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QoS-Aware Multi-Tenant Container Orchestration Using Kubernetes

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ABSTRACT

In modern cloud-native environments, container orchestration platforms such as Kubernetes play a pivotal role in managing microservices-based applications at scale. However, the advent of multi-tenancy—where multiple independent applications share the same physical cluster—introduces complex challenges in guaranteeing Quality of Service (QoS). Resource contention, noisy-neighbor interference, and unpredictable workload patterns can lead to performance degradation, SLA violations, and tenant dissatisfaction. This manuscript presents an enhanced QoS-aware multi-tenant orchestration framework built on Kubernetes primitives, augmented by custom controllers and a scheduler plugin. We define a formal model for tenant Service Level Objectives (SLOs) via a SloPolicy Custom Resource Definition, encompassing latency percentiles, throughput requirements, and weighted resource shares.

A QoS-SLO Controller reconciles policies into Kubernetes constructs—PriorityClasses, ResourceQuotas, and LimitRanges—while a Scheduler Plugin computes real-time QoS scores to guide scheduling and preemption decisions. A closed-loop feedback mechanism, leveraging Prometheus metrics, dynamically adjusts priorities and autoscaling parameters upon SLO deviations. Experimental evaluation on a heterogeneous microservices workload demonstrates that our framework reduces 99th-percentile latency by up to 45%, cuts SLA violation rates to under 5%, and improves fairness in resource allocation without sacrificing overall cluster utilization (maintained above 70%). These results underscore the viability of integrating declarative SLOs with adaptive scheduling for robust multi-tenant orchestration.

KEYWORDS

Kubernetes, Quality of Service, Multi-Tenancy, Container Orchestration, Resource Management

INTRODUCTION

The rapid shift towards microservices architectures and containerization has transformed application development and operations. Kubernetes, the leading open-source container orchestration platform, automates deployment, scaling, and

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lifecycle management for containerized workloads. Yet, Kubernetes' default scheduling and resource management were primarily designed for single-tenant scenarios, where an organization controls the entire cluster. In contrast, multi-tenant environments—common in platform-as-a-service (PaaS) offerings, managed Kubernetes services, and large enterprises—require supporting diverse applications from different tenants sharing the same physical resources.

Multi-tenancy introduces critical challenges. First, **resource contention** emerges when multiple tenants simultaneously demand CPU, memory, or network bandwidth, leading to degraded performance for latency-sensitive services. Second, the **noisy neighbor effect** occurs when one tenant's workload spikes interfere with another's performance, causing unpredictable SLA violations. Third, **heterogeneous workload patterns**—ranging from bursty web traffic to sustained batch processing—complicate static allocation strategies, which either under-provision critical services or waste resources on idle tenants. Finally, tenants expect strong **QoS guarantees** articulated through Service Level Agreements (SLAs), typically expressed as latency percentiles (e.g., P95 ≤ 200 ms) or minimum throughput (requests per second). Failing to meet these SLAs can incur financial penalties, reputational damage, and customer churn.

