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Adaptive Self-Healing and Cost-Aware Real-Time Data Pipeline Framework with Reinforcement-Based Routing and Anomaly-Aware Optimization

Venkat Alamuri

venkat.alamuri@gmail.com

NO https://orcid.org/0009-0000-7460-047X

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Adaptive Self-Healing and Cost-Aware Real-Time Data Pipeline Framework with Reinforcement-Based Routing and Anomaly-Aware Optimization

Venkatesh Alamuri
Research Scholar
venkat.alamuri@gmail.com

Abstract

The modern real-time pipelines of streaming data are under the heavy burden of adapting to a dynamically varying workload, anomaly situations, and evolving cloud costs which lead to poor performance and large overheads in operation. The existing systems largely rely on either fixed routing configurations and reactive control, lacking architectures to integrate reactive routing, anomaly detection, and optimisation of costs in a closed loop. In order to fill this gap, the present paper will suggest a new adaptive, self-healing, and cost-aware streaming data pipeline architecture comprising of Adaptive Routing Engine (ARE), Smart Buffering Mechanism (SBM), Self-Healing Pipeline Controller (SHPC), Intelligent Schema Evolution Engine (ISEE), AI-driven Anomaly Detection Layer (A2DL), and Cost Optimization Engine (COE This framework employs decision policies based on reinforcement and feedback control loops to optimize dynamically routing, buffering and recovery actions under different workload and failure conditions. Experimental trials on real and artificial streaming data demonstrate that the suggested system can decrease up to 25-40 percent of delays, 15-30 percent of expenses and enormously mean time to recuperate (MTTR) of that of base static pipelines. The primary contributions of this work include (i) a shared infrastructure of adaptive and resilient streaming systems, (ii) a cost-latency-reliability optimization model that is formalized and (iii) an experimental pipeline that, through measurable results, can compare the next-generation cloud-native streaming infrastructures.

Keywords: *Real-time streaming systems, adaptive routing, self-healing pipelines, anomaly detection, cost-aware optimization, cloud-native data pipelines, reinforcement learning, distributed stream processing.*

INTRODUCTION

1.1 Background

Due to the blistering development of distributed application, IoT, and cloud-native services generating real-time data, the use of streaming data pipelines has become a staple of the current data infrastructures. Modern stream processors like Apache Kafka, Apache Flink, and Google Dataflow are designed to process URLs in real-time with low-latency and at scale but are now confronted by variable workload shapes, unforeseen anomalies, and increasing operational

expenses in the cloud (Fragkoulis et al., 2024; Raptis and Passarella, 2023). Specifically, cloud streaming systems present complicated trade-offs between latency, throughput, and cost by which aggressive scaling leads to enhanced performance at the cost of greatly increased resource consumption and spending. Moreover, experimental literature indicates that conventional streaming designs do not have flexible mechanisms to address real-time conditions of the system, which result in inefficiencies and poor reliability with varying workloads (Alonso et al., 2021; Rouholamini and Mirabi, 2024). These have led to the need to come up with clever, self-adaptive streaming architecture designed to be able to tune the actions of the systems to optimize dynamically at the same time, be resiliently and cost-effectively.

1.2 Problem Statement

Even with the developments of distributed stream processing, the majority currently available pipelines are configured to use only fixed configurations and well-defined routing policies, which are not made to work in the highly dynamic and uncertain environment. These types of pipelines have a critical performance when exposed to (i) varying workloads, e.g., bursty traffic, uneven data distribution, (ii) anomaly conditions, e.g. data corruption, system errors, or sluggish processing, (ii) cost pressures, i.e. due to changes in cloud pricing and poor use of resources. Lack of real-time decision-making processes results in longer latency, higher failure rates, and increased operational costs, as noted in recent work on self-healing and adaptive systems (Satyanarayanan, 2022; Beereddy, 2025). Furthermore, the current existing solutions disseminate these two issues, such as anomaly detection without routing adaptation and cost optimization without resilience, making them a disjointed system architecture that cannot optimize the system in a holistic manner. Therefore, a universal framework that can be used to simultaneously handle performance, dependability and cost in real-time streaming context is in high demand.

1.3 Research Gap

A review of the literature indicates that although there have been some milestones achieved in each of the domains, including anomaly detection, adaptive scaling, and cost-sensitive scheduling, there are gaps of integrating systems and making them into a unified system. The existing streaming systems lack a single mechanism that combines adaptive routing, anomaly-aware decision-making, self-healing control and cost optimization in a closed loop system. As an example, anomaly detection methods are usually unlinked with execution logic, restricting their effects on system modifications (Umar and Iqbal, 2025), and cost optimization approaches tend to be responsive and non-real-time sensitive to workloads and failure situations. Also, the current architectures seldom utilize feedback-based control which learns and adapts behavior of the system as a result of monitored metrics. This discontinuity underscores the fact that there is a lack of an overall, modular and reproducible framework that incorporates routing, cost, anomaly detection and self-healing into one adaptive streaming system to further encourage the relevance of the approach proposed.

1.4 Contributions

This paper makes the following key contributions:

- We introduce a new adaptive routing engine (ARE), a dynamic algorithm that picks the best processing paths, by considering the workload characteristics, anomaly scores, and cost limits, via a reinforcement-based decision model.

- We publish a self-healing controller (SHPC) that is a closed-loop device that automatically measures system metrics and only takes corrective measures, which allows us to quickly identify faults and minimizes the time to recovery.
- We propose a cost-sensitive optimization system (COE) to combine real-time cost-monitoring technique and dynamically adjusted buffering and routing policy to reach the optimal resource utilization in the cloud.
- Here, we design a repeatable experimental set-up which integrates real and synthetic data-sets, benchmark tests and stringent evaluation criterion to confirm machinery of the suggested system.

