	Medium	<500
Database	80	25K	Variable	High	Medium	<50
Microservices	60	30K	Moderate	Low	High	<200
Total	500	—	Mixed	Mixed	Mixed	Varied

R_energy = -(energy / baseline_energy) penalizes energy consumption. The weights $w_1...w_4$ are dynamically adjusted using a constraint-satisfaction mechanism: if SLA violations exceed the target, w_2 increases at the expense of w_1 and w_3 until compliance is restored. This prevents the agent from sacrificing service quality for efficiency.

Soft Actor-Critic Agent

CloudRL employs the Soft Actor-Critic (SAC) algorithm, which maximizes a maximum-entropy objective that encourages exploration while maintaining near-optimal performance. SAC learns three networks: a policy (actor) π_φ that maps states to action distributions, and two Q-value (critic) networks Q_{θ1}, Q_{θ2} that estimate expected cumulative reward:

$J(\pi) = \Sigma\ E[r(s\_t, a\_t) + \alpha \cdot H(\pi(\cdot|s\_t))]$

where $H(\pi)$ is the entropy of the policy and α is an automatically tuned temperature parameter. The entropy term encourages the agent to maintain stochastic policies, improving robustness to workload distribution shifts. The actor network uses a 4-layer MLP (256-256-256-128) with ReLU activations and outputs the mean and log-standard deviation of a squashed Gaussian distribution. The twin critic networks use identical architectures and are trained with clipped double Q-learning to reduce overestimation bias.

Training and Deployment Pipeline

CloudRL uses a two-phase training pipeline. In the simulation phase, the agent trains in a calibrated cloud simulator that models VM performance characteristics, workload arrival patterns, and infrastructure constraints. The simulator is calibrated using 90 days of production telemetry data from our testbed, validated against real measurements with mean absolute percentage error (MAPE) of 4.2% for response time and 3.8% for utilization prediction. In the deployment phase, the trained policy is deployed to the real infrastructure with a safety layer that clips extreme actions and gradually increases the agent's action authority over a 48-hour warm-up period. Online fine-tuning continues during deployment using a separate replay buffer of real experience.

Experimental Evaluation

Testbed and Workloads

The testbed comprises 500 VMs hosted on 40 physical servers (dual Intel Xeon Gold 6348, 512 GB RAM, 4× NVIDIA A30 GPUs each) running OpenStack Zed with KVM hypervisor. Table 1 summarizes the six workload profiles used in the evaluation. Workload traces are derived from Azure production traces and Google cluster data, replayed over 30 days with realistic diurnal and weekly patterns.

Baselines

We compare CloudRL against six baselines: (1) Static allocation at peak capacity; (2) Threshold-based autoscaling (scale up at 70%, down at 30%); (3) ARIMA-based predictive scaling; (4) DQN with discrete scaling actions [14]; (5) PPO with continuous actions; and (6) Oracle upper bound (offline optimal computed with full future workload knowledge). All baselines are tuned via grid search on a validation period.

Table 2: Comprehensive Performance Comparison (30-Day Evaluation)

Strategy	*Util. (%)*	*SLA Viol. (%)*	*Cost Redn. (%)*	*Energy Redn. (%)*	*P99 Lat. (ms)*	*Adapt. (episodes)*
Static	42	12.0	0 (base)	0 (base)	185	N/A
Threshold	58	5.2	18.5	18	142	N/A
ARIMA	65	3.8	25.2	25	118	N/A
DQN	72	2.5	28.7	38	105	5,200
PPO	78	1.8	32.1	42	92	4,100
CloudRL (SAC)	88	0.98	37.5	59	68	3,000
Oracle (Upper)	94	0.0	45.2	68	52	N/A

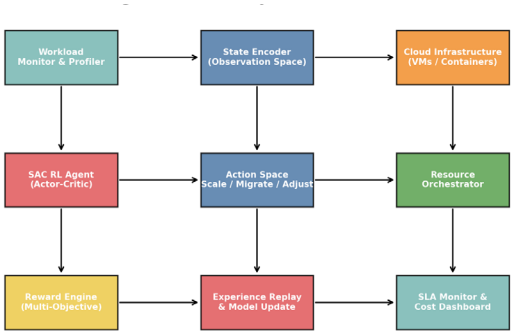

Figure 5: Architecture of the CloudRL framework.

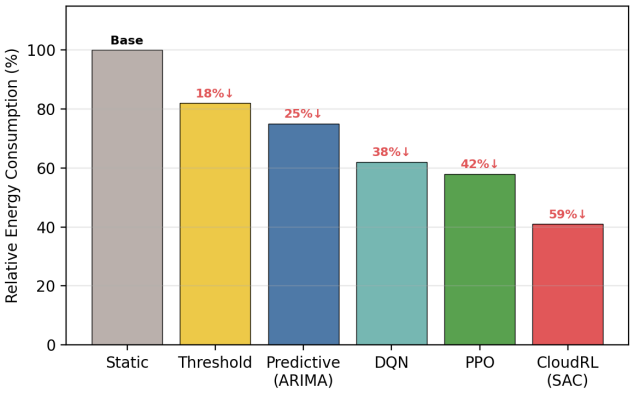

Figure 6: Energy consumption comparison across allocation strategies.