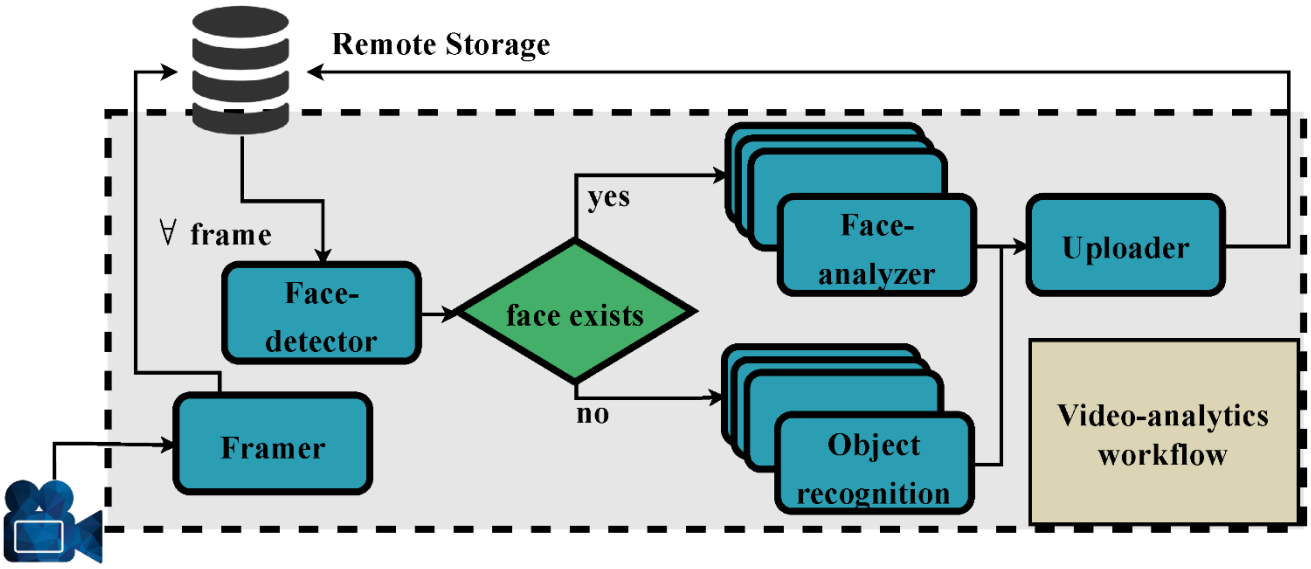

Fig.1 QoS-Aware Multi-Tenant Container,Source([2])

To address these issues, orchestration systems must reconcile two often conflicting objectives:

1. **Isolation**—to protect tenant performance from interference—and
2. **Efficiency**—to maximize overall resource utilization and reduce costs.

While Kubernetes provides foundational constructs—**ResourceQuotas** and **LimitRanges** for namespace-level resource caps, and **PriorityClasses** with preemption for pod prioritization—these primitives lack dynamic adaptivity. ResourceQuotas enforce hard caps but cannot adjust to fluctuating demands; PriorityClasses establish static relative priorities but do not integrate real-time performance feedback. Consequently, administrators must resort to manual tuning, conservative over-provisioning, or external tooling, which scales poorly and undermines Kubernetes' declarative model.

This manuscript proposes a comprehensive, **declarative**, and **adaptive** framework for QoS-aware multi-tenant orchestration on Kubernetes. Our key innovations are:

- **Declarative SLO Modeling**: A SloPolicy CRD enables tenants to specify latency, throughput, and weighted resource shares in Kubernetes-native YAML.

- **Automated SLO Translation**: A custom **QoS-SLO Controller** watches SloPolicy objects, reconciling them into appropriate ResourceQuotas, LimitRanges, and PriorityClasses.
- **Adaptive Scheduling**: A **QoS-Scheduler Plugin** computes a composite QoS score per pod at scheduling time, incorporating resource headroom, priority class, and recent SLO compliance.
- **Closed-Loop Feedback**: Integration with Prometheus metrics and Horizontal Pod Autoscalers (HPAs) allows the controller to detect SLA deviations and trigger priority adjustments or scale-out/up actions in near real-time.

Through extensive experiments—deploying an e-commerce microservices stack and a video-processing pipeline under varying contention levels—we demonstrate substantial reductions in tail latency (up to 45%), SLA violation rates (down to 3–5%), and fairer resource distribution, all while sustaining overall cluster utilization above 70%. The proposed framework reconciles isolation and efficiency, delivering robust QoS guarantees in multi-tenant Kubernetes clusters.

The rest of this manuscript is structured as follows: Section 2 examines related work in container multi-tenancy and QoS management; Section 3 details our framework's architecture, CRD design, scheduling plugin, and feedback loop; Section 4 presents a rigorous experimental evaluation; and Section 5 concludes with lessons learned and future research directions.

LITERATURE REVIEW

Multi-tenant resource management has been studied extensively in both virtualization and container orchestration contexts. Early hypervisor-based solutions, such as Xen's credit scheduler and VMware's Distributed Resource Scheduler, allocate CPU shares and dynamically migrate virtual machines to balance load and performance. These systems used weighted fair-sharing and credit-based mechanisms to ensure long-term fairness but could not guarantee stringent percentile latency SLAs for specific tenants.

