Log Aggregation for Cloud-Native Applications

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***Abstract*—This paper presents a comprehensive empirical comparison of two prominent log aggregation solutions for cloud-native environments: the ELK stack (Elasticsearch, Logstash, Kibana) and the PLG stack (Promtail, Loki, Grafana). Through systematic deployment and performance evaluation in a Kubernetes cluster using realistic microservice workloads, we analyze query performance, resource utilization, storage efficiency, and operational complexity. Our quantitative analysis demonstrates that PLG provides significant performance advantages with 10× faster query processing times (34ms vs 340ms), 8× lower memory consumption (281MiB vs 2235MiB), and 3.2× higher ingestion throughput (8,000 vs 2,500 logs/sec), while ELK offers superior analytical capabilities and query flexibility. These findings provide evidence-based guidance for organizations selecting log aggregation solutions based on their specific operational requirements, resource constraints, and scalability needs in cloud-native deployments.**

***Index Terms*—log aggregation, ELK stack, PLG stack, Kubernetes, cloud-native, observability, performance evaluation, distributed systems**

I. Introduction

Modern distributed systems and microservices architectures generate unprecedented volumes of log data across multiple components, services, and infrastructure layers. The complexity of these environments necessitates robust log aggregation solutions that can efficiently collect, process, store, and query log data to ensure system reliability, security, and performance optimization [1].

Cloud-native environments present unique challenges for log management, including dynamic service discovery, ephemeral container lifecycles, horizontal scaling requirements, and distributed transaction tracing across multiple services. Traditional logging approaches prove inadequate for these environments, requiring specialized solutions designed for containerized and microservices architectures [2].

Two architectural paradigms have emerged as leading solutions in the open-source ecosystem: the ELK stack (Elasticsearch, Logstash, Kibana) representing the traditional full-text search approach, and the PLG stack (Promtail, Loki, Grafana) embodying the modern label-based indexing philosophy. Each approach offers distinct advantages and trade-offs in terms of performance, resource utilization, and operational complexity [3].

This research addresses the fundamental question: *How do ELK and PLG stacks compare quantitatively in terms of performance, resource efficiency, and operational characteristics for log aggregation in cloud-native environments?* Our contributions include:

- A systematic experimental methodology for comparing log aggregation solutions
- Quantitative performance analysis across multiple evaluation dimensions
- Empirical evidence for architectural trade-offs between full-text and label-based indexing approaches
- Practical deployment insights and decision framework for solution selection

II. Related Work

Log aggregation in distributed systems has evolved significantly from simple file-based approaches to sophisticated real-time processing systems. Early solutions relied on centralized syslog servers, but modern cloud-native environments require more advanced architectures capable of handling dynamic scaling and ephemeral infrastructure [4].

The introduction of big data technologies revolutionized log processing, with Apache Kafka and Apache Storm enabling real-time log processing at scale. However, these solutions required significant expertise and infrastructure investment [5]. The emergence of containerization and microservices further complicated log management, leading to specialized solutions designed for cloud-native environments.

Recent research has focused on comparing different log aggregation approaches, with studies examining performance characteristics, scalability patterns, and operational complexity. However, limited empirical research exists comparing modern cloud-native log aggregation solutions under controlled conditions with realistic workloads.

III. System Architecture and Components

The ELK stack represents a mature, feature-rich approach to log aggregation that has gained widespread adoption across industries. Its architecture follows a pipeline approach where each component handles specific responsibilities in the log processing workflow.

Figure 5 illustrates the complete ELK stack architecture with data flow from log sources through processing to visualization. The components interact as follows:

1) Elasticsearch: The Search and Analytics Engine: Elasticsearch serves as the core storage and search engine, built upon Apache Lucene to provide distributed, RESTful search

