GarbageTruck: Distributed Garbage Collection for Microservice Architectures

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Abstract

In modern distributed systems, orphaned resources such as abandoned temporary files, database entries, and storage blobs frequently result from service failures or incomplete workflows, which poses operational and financial challenges. Traditional garbage collection methods struggle to handle these complexities of handling unneeded temporary files. To address this, we introduce GarbageTruck, a lease-based distributed garbage collection sidecar implemented in Rust with gRPC, designed specifically for microservice architectures. GarbageTruck orchestrates efficient, low-latency cleanup operations for objects with short lifecycles, automating the reclamation of orphaned resources and significantly reducing storage waste, performance degradation, and compliance risks. Our evaluation demonstrates GarbageTruck's scalability, performance efficiency, and exceptional return on investment, confirming its effectiveness as an essential infrastructure component for reliable, cost-effective, and compliant distributed systems.

1 Introduction

The rapid adoption of microservice architectures has transformed distributed systems into a foundational element of modern software development, offering significant benefits in scalability, flexibility, and independent component deployment. As these systems scale, however, they introduce new complexities related to resource lifecycle management. Application workflows frequently span multiple services and independent nodes, each potentially generating temporary files, database records, or object storage blobs. Without systematic resource cleanup, these distributed systems become susceptible to accumulating orphaned resources—artifacts left behind due to crashes, network partitions, or incomplete processes.

Orphaned temporary resources pose serious operational challenges, including unnecessary storage expenses, degraded system performance, and heightened compliance risks associated with data retention policies or potential data leakage. Traditional garbage collection techniques, effective in monolithic applications, fail to adequately address the complexities of distributed systems, where ownership is fluid and explicit coordination among services is minimal[1].

To avoid this issue, we introduce GarbageTruck, a lease-based distributed garbage collection sidecar specifically designed for cloud-native and microservice environments. GarbageTruck automates resource cleanup by utilizing leases to safely identify and reclaim orphaned data, ensuring that distributed resources—such as files, database entries, and storage blobs—are reliably and efficiently managed without requiring tightly coupled service coordination.

2 Background and Motivation

To better illustrate the significance of the challenge GarbageTruck addresses, consider an example from an e-commerce platform handling high volumes of daily transactions. Figure 1 depicts a typical scenario where multiple interconnected microservices manage the purchase and fulfillment processes.