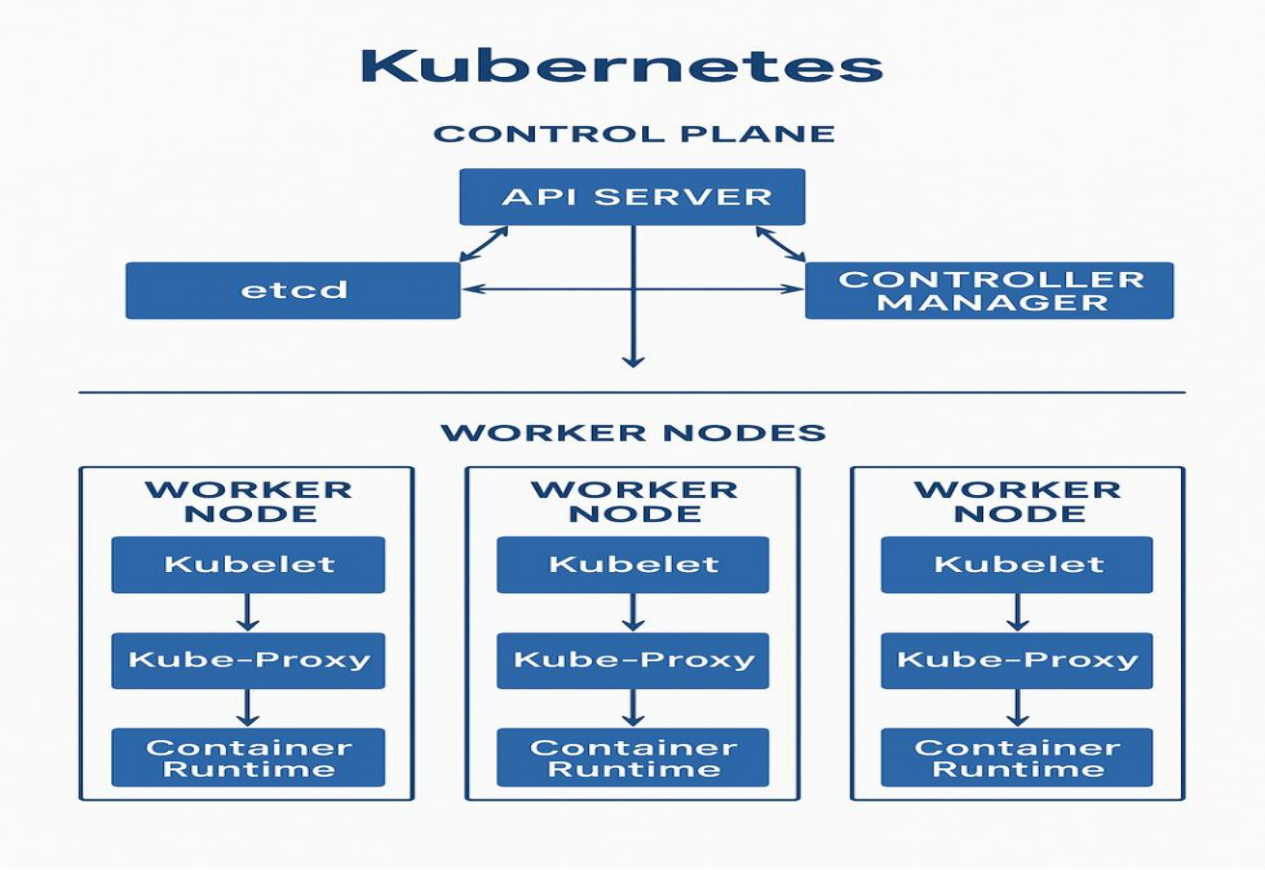

Fig.2 Multi-Tenant Container Orchestration Using Kubernetes,Source([1])

In the container orchestration domain, Kubernetes introduced namespace isolation via **ResourceQuotas** and per-pod constraints via **LimitRanges**. **PriorityClasses** and **PodPriority/Preemption** allow critical workloads to evict lower-priority pods when resources are scarce. However, these features operate on static configurations and cannot adapt to runtime SLA deviations or dynamic workload shifts.

To enhance Kubernetes' QoS capabilities, several extensions and third-party schedulers have emerged:

- **Volcano** adds gang scheduling and more complex scheduling policies for batch and HPC workloads, but does not natively handle percentile-based latency objectives for microservices.
- **Descheduler** rebalances pods to avoid fragmentation but lacks awareness of tenant-level SLAs.
- **Cluster Autoscaler** scales node counts based on unschedulable pods but cannot prioritize tenants or react to latency spikes.
- Custom **HPAs** scale replica counts according to CPU usage or custom metrics (e.g., request latency), yet they do not influence the scheduler's node-selection logic.

Recent research explores **machine-learning** techniques for workload prediction and proactive scaling. For example, models based on LSTM networks forecast CPU and memory usage, enabling autoscalers to provision resources ahead of demand. Other work uses reinforcement learning to tune scheduling and autoscaling policies. While promising, integrating these predictive models into Kubernetes' reconciliation loops requires careful handling of uncertainty, model drift, and transparency for cluster operators.