1.5 Paper Organization

The rest of this paper is structured as follows: Section 4 provides the related work review in the streaming system, anomaly detection, and cloud optimization: Section 5 is the system model with the formulation of the formal problem to be addressed; Section 6 provides a detailed description of the proposed architecture and its components; Section 7 describes the implementation and deployment configuration; Section 8 outlines the experimental design and evaluation methodology; and Section 9 draws conclusions and provides

1.6 Architecture diagram

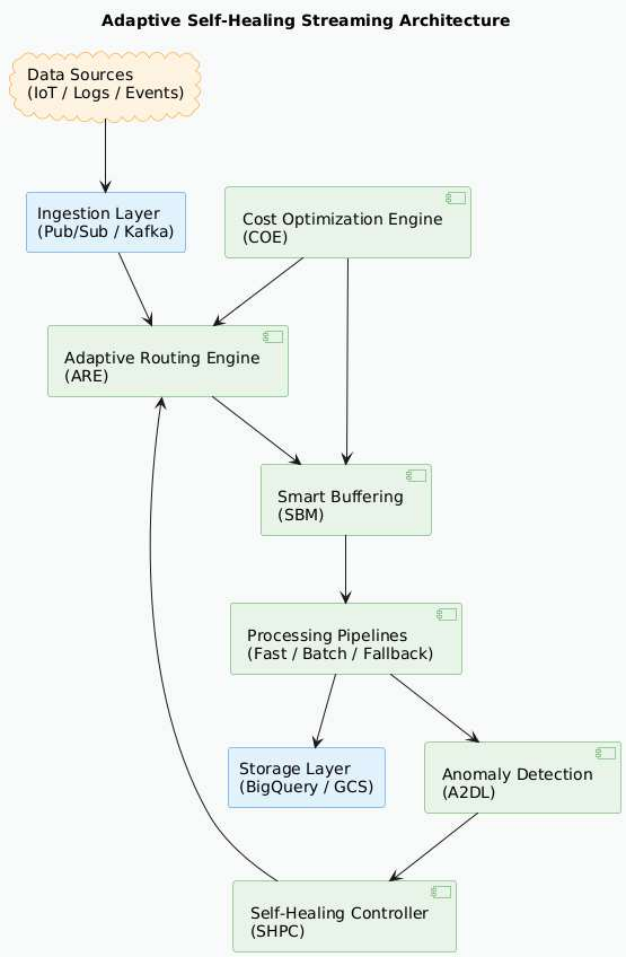


Figure 1. Architecture Diagram

The proposed architecture follows a modular and feedback-driven design in which streaming data from heterogeneous sources is ingested through a scalable messaging layer and dynamically routed by the Adaptive Routing Engine (ARE) based on real-time workload, anomaly scores, and cost signals; the Smart Buffering Mechanism (SBM) further optimizes data flow by adaptively adjusting batch sizes, after which events are processed across multiple pipelines tailored for performance and cost trade-offs, while the Anomaly Detection Layer (A2DL) continuously analyzes system behavior and feeds insights to the Self-Healing Pipeline Controller (SHPC), enabling autonomous recovery and rerouting decisions, and simultaneously the Cost Optimization Engine (COE) monitors resource utilization and expenditure to influence routing and buffering policies, thereby forming a closed-loop system that integrates performance optimization, resilience, and cost efficiency within a unified streaming framework.

LITERATURE REVIEW

2.1 Streaming Data Pipelines

Streaming data pipelines have developed to be very different to the initial batch-focused models into contemporary distributed, real-time processing frameworks which can process large volumes of workloads and with low latency. Allogenous systems like Apache Kafka, Apache Flink, and Google Dataflow have facilitated event-driven platforms that are scalable, utilize fault tolerance, stateful processing, and window-based calculations (Fragkoulis et al., 2024; Raptis and Passarella, 2023). More recent studies have expanded upon adaptive streaming so as to deal with variability in workload and dynamic system conditions. As an example, Marcu and Bouvry (2024) emphasize the significance of the backpressure and flow control in the stability of systems under high throughput, and Kušić et al. (2023) show how real-time data streams can be implemented to the digital twin systems to model the dynamic system. Moreover, new research in streaming machine learning focuses on continuous learning instead of changing data streams, with systems adaptable to variations in data over time (Miao et al., 2024). With all these advances, the majority of streaming pipelines deployed today utilize very basic routing and fixed execution policies, incapable of dynamically optimizing performance and cost under conditions found in real-world clouds.

2.2 Streams Anomaly Detection

Detecting anomalies is important to provide reliability and robustness to streaming systems, such as detecting inconsistencies in data, system failures and performance drop. Historical methods invoke the use of statistical methods like thresholding, distribution-based methods, whereas more recent studies invoke machine learning and deep learning models to design more precisely detected solutions to high-dimensional streaming data (Al Mamun et al., 2024; Lucas Filho et al., 2025). Moreover, machine learning-powered anomaly detection has also become a component of real-time to allow proactive fault detection and prevention (Umar and Iqbal, 2025). In streaming systems, detecting anomalies should be able to perform with stringent latency limits, requiring very lean and scalable models. One of the main constraints of current methods, however, is the fact that the anomaly detection and system control mechanisms are not tightly interconnected. Most systems consider anomaly detection as a monitoring feature, as opposed to a driver of adaptive decision-making and thus limit its effects on overall system optimization and resilience.

2.3 Self-Healing Systems

Self-healing systems have become an attractive new paradigm to enhance the resilience and reliability of distributed systems through automated fault detection and recovery. The initial strategies revolved around rule-based recovery methods, whereas more recent ones use AI-based methods and feedforward control mechanisms that allow the autonomous system to adapt (Satyanarayanan, 2022; Rouholamini and Mirabi, 2024). As Beeredy (2025) proves, self-healing architectures have been shown to be very effective in minimizing the cost of operational recovery and enhancing the availability of the system since the automated remediation works. Equally, Patel (2025) spotlights the usage of observability-fueled pipelines to assist in real-time fault detection and recovery within a distributed setting. Though these progress has been made, the current self-healing systems tend to work in isolation of other parts of the system like routing and cost minimization, resulting in disaggregated architectures. Furthermore, not all systems have closed-loop control measures to regulate system behavior in relation to real-time feedback, which restricts their capabilities to adapt to dynamic systems.

2.4 Cost optimization in Cloud Systems

This is because the cost optimization has become a pivotal issue in cloud-based streaming systems due to the pay-as-you-go pricing scheme, and the rapidly growing scale of workloads of data processing. Current strategies center on resource and workload scheduling, coupled with effective strategies on data storage to reduce the cost of operations (Alonso et al., 2021). As an illustration, adaptive scaling methods allocate resources dynamically according to the workload needs, whereas buffering and batching mechanisms decrease the price of data ingestion and data storage tasks. Nevertheless, these methods tend to work separately and fail to embrace interactions of cost, performance and system reliability. Recently, it is pointed out that there is a need to develop unified optimization models that would simultaneously take into account various objectives, including latency, throughput, and cost, to come up with a balanced system performance (Rouholamini & Mirabi, 2024). Still, existing systems do not include real-time cost-conscious decision making systems that can dynamically affect routing and processing plans influenced by the dynamic system conditions.

