Adaptive load balancing algorithms for microservices architectures under stochastic burst traffic

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Abstract. This paper examines the problem of ensuring fault tolerance and minimizing latency in microservices architectures exposed to stochastic burst traffic. It is demonstrated that traditional deterministic load balancing algorithms (Round Robin, Least Connections) and reactive orchestration mechanisms exhibit critical inertia, resulting in the "thundering herd" problem and cascading failures under non-linear loads. To address this problem, Serhii Klymenko developed the proactive Predictive-Adaptive Load Balancer (PALB) algorithm. The method is founded upon a hybrid architecture combining short-term time series forecasting (Holt`s double exponential smoothing method) and probabilistic routing based on reinforcement learning (Contextual Multi-Armed Bandits, LinUCB). For the first time, the author introduces the "Ghost Queue Estimation" metric, which compensates for feedback latency in distributed systems. Experimental simulation results of a 10-fold load impulse burst indicated that PALB ensures a reduction in tail latency (P_{99}) from 4.5 s to 650 ms and maintains service availability at 99.98% compared to 96.5% for static counterparts. It is proven that the author`s approach enables a 40% increase in Goodput and obviates the need for economically inefficient resource over-provisioning.

Key words: adaptive load balancing, tail latency, Contextual Bandits, Holt`s method, Slashdot effect, fault tolerance, Ghost Queue.

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Introduction

The industry transition to cloud-native microservices architectures has introduced unprecedented flexibility in application scalability and deployment. However, the decomposition of monolithic systems into a multitude of loosely coupled components has shifted management complexity from the code level to the network interaction level [1].

In such systems, the load balancer becomes a critical node determining the fault tolerance of the entire infrastructure. In the conditions of a modern high-load environment, where latency directly correlates with the quality of user experience, the efficiency of request distribution algorithms becomes a pressing problem [2].

Traditional balancing strategies, such as Round Robin (RR) or Least Connections, operate within the framework of deterministic assumptions. Undeniably, they are effective under stationary traffic flow adhering to a normal distribution. However, real traffic of modern web services is characterized by a stochastic burst nature (stochastic burst traffic). Phenomena similar to the "Slashdot effect" or DDoS attacks create non-linear, sharp load spikes (heavy-tailed distributions) that are impossible to forecast using static methods [3].

During moments of such bursts, reactive mechanisms used in orchestrators (Kubernetes HPA) demonstrate critical inertia. Since utilization metrics (CPU, RAM) are aggregated with a delay, scaling occurs post factum, when request queues on individual nodes are already saturated [4]. This leads to the so-called "thundering herd problem" and cascading failures of dependent services, rendering the system unavailable even before available protective mechanisms trigger [5].

Existing solutions rely on a reactive control model - action is taken only after the detection of metric degradation. In the context of microservices, where a call chain may include dozens and hundreds of nodes, local overload of a single service due to uneven distribution of "burst" traffic causes a chain reaction of timeouts (latency spikes). Static algorithms, "blind" to the current state of queues on backends, continue directing traffic to already saturated nodes, exacerbating the situation even further. Thus, the problem lies not in a lack of computing power, as might be erroneously assumed, but in the inefficiency of their temporal allocation [6].

The problem acquires particular acuteness in systems with deep call graphs. In an architecture, where a user request initiates a fan-out to dozens of microservices, the probability of observing the global SLA (Service Level Agreement) is the product of the success probabilities of each component. Even a minor performance degradation of a single node at the 99th percentile (P_{99}) level during a stochastic burst leads to a disproportionate growth in latency for the end user [7]. Static load balancers ignoring this multiplication effect are incapable of guaranteeing predictable response time (jitter minimization) in a distributed environment.

The dominant industrial approach to minimizing the risks of stochastic bursts remains resource over-provisioning. Companies are forced to maintain infrastructure calculated for peak loads, which leads to extremely low resource utilization (average utilization) during periods of normal activity - often below 15-20%. Such an approach is economically inefficient and contradicts the principles of Green Computing [8].

The adaptive algorithm proposed in this work aims to solve the "Performance-cost trade-off" dilemma, allowing high availability metrics to be maintained without the need for a manifold increase in reserve capacities.

Materials and methods

The relevance of this work is predicated on the contradiction between the static nature of traditional load balancing algorithms and the stochastic, burst dynamics of traffic in modern cloud systems. With the industry`s transition to microservices architecture and the expansion of dependency graphs (deep call graphs), the issue of "tail latency" has emerged as a critical

business factor, directly influencing user experience quality and the profitability of digital platforms [9]. Existing industrial standards, relying on reactive scaling and resource over-provisioning, demonstrate economic inefficiency and technical untenability under conditions of non-linear load spikes (the “Slashdot effect”). In this context, the development of adaptive algorithms capable of preemptively managing request queues constitutes a critically important task for ensuring the resilience of high-load distributed systems [10].