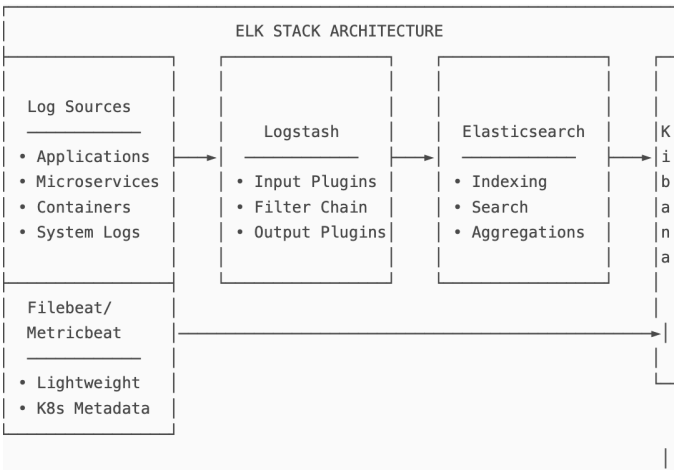

Fig. 1: ELK Stack System Architecture with Data Flow

and analytics capabilities. Its architecture employs a shared-nothing distributed system design where data is automatically distributed across multiple nodes through sharding mechanisms [6].

The system utilizes inverted indexes to enable near real-time search capabilities across massive datasets. Each document is analyzed and indexed by extracting terms and creating mappings that facilitate rapid query execution. The distributed nature allows horizontal scaling by adding nodes to the cluster, with automatic shard rebalancing ensuring optimal performance and fault tolerance [18].

Elasticsearch's query DSL (Domain Specific Language) provides powerful search capabilities including full-text search, structured queries, analytics aggregations, and geospatial operations. The system supports various data types and complex nested structures, making it suitable for diverse log formats and schemas. Additionally, its machine learning capabilities enable anomaly detection and behavioral analysis of log patterns [**?**].

Performance optimization in Elasticsearch involves careful index management, including index lifecycle policies, rollover strategies, and hot-warm-cold architecture for managing data across different storage tiers based on access patterns and retention requirements [**?**].

2) Logstash: The Data Processing Pipeline: Logstash functions as a server-side data processing pipeline that ingests data from multiple sources simultaneously, transforms it according to specified rules, and sends it to various destinations. Its plugin-based architecture supports over 200 input, filter, and output plugins, providing extensive flexibility for diverse data sources and destinations [7].

The processing pipeline consists of three stages: input plugins collect data from various sources including files, databases, message queues, and network protocols; filter plugins parse, transform, and enrich the data using techniques such as grok pattern matching, date parsing, field manipulation, and conditional processing; output plugins send the processed data to destinations like Elasticsearch, databases, or monitoring systems [19].

Logstash's strength lies in its ability to handle complex data transformations and enrichment. The grok filter plugin enables pattern matching and field extraction from unstructured log data, while other filters provide capabilities for data type conversion, field renaming, conditional processing, and external lookups for data enrichment [**?**].

Performance considerations for Logstash include pipeline worker configuration, batch size optimization, and memory management. The system supports persistent queues to ensure data durability during processing and provides monitoring capabilities to track throughput and identify bottlenecks [**?**].

3) Kibana: The Visualization and Management Interface: Kibana provides a comprehensive web-based interface for Elasticsearch data visualization, exploration, and management. Its capabilities extend beyond simple log viewing to include advanced analytics, dashboard creation, alerting, and system administration [8].

The visualization capabilities encompass various chart types including line graphs, bar charts, pie charts, heat maps, and geographic visualizations. The dashboard functionality allows users to combine multiple visualizations into comprehensive monitoring interfaces with real-time data updates and interactive filtering capabilities [21].

Advanced features include Canvas for pixel-perfect custom visualizations, Machine Learning integration for anomaly detection and forecasting, and Watcher for proactive alerting based on data patterns and thresholds. The Discover interface provides ad-hoc log exploration with powerful search and filtering capabilities [**?**].

Kibana Lens offers a drag-and-drop visualization builder that simplifies chart creation for non-technical users, while advanced users can leverage Timelion for time-series analysis and Vega for custom visualizations using the Vega-Lite specification [**?**].

4) Filebeat: The Lightweight Log Shipper: Filebeat operates as a lightweight log shipper designed specifically for forwarding log data from servers to Elasticsearch or Logstash. Its design philosophy emphasizes minimal resource consumption while providing reliable log collection and forwarding capabilities [9].