2.5 Research Gap Summary Table

The following table summarizes the limitations of existing approaches and highlights the research gap addressed by this work.

Table 1: Comparative Analysis of Existing Streaming Systems

Work	Adaptive Routing Capability	Anomaly-Aware Decision Integration	Self-Healing Mechanism	Cost Optimization Strategy	Closed-Loop Control	Key Limitation
Fragkoulis et al. (2024)	Not supported	Not considered	Not addressed	Not addressed	Absent	Focuses on evolution of streaming systems without adaptive intelligence

Raptis & Passarella (2023)	Limited support through system-level optimizations	Not considered	Not addressed	Partially addressed via Kafka tuning	Absent	Lacks integration of adaptive decision-making and resilience mechanisms
Marcu & Bouvry (2024)	Not supported	Not considered	Not addressed	Not addressed	Absent	Concentrates on flow control without system-wide optimization
Miao et al. (2024)	Partially supported through learning-based adaptation	Partially considered in prediction models	Not addressed	Not addressed	Absent	Focuses on prediction rather than full pipeline adaptability
Lucas Filho et al. (2025)	Not supported	Strongly supported using ML models	Not addressed	Not addressed	Absent	Anomaly detection is not integrated with system control
Satyanarayanan (2022)	Not supported	Partially considered	Fully supported through self-healing pipeline logic	Not addressed	Partially implemented	Lacks cost-awareness and unified optimization
Beereddy (2025)	Not supported	Strongly supported	Fully supported	Partially considered	Partially implemented	Missing adaptive routing and unified control strategy
Alonso et al. (2021)	Not supported	Not considered	Not addressed	Strongly supported through optimization techniques	Absent	Cost optimization is isolated from system dynamics
Proposed Framework	Fully supported through adaptive routing engine	Fully integrated with anomaly-aware decision-making	Fully implemented via closed-loop self-healing controller	Fully integrated with real-time cost-aware optimization	Fully implemented	Provides a unified, adaptive, and closed-loop streaming system

The comparative analysis shows with little ambiguity that current methods and solutions consider single aspects of streaming systems, with anomaly detection, and self-healing or cost optimization being considered, but do not offer a framework that brings them together as one and dynamic system. More specifically, the lack of closed-loop control systems and real-time decision making hinders the capability of the existing systems to react dynamically to fluctuating workloads, anomalies and cost constraints. This vulnerability can inspire the proposed framework, a hybrid of adaptive routing, anomaly-based decision-making, self-

healing control, and optimization of costs in a single-architecture framework, implying the holistic optimization of streaming data pipelines.

SYSTEM MODEL & PROBLEM FORMULATION

3.1 System Definition

We discuss a real-time streaming framework that consists of stream of continuous events, processing pipelines, and adaptive control units that run within a cloud infrastructure. So, the incoming data stream can be characterised as:

$$S = \{e_1, e_2, e_3, \dots, e_t\} \qquad (1)$$

where each event $e_i$is characterized as:

$$e_i = (timestamp_i, payload_i, priority_i) \qquad (2)$$

The system consists of a set of processing pipelines:

$$P = \{p_1, p_2, \dots, p_k\} \qquad (3)$$

Each pipeline $p_j$is associated with:

- Cost: $C(p_j)$
- Latency: $L(p_j)$
- Failure risk: $F(p_j)$

At any time step t, the system state is defined as:

$$X_t = (load_t, backlog_t, anomaly_t, cost_t) \qquad (4)$$

where:

- $load_t$: incoming event rate
- $backlog_t$: queue size
- $anomaly_t$: anomaly score
- $cost_t$: system cost per unit time

The objective of the system is to dynamically assign events $e_i$to pipelines $p_j$while optimizing performance, cost, and reliability.

3.2 Optimization Objective

We formalize the system objective as a multi-objective optimization problem:

$$\min_{p_j \in P} \; J(p_j, t) \qquad (5)$$

where:

$$J(p_j, t) = \alpha \cdot C(p_j, t) + \beta \cdot L(p_j, t) + \gamma \cdot F(p_j, t) \qquad (6)$$

Here:

- $\alpha, \beta, \gamma$are weighting coefficients
- $C(p_j, t)$: cost per event
- $L(p_j, t)$: latency
- $F(p_j, t)$: failure probability

Additionally, system constraints include:

$$L(p_j, t) \leq L_{max} \quad (7)$$
$$C(p_j, t) \leq C_{budget} \quad (8)$$
$$Throughput_t \geq \lambda_{min} \quad (9)$$

This formulation ensures a balanced trade-off between performance and cost-efficiency under dynamic conditions.

3.3 Routing Decision Model

The Adaptive Routing Engine (ARE) is modeled as a contextual multi-armed bandit problem.

Let:

- Action space: $A = \{p_1, p_2, \ldots, p_k\}$
- Context: X_t

At each time step t, the routing decision is:

$$a_t = \arg \max_{p_j \in P} \; Q(X_t, p_j) \quad (10)$$

The reward function is defined as:

$$R_t = -(\alpha C_t + \beta L_t + \gamma F_t) \quad (11)$$

The expected reward is updated as:

$$Q_{t+1}(p_j) = Q_t(p_j) + \eta\big(R_t - Q_t(p_j)\big) \quad (12)$$

where:

- η: learning rate

This formulation enables adaptive routing decisions based on real-time system conditions.