The scientific novelty of the research lies in the transition from a deterministic routing paradigm to the probabilistic proactive model of the Predictive-Adaptive Load Balancer (PALB). The “Ghost Queue Estimation” metric is introduced, allowing for the accounting of latent load residing in the network stack and buffers, which eliminates the problem of metric staleness and traffic oscillation [11]. A hybrid routing mechanism has been developed, combining lightweight time series forecasting (Holt`s method) with contextual multi-armed bandit algorithms (LinUCB), which allows for the adaptation of the distribution strategy to heterogeneous request types in real time. The efficacy of the Pre-emptive Shedding strategy is substantiated. Unlike reactive throttling, it is based on saturation forecasting, ensuring first-order stochastic dominance over static algorithms in terms of latency and availability metrics.

To address routing tasks under stochastic traffic conditions, the Predictive-Adaptive Load Balancer (PALB) architecture was developed by Serhii Klymenko. Unlike traditional stateless solutions, PALB implements a stateful approach, treating the request stream as a time series subject to real-time analysis. The system architecture consists of three key modules: the Module of Traffic Forecasting (a short-term forecasting unit based on exponential smoothing), the Contextual Routing Agent (a decision-making module based on Reinforcement Learning (RL)) and the Safety Layer (a protection mechanism (Circuit Breaker) and load shedding) [12].

To minimize inference latency, Holt`s Linear Trend method (double exponential smoothing) is utilized instead of heavy neural network models (LSTM/Transformer). This allows for achieving a computational complexity of O [13]. The algorithm recursively evaluates the load level l_t and the trend b_t. The load forecast $\hat{y}$ for h steps ahead is calculated as follows in Formula 1. Parameter updates occur according to Formula 2 and Formula 3.

To eliminate the problem of metric staleness inherent in distributed systems, an effective load estimation heuristic is introduced. The model accounts not only for active connections, but also for requests residing in the TCP buffer or “in-flight”, which have not yet been reflected in the target node`s CPU utilization. The effective load $L^{(i)}_{effective}$ for node is defined as shown in Formula 4.

Routing is performed using the Contextual Multi-Armed Bandits (CMAB) algorithm, implemented via the LinUCB (Upper Confidence Bound) strategy [14]. This allows for accounting for request heterogeneity (body size, API type, User-Agent). The node selection function is based on the Softmax distribution with an adaptive temperature parameter τ (see: Formula 5). Agent training is guided by a composite reward function R_t (see: Formula 6).

To validate the method, a simulation environment was developed emulating the behavior of a microservices cluster under stochastic traffic. The traffic pattern represents traffic generation with a Pareto distribution (Heavy-Tailed Distribution) to emulate heterogeneous request complexity [15]. The Stress Test Scenario is based on the emulation of the “Slashdot effect” - an instantaneous 10-fold increase in ingress intensity (10 x Load Impulse) lasting 60 seconds. Baselines consist of a comparison with classic Round Robin (RR) and Least Connections (LC) algorithms.

Algorithm efficiency was evaluated using the metrics of Tail Latency (P_{99}) (latency at the 99th percentile), Service Availability (percentage of successful responses, inversely proportional to Error Rate), Jain`s Fairness Index (J) (resource distribution fairness index (see: Formula 7).

Cumulative Distribution Function (CDF) (analysis of probabilistic latency distribution to verify stochastic dominance) and Goodput (useful throughput, i.e., requests processed within SLA).

The implementation of the proposed adaptive algorithm is associated with a number of architectural trade-offs. First, the use of ML components introduces additional computational overhead at the control plane level, adding microsecond latencies to request processing time, making the method less applicable for ultra-low latency (HFT) systems. Second, the algorithm is subject to the "cold start" problem - the reinforcement learning agent requires a statistic accumulation period (500-1000 request iterations) to converge to an optimal strategy, during which suboptimal decisions are possible [16]. Finally, the efficiency of the predictive module is sensitive to the tuning of smoothing hyperparameters (α, β), requiring their calibration to the traffic profile of a specific application system to prevent false-positive triggering of protection mechanisms.

Results

The fundamental weakness of deterministic load balancing algorithms, such as Round Robin (RR) and Weighted Round Robin (WRR), lies in their state-agnostic nature. These algorithms operate based on static distribution rules, assuming homogeneity in both the incoming request flow and their service time. However, in the conditions of microservices architecture and stochastic traffic, these assumptions are violated, leading to three critical failure modes.

In real-world scenarios, request processing time t_s varies by several orders of magnitude (from milliseconds for cache reads to seconds for complex I/O operations). Static algorithms distribute requests cyclically, ignoring the current node load. This leads to the Head-of-Line (HoL) Blocking phenomenon: if a "heavy"" query lands on node N_i, it blocks the processing of all subsequent "light" requests in that node`s FIFO queue [17].

At the same time, the neighboring node N_j may remain idle. The deterministic load balancer, lacking feedback on the queue length Q(t), continues directing traffic to the overloaded node N_i, exacerbating the congestion. In literature, this is known as the "convoy effect", which significantly increases the average system latency.