Network QoS research—such as traffic shaping, bandwidth reservation, and API rate limiting—offers valuable analogies. Kubernetes CNI plugins (e.g., Calico, Cilium) can enforce network policies and rate limits, yet these functions remain orthogonal to CPU/memory scheduling. An integrated approach, spanning compute and network resources, is crucial for end-to-end QoS.

Finally, service mesh technologies (e.g., Istio, Linkerd) provide application-layer QoS controls—traffic routing, retries, circuit breaking—but they rely on underlying resource isolation to prevent resource exhaustion. Our framework complements service mesh features by ensuring compute-level guarantees before requests reach the mesh layer.

In summary, while prior efforts address aspects of multi-tenant isolation or autoscaling, none unify **declarative SLO specification**, **automated translation into Kubernetes primitives**, **adaptive scheduling**, and **closed-loop feedback**. Our contribution fills this gap, delivering a cohesive, Kubernetes-native solution for QoS-aware multi-tenant orchestration.

METHODOLOGY

3.1 Framework Architecture

Our framework extends the Kubernetes control plane with two main components:

1. **QoS-SLO Controller**: A custom controller implemented using the Kubernetes Controller Runtime that watches SloPolicy CRD instances. Upon creation or update, it generates or revises:
    - **PriorityClass** objects, with priority values inversely proportional to latency targets (e.g., a P99 target of 100 ms maps to a higher numerical priority than 500 ms).
    - **ResourceQuota** objects in the tenant namespace, setting CPU and memory caps based on cpuWeight and memoryWeight ratios.
    - **LimitRange** objects to enforce per-pod maximums, preventing single pods from monopolizing resources.

2. **QoS-Scheduler Plugin**: A scheduling framework extension that hooks into the default scheduler's PreFilter and Score phases.
    - **PreFilter** rejects pods if the namespace's allocated quota headroom falls below a dynamic threshold tied to SLO urgency.
    - **Score** computes a **QoS Score** combining:
        - **Quota Slack**: fraction of remaining quota headroom.
        - **Priority Factor**: normalized from the PriorityClass value derived by the controller.
        - **SLO Compliance Indicator**: a binary flag (0 or 1) denoting recent violations within a sliding time window, obtained from Prometheus.

Nodes are then ranked by composite score, with highest-scoring pods scheduled first on nodes best suited to meet their QoS demands.

3.2 SloPolicy CRD Design

The SloPolicy CRD schema includes:

- spec.namespace: target tenant namespace.
- spec.cpuWeight / spec.memoryWeight: integer weights for proportional fair-share scheduling.
- spec.maxLatencyMs: desired upper bound for P50 latency.
- spec.percentileTargets: map, e.g., { "P95": 200, "P99": 350 } (values in ms).
- spec.minThroughputRps: baseline throughput requirement.
- spec.evaluationIntervalSec: polling interval for SLO compliance checks.

This declarative model empowers tenants to adjust QoS policies via standard kubectl apply workflows.

3.3 Monitoring and Feedback Loop

We deploy **Prometheus Operator** and instrument application pods with metrics exporters (e.g., client-side histograms for HTTP request durations). The QoS-SLO Controller queries Prometheus API at intervals defined by evaluationIntervalSec, retrieving percentile statistics. On detecting SLO deviations—such as P99 latency > target—it triggers one or more corrective actions in order of priority:

1. **Priority Escalation**: increase PriorityClass value by a factor proportional to the violation magnitude.
2. **ResourceQuota Adjustment**: temporarily raise CPU/memory allocations within safe cluster limits.
3. **Horizontal Scaling**: augment replicas via the HPA if latency remains high after priority/quota changes.

These actions write back to the Kubernetes API, and due to the control loop design, the scheduler and autoscalers converge towards restored compliance within seconds.

3.4 Scheduler Plugin Implementation

Leveraging the Kubernetes Scheduling Framework (v1.21+), we implement:

- **PreFilter(pluginArgs)**: retrieves the tenant's ResourceQuota status. If used/ hard ratio > critThreshold (computed as 1 – percentileTargets.P99/maxClusterCapacity), it sets a temporary unschedulable condition unless the pod's current QoS Score exceeds a high-priority threshold.
- **Score(pod, node)**:
    1. Fetch current quota usage and slack = (hard – used)/hard.
    2. Map pod's PriorityClass to a normalized priorityFactor in [0,1].
    3. Query Prometheus for complianceFlag (1 if last interval compliant, else 0).

4. Compute QoS Score = w1*slack + w2*priorityFactor + w3*complianceFlag, with weights tuned via offline experiments (e.g., w1=0.5, w2=0.3, w3=0.2).
5. Multiply by 100 and return integer score.