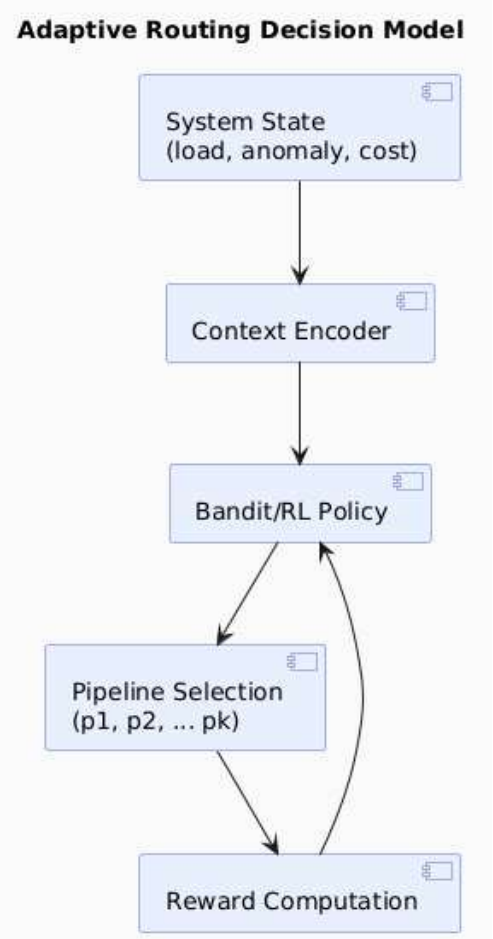


Figure 2. Adaptive Routing Decision Model

3.4 Buffering Model

The Smart Buffering Mechanism (SBM) dynamically adjusts batch sizes to balance latency and cost.

The batch size at time $t$is defined as:

$$BatchSize_t = f(load_t, latency_t, cost_t) \qquad (13)$$

We model this as:

$$BatchSize_t = \delta \cdot \frac{load_t}{1 + \lambda \cdot latency_t} + \mu \cdot cost_t \qquad (14)$$

where:

- δ, λ, μ: tuning parameters

Latency under batching:

$$Latency_t = ProcessingTime_t + QueueDelay_t \qquad (15)$$

Cost reduction through batching:

$$Cost_t \propto \frac{1}{BatchSize_t} \qquad (16)$$

This model ensures:

- high load → larger batches → lower cost
- low load → smaller batches → lower latency

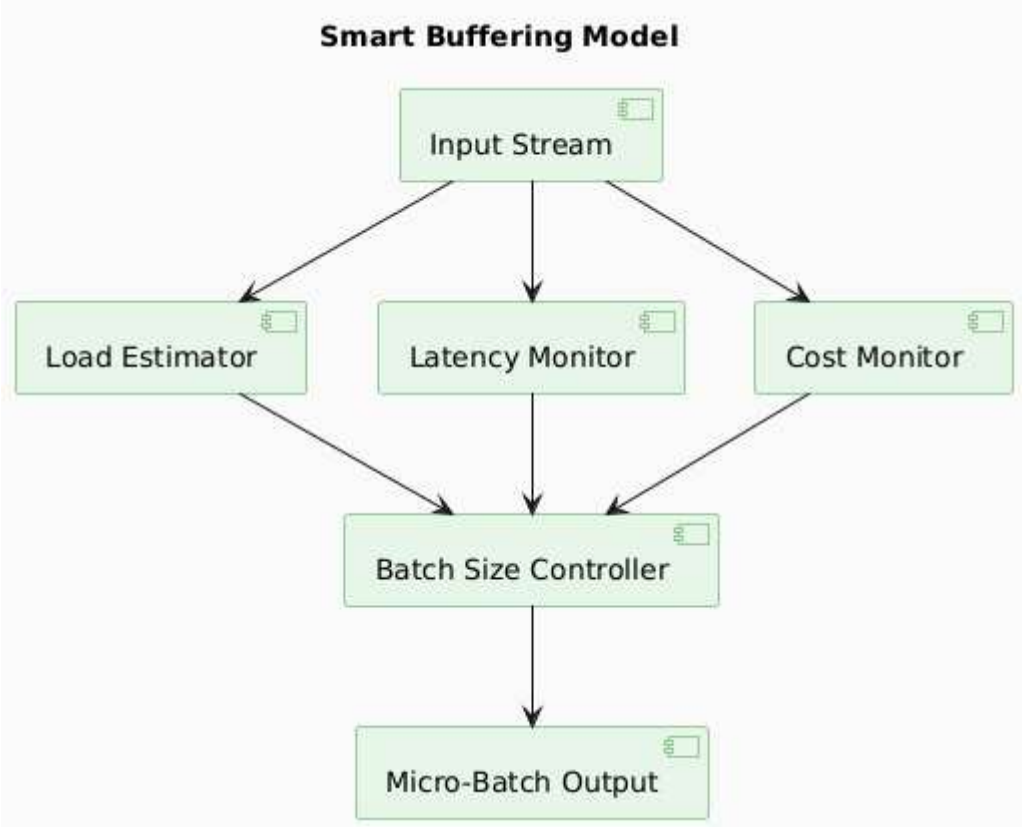


Figure 3. Smart Buffering Model

3.5 Control-Theoretic Model (SHPC)

The Self-Healing Pipeline Controller (SHPC) is modeled as a feedback control system.

Define system error:

$$e(t) = y_{target}(t) - y_{observed}(t) \qquad (17)$$

where:

- y: system metric (latency, backlog, etc.)

We apply a PID controller:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \qquad (18)$$

The control action $u(t)$influences:

- routing decisions

- scaling policies
- pipeline restarts

State update:

$$X_{t+1} = X_t + u(t) \qquad (19)$$

This ensures:

- fast recovery from failures
- stability under workload fluctuations

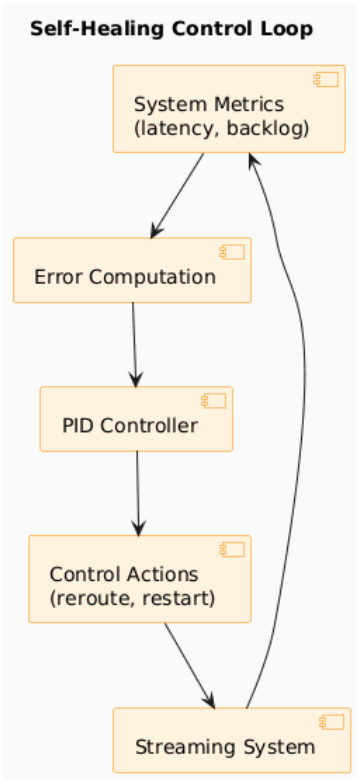


Figure 4. Self-Healing Control Loop

PROPOSED ARCHITECTURE

4.1 Overall System Architecture

The framework being proposed is a modular, adaptive, and closed-loop streaming platform with the view to streamline latency, cost, and resilience when working under dynamic loads. The architecture combines various intelligent elements Adaptive Routing Engine (ARE), Smart Buffering Mechanism (SBM) and Anomaly Detection Layer (A2DL) and Self-Healing Pipeline Controller (SHPC) and Schema Evolution Engine (ISEE) and Cost Optimization Engine (COE) into one pipeline which is running over cloud-native infrastructure.

