# Objective

To intelligently and autonomously optimize CPU and memory resource limits for multiple microservices deployed in a Kubernetes environment, such that:

Application latency remains within acceptable bounds, defined as no more than certain percentage of degradation from the service-specific baseline latency under normal load.

Resource configurations adapt dynamically and continuously, without relying on statically defined Critical Reduction Points (CRPs) or manual tuning thresholds.

# Expanded Sub-Objectives

1. Resource Efficiency

* Reduce overprovisioning of CPU and memory requests/limits.
* Automatically discover and apply the minimum safe resources required to meet Service-Level Objectives (SLOs), thereby minimizing infrastructure costs.

1. SLA Adherence

* Continuously ensure that latency does not exceed a certain amount of the baseline latency observed at initial overprovisioned levels.
* Latency-aware adjustments must be consider individual behavior and load profiles.

1. Dynamic & Continuous Adaptation

* Adjust CPU and memory resource limits at runtime based on real-time telemetry (e.g., latency, request rates, usage).
* Avoid one-time profiling or offline stress testing; instead, leverage on-the-fly observations for decision-making.

1. Online Learning Without CRPs

* Replace CRP-based static analysis (which identifies “safe-to-reduce” breakpoints) with adaptive feedback control that responds continuously to observed performance impacts.
* Learn the performance/resource tradeoff implicitly over time through interaction with the system and feedback loops.

1. Service and Multi-Stage Optimization

* Support microservices with potentially diverse performance/resource characteristics.
* Allow the system to generalize and specialize across services without manual tuning heuristics.

## Overall Strategy

Instead of relying on statically identified Critical Reduction Points (CRPs) - which are brittle, labor-intensive to compute, and specific to individual services - this strategy embraces a dynamic, learning-driven control approach. It continuously adjusts resource limits based on real-time feedback, learned performance patterns, and SLA-aware policies.

This approach centers on three pillars:

**1. Online Learning of Performance–Resource Relationships**

Rather than conducting offline profiling or defining "safe" thresholds (e.g., the lowest CPU limit before latency spikes), we let the system learn how resource allocations affect performance in real-time:

* Continuously observe metrics, including:
  + CPU and memory usage
  + CPU and memory limits
  + P95/P99 Latency
* Build lightweight predictive models (e.g., regression trees, online linear models, or streaming learners likeRiver) that estimate:
  + How changes in CPU/memory limits are likely to impact latency  
    What resource setting is likely to meet the latency target under current load
* These models are continuously retrained as new data arrives, allowing the system to adapt to workload shifts, code changes, or traffic anomalies without human intervention.

**Example:** If the model observes that reducing memory from 512Mi to 384Mi causes only a 2% latency increase during normal load, it registers this as a safe trade-off and continues testing smaller limits.

**2. SLA-Aware Dynamic Feedback Control**

This layer acts like a closed-loop controller: it makes adjustments to resource settings and observes the impact, treating the system as a black box.

* At regular intervals (e.g., every 5–10 minutes), the controller:
  + Proposes small, controlled changes (e.g., reduce CPU limit by 100m)
  + Observes resulting performance impact (especially latency)
  + Evaluates change with respect to defined SLA boundaries (e.g., "latency must remain within 20% of baseline")
* **Positive feedback loop**:
  + If latency remains within acceptable bounds, and usage stays below limit → further reduce resources.
  + If latency improves or remains stable → keep reducing in smaller steps.
* **Negative feedback loop**:
  + If latency spikes beyond the SLA threshold → revert to previous settings and reduce step size.
  + If utilization becomes dangerously close to limits (e.g., CPU throttling begins) → increase limits slightly.

This forms a hill-climbing optimization loop with built-in safety mechanisms:

* The system climbs "down" in resource usage until it hits a boundary (latency breach).
* Then it rolls back slightly and tries smaller or orthogonal adjustments (e.g., reduce memory instead of CPU).