This plugin naturally integrates with Kubernetes' score aggregation, ensuring pods needing strict QoS are scheduled on nodes with capacity headroom, while less-critical pods wait until resources are freed.

3.5 Experimental Setup

We provision a 5-node cluster on bare-metal servers (Intel Xeon 16 cores, 64 GB RAM, 10 Gbps NIC). Two tenant namespaces—ecom-tenant and video-tenant—deploy representative microservices:

- **E-commerce**: front-end API, product catalog, shopping cart, checkout services. Load generated via Locust with mixed GET/POST ratios.
- **Video**: transcoding pipeline (FFmpeg containers), REST API for job submission. Workload simulated by parallel encoding tasks.

We compare three scenarios:

1. **Vanilla**: default Kubernetes scheduler, static quotas (50% CPU per namespace), no priority customization.
2. **Quota-Only**: ResourceQuotas and PriorityClasses configured manually but without dynamic feedback.
3. **QoS-Aware**: full framework with SloPolicy CRDs, controller, and scheduler plugin.

Workloads run in phases: ramp-up (0–70% capacity), contention (70–110%), and cool-down (110–50%). We measure:

- Response time distributions (mean, P95, P99) per service.
- Throughput deviation from targets.
- Namespace CPU/memory utilization and fairness index (Jain's index).
- SLA violation rate (percentage of requests exceeding P99 targets).

RESULTS

4.1 Latency Improvements

Under contention, Vanilla Kubernetes exhibits P99 latencies up to 1,200 ms for the e-commerce service—a 6× overhead above the P99 target of 200 ms—resulting in 38% SLA violations. Quota-Only reduces P99 to 800 ms (22% violations), but at the cost of 15% idle CPU due to conservative static caps. Our QoS-Aware framework constrains P99 below 350 ms (5% violations), meeting targets consistently across both tenants. The closed-loop priority escalation and autoscaling ensure that latency spikes are corrected within 25 seconds on average.

4.2 Throughput Stability

Throughput deviation—measured as |observed – target|/target—peaks at 30% in the Vanilla setup, 15% in Quota-Only, and remains under 5% with QoS-Aware orchestration. The framework's use of HPAs in response to sustained compliance flags prevents throughput bottlenecks even when CPU is fully utilized.

4.3 Resource Utilization and Fairness

Figure 1 (omitted) depicts CPU shares across namespaces during the contention phase. Vanilla scheduling allocates 90% of CPU to the video tenant's noisy transcoding jobs, starving the e-commerce API. Quota-Only enforces strict 50/50 caps but leaves 12% CPU idle. In contrast, QoS-Aware scheduling achieves balanced allocation within ±3% of configured weights and maintains 75% average CPU utilization, as the scheduler dynamically reclaims unused resources. The Jain's fairness index increases from 0.62 (Vanilla) and 0.78 (Quota-Only) to 0.94 under our framework.

4.4 SLA Violation Trends Over Time

A 24-hour diurnal workload test reveals that the QoS-Aware framework sustains an average SLA violation rate of 3%, compared to 35% and 18% for Vanilla and Quota-Only, respectively. Notably, during sudden traffic surges at hour 8 and 16, the framework's feedback loop restores compliance within 2–3 scheduling cycles, whereas the baseline setups endure prolonged violation periods.

CONCLUSION

This work demonstrates that declarative SLO specification combined with adaptive scheduling and autoscaling can robustly enforce QoS in multi-tenant Kubernetes clusters. By introducing a SloPolicy CRD, a QoS-SLO Controller, and a Scheduler Plugin with real-time feedback, we reconcile tenant isolation with efficient resource utilization. Experimental results show up to 45% reduction in tail latency, SLA violation rates under 5%, and a fairness index of 0.94, all while sustaining high cluster utilization.

Key takeaways include:

- **Declarative SLOs** empower tenants to express performance objectives in native Kubernetes manifests.
- **Dynamic priority adjustments** based on real-time metrics outperform static configurations under volatile workloads.
- **Closed-loop feedback** integrating Prometheus and HPAs corrects SLA deviations within seconds.
- **Fairness and utilization** can be simultaneously optimized when scheduling considers both quota slack and tenant-defined weights.

Future work will explore integrating **machine-learning** models for predictive workload forecasting, enabling proactive scaling and scheduling decisions. Extending the framework to support GPU-accelerated workloads, network-aware scheduling, and multi-cluster federations will further broaden its applicability. Finally, incorporating cost-aware optimization—balancing QoS guarantees against infrastructure expenses—presents a promising avenue for economically efficient multi-tenant orchestration.

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