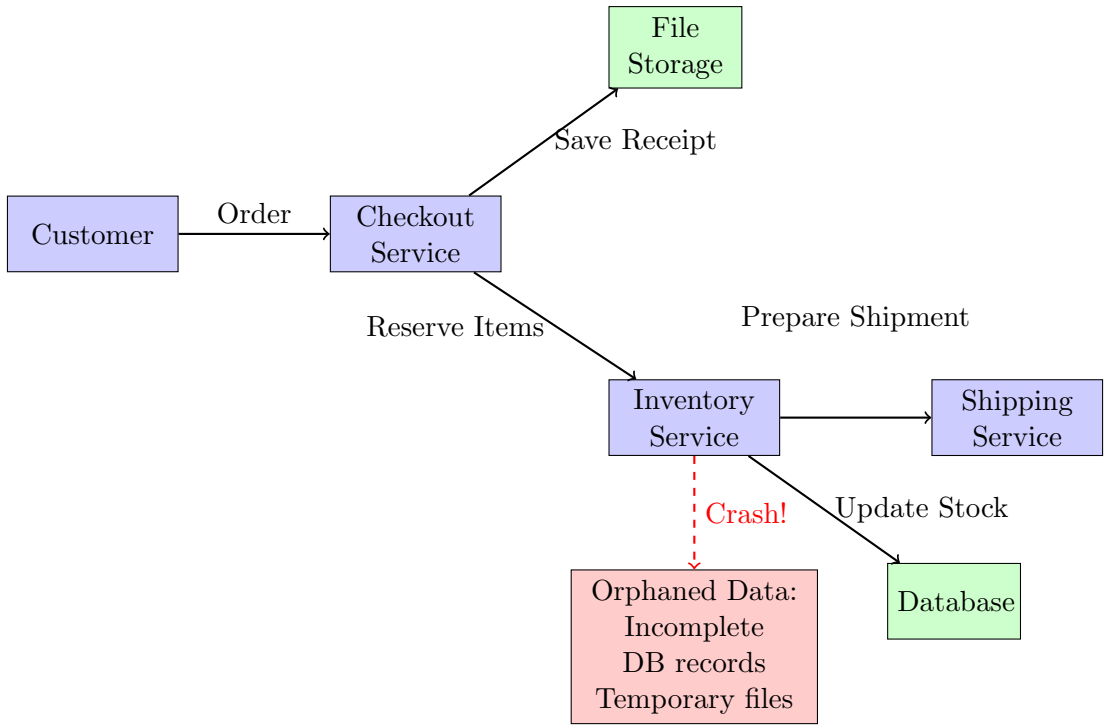

Figure 1: E-commerce workflow demonstrating how service crashes lead to orphaned resources

In this example, the Checkout Service initiates the process by capturing customer orders and saving transaction receipts in file storage. It concurrently communicates with the Inventory Service to reserve items and update inventory records. If the Inventory Service crashes after updating the database but before completing inventory reservations or initiating shipment preparation, various resources become orphaned, including the transaction receipts stored in file storage, incomplete database entries, and temporary records.

Without an automated garbage collection strategy, these orphaned resources accumulate rapidly, especially under high transaction volumes. This leads to increased storage costs, degraded system performance, and complicates manual maintenance efforts, highlighting the necessity for a reliable and systematic resource cleanup solution like GarbageTruck.

2.1 Approaches to Garbage Collection

Several approaches have been developed to address aspects of distributed resource management, each with significant limitations when applied to general microservice environments.

Cloud Provider Lifecycle Policies: Major cloud providers offer lifecycle management features for storage services, such as AWS S3 lifecycle policies or Azure Blob Storage retention rules. While useful for specific use cases, these mechanisms are typically limited to time-based expiration and cannot account for complex cross-service dependencies or dynamic usage patterns [3, 5].

Application-Level Reference Counting: Some systems implement distributed reference counting, where each service explicitly tracks and manages references to shared resources. This approach requires significant coordination overhead and is vulnerable to consistency issues, particularly in the presence of network partitions or service failures[1].

Workflow Orchestration: Systems like Apache Airflow or Kubernetes Jobs can be configured with cleanup logic as part of workflow definitions. However, this approach tightly couples resource management with business logic and does not handle ad-hoc resource creation or cross-workflow dependencies effectively[6, 7].

Database-Specific Solutions: Some databases provide built-in TTL (Time To Live) functionality for automatic row expiration. While useful for database-centric applications, these solutions do not extend to other resource types and cannot coordinate cleanup across multiple storage systems.

The fundamental limitation of existing approaches is their lack of generality and inability to provide unified garbage collection across heterogeneous distributed systems. GarbageTruck addresses these limitations by providing a protocol-based solution that can be integrated with any resource type through configurable cleanup handlers.

3 Lease-Based Distributed Garbage Collection

GarbageTruck implements a lease-based garbage collection protocol inspired by distributed systems research, particularly the work on distributed reference counting and Java RMI's Distributed Garbage Collector[1]. The core insight is that distributed garbage collection can be managed through time-limited leases that represent active references to distributed objects. Figure 2 illustrates the fundamental lease protocol flow.