**3. Reward-Based Control System (Reinforcement Learning Agent)**

To further enhance the system’s intelligence, a Reinforcement Learning (RL) agent can be introduced. The agent learns from trial and error over time, gradually optimizing its policy to achieve long-term goals:

* **State Space**:
  + Current CPU and memory limits
  + Current CPU and memory usage
  + Observed P95 latency
  + Request rate or concurrency
  + Historical deltas (e.g., last adjustment and result)
* **Action Space**:
  + Increase, decrease, or hold CPU/memory limits (individually or jointly)
  + Adjust in small, medium, or large steps
* **Reward Function** (carefully crafted to balance goals):
  + **Positive reward** for resource savings (smaller limits, especially if underutilized)
  + **Negative reward** for SLA violations (latency > 1.2× baseline)
  + **Moderate penalty** for being too conservative (underutilization + no cost benefit)
  + **Bonus** for stability and minimal oscillations (reducing thrashing)
* The RL agent can be implemented using frameworks like Stable-Baselines3 (PPO/DDPG agents) or Ray RLlib, and it can be:
  + **Trained in a simulated environment** (using historical data or performance models)
  + **Fine-tuned in production**, continuously improving from live feedback

Over time, the RL agent develops sophisticated, service-specific optimization policies that outperform static heuristics or hand-coded strategies.

**Example**: The RL agent may learn that during peak traffic hours, reducing CPU leads to SLA violations, but memory can be trimmed — and vice versa at night.

## Summary of Overall Strategy

By combining these three components, the system forms a self-improving, SLA-aware, CRP-free resource optimizer that:

* Adjusts limits with high granularity and safety
* Learns from its own behavior
* Improves over time, even under evolving workloads
* Eliminates the need for manually defined "safe reduction points"

This architecture mirrors human intuition: observe → act → learn → refine — but at machine speed and scale.

### **Data Collection Module**: Real-Time Observability Backbone

To enable dynamic resource optimization, our system must continuously collect key runtime metrics - even from services that aren’t natively instrumented for Prometheus. This module acts as the data foundation for all learning, feedback, and control components.

**Goals**

* Observe CPU and memory usage vs. limits
* Measure latency per request (P95 or average)
* Monitor request load (rate, concurrency)

All without requiring internal application changes or native Prometheus instrumentation.

**Core Metrics to Collect**

1. CPU and Memory Usage + Limits

What to track:

* CPU usage: in millicores (mCPU)
* Memory usage: in bytes (working set, RSS)
* CPU limit and Memory limit per container

How to collect without app instrumentation:

* Use Kubernetes-native telemetry:
  + cAdvisor (via kubelet) collects container-level usage metrics.
  + Prometheus scrapes from kubelet, kube-state-metrics, or node-exporter.

Key Prometheus metrics:

* Container\_cpu\_usage\_seconds\_total
* Container\_memory\_working\_set\_bytes
* Kube\_pod\_container\_resource\_limits\_cpu\_cores
* Kube\_pod\_container\_resource\_limits\_memory\_bytes

These allow us to:

* Detect overprovisioning (usage << limit)
* Identify throttling risks (usage ~ limit)
* Feed usage-efficiency into RL/ML reward functions

1. Latency per Request (P95 or average)

**Problem**: Our applications do not expose latency metrics.

**Solution**: Use sidecar proxies, service mesh, or ingress controllers to externally observe and emit latency metrics - no code changes required.

Approaches:

**Option A: Envoy Proxy / Istio Sidecar**

* Add Istio or standalone Envoy as a sidecar proxy to each service.
* Envoy tracks per-request latency and emits metrics in Prometheus format.

*Sample Envoy metric:*envoy\_cluster\_upstream\_rq\_time\_bucket

*Then compute latency percentiles using PromQL:* histogram\_quantile(0.95, rate(envoy\_cluster\_upstream\_rq\_time\_bucket[5m]))

**Option B: Ingress Controller (NGINX, Traefik)**

* If all external traffic flows through a single ingress (e.g., NGINX), enable its Prometheus module to export:
  + Request durations
  + Response codes
  + Request counts
* This provides coarse-grained latency and load data without touching internal services.

**Option C: OpenTelemetry Collector Sidecar**

* Deploy an OpenTelemetry collector as a sidecar alongside each app.
* It can sniff traffic and record:
  + Latency
  + Throughput
  + Errors
* Pushes data to Prometheus or another backend (e.g., Tempo, Jaeger)

1. Load Monitoring (Request Rate and Concurrency)

What to track:

* Request rate (requests per second)
* Concurrency (in-flight requests)

**Collection methods**:

I. Sidecar proxies (Envoy, Istio) again prove helpful here:

* Track how many requests per second go to each backend.
* Track how many are active simultaneously.