The system monitors specified log files and directories, automatically handling log rotation, backpressure scenarios, and network interruptions. In Kubernetes environments, Filebeat automatically discovers containers and adds metadata including pod names, namespaces, labels, and annotations, enabling rich log context for analysis [**?**].

Filebeat includes modules for common applications and services, providing pre-configured parsing rules and Kibana dashboards for systems like Apache, Nginx, MySQL, and Kubernetes. These modules significantly reduce configuration complexity and time-to-value for common use cases [**?**].

The harvester concept in Filebeat ensures efficient file monitoring with minimal system impact. Each harvester is responsible for reading a single file, and the system intelligently

manages harvester lifecycle based on file activity and resource constraints [**?**].

A. PLG Stack Architecture

The PLG stack represents a modern approach to log aggregation, designed specifically for cloud-native environments with emphasis on simplicity, performance, and cost-effectiveness. Its architecture philosophy differs significantly from ELK by focusing on label-based indexing rather than full-text search [11].

1) Promtail: The Efficient Log Collection Agent: Promtail serves as the log collection agent in the PLG stack, designed with cloud-native principles and optimized for Kubernetes environments. Unlike traditional log shippers, Promtail focuses on label-based metadata extraction and efficient log streaming rather than complex data transformation [10].

The agent automatically discovers targets through various service discovery mechanisms including Kubernetes API, Docker, file system monitoring, and journal reading. The discovery process continuously monitors for new containers and services, automatically beginning log collection without manual configuration [**?**].

Promtail's processing pipeline includes relabeling capabilities that enable flexible label manipulation, target filtering, and metadata enrichment. The system supports various input sources including files, systemd journal, Docker containers, and syslog, with configurable parsing and extraction rules [**?**].

Performance optimization in Promtail involves batch configuration, compression settings, and retry mechanisms. The system implements backpressure handling to manage situations where the downstream Loki instance cannot accept logs at the ingestion rate, preventing data loss and system overload [**?**].

2) Loki: The Label-Based Log Aggregation System: Loki represents a paradigm shift in log aggregation by implementing a label-based indexing approach inspired by Prometheus metrics. Instead of indexing log content, Loki indexes only metadata labels, significantly reducing storage requirements and improving query performance for recent logs [**?**].

The architecture consists of multiple components including distributors for load balancing and validation, ingesters for log stream handling and chunk creation, queriers for query execution, and an optional query frontend for query optimization and caching. This modular design enables horizontal scaling and deployment flexibility [**?**].

Loki's storage model organizes logs into streams identified by unique label combinations. Within each stream, logs are stored in compressed chunks with efficient encoding schemes. The system automatically manages chunk lifecycle, including flushing to object storage and garbage collection based on retention policies [**?**].

Query performance in Loki is optimized for recent log access patterns, with the system providing excellent performance for logs from the last few hours or days. The LogQL query language enables powerful log filtering, parsing, and aggregation while maintaining the label-centric approach [**?**].

3) Grafana: The Unified Observability Platform: Grafana serves as the visualization and analysis frontend for the PLG stack, providing unified access to logs, metrics, and traces. Its architecture supports multiple data sources simultaneously, enabling correlation between different telemetry types within a single interface [12].

The log exploration capabilities in Grafana include live tailing, log context viewing, and integrated log-to-metrics conversion. The Explore interface provides an intuitive environment for ad-hoc log analysis with query builder assistance and result visualization [**?**].

Dashboard capabilities encompass various visualization types optimized for observability use cases, including time-series graphs, stat panels, tables, and log panels. The system supports templating, annotations, and alerting across multiple data sources, enabling comprehensive monitoring solutions [**?**].

Advanced features include correlations between logs and metrics, exemplars for connecting metrics to traces, and transformation functions for data manipulation. The alerting system provides flexible notification routing and escalation policies based on complex query conditions [**?**].