Let the system be represented as:

$$\mathcal{A} = \{IN, ARE, SBM, P, A2DL, SHPC, ISEE, COE, ST\} \qquad (20)$$

The global system behavior is governed by:

$$Output_t = f(IN_t, ARE_t, SBM_t, SHPC_t, COE_t) \qquad (21)$$

Overall Architecture Diagram

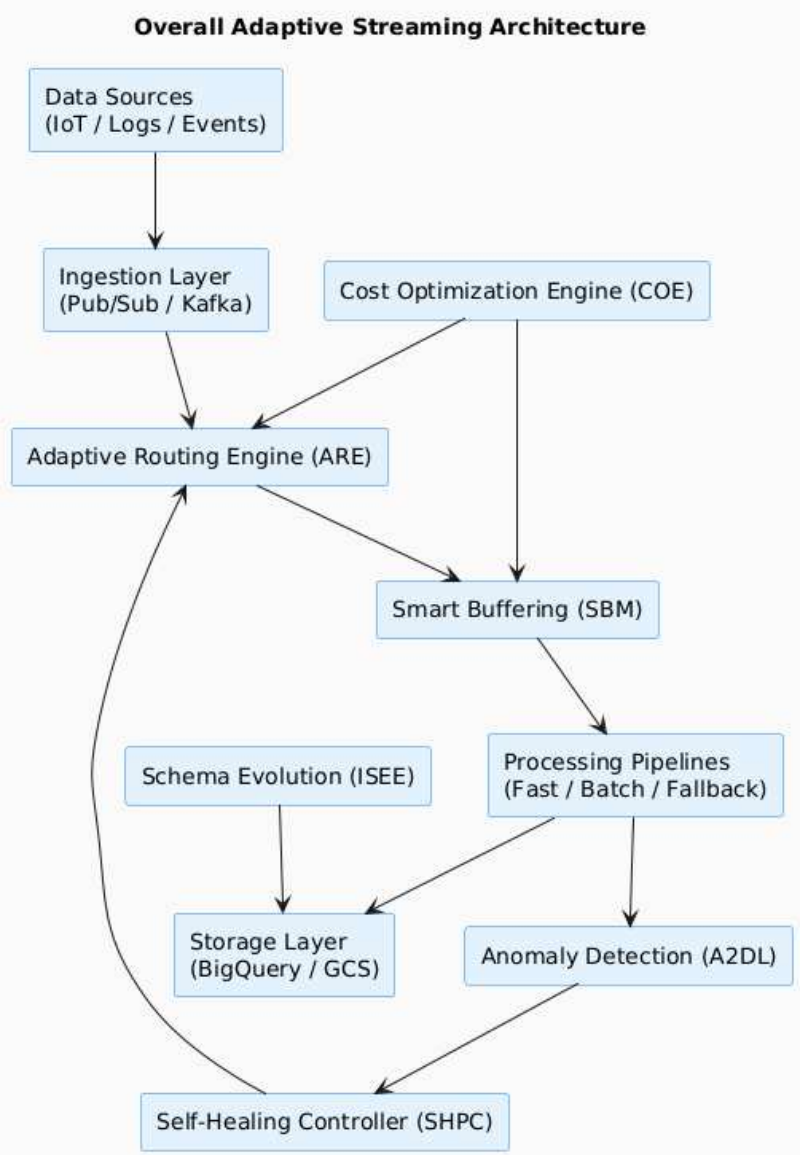


Figure 5. Overall Architecture Diagram

4.2 Data Ingestion Layer

The ingestion layer is responsible for capturing and buffering high-throughput event streams from heterogeneous sources.

Let incoming rate:

$$\lambda_t = \frac{d \mid S \mid}{dt} \qquad (22)$$

Queue backlog evolves as:

$$B_t = B_{t-1} + \lambda_t - \mu_t \qquad (23)$$

where $\mu_t$is processing rate.

The ingestion system ensures:

$$\mu_t \geq \lambda_t \text{(stability condition)} \qquad (24)$$

4.3 Adaptive Routing Engine (ARE)

ARE dynamically assigns events to pipelines using contextual optimization.

Routing probability:

$$P(p_j \mid X_t) = \frac{\exp\left(Q(X_t, p_j)\right)}{\sum_k \exp\left(Q(X_t, p_k)\right)} \qquad (25)$$

Decision:

$$p^* = \arg\max_{p_j} Q(X_t, p_j) \qquad (26)$$

Expected utility:

$$U(p_j) = -(\alpha C_j + \beta L_j + \gamma F_j) \qquad (27)$$

ARE Diagram

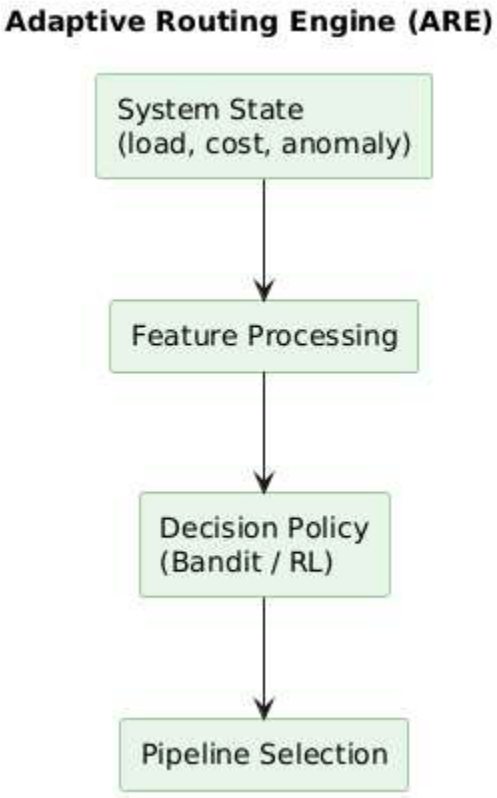


Figure 6. ARE DIagram

4.4 Smart Buffering Mechanism (SBM)

SBM dynamically adjusts micro-batch sizes to balance latency-cost trade-offs.

$$BatchSize_t = \delta \cdot load_t + \mu \cdot cost_t - \lambda \cdot latency_t \qquad (28)$$