Example Prometheus metrics:

* rate(envoy\_cluster\_upstream\_rq\_total[1m])
* envoy\_http\_downstream\_rq\_active

Ii. Ingress metrics:

* If requests go through a single entrypoint (e.g., NGINX):
  + nginx\_ingress\_controller\_requests
  + nginx\_ingress\_controller\_request\_duration\_seconds\_bucket

These load metrics let the optimizer correlate latency/resource usage with traffic intensity, enabling intelligent scaling and adaptation.

#### Tooling Stack

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| --- | --- |
| Tool | Role |
| Prometheus | Scrapes kubelet, cAdvisor, sidecars, ingress, etc. |
| Grafana | Visualizes resource/latency/load trends |
| Envoy/Istio | Captures latency/load without app code |
| OpenTelemetry Collector | Optional: collect and forward latency spans or metrics |
| kube-state-metrics | Exposes current resource limits/requests for all pods |
| Node Exporter / Kubelet | Provides node- and pod-level resource usage |

##### Summary

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| --- | --- | --- |
| **Metric** | **Source** | **Description** |
| CPU/Memory Usage | cAdvisor, kubelet | Native Kubernetes metrics from nodes |
| CPU/Memory Limits | kube-state-metrics | Declared values in pod specs |
| Latency (P95/P99) | Envoy / Istio / NGINX | Observed at proxy/ingress layer |
| Request Rate | Envoy / NGINX / Traefik | Measured at entry point or sidecar |
| Concurrency | Envoy / OpenTelemetry | Active connections or spans |

### 2. Online ML Predictor Using DARE(Dynamic Adaptive Resource Estimater) Architecture

The Online ML Predictor based on the DARE model is a continuously learning and adapting module that eliminates the need for explicitly identifying CRPs (Critical Reduction Points). Instead, it intelligently learns patterns and predicts the optimal CPU and memory resource limits based on real-time observations of load and latency — while staying within SLA boundaries.

**Primary Goals**

* Predict the "next safe step" for adjusting CPU and memory limits under the current load.
* Estimate the risk of latency degradation for each candidate resource configuration.
* Continuously learn from live traffic, gradually improving predictions.
* Adapt to changing usage patterns, workloads, and traffic profiles without retraining from scratch.

#### Architecture Overview (DARE)

The DARE-based predictor has three key components:

1. **Trend Learners (TL)**

The Trend Learners (TL) component is the foundational intelligence layer of the DARE system. Its job is to model, track, and predict how microservice resource consumption evolves over time, under varying load conditions. It doesn’t just react to spikes or drops in usage — it proactively learns temporal trends and estimates safe operating zones, which is essential for stable and efficient resource management.

Trend Learners use online regression models or Exponential Moving Average (EMA)-enhanced predictors to learn the mapping:

(Current Load Conditions) ⟶ (Resource Requirements)

This includes:

* How CPU and memory usage scale with changes in incoming request rate.
* Whether the current limits are higher or lower than needed (overprovisioning vs underprovisioning).
* How fast or slowly the resource demand is trending (e.g., is memory steadily increasing, or spiking erratically?).

### Model Types:

The TL can be implemented using:

1. **Online Linear Regression**

A continuously updating linear model such as:

CPU\_usage(t) ≈ a₁ \* RequestRate(t) + b₁

Memory\_usage(t) ≈ a₂ \* RequestRate(t) + b₂

Weights a₁, a₂, b₁, and b₂ are updated at each time step using stochastic gradient descent (SGD) or recursive least squares.

1. **EMA-Augmented Models**

To smooth noise and provide more stable predictions:

EMA\_CPU(t) = α \* CPU\_usage(t) + (1 - α) \* EMA\_CPU(t-1)

These models:

* Smooth out short-term fluctuations
* Highlight sustained trends in usage
* Are lightweight, perfect for edge or in-cluster deployment

#### Inputs:

The TL takes as input the raw usage and limit metrics, which are either collected through a Prometheus exporter or pulled directly from Kubernetes metrics APIs:

* CPU\_usage(t): Actual CPU usage in millicores
* Memory\_usage(t): Actual memory usage in MiB
* RequestRate(t): Number of incoming requests per second or minute
* CPU\_limit(t) and Memory\_limit(t): The current configured resource limits in Kubernetes

Optionally, we may also include:

* Time of day (to capture diurnal patterns)
* Recent request rate deltas (to spot load surges)

#### Outputs:

The TL provides two critical outputs:

**1. Estimated Future Usage:**

It forecasts what the CPU and memory usage are likely to be in the near future, e.g., 5–10 minutes ahead, under the assumption that the load trend continues.