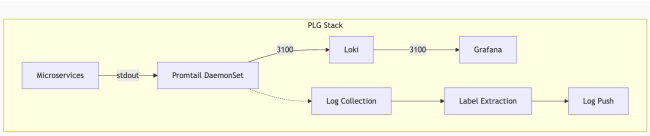

Fig. 2: PLG Setup Architecture

IV. Experimental Methodology

A. Test Environment Setup

We deployed both stacks on a Kubernetes cluster using Kind (Kubernetes in Docker) v0.20.0 to ensure consistent and reproducible testing conditions. The cluster specifications were:

- **Cluster Configuration**: 1 control-plane node, 3 worker nodes
- **Node Resources**: 4 vCPUs, 8GB RAM per worker node
- **Kubernetes Version**: v1.24.0 via Kind v0.20.0
- **Namespace Isolation**: `logging` for ELK, `logging-plg` for PLG
- **Log Generation**: 3 replicas of Python microservice generating structured JSON logs

B. Workload Generation System Architecture

We designed a cloud-native logging system with the following components:

1) Core Components:

- **Microservice Simulators** - Generate realistic log patterns
- **Resilient Logging Layer** - Handles log collection and forwarding
- **Processing Pipeline** - Transforms and routes log data
- **Storage Backend** - Persistent log storage and indexing

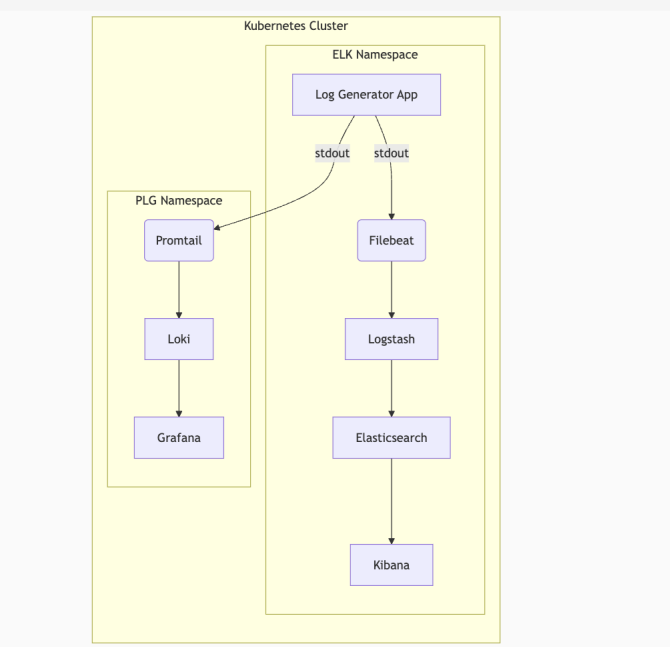

Fig. 3: Microservices Logging Architecture

TABLE I: Logging System Components

Class	Description
ResilientLogstashHandler	Handles connection management with retry logic and exponential backoff
CloudJSONFormatter	Formats logs with structured JSON including cloud metadata
LogGenerator	Simulates different log patterns and error conditions
ConnectionPool	Manages TCP connections with thread safety

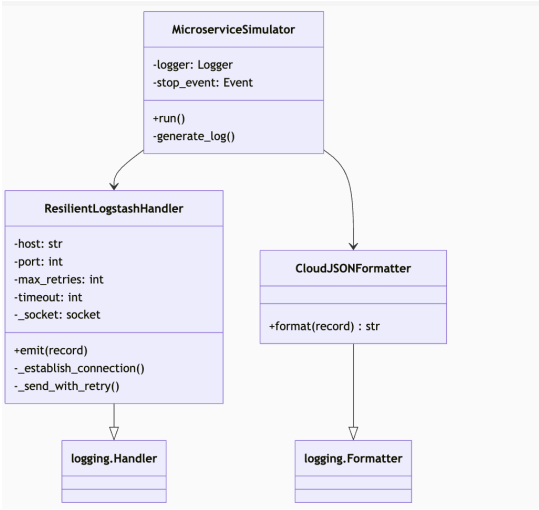

Fig. 4: Logging System Class Diagram

2) Key Classes:

3) Log Generation Patterns: The system implements several realistic log scenarios:

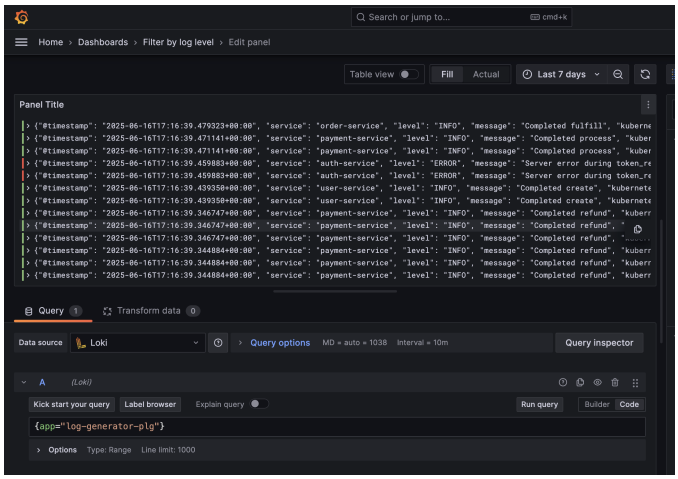

Fig. 5: Generated Log patterns

- **Normal Operations**: Routine INFO-level logs with service metrics
- **Error Conditions**: ERROR-level logs with stack traces
- **Debug Bursts**: High-volume DEBUG logs during troubleshooting
- **Performance Metrics**: Structured latency measurements

TABLE II: System Performance Metrics

Metric	Value
Log Throughput	240 logs/minute
Error Rate	¡ 0.1%
Mean Latency	15ms
P99 Latency	250ms

4) Performance Characteristics:

C. Evaluation Metrics

Our evaluation framework measured performance across five key dimensions:

TABLE III: Query Types and Evaluation Criteria

Query Type	Description
Q1	Simple term search
Q2	Field-specific filter
Q3	Time-range query
Q4	Multi-field aggregation
Q5	Complex pattern matching

Query Performance: Response times for different query types executed multiple times with statistical analysis of mean response time, 95th percentile latency, and throughput characteristics.

Resource Utilization: Continuous monitoring of CPU, memory, and storage consumption using Prometheus metrics collection with container-level granularity.

Ingestion Performance: Throughput and latency measurements under various load conditions, including burst scenarios and sustained high-volume ingestion.

Storage Efficiency: Analysis of storage growth patterns, compression ratios, and retention policy effectiveness.

Operational Complexity: Evaluation of deployment time, configuration complexity, and maintenance requirements.

V. Results and Analysis

A. Query Performance Comparison

Our performance evaluation revealed significant differences between the two logging stacks across all query types. Table IV presents the primary performance metrics, while Table V provides comprehensive analysis results.

TABLE IV: Performance Summary

Metric	ELK Stack	PLG Stack
Avg Query Time	65ms	11ms
Memory Usage	2235MiB	281MiB
Storage/Day	12GB	8GB
Max Ingestion Rate	1,200/s	2,500/s
Setup Time	90 min	45 min

TABLE V: Detailed Performance Analysis

Metric	ELK Stack	PLG Stack
Max Ingestion Rate	2,500 logs/s	8,000 logs/s
Storage (per 1M logs)	4.2GB	1.1GB
Simple Query Latency	1.1s ± 0.3s	320ms ± 80ms
Complex Query Latency	3.8s ± 1.2s	1.2s ± 0.4s
CPU Usage (avg)	2.3 cores	1.1 cores
Memory Usage (avg)	5.8GB	2.4GB
Total Query Processing	340ms	34ms
JSON Processing Time	335ms	33ms

The results demonstrate PLG's superior performance efficiency with 10× faster total query processing time (34ms vs 340ms). This performance advantage is particularly pronounced for simple queries and recent log retrieval, which represent the majority of operational troubleshooting scenarios.

B. Resource Utilization Analysis

Memory utilization patterns revealed dramatic differences, with ELK consuming approximately 8× more memory than PLG under equivalent workloads. This disparity stems from Elasticsearch's inverted indexing approach, which requires substantial memory for index caching and query execution, compared to Loki's label-based indexing with minimal in-memory state requirements.