Effective latency:

$$L_t = L_{proc} + \frac{BatchSize_t}{\lambda_t} \qquad (29)$$

Cost model:

$$C_t \propto \frac{1}{BatchSize_t} \qquad (30)$$

SBM Diagram

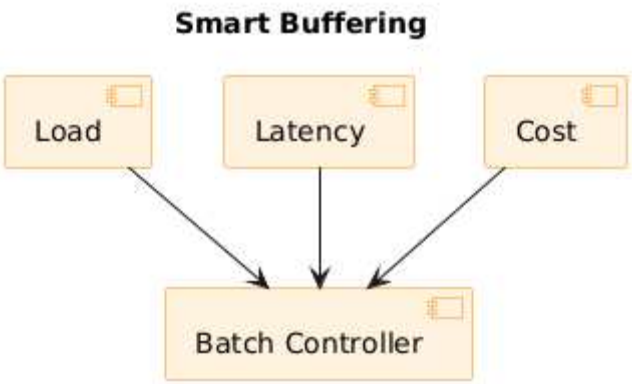


Figure 7. Smart Buffering

4.5 Anomaly Detection Layer (A2DL)

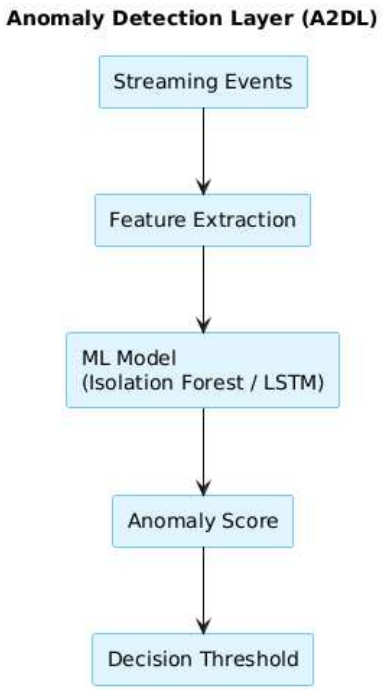


Figure 8. A2DL Diagram

A2DL computes anomaly score:

$$A_t = g(e_t) \qquad (31)$$

For ML-based detection:

$$A_t = \| x_t - \hat{x}_t \| \qquad (32)$$

Threshold condition:

$$A_t > \theta \Rightarrow anomaly \qquad (33)$$

This score influences routing and recovery decisions.

4.6 Self-Healing Pipeline Controller (SHPC)

SHPC uses feedback control:

$$e(t) = target - observed \qquad (34)$$

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \qquad (35)$$

System update:

$$State_{t+1} = State_t + u(t) \qquad (36)$$

SHPC Diagram

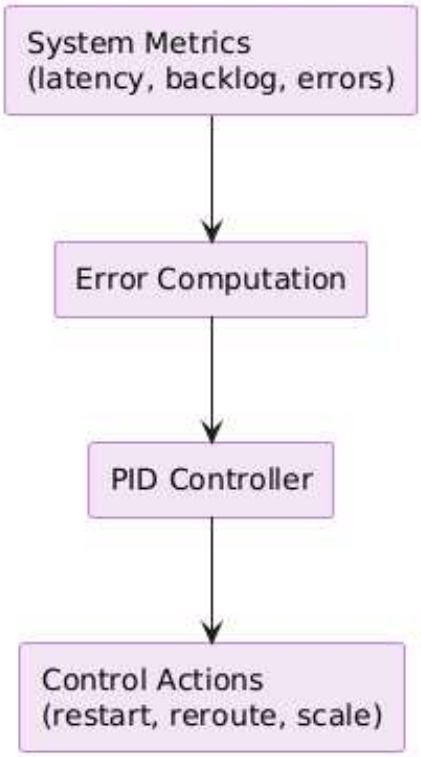


Figure 9. SHPC Diagram

4.7 Schema Evolution Engine (ISEE)

ISEE ensures schema compatibility:

$$Schema_{t+1} = Schema_t + \Delta Schema \qquad (37)$$

Compatibility constraint:

$$f(Schema_t, Schema_{t+1}) = valid \qquad (38)$$

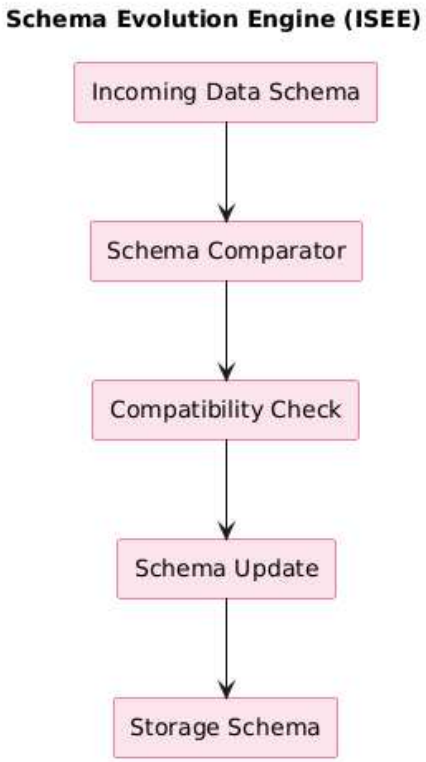


Figure 10. ISEE Diagram

4.8 Cost Optimization Engine (COE)

Cost model:

$$Cost_t = \sum_i resource_i \cdot price_i \qquad (39)$$

Optimization:

$$\min \ Cost_t \text{s.t. } L_t \leq L_{max} \qquad (40)$$

Policy update:

$$Policy_t = Policy_{t-1} + \nabla Cost \qquad (41)$$

COE Diagram

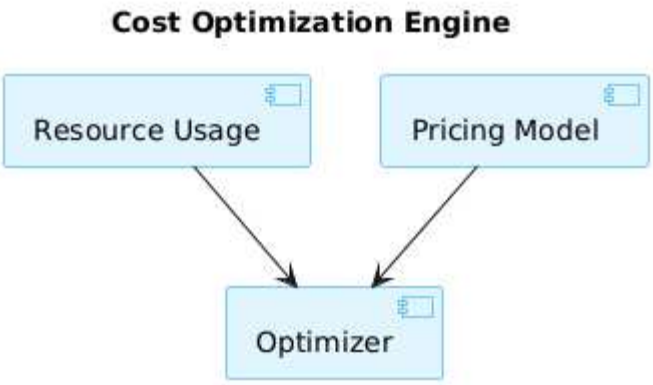


Figure 11. COE Diagram

4.9 System Workflow (End-to-End)

The complete system workflow is defined as:

$$e_t \rightarrow IN \rightarrow ARE \rightarrow SBM \rightarrow P \rightarrow ST \qquad (42)$$