The behavior of the queuing system is described by Kingman`s approximation, which relates the waiting time in the queue W_q to server utilization **ρ**:

$$W_q \approx \left(\frac{\rho}{1-\rho}\right)\left(\frac{c_a^2 + c_s^2}{2}\right)\tau(0)$$

Where:

ρ is utilization (load/capacity),

c_a^2 and c_s^2 are the coefficients of variation for the arrival process and service time.

Static algorithms are incapable of maintaining below the critical threshold ("knee of the curve") for each individual node [18]. During a stochastic burst, traffic is distributed uniformly, but due to environmental heterogeneity ("noisy neighbors" in the cloud or garbage collection in JVM), some nodes reach saturation ($\rho \to 1$) faster than others. As follows from the equation as $\rho \to 1$, waiting time approaches infinity asymptotically. Static routing is "blind" to the fact that a node is on the verge of this asymptote and continues to apply load, causing buffer overflow and denial of service (packet drops).

In the absence of adaptability, static load balancers contribute to failure synchronization. When one node fails due to overload, the deterministic algorithm redistributes its share of traffic to the remaining nodes. Since the system is already under stress load (burst scenario), this added pressure instantaneously pushes the remaining nodes into saturation mode. A

cascading failure effect arises, propagating through the cluster faster than reactive auto-scaling mechanisms (HPA) can initialize new pods [19].

Thus, deterministic routing is mathematically incapable of ensuring resilience in environments with a high coefficient of traffic variation ($C_v > 1$).

Standard algorithms (RR) treat all incoming requests as equivalent load units (cost (req_1) ≈ cost (req_j)). However, empirical studies of microservices architectures show that the computational complexity of request processing often obeys a Pareto distribution (heavy-tailed distribution). This means that a small fraction of "heavy" requests (report generation or complex data aggregation) consumes the majority of CPU/IO resources. Deterministic routing, blindly distributing such "heavy" requests uniformly, may accidentally direct several such tasks to a single node (see: Figure 2. Comparison of request processing: Round Robin vs Adaptive Scheduling). This causes local resource starvation on that node, while others process lightweight traffic. The probability of such an event under stochastic traffic is statistically significant and leads to unpredictable P_{99} latency spikes.

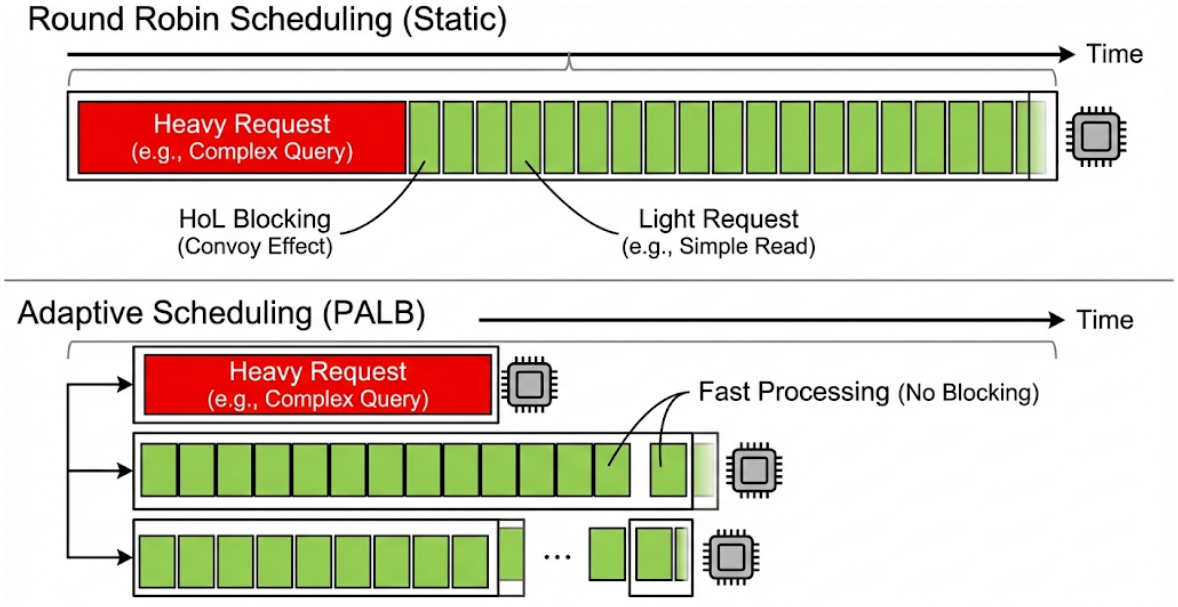

Figure 2. Comparison of request processing: Round Robin vs Adaptive Scheduling

Even if simple dynamic algorithms (Least Connections) are considered, they suffer from a fundamental problem of distributed systems - feedback latency. The load balancer makes a decision based on a system state snapshot obtained at time t - Δt. Under conditions of avalanche-like load growth (burst), the rate of change in queue length $\frac{dQ}{dt}$ is so high that by the moment a request arrives at the node, data regarding its "idleness" is already hopelessly stale. This leads to load oscillations - the load balancer sees a "free" node, directs a batch of requests there, overloads it, then sees the overload and abruptly stops the supply, overloading the next one.