This forecast supports proactive decisions like:

* “Usage is trending upward; we should avoid cutting resources now.”
* “Usage is declining and stable; we can try stepping down the limits.”

**2. Safe Resource Range Suggestions:**

Based on the forecasted usage and past adjustment outcomes, the TL outputs a range of recommended CPU and memory values:

* Minimum Safe CPU (e.g., 300m)
* Maximum Safe CPU (e.g., 500m)
* Minimum Safe Memory (e.g., 400Mi)
* Maximum Safe Memory (e.g., 600Mi)

These ranges provide flexibility for the decision engine to choose from — potentially selecting tighter or looser margins based on risk.

#### Use Case Example:

Let’s say at time t:

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| --- | --- |
| **Metric** | **Value** |
| CPU Usage | 250m |
| CPU Limit | 500m |
| Request Rate | 300 rps |
| Memory Usage | 500Mi |
| Memory Limit | 800Mi |

The Trend Learner notices:

* CPU usage is stable and dropping by 10m per 5-minute interval
* Memory usage is slowly increasing by 15Mi per interval
* Request rate is stable

**Forecasted Next Usage:**

* CPU: 240m
* Memory: 515Mi

**Suggested Range:**

* CPU: 260–300m
* Memory: 520–600Mi

This tells the decision engine: "You’re overprovisioned. It’s safe to reduce CPU and memory limits slightly, but keep an eye on memory."

#### How TL Improves Adaptivity:

* **Learns per-microservice trends** — instead of assuming uniform behavior
* **Reduces risk of overreacting** to one-off spikes or dips
* **Enables intelligent step sizing** — instead of fixed increments, step sizes are informed by trend slopes

**Why Online Regression Models?**

**1. Incremental Learning in Real Time**

Unlike batch learning models (e.g., traditional linear regression), online regression models update their parameters continuously as new data arrives. This is essential for Kubernetes environments where:

* Workloads shift frequently (e.g., due to time of day or traffic surges),
* We can’t afford to retrain models offline repeatedly,
* We need low-latency model updates.

**Why it matters**: We get a constantly adapting model that keeps pace with live system behavior.

**2. Lightweight & Efficient**

Online regressors (like SGDRegressor in scikit-learn, or River's online models) are memory-efficient, require low compute, and can run:

* On the same node as the application,
* In a sidecar container,
* Or in a lightweight central controller.

**Why it matters**: Ideal for resource-constrained or distributed environments typical of Kubernetes.

**3. Interpretability**

Online linear models are easy to interpret:

* We can see the coefficients for features like request rate or CPU usage,
* We know exactly how each metric influences predicted future usage or resource requirements.

**Why it matters**: This helps with debugging, tuning, and trust in the system — especially in production.

**4. Direction + Rate of Change (i.e., Trend)**

These models can naturally learn both:

* **Direction** of usage (↑ or ↓),
* **Speed** (e.g., 50m CPU increase per 10 rps).

**Why it matters**: It helps in proactive decisions like: “Reduce memory soon — usage is slowly dropping.”

**Why Exponential Moving Average (EMA)?**

**1. Smooths Out Noisy Metrics**

Usage data in Kubernetes (especially for latency or memory) is often spiky due to:

* GC events,
* JIT warm-ups,
* Bursty traffic.

EMA applies exponential decay, giving more weight to recent data, and less to old data:

EMA(t) = α \* x(t) + (1 - α) \* EMA(t-1)

where α is a smoothing factor.

**Why it matters**: Reduces false triggers caused by outliers or short-lived spikes.

**2. Very Low Computational Cost**

EMA is cheap to compute — just one multiplication and one addition per new data point.