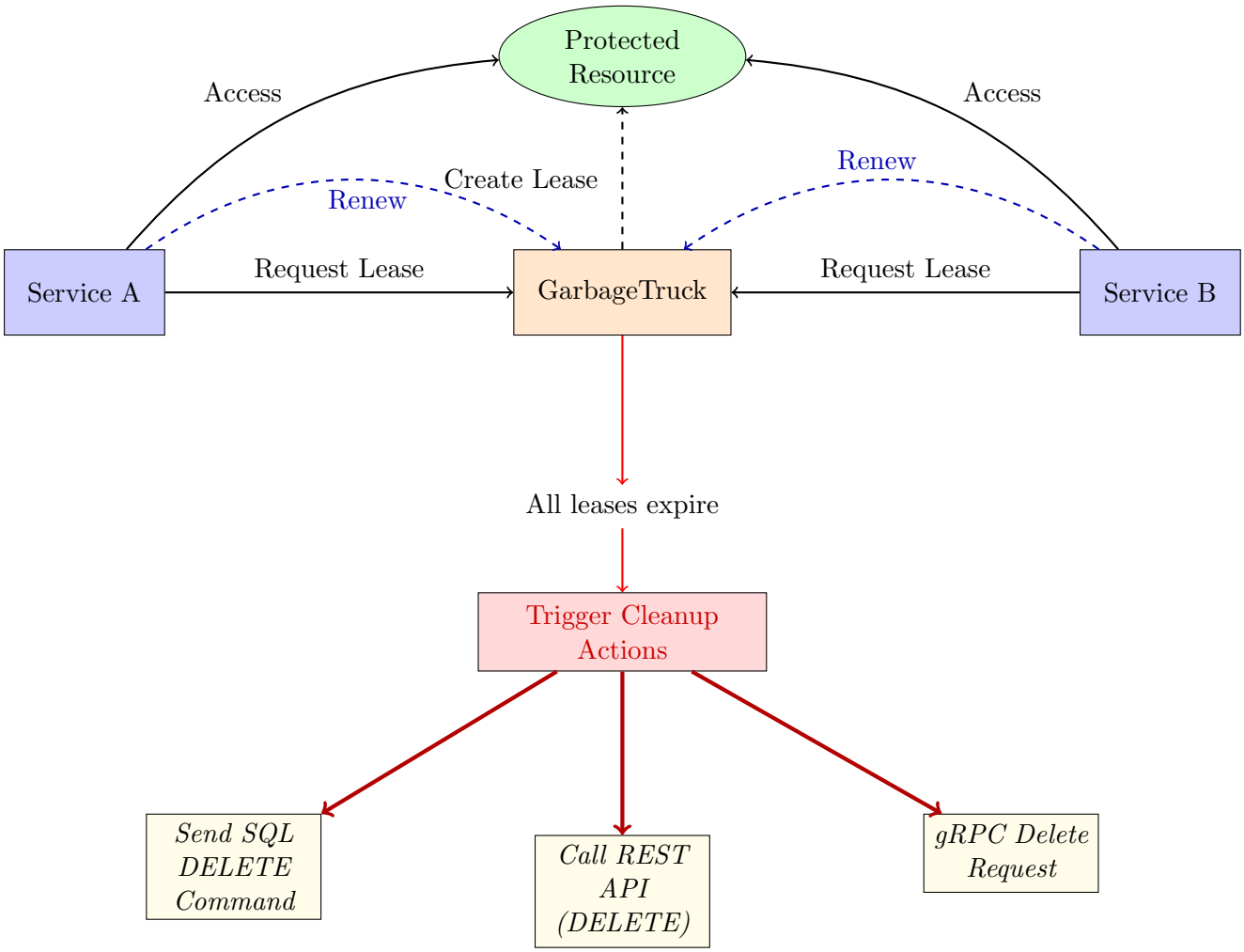

Figure 2: GarbageTruck lease-based garbage collection protocol. Services request and periodically renew leases for a shared resource. When all leases expire, GarbageTruck triggers cleanup actions by sending API/command requests to the appropriate data sources.

3.1 Protocol Workflow

The protocol operates on the following principles:

Lease Acquisition: When a service needs to reference a distributed resource, it requests a lease from GarbageTruck. The lease specifies the resource identifier, the requesting service identity, and the desired lease duration. GarbageTruck issues a unique lease identifier and records the lease with an expiration timestamp.