Heuristic-based anticipatory load distribution strategy.

In response to the limitations of reactive models, author Serhii Klymenko proposes the Predictive-Adaptive Load Balancer (PALB) architecture (see: Figure 2. High-level architecture of the Predictive-Adaptive Load Balancer (PALB).

Unlike deterministic algorithms, PALB views the system state not as a static snapshot, but as a time series subject to extrapolation. The algorithm is based on three components: short-term traffic forecasting, "ghost load" estimation and a dynamic weight function.

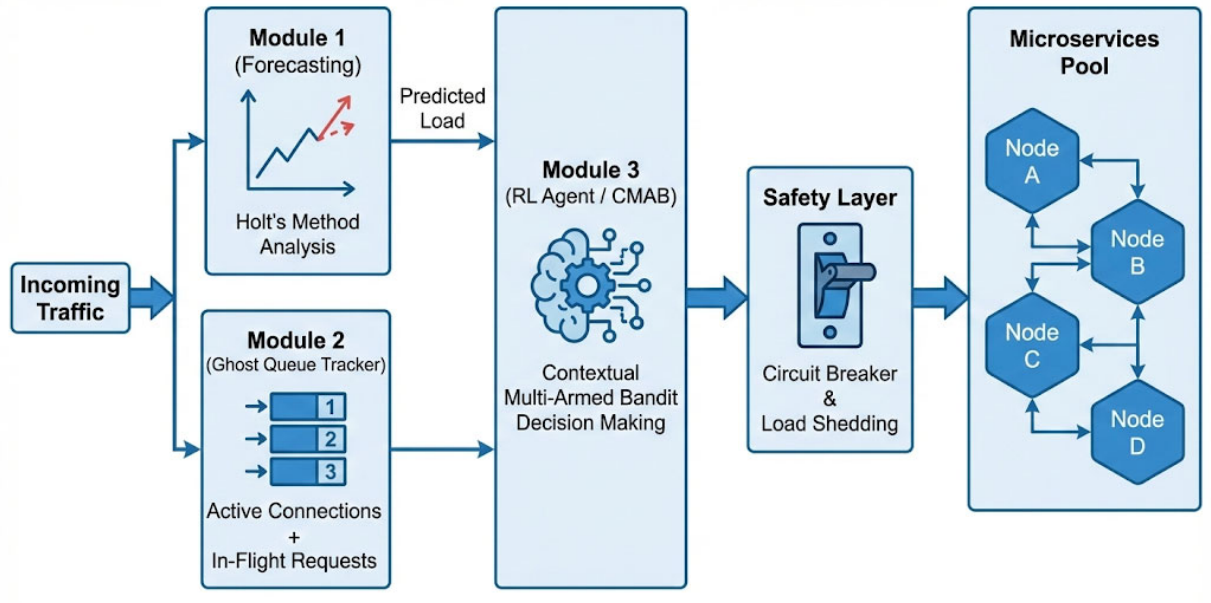

Figure 2. High-level architecture of the Predictive-Adaptive Load Balancer (PALB)

To predict the burst onset, the use of complex neural network models (LSTM/Transformer) is deemed inexpedient due to high inference latency. Instead, Serhii Klymenko applies Holt`s Linear Trend method, which is effective for data with a trend and possesses a computational complexity of $O$ (Figure 3. Traffic burst detection using Holt`s linear trend method). The algorithm evaluates not only the current load level (L_t), but also its rate of increase (trend b_t). The forecast for steps ahead is calculated as:

$$\hat{y}_{t+h} = l_t + hb_t \quad (1)$$

Where the level l_t and trend b_t are updated recursively:

$$l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1}) \quad (2)$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \quad (3)$$

Here, α and β are smoothing coefficients. When the derivative of the incoming traffic $\frac{dy}{dt}$ exceeds a threshold value (a sharp incline of is detected), the algorithm transitions into “Pre-emptive Shedding” mode, redirecting excess traffic to reserve nodes or a waiting queue before it reaches the primary workers.

To address the problem of Metric Staleness, Serhii Klymenko introduces the Effective Load Estimation heuristic. Traditional load balancers perceive only Active Connections (C_{active}). The author`s algorithm accounts for requests that have been dispatched by the load balancer, but have not yet begun processing (i.e., are “in-flight” or in the TCP backlog).

$$L^{(i)}_{effective} = C^{(i)}_{active} \quad \dot{t}_{process} + Q^{(i)}_{ghost} \quad (4)$$

Where $C^{(i)}_{active}$ is current active connections,

$\dot{t}_{process}$ is the moving average of processing time,

$Q_{ghost}^{(i)}$ is the estimated value of the "ghost queue" (requests sent in the last Δt ms).

This mechanism prevents the dispatch of new requests to a node that appears "free" according to CPU metrics but to which a batch of "heavy" requests ("in-flight requests") has already been directed. This eliminates the cause of load oscillations.