**Why it matters**: Perfect for real-time systems with tight performance budgets.

**3. Captures Short-Term Trends Quickly**

We can tune α:

* A **high α** (e.g., 0.8) makes EMA sensitive to recent changes (good for reactive tuning),
* A **low α** (e.g., 0.2) makes it smoother and more stable (good for gradual trends).

**Why it matters**: We can match the EMA’s sensitivity to your desired aggressiveness in tuning.

**Why These Models?**

|  |  |  |
| --- | --- | --- |
| **Feature** | **Online Regression Models** | **EMA-Enhanced Predictors** |
| Adaptive | Updates with each sample | Reacts to recent changes |
| Lightweight | Low CPU/memory | Extremely low overhead |
| Interpretable | Clear coefficients | Less interpretable |
| Captures trends | Learns trend slopes | Smooths and highlights |
| Handles noise | Somewhat susceptible | Very effective |
| Suitable for K8s feedback | Yes | Yes |

These models are not just simple — they’re deliberately minimal, real-time-compatible, and production-safe.

**Why Not Other models?**

It’s not that other models are inherently bad — it's that many popular ML models are not suitable for real-time, adaptive Kubernetes environments due to specific trade-offs in latency, compute cost, data requirements, interpretability, and retraining complexity.

**1. Deep Learning Models (e.g., LSTM, CNN, Transformers)**

**Why they’re problematic:**

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| --- | --- |
| **Issue** | **Explanation** |
| **High computation** | Require GPUs or significant CPU cycles — not ideal for lightweight, real-time adaptation inside Kubernetes. |
| **Long training times** | Not suitable for continuous online learning unless we heavily engineer it. |
| **Require large datasets** | Kubernetes workloads may not generate enough data per service to justify such complexity. |
| **Opaque (Black Box)** | Difficult to interpret why a decision was made — risky in production SLAs. |
| **Overkill** | Predicting CPU/memory usage trends doesn’t require thousands of parameters. |

Use these only for long-term forecasting or batch training offline, not live tuning.

**2. Random Forests / Gradient Boosted Trees (e.g., XGBoost, LightGBM)**

**Why they’re problematic:**

|  |  |
| --- | --- |
| **Issue** | **Explanation** |
| **No true online training** | These are batch models — we need to retrain them completely for new data. |
| **Model staleness** | We can’t incrementally adapt to new trends or behaviors in live traffic. |
| **Heavy retraining cost** | Even small updates require full-tree regeneration and memory access. |
| **Latency** | Inference is fast, but updates are slow and non-incremental. |

Great for offline modeling and initial bootstrapping, but not live systems.

**3. Bayesian Models (e.g., Gaussian Processes)**

**Why they’re problematic:**

|  |  |
| --- | --- |
| **Issue** | **Explanation** |
| **Poor scalability** | Gaussian Processes scale poorly with the number of data points (O(n³)). |
| **Heavy memory footprint** | Too costly to maintain posterior distributions for every microservice. |
| **Complex implementation** | Too sophisticated for quick resource tuning tasks. |

Best used for offline exploration (e.g., Bayesian Optimization), not real-time adjustments.

**4. K-Nearest Neighbors (KNN)**

**Why they’re problematic:**

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| --- | --- |
| **Issue** | **Explanation** |
| **No real learning** | KNN stores data but doesn’t generalize. Requires all historical data at inference. |
| **Memory heavy** | Needs to store all previous data points. |
| **Slow inference** | Each prediction requires computing distances to all stored points. |

Unsuitable for resource-constrained, latency-sensitive environments.

Why Lightweight Online Models Win?

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model Type** | **Online Learning** | **Real-Time Compatible** | **Lightweight** | **Interpretability** | **Suitable for K8s?** |
| Online Linear Regression | Yes | Yes | Yes | Yes | Yes |
| EMA | Yes | Yes | Yes | Partial | Yes |
| Deep Learning | No | No | No | No | No |
| Random Forest / XGBoost | No | Fast inference | No | Yes | No |
| Gaussian Process | No | No | No | Yes (but complex) | No |
| KNN | Lazy learner | No | No | Yes (but not scalable) | No |

Just because a model is powerful doesn’t mean it’s practical. In Kubernetes environments, the *best* model is the one that:

* Learns online,
* Adapts quickly,
* Uses minimal resources, and
* Provides transparent decisions.

That’s why Online Regression + EMA is a smart, pragmatic, production-ready choice.