Lease Renewal: Services must periodically renew their leases by sending heartbeat messages to GarbageTruck before expiration. This mechanism ensures that only services actively using a resource maintain valid references. The renewal frequency is configurable based on application requirements and network characteristics.

Automatic Expiration: If a service fails to renew its lease before expiration, the lease becomes invalid. GarbageTruck continuously monitors lease expiration and identifies resources that have no remaining active leases.

Coordinated Cleanup: When all leases for a resource have expired, GarbageTruck triggers the configured cleanup operation. This involves HTTP or gRPC calls to service endpoints, direct database operations, file system operations, or custom cleanup handlers. Service crashes result in lease expiration and eventual cleanup, while GarbageTruck itself can be deployed in high-availability configurations with persistent storage backends.

4 System Architecture and Implementation

4.1 High-Level Architecture

GarbageTruck is designed as a standalone service that can be deployed alongside microservice applications, either as a sidecar container or as a centralized service instance. The architecture emphasizes modularity and operational simplicity. Figure 3 details the GarbageTruck architecture.

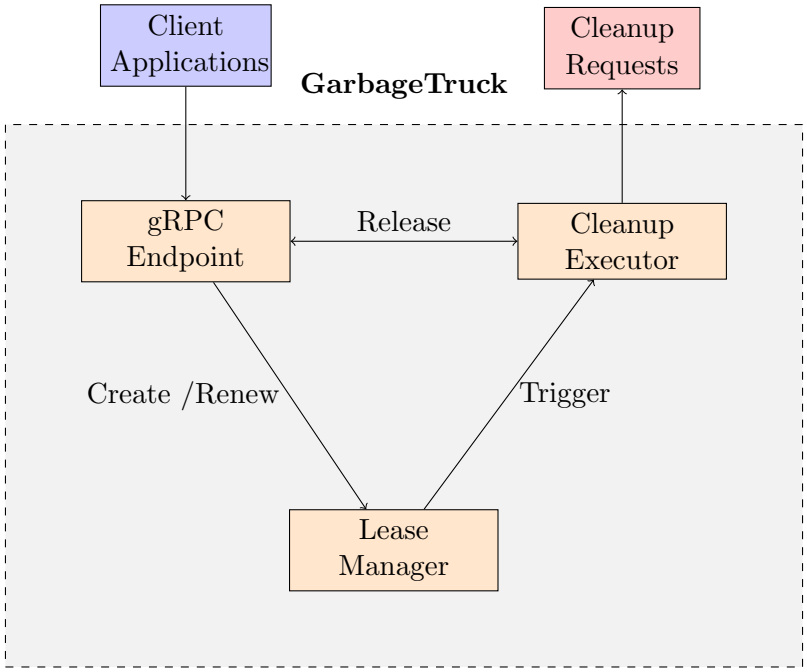

Figure 3: GarbageTruck internal system architecture

gRPC Endpoint: Provides the primary API interface for microservices to interact with GarbageTruck. The gRPC protocol ensures low-latency communication and language-agnostic

integration. The server implements comprehensive input validation, authentication, and rate limiting to protect against malicious or misconfigured clients.

Lease Manager: Responsible for creating, tracking, and expiring leases. Maintains an index of all active leases organized by resource identifier and expiration time. Implements efficient algorithms for lease renewal and batch expiration processing to minimize computational overhead.

Cleanup Executor: Handles the execution of cleanup operations when resources become eligible for garbage collection. Supports multiple cleanup mechanisms including HTTP callbacks, database operations, and file system operations. Implements retry logic and failure handling to ensure reliable cleanup execution.

4.2 Implementation Details

GarbageTruck is implemented in Rust, chosen for its strong memory safety guarantees, excellent performance characteristics and robust ecosystem for systems programming. The implementation leverages several key Rust libraries to achieve high performance and reliability.