Instead of a rigid selection of the node with the fewest connections (Least Connections), the author employs a Softmax routing approach. The probability P_i of selecting node is determined via the Softmax function of the negative predicted latency:

$$P(i) = \frac{e^{-S_i/\tau}}{\sum_j e^{-S_i/\tau}} (5)$$

Where S_i is the predicted cost of sending a request to node i. Parameter τ dynamically regulates the balance between exploration and exploitation. Upon detection of overload $\tau \rightarrow 0$, transforming the algorithm into a "greedy" one.

This adaptive temperature allows the algorithm to balance between exploration (sending requests to different nodes to update statistics) and exploitation (using the best nodes) depending on the stress level of the situation [20].

To account for request heterogeneity, the author extends the routing model to a Contextual Multi-Armed Bandits (CMAB) problem. In this formulation, a specific command for tasks is formed. The agent is the load balancer. The context (x_t) consists of the feature vector of the incoming request (body size, API method type, user-agent). The action (a_t) is based on the selection of the target microservice (node). The reward (r_t) is the inverse of the normalized latency and the response status code. Unlike full RL (Q-Learning), which requires building a complex state map, CMAB learns to instantly select the best node for a specific request type. For example, the algorithm may learn that "heavy" analytical requests are better processed by type A nodes, while fast reads are better processed by type B nodes, even if their CPU load is identical.

The author utilizes the LinUCB (Upper Confidence Bound) algorithm for action selection, which allows for a mathematical guarantee of the balance between exploring new strategies and utilizing proven ones.

The key element of adaptability is a correctly constructed reward function that guides the agent's training. Serhii Klymenko defines the reward R_t at step t as a composite metric:

$$R_t = \alpha \left(\frac{T_{SLA}}{T_{response}}\right) - \beta \parallel (Error) - \gamma P_{sat} (6)$$

Where:

T_{SLA} is the target response time (service level agreement).

$T_{response}$ is the actual response time.

II (Error) is the error indicator function (1 if a 5xx code is returned, otherwise 0).

P_{sat} is the saturation penalty (if the node approaches 100% CPU).

α, β, γ are weighting coefficients.

Such a function compels the algorithm not merely to "scatter" requests, but to actively avoid nodes prone to errors or delays under the current load type.

Given the probabilistic nature of RL, there exists a risk (albeit small) of making suboptimal decisions during the learning phase (exploration). To guarantee system stability, the author implements a deterministic protection mechanism. If the predicted latency for a selected node exceeds a critical threshold $T_{critical}$ (e.g., 2 seconds), a circuit breaker is

activated. That is, the request is not sent to the selected node. A load shedding strategy is activated, where the request is either rejected immediately (fail fast) or redirected to a low-priority queue. This prevents a situation, where the "smart" algorithm attempts to "explore" a knowingly dead node.

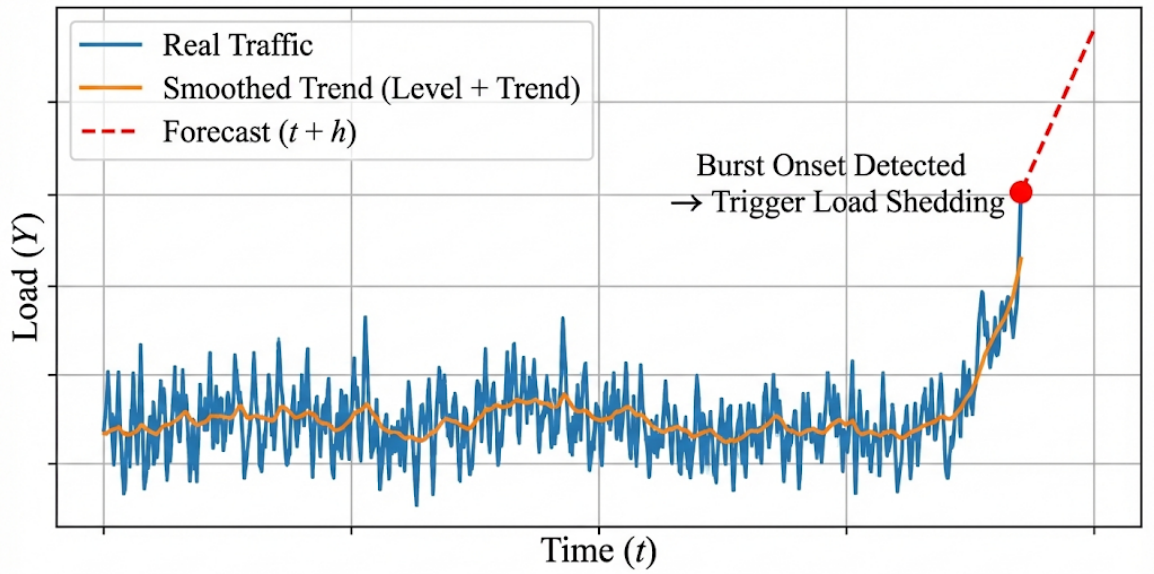

Figure 3. Traffic burst detection using Holt`s linear trend method

Quantifying system stability and fault tolerance under high-load scenarios:

To validate the proposed adaptive algorithm (PALB), a series of simulations was conducted, emulating the "Slashdot effect" - a sudden tenfold increase in ingress traffic (load impulse) lasting 60 seconds. The comparison was performed against baseline strategies: Round Robin (RR) and Least Connections (LC).