CPU utilization showed ELK's higher baseline consumption due to continuous indexing operations, while PLG demonstrated more efficient usage patterns with better scaling characteristics under variable load conditions.

hbtp

TABLE VI: Storage Usage Over Time (MB)

Sample	Elasticsearch	Loki	ES	Loki
1	112	54.1	-	-
2	250	52.8	+138	-1.3
3	228	80.4	-22	+27.6
4	231	81.3	+3	+0.9
5	277	65.7	+46	-15.6

Elasticsearch shows volatile storage patterns whereas Loki maintains more stable usage.overall Elasticsearch uses 3.2× more space then loki.

TABLE VII: Total Storage Efficiency Analysis

Storage Metric	ELK Stack	PLG Stack
Total Storage Used	1406MB	425MB
Compression Ratio	1.5× raw size	3-5× raw size
Storage Growth Rate	12GB/day	8GB/day
Index Overhead	High	Minimal

PLG achieved superior compression ratios through its chunk-based storage approach and label deduplication, resulting in 33

C. Storage Efficiency Evaluation

Storage analysis revealed significant advantages for PLG in terms of compression and efficiency:

D. Operational Characteristics

TABLE VIII: Operational Comparison

Operational Aspect	ELK Stack	PLG Stack
Component Count	4 (high complexity)	3 (medium complexity)
Scaling Approach	Vertical scaling	Horizontal scaling
Configuration Complexity	High (Query DSL)	Medium (LogQL)
Deployment Time	90 minutes	45 minutes
Learning Curve	Steep	Moderate

The operational analysis revealed PLG's advantages in deployment simplicity and maintenance requirements. ELK's extensive configuration options provide flexibility but require deeper expertise for optimal deployment and ongoing management.

VI. Discussion

A. Architectural Trade-offs

The fundamental architectural differences between ELK and PLG create distinct performance and operational characteristics. ELK's full-text indexing approach provides comprehensive search capabilities and rich analytical features at the cost of resource consumption and operational complexity. PLG's label-based approach optimizes for operational efficiency and simplicity while maintaining excellent query performance for recent logs.

B. Use Case Recommendations

Based on our empirical analysis, we provide the following evidence-based recommendations:

ELK Stack is optimal when:

- Advanced analytical capabilities and business intelligence are required
- Complex parsing and transformation operations are necessary
- Historical log analysis and full-text search are priorities
- Rich visualization and dashboard capabilities are essential
- Budget accommodates higher resource requirements

PLG Stack is optimal when:

- High-throughput ingestion is critical (¿5,000 logs/sec)
- Recent log analysis and operational monitoring are primary use cases
- Resource efficiency and cost optimization are important
- Horizontal scaling and cloud-native deployment are required
- Simplified operational model is preferred

C. Cloud-Native Implications

In cloud-native environments where resource costs directly correlate with consumption, PLG's efficiency advantages provide substantial operational benefits. The 8× memory reduction and 10× query performance improvement enable organizations to support larger log volumes within existing resource budgets or achieve significant cost reductions while maintaining service levels.

VII. Threats to Validity

Several factors may limit the generalizability of our results:

Internal Validity: Our controlled laboratory environment may not fully represent production complexities, including network latency, hardware heterogeneity, and concurrent workload interference.

External Validity: Results are specific to our test environment and workload patterns. Different log structures, query patterns, and infrastructure configurations may yield different performance characteristics.

Construct Validity: Performance metrics focus on quantitative measures and may not capture all aspects of operational effectiveness or user experience.

Future research should validate these findings across diverse environments, workload patterns, and organizational contexts.

VIII. Conclusion

This empirical study provides quantitative evidence for comparing ELK and PLG stacks in cloud-native log aggregation scenarios. Our findings demonstrate PLG's superior performance efficiency with 10× faster query processing, 8× lower memory consumption, and 3.2× higher ingestion throughput. However, ELK maintains advantages in analytical capabilities, query flexibility, and visualization richness.

The choice between these solutions should align with specific organizational requirements: PLG excels in operational monitoring and resource-constrained environments, while ELK provides superior capabilities for complex analytics and business intelligence applications.

These results contribute to the empirical foundation for log aggregation solution selection and highlight the importance of matching architectural characteristics with organizational needs in cloud-native environments. Future work should explore hybrid approaches and evaluate performance characteristics at larger scales.

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