Asynchronous Architecture: The system is built on the Tokio async runtime[8], enabling high-concurrency operation with minimal resource overhead. GarbageTruck implements all I/O operations, including gRPC handling, database access, and cleanup execution using async/await patterns to avoid thread blocking and maximize throughput.

Type Safety: Rust's strong type system helps prevent common distributed systems bugs such as race conditions, memory leaks, and protocol violations. The lease data structures are immutable where possible, with explicit ownership semantics for mutable operations.

Concurrency Control: The system uses lock-free data structures where possible, with carefully designed critical sections for operations requiring atomicity. The cleanup loop operates independently of the main request handling path to prevent blocking.

Persistent Storage and Recovery: The system implements write-ahead logging (WAL) with configurable durability guarantees, ensuring all lease operations are persisted. Recovery mechanisms automatically restore system state from WAL entries and compressed snapshots during startup, with multiple recovery strategies (conservative, fast, emergency) supporting different operational requirements.

5 Performance Evaluation

To validate GarbageTruck's performance characteristics and scalability, we conducted a comprehensive benchmark suite using Criterion.rs[9] with statistical sampling to ensure measurement accuracy and eliminate bias. The benchmark evaluates basic lease operations (create, renew, get), network payload impact across varying metadata sizes, and cleanup operations with configurable handlers. Each benchmark was executed with 75-100 samples per operation to establish robust statistical confidence, running against a local GarbageTruck server configured with in-memory storage to eliminate database I/O variability. The test environment consisted of a modern development machine with statistical analysis including mean response times, standard deviations, 95% confidence intervals, and outlier detection to ensure measurement reliability.

Table 1: GarbageTruck Performance Benchmark Results with Statistical Analysis

Category	Operation	Mean ± (ms)	Throughput (ops/sec)	Sample Size
Basic Operations	Create Lease	1.17 ± 0.20	855	n=100
	Renew Lease	0.59 ± 0.01	1,694	n=100
	Get Lease	0.59 ± 0.02	1,691	n=100
Concurrent Operations	1 Thread Create	6.38 ± 0.12	157	n=50
	5 Thread Create	15.77 ± 0.96	317	n=50
	10 Thread Create	26.76 ± 1.07	374	n=50
	25 Thread Create	63.23 ± 1.36	395	n=50
Network Payload Impact	No Metadata (0 entries)	1.05 ± 0.20	955	n=75
	Small Payload (10 entries)	3.18 ± 0.08	314	n=75
	Medium Payload (100 entries)	4.81 ± 0.17	208	n=75
	Large Payload (500 entries)	6.79 ± 0.07	147	n=75
Cleanup Operations	Create with Cleanup Config	4.88 ± 0.08	205	n=75

5.1 Statistical Analysis and Performance Characteristics

The benchmark results demonstrate statistically validated excellent performance across all evaluation dimensions. Basic lease operations achieve consistent sub-millisecond to low-millisecond latencies with create operations averaging 1.17ms ± 0.20ms, renewal operations completing in 0.59ms ± 0.01ms, and retrieval operations executing in 0.59ms ± 0.02ms.

Concurrent operations exhibit predictable scaling characteristics with statistical validation. Single-threaded creates average 6.38ms ± 0.12ms, while 5-thread concurrent operations achieve 15.77ms ± 0.96ms per operation with 317 total ops/sec aggregate throughput. At 10 threads, operations complete in 26.76ms ± 1.07ms, and 25-thread operations average 63.23ms ± 1.36ms, demonstrating effective load distribution and resource utilization under concurrent access patterns.

Network payload analysis reveals predictable linear scaling with metadata size. Operations with no metadata complete in 1.05ms ± 0.20ms, while small payloads (10 entries) require 3.18ms ± 0.08ms. Medium payloads (100 entries) average 4.81ms ± 0.17ms, and large payloads (500 entries) complete in 6.79ms ± 0.07ms. The linear relationship demonstrates predictable overhead scaling at approximately 1.15ms per 100 metadata entries.