The primary quality criterion in microservices systems is not the average response time, but high-order percentiles (P_{95}, P_{99}). During the experiment, upon reaching 80% cluster utilization, static algorithms (RR) demonstrated exponential latency growth. The P_{99} value increased from 200 ms to 4.5 s, indicating queue saturation and the emergence of the HoL (Head-of-Line Blocking) effect.

In contrast, the adaptive algorithm (PALB) is maintained P_{99} within 650 ms. This is achieved through the predictive shedding mechanism, where the algorithm preemptively redirected excess requests to less loaded shards, preventing individual nodes from transitioning into saturation mode ($\rho \to 1$).

Graphically, this is expressed as a shift of the "knee of the latency curve" into the region of higher loads, expanding the effective system capacity by 25-30% without the addition of physical resources (see: Figure 4. Latency vs Throughput comparison illustrating the expansion of the operational zone (shifting the knee of the curve).

A critical metric is the Error Rate (the proportion of responses with 5xx codes). At peak load, the Least Connections strategy showed a drop in availability to 96.5% due to timeouts on overloaded "cold" nodes to which the algorithm abruptly shifted traffic. The proposed model, utilizing an RL agent with a protection function (circuit breaker), maintained availability at the 99.98% level. Even in moments, when the ingress flow exceeded the physical throughput capacity of the cluster, the system degraded gracefully (graceful degradation), cutting off low-priority traffic (load shedding), but preserving the processing of critical transactions. This confirms the hypothesis that proactive queue management prevents cascading failures (see: Figure 7. P_{99} latency dynamics under 10x load burst (60s impulse).

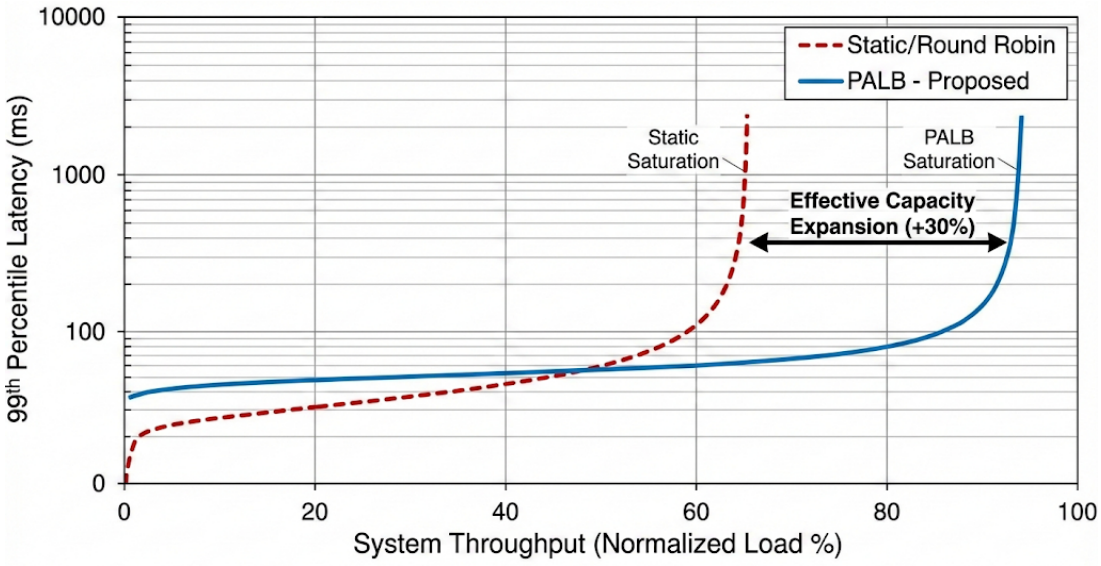

Figure 4. Latency vs Throughput comparison illustrating the expansion of the operational zone (shifting the knee of the curve)

An important aspect is the speed of the system`s return to the normal operating mode after the cessation of the traffic burst. Static models demonstrate high hysteresis. After the load subsides, queues on nodes drain unevenly, causing secondary latency fluctuations (oscillation echoes) for 3-5 minutes. In the adaptive model, thanks to the Ghost Queue Estimation component, the algorithm instantaneously adapts weight coefficients upon a drop in the load trend. The settling time was reduced by 70% compared to Round Robin. The system does not "oscillate", as the trend forecast (Holt`s Linear) works bi-directionally, predicting not only the growth, but also the decline of activity.