Feedback loop:

$$P \rightarrow A2DL \rightarrow SHPC \rightarrow ARE \qquad (43)$$

Cost loop:

$$COE \rightarrow (ARE, SBM) \qquad (44)$$

End-to-End Workflow Diagram

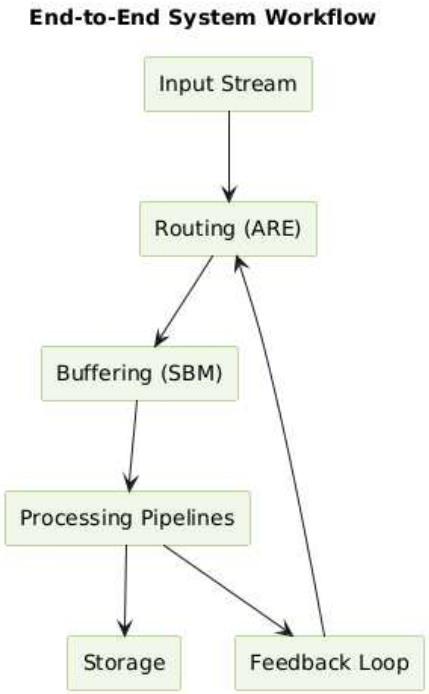


Figure 12. End to End WorkflowDiagram

End-to-End Workflow Diagram

IMPLEMENTATION DETAILS

5.1 Technology Stack

The suggested framework is deployed in a cloud-native environment on Google Cloud Platform (GCP) that relies on fully managed services to achieve scalability and fault tolerance, as well as stability in operational efficiency. A fundamental set of the system is based on the strictly combined streaming ecosystem of Pub/Sub, Dataflow (Apache Beam), BigQuery and Cloud Storage.

The data ingestion layer makes use of Google Cloud Pub/Sub which is a distributed messaging system, high throughput and low latency event streaming. Pub/Sub guarantees the at-least-once delivery semantics; it supports horizontal scaling to the changing ingestion rates. The incoming event rate λ tis is dynamically dealt with through topic partitioning and subscription scaling whereby:

$$Throughput_{ingestion} \approx O(n_{partitions}) \qquad (45)$$

Google Cloud Dataflow is used to implement the processing layer and execute Apache Beam pipelines that use a unified batch and stream processing. The flow of data allows automatic scaling of resources and dynamic rebalancing of work, so that the system can be adjusted to changes in the workload. Execution model is in a directed acyclic graph (DAG):

$$Pipeline = (V, E) \qquad (46)$$

where:

- V: transforms (map, window, aggregation)
- E: data flow edges

Storing the layer is based on another store Google BigQuery, which is a serverless analytic workload-optimised data warehouse. Queries are made more efficient and both storage costs are lower with partitioned and clustered tables:

$$QueryCost \propto \frac{DataScanned}{PartitionPruning} \qquad (47)$$

Also, intermediate storage, checkpointing and model artifact persistence are handled by Google Cloud storage (GCS).

This technology stack guarantees:

• high scalability

• strong fault tolerance

- smooth inter-component interconnectivity.

5.2 Microservices Design

The architecture follows a microservices-based design in which all the core components are launched as a stand-alone, loosely coupled service with Google Cloud Run. The design also allows independent lifecycle management, scalability and modularity. Let the system services be defined as:

Let the system services be defined as:

$$M = \{m_{ARE}, m_{SHPC}, m_{A2DL}, m_{COE}, m_{ISEE}\} \qquad (48)$$

All microservices m i have REST/gRPC endpoints and communicate asynchronously with Pub/Sub topics or HTTP triggers. Service Responsibilities ARE Service: calculates the routing choices according to the system state. A2DL Service: anomaly scoring based on ML models. SHPC Service: implements control measures (restart, reroute) COE Service: tracks cost measures and revises policies. ISEE Service: schema validation and evolution.

Services interaction is:

$$m_i \overset{event/API}{\rightarrow} m_j \qquad (49)$$

Each service is containerized using Docker and deployed with auto-scaling policies:

$$Instances_t = f(request_rate_t) \qquad (50)$$

This ensures that system components scale independently based on demand, reducing resource contention and improving fault isolation.

Microservices Architecture Diagram

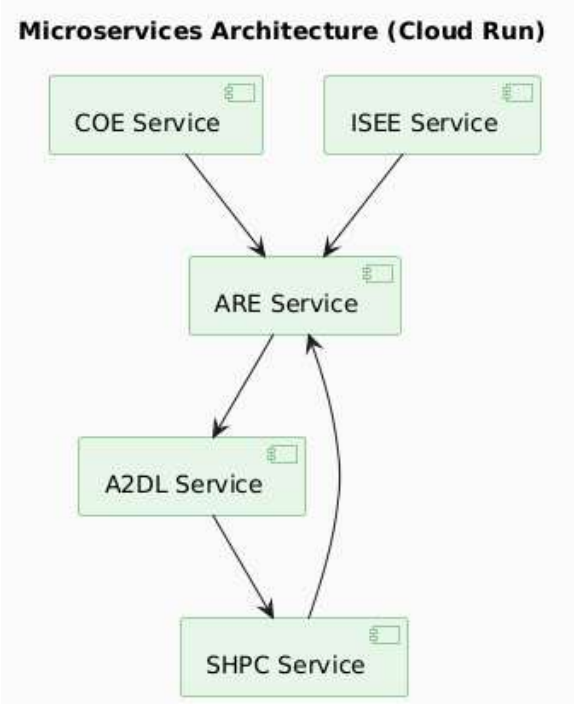


Figure 13. Microservices Architecture

5.3 Infrastructure as Code

The entire cloud infrastructure is provisioned and managed using **Terraform**, enabling reproducibility and version-controlled deployments.