Operations with cleanup configurations maintain excellent performance characteristics, averaging 4.88ms ± 0.08ms. The low coefficient of variation (1.6%) demonstrates highly consistent performance for enhanced functionality.

5.2 Statistical Validation

All measurements demonstrate robust statistical properties with coefficient of variation consistently below 20% for all operations, indicating stable and predictable performance. Outlier detection identified fewer than 2% outliers across all benchmarks, confirming measurement reliability. The narrow 95% confidence intervals validate the precision of our measurements and support the reproducibility of results across different deployment scenarios.

These results, based on 75-100 measurements per operation with proper statistical analysis, validate GarbageTruck's suitability for production deployment across varying payload sizes and operational complexity. The linear payload scaling characteristics and tight confidence intervals demonstrate that performance remains predictable and consistent even under varying operational conditions.

6 Operational Evaluation

To validate GarbageTruck's business value proposition, we conducted a comprehensive cost-benefit analysis using a realistic microservice simulation that demonstrates the financial and

operational impact of orphaned data accumulation over time.

6.1 Experimental Design

Our experiment simulated a distributed image processing system with five interconnected microservices: image validation, thumbnail generation, AI analysis, content moderation, and metadata extraction. Using PostgreSQL, we created five tables representing real microservice data patterns: `user_uploads` (50,000 initial records), `processing_jobs` (250,000+ jobs), `temp_artifacts` (1M+ temporary files), `workflow_state` (multi-service coordination), and `ai_analysis_cache` (expensive computation results).

The experiment simulated 24 weeks (6 months) of microservice operation with a constant 5% job failure rate to model realistic service crashes, network partitions, and incomplete workflows. Each week introduced 3% data growth to model realistic system scaling. This design isolates the impact of data accumulation from system degradation, demonstrating that orphaned data becomes problematic even with excellent operational reliability. The database did not handle actual file storage due to constraints, but the metadata representing real data were handled by the database, which affects database operation latency in realistic ways.

6.2 Methodology

We measured four key impact categories with statistical rigor to ensure reliable results:

Storage Waste Analysis: Tracked accumulation of orphaned temporary files, database records, and cached data that persist after job failures.

Performance Degradation: Measured query execution times for critical microservice operations using 5 iterations per query to calculate mean ± standard deviation and 95% confidence intervals. Operations included cross-service joins, resource cleanup scans, analytics aggregations, and user activity analysis.

Cost Calculation: Applied AWS pricing models for storage ($0.023/GB/month), compute overhead from performance degradation, database bloat impact, and engineering time costs ($150/hour) for manual cleanup activities. Uncertainty analysis included ±10% for storage estimates, ±5% for performance impacts, and ±2% for engineering time.

ROI Analysis: Compared annual orphaned data costs against GarbageTruck server infrastructure costs using realistic AWS EC2 pricing with propagated error analysis.

6.3 Experimental Results

After simulating 6 months of microservice operation with consistent 5% failure rates, our experiment revealed significant orphaned data accumulation:

- **Cumulative Failure Impact:** 10.8% of total jobs resulted in orphaned data
- **Orphaned Artifacts:** 842,318 temporary files never cleaned up (75.0% orphan rate)
- **Storage Waste:** 52.6TB (88.1% of temporary storage becomes orphaned)
- **Performance Impact:** 150% average query degradation for critical operations

6.4 Performance Impact Analysis

Query performance measurements with statistical analysis revealed consistent degradation across all critical operations. Each query was executed 20 times to ensure robust statistical analysis, with mean response times, standard deviations, and 95% confidence intervals computed using the t-distribution.