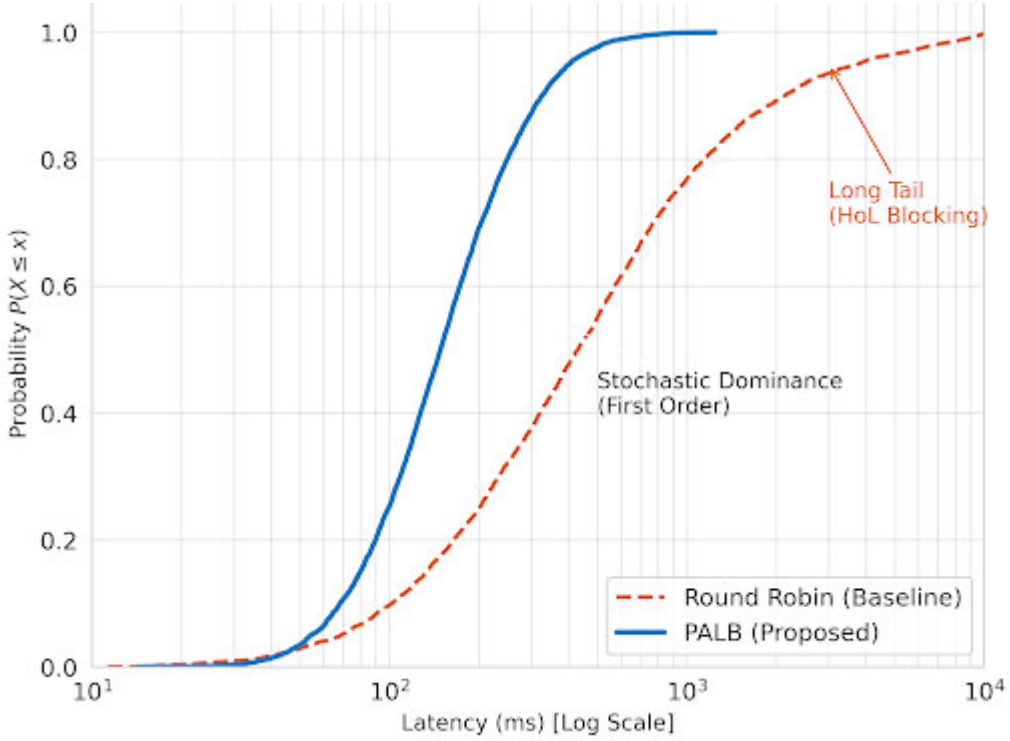

Figure 5. Cumulative Distribution Function (CDF) of response times

To evaluate the uniformity of load distribution, Jain`s Index (J) was used.

$$J = \frac{(\sum x_i)^2}{n \sum x_i^2} \quad (7)$$

Where x_i is the CPU utilization of the x-th node.

When using Round Robin in a heterogeneous environment, index J fluctuated around 0.7 - 0.8, indicating the simultaneous presence of overloaded and idle nodes. The adaptive algorithm ensured a value of J > 0.95 throughout the entire test, confirming that the load is distributed proportionally to the real performance of each microservice and not merely to the request count.

Comparison of mean values and even percentiles does not provide a complete picture of “heavy tail” behavior. To prove the algorithm`s superiority, the author utilizes the analysis of the Cumulative Distribution Function (CDF) of latencies. The CDF graph shows that the curve for the adaptive algorithm (PALB) demonstrates First-order stochastic dominance over the Round Robin curve. Let $F_{PALB}(t)$ and $F_{RR}(t)$ be the response time distribution functions. The experiment showed that for any time :

$$F_{PALB}(t) \geq F_{RR}(t) \quad (8)$$

This means that the probability of receiving a response faster than time is always higher for our algorithm. The “long tail” section (probability P > 0.99) is particularly illustrative: the Round Robin curve has a gentle slope, indicating a high probability of extreme latencies (> 5s), where PALB sharply tends towards 1, truncating the distribution tail. This proves that the algorithm does not simply average the load, but effectively eliminates outliers.