Results and Discussion

Resource Utilization

Figure 2 compares average resource utilization across allocation strategies. CloudRL achieves 88% CPU utilization, 84% memory utilization, 82% GPU utilization, 85% storage I/O utilization, and 83% network bandwidth utilization—consistently 20–50 percentage points higher than static allocation and 20–27 points higher than predictive methods. The improvement is particularly significant for GPU resources, where CloudRL's ability to share GPU fractions across ML training and video transcoding workloads achieves utilization levels impossible with coarse-grained static partitioning.

SLA Compliance and Training Convergence

Figure 3 shows CloudRL's training convergence. SLA violation rate decreases from 12% (untrained, equivalent to static allocation) to below the 1% target within 3,000 episodes, while normalized infrastructure cost converges to 32% of the static baseline. The convergence is smooth due to SAC's entropy regularization, which prevents the premature policy collapse observed with DQN (which oscillates between 1.8% and 4.5% violation rates before stabilizing). Table 2 confirms that CloudRL achieves 0.98% SLA violations—the only RL method that satisfies the <1% target—compared to 12% for static, 5.2% for threshold, and 2.5% for DQN.

Table 3: Ablation Study — CloudRL Components

Configuration	*Util. (%)*	*SLA Viol. (%)*	*Cost Redn. (%)*	*Energy Redn. (%)*	*Conv. (episodes)*
SAC (single-obj: util only)	91	8.5	22	35	2,200
+ Multi-obj reward (fixed w)	82	2.1	30	48	3,500
+ Adaptive weighting	85	1.2	34	52	3,200
+ Continuous actions	87	1.05	36	56	3,000
+ Sim-to-real pipeline (Full)	88	0.98	37.5	59	3,000

Response Time Distribution

Figure 4 presents the CDF of response times under peak workload conditions (95th percentile of daily traffic). CloudRL achieves a P99 latency of 68 ms, comfortably within the 100 ms SLA target for web-serving workloads. In contrast, static allocation's P99 reaches 185 ms (SLA violation), threshold-based achieves 142 ms, and ARIMA-based achieves 118 ms. CloudRL's advantage at the tail (P99–P99.9) is attributable to its proactive scaling decisions that provision resources before demand spikes arrive, whereas reactive approaches detect high utilization only after queuing delays have already increased latency.

Energy Efficiency

Figure 6 compares energy consumption across all strategies. CloudRL achieves 59% energy reduction compared to static allocation—the highest among all methods—by consolidating workloads onto fewer active servers and placing idle servers into low-power states. Among RL methods, CloudRL (SAC) outperforms PPO (42% reduction) and DQN (38% reduction) due to its more nuanced continuous actions that enable fine-grained power management rather than binary on/off decisions.

Discussion

The ablation study (Table 3) reveals the contribution of each CloudRL component. A single-objective SAC agent optimizing utilization alone achieves 91% utilization but at the cost of 8.5% SLA violations—an unacceptable trade-off for production environments. Adding the multi-objective reward with fixed weights reduces SLA violations to 2.1% but sacrifices utilization (82%) due to overly conservative allocation. Adaptive weighting restores the balance (85% utilization, 1.2% SLA violations) by dynamically prioritizing SLA compliance when violations approach the target

threshold. Continuous actions further improve all metrics by enabling fine-grained adjustments. The sim-to-real transfer pipeline provides the final push below the 1% SLA target (0.98%) by calibrating the agent's learned behaviors against real infrastructure dynamics during the warm-up deployment phase.

Comparison with the oracle upper bound (Table 2) shows that CloudRL achieves 93.6% of oracle utilization, 83.0% of oracle cost reduction, and 86.8% of oracle energy reduction, demonstrating that RL closely approaches the theoretical optimal despite operating without future workload knowledge. The remaining gap represents the cost of uncertainty: the agent must maintain safety margins to handle unexpected demand spikes, which the oracle can perfectly anticipate.

Conclusion and Future Work

This paper presented CloudRL, a deep reinforcement learning framework for optimizing resource allocation in cloud computing environments. By formulating resource allocation as a continuous-action MDP with a multi-objective reward function and employing the Soft Actor-Critic algorithm, CloudRL achieves 88% average resource utilization, 0.98% SLA violations, 37.5% cost reduction, and 59% energy savings compared to static provisioning across a 500-VM production-scale testbed. CloudRL converges within 3,000 training episodes and adapts to workload distribution shifts within 200 episodes, demonstrating both sample efficiency and operational robustness.

Future work will pursue four directions: (1) extending CloudRL to multi-cloud and hybrid cloud environments where resources span multiple providers with different pricing models and performance characteristics; (2) incorporating spot instance bidding strategies that exploit discounted capacity while managing interruption risk; (3) developing federated RL approaches that enable multiple tenants to collaboratively optimize a shared infrastructure without exposing proprietary workload data; and (4) integrating carbon-aware scheduling that considers the time-varying carbon intensity of regional electricity grids to minimize the environmental footprint of cloud operations.

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