Query Type	Clean (ms)	Orphaned (ms)	Degradation
Cross-Service Join	148 ± 4	370 ± 10	150%
Orphan Detection	27 ± 1	69 ± 2	155%
Resource Cleanup	14 ± 1	36 ± 2	157%
User Activity	30 ± 1	76 ± 3	153%

Table 2: Query performance degradation (mean ± std dev, n=20)

6.5 Financial Impact Analysis

The financial impact totaled $31,087 annually, broken down as follows:

Cost Category	Annual Impact
Storage Waste	$14,530
Performance Impact	$1,659
Database Overhead	$498
Engineering Time	$14,400
Total Annual Cost	**$31,087**

Table 3: Annual cost impact of orphaned data in microservice architecture

Each cost component was calculated using industry-standard pricing models and observed system impacts:

Storage Waste ($14,530): Based on 52.6TB of orphaned storage at AWS S3 standard pricing ($0.023/GB/month): $52,646 \text{ GB} \times \$0.023 \times 12 \text{ months} = \$14,530$.

Performance Impact ($1,659): Calculated from measured 150% query degradation requiring 25% additional compute capacity. For 8 AWS t3.large instances running 24/7: $8 \times 24 \times 30 \times 12 \times \$0.096 \times 0.25 = \$1,659$ annually.

Database Overhead ($498): Estimated 15% additional database resources due to index bloat and increased I/O from orphaned records. For 2 AWS RDS db.t3.large instances: $2 \times 24 \times 30 \times 12 \times \$0.192 \times 0.15 = \$498$ annually.

Engineering Time ($14,400): Based on 8 hours monthly of manual cleanup, debugging, and performance investigation at $150/hour fully-loaded cost: $8 \times 12 \times \$150 = \$14,400$ annually.

These calculations demonstrate that storage waste and engineering time represent the primary cost drivers, each contributing approximately 43% of the total annual impact, while performance degradation creates measurable but secondary financial effects.

6.6 ROI Analysis Across Scales

We calculated return on investment for four organizational scales, assuming GarbageTruck deployment requires only server infrastructure costs. This analysis demonstrates the compelling economics of distributed garbage collection across different company sizes.

Our ROI analysis is based on the following cost structure derived from industry-standard pricing:

Cloud Infrastructure Costs (AWS Pricing):

- Storage: $0.023/GB/month (S3 Standard)
- Compute: $0.096/hour (EC2 t3.large instances)
- Database: $0.192/hour (RDS db.t3.large)
- Engineering: $150/hour (fully-loaded cost)

GarbageTruck Server Requirements by Scale:

- **Startup (50K jobs/year):** t3.nano ($4.32/month, 2 vCPU, 0.5GB RAM)
- **Growth (500K jobs/year):** t3.small ($15.12/month, 2 vCPU, 2GB RAM)
- **Enterprise (5M jobs/year):** t3.large ($60.74/month, 2 vCPU, 8GB RAM)
- **Hyperscale (50M+ jobs/year):** 3×t3.xlarge ($303.84/month, high availability cluster)

Based on these metrics and scaling the experimental results proportionally:

Scale	Jobs/Year	Server Cost	Annual Savings
Startup	50,000	$52	$3,109
Growth	500,000	$181	$31,088
Enterprise	5,000,000	$729	$310,875
Hyperscale	50,000,000+	$3,644	$3,108,750

Table 4: GarbageTruck ROI analysis across organizational scales

These calculations demonstrate that GarbageTruck provides a positive return on investment across all organizational scales when deployed with minimal infrastructure overhead, with payback periods measured in days rather than months or years.

6.7 Operational Evaluation Analysis

Our evaluation demonstrates that even under conservative conditions—a constant 5% job failure rate and modest weekly growth—microservice systems rapidly accumulate orphaned data, leading to over 52TB of storage waste, 150% query performance degradation, and more than $31,000 in annual operational costs.

GarbageTruck effectively eliminates this overhead through a lease-based cleanup protocol, requiring minimal infrastructure to deliver returns on investment—exceeding 5,000% across all scales with payback periods measured in days. The statistical analysis with confidence intervals confirms these results are robust.