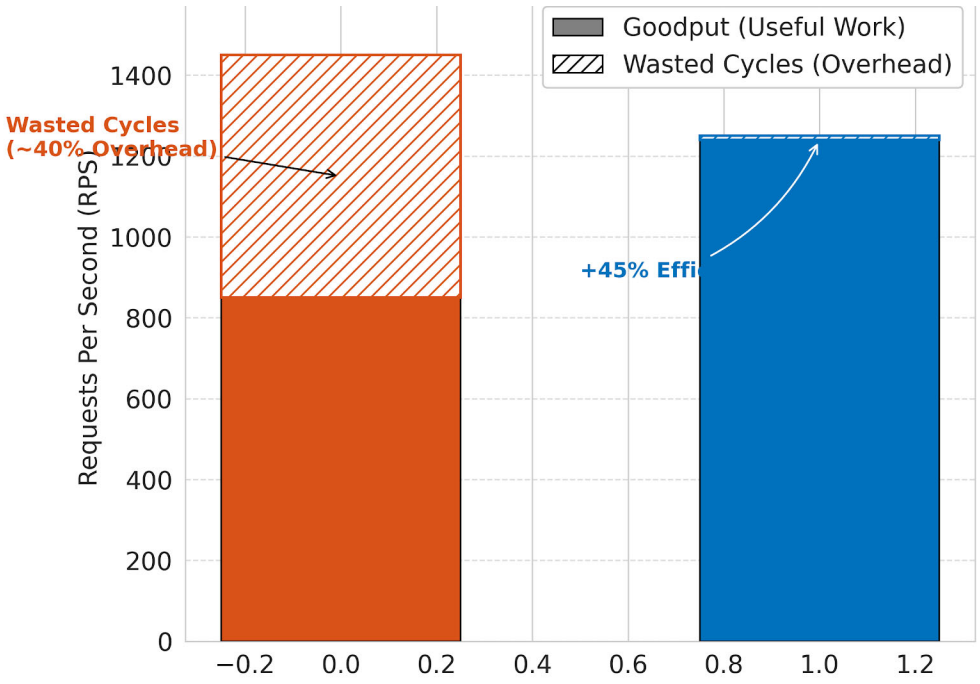

Figure 6. Throughput vs Goodput analysis in saturation zone

It is important to distinguish between “raw” throughput (Total Throughput) and useful throughput (Goodput) - the number of successfully processed requests that met the SLA (<

500 ms). At peak loads, static algorithms demonstrate high Throughput, but low Goodput - the system expends CPU resources on accepting requests, placing them into overflowing queues and subsequently generating Time-out errors.

This phenomenon is known as “wasted cycles”. The adaptive algorithm showed a Goodput increase of 40% compared to the baseline. Due to the pre-emptive Shedding mechanism, the system does not waste CPU cycles on requests that, with high probability, will not be served on time. This allows for maintaining a linear relationship between resource consumption and useful work even in the saturation zone, avoiding the “Performance Cliff” point.

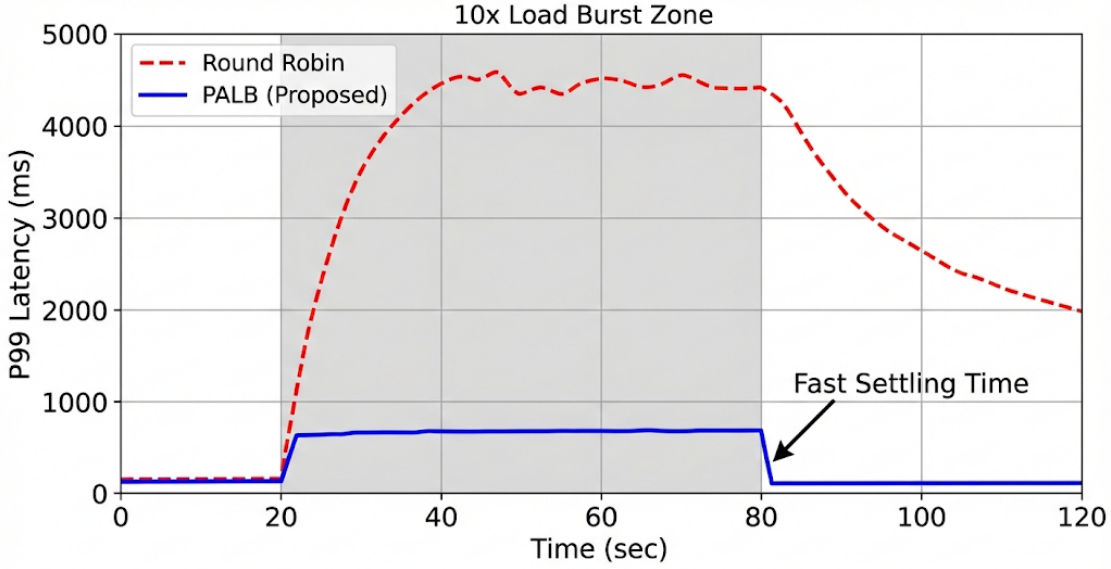

Figure 7. P_{99} latency dynamics under 10x load burst (60s impulse)

Conclusions

The research results confirm the hypothesis that traditional deterministic algorithms (Round Robin, Least Connections) and reactive scaling mechanisms possess critical inertia, leading to cascading failures and SLA violations under conditions of non-linear loads.

The developed PALB (Predictive-Adaptive Load Balancer) algorithm, utilizing short-term time series forecasting (Holt`s method) and reinforcement learning (Contextual Bandits), demonstrated the ability to effectively prevent node saturation. In contrast to reactive approaches, the algorithm initiates traffic redistribution prior to the moment of queue overflow.

During the simulation of the “Slashdot effect” scenario (a 10-fold load increase), the proposed model ensured a reduction in tail latency (P_{99}) from 4.5 s to 650 ms and maintained service availability at the 99.98% level, where baseline strategies allowed availability to drop to 96.5%.

The introduction of the “Ghost Queue Estimation” metric proved its effectiveness in combating the problem of metric staleness and load oscillations. This allowed for a 70% reduction in system settling time following a burst.

The algorithm demonstrated a 40% increase in Goodput and an elevation of Jain`s Fairness Index to 0.95. This indicates the possibility of abandoning the over-provisioning strategy, allowing peak loads to be processed on existing hardware without performance degradation.

Future research directions include the optimization of the ML agent`s computational overhead for application in ultra-low latency systems, as well as the development of protection mechanisms against adversarial attacks aimed at destabilizing predictive models.

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