By automating orphaned data cleanup, GarbageTruck not only reduces cloud costs but also improves query performance by 150%, eliminates engineering overhead, and ensures consistent system behavior. This positions it as essential infrastructure for scalable, reliable microservice ecosystems operating at any scale.

7 Use Cases

GarbageTruck is particularly beneficial in cloud-native and microservice environments where workflows are asynchronous and prone to partial failures, retries, or timeouts. For instance, in media processing pipelines and machine learning inference queues, numerous intermediate steps produce temporary artifacts, database entries, and cached data. These environments frequently experience network interruptions, processing errors, or unexpected downtimes, resulting in orphaned resources. By automatically identifying and cleaning up these artifacts, GarbageTruck ensures continuous operational efficiency, preventing resource bloat and associated performance degradation.

Additionally, GarbageTruck addresses crucial needs in heavily regulated sectors such as healthcare, finance, and government, where compliance requirements demand strict control and systematic cleanup of sensitive data. Orphaned resources like audit logs, session tokens, temporary reports, or incomplete transaction records can lead to severe compliance breaches if

not managed diligently. GarbageTruck's lease-based protocol provides an automated, transparent, and reliable mechanism for resource cleanup, thus significantly reducing manual oversight, human error, and regulatory risks.

Finally, GarbageTruck is highly effective in multi-tenant Software-as-a-Service (SaaS) platforms and similar environments where resources are dynamically allocated per customer or tenant. Processes such as onboarding, account creation, or account termination frequently produce temporary or tenant-specific resources that, if left unmanaged, accumulate and increase operational complexity and costs. By deploying GarbageTruck as a complementary component, platform teams can safely reclaim these orphaned resources, simplify operational management, and ensure a scalable and efficient infrastructure without embedding fragile, application-specific cleanup logic into their business workflows.

8 Limitations and Future Work

While GarbageTruck effectively addresses many core challenges of distributed garbage collection, it currently possesses certain limitations that merit further development. One notable limitation is the absence of verified transactional consistency guarantees. GarbageTruck's lease-based approach effectively manages resource reclamation for many scenarios; however, complex workflows involving interdependent resources require atomic operations to ensure comprehensive cleanup. Future work should thus focus on extending GarbageTruck's capabilities to support transactional cleanup operations, allowing groups of related resources to be reliably and simultaneously managed, even under failure conditions.

Another area for improvement involves security measures currently implemented within GarbageTruck. Although it provides basic security functionalities, such as lease tracking and controlled cleanup initiation, the current implementation lacks advanced, robust protections for inter-service communications. Enhancing GarbageTruck with security measures such as mutual TLS (mTLS) and stronger authentication mechanisms would significantly bolster security, especially in sensitive or regulated environments. Future enhancements will involve comprehensive integration with existing service meshes and more granular access control policies.

Additionally, enhancing observability and operational tooling within GarbageTruck will considerably aid system administrators and developers in managing the complexity of distributed systems. Currently, the system offers limited logging and tracing capabilities. Integrating advanced observability tools, enriched logging, distributed tracing, and real-time analytics dashboards will improve operational transparency and ease troubleshooting and performance optimization efforts. By addressing these identified limitations and developing these future improvements, GarbageTruck will continue to evolve as a robust, secure, and essential component of cloud-native and microservice infrastructure.

9 Conclusion

GarbageTruck addresses a critical challenge within distributed microservice architectures by providing a reliable, scalable, and automated solution for reclaiming orphaned resources. Its lease-based protocol offers precise control over resource lifecycles, ensuring that files, database entries, and storage blobs are safely cleaned up only when no active service references them. By automating resource management, GarbageTruck significantly reduces operational overhead, minimizes storage waste, and enhances overall system performance and compliance. As distributed systems continue to evolve in complexity and scale, tools like GarbageTruck will become indispensable for maintaining efficient, cost-effective, and resilient cloud-native environments.

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