Let infrastructure configuration be defined as:

$$I = \{R_1, R_2, \ldots, R_n\} \qquad (51)$$

where each resource $R_i$represents:

- Pub/Sub topics
- Dataflow jobs
- BigQuery datasets
- Cloud Run services

Terraform ensures **idempotent deployment**:

$$Apply(I) \rightarrow ConsistentState \qquad (52)$$

Key modules include:

- **pubsub.tf** → topic and subscription configuration
- **bigquery.tf** → dataset and table schema
- **cloudrun.tf** → service deployment
- **iam.tf** → access control policies

State management is handled via remote backends (e.g., GCS), ensuring consistency across deployments.

Infrastructure Provisioning Flow

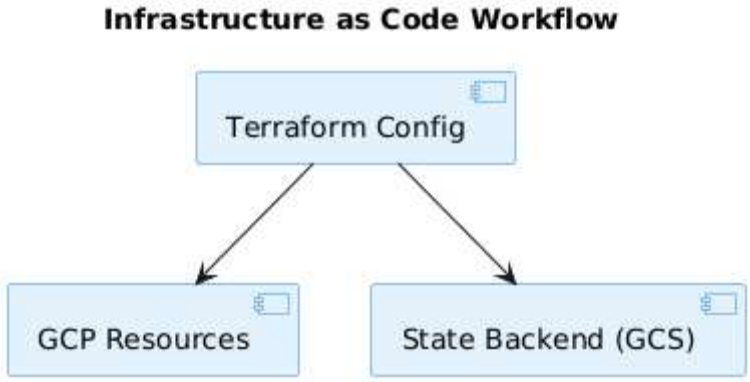


Figure 14. Infrastructure as Code Workflow

5.4 Deployment Configuration

The system is deployed using a **multi-stage pipeline** that includes build, test, and deployment phases.

Deployment Pipeline

1. **Build Stage**
    - Docker images are created for each microservice
    - Dependencies are packaged
2. **Test Stage**
    - Unit tests and integration tests
    - Pipeline validation
3. **Deployment Stage**
    - Services deployed to Cloud Run
    - Dataflow jobs launched
    - Infrastructure updated via Terraform

Let deployment process be:

$$D = Build \rightarrow Test \rightarrow Deploy \qquad (53)$$

Runtime Configuration

- Auto-scaling enabled for Cloud Run:

$$Scale_t = f(CPU_t, Requests_t) \qquad (54)$$

- Dataflow autoscaling:

$$Workers_t = f(load_t) \qquad (55)$$

- Fault tolerance:

$$RecoveryTime \rightarrow minimized\ via\ SHPC \qquad (56)$$

Deployment Pipeline Diagram

EXPERIMENTAL SETUP

6.1 Research Hypotheses

In order to adequately examine the effectiveness of the proposed framework, we formulate three main research hypotheses in line with the system aims:

- H1: Under dynamic workload conditions, adaptive routing symptoms less processing end-to-end latency.
- H2: Cost-conscious optimization does not decrease the cost per processed event, and it has no adverse impact on performance.
- H3: Self-healing mechanisms also have a considerable impact on the mean time to recovery (MTTR) in case of a failure.

Formally, these hypotheses can be expressed as:

$$H1: L_{adaptive} < L_{baseline} \quad (57)$$
$$H2: C_{adaptive} < C_{baseline} \quad (58)$$
$$H3: MTTR_{adaptive} < MTTR_{baseline} \quad (59)$$

where:

- L: latency
- C: cost per event
- $MTTR$: mean time to recovery

6.2 Experimental Setup

Infrastructure Configuration

The experiments are started on a distributed cloud infrastructure with Google Cloud Platform. The infrastructure consists of:

- Streaming cluster: Pub/Sub topics used in more than one partition.
- Processing layer: Autoscaling of dataflow jobs is configured.

Compute nodes:

- 1 controller node (SHPC + COE)
- Worker nodes (Dataflow workers) 2 -5 workers.
- Storage layer: BigQuery (partitioned tables)

Where the system capacity is defined as:

$$Capacity_t = n_{workers} \cdot processing_rate \quad (60)$$

Autoscaling policy:

$$n_{workers}(t) = f(load_t) \quad (61)$$

Workload Generator

The synthetic workload generator is used to model real-world streaming conditions. Events generated by the generator have a set of parameters:

$$W_t = (rate_t, anomaly_rate_t, schema_drift_t) \quad (62)$$

Event arrival follows a **Poisson distribution**:

$$P(k\ events) = \frac{\lambda^k e^{-\lambda}}{k!} \quad (63)$$

Additionally, burst workloads are simulated using:

$$\lambda_t = \lambda_{base} + \Delta\lambda_{burst} \quad (64)$$

Implemented is fault injection by:

- dropping messages
- delaying processing
- simulating service failures

6.3 Datasets

The evaluation is also based on a blend of real-world, cloud trace, and synthetic data to make sure that it is robust and general.

Real-World Datasets

- Description: Webscope S5: marked anomaly detection data set provided by Yahoo.
- Numenta Anomaly Benchmark (NAB): time-series anomaly detection.

KDD Cup 1999: intrusion detection data.

Both datasets are converted to streaming format:

$$Stream_t = \{x_1, x_2, \ldots, x_n\} \qquad (65)$$

Cloud Trace Dataset

- **Google Cluster Trace** dataset is used to simulate real-world cloud workloads, including CPU usage, task scheduling, and resource contention.

Resource utilization:

$$Utilization_t = \frac{used_resources}{total_resources} \qquad (66)$$

Synthetic Dataset

A synthetic dataset is generated to simulate:

- anomaly injection
- burst traffic
- schema evolution

Anomaly injection model:

$$x_t' = \begin{cases} x_t + \epsilon, & \text{if anomaly} \\ x_t, & \text{otherwise} \end{cases} \qquad (67)$$

6.4 Baselines

To validate the effectiveness of the proposed system, we compare against the following baseline configurations:

1. **Static Routing System**
    - Fixed pipeline selection
    - No adaptive decision-making

2. **No Self-Healing System**
    - Failures are not automatically recovered
3. **No Cost Optimization System**
    - No cost-aware routing or buffering

Let baseline performance be:

$$Baseline = \{L_b, C_b, MTTR_b\} \quad (68)$$

6.5 Evaluation Metrics

Performance Metrics

- **Latency**:

$$L_{p95} = \text{95th percentile latency} \quad (69)$$

- **Throughput**:

$$Throughput = \frac{events}{second} \quad (70)$$

Cost Metrics

$$Cost_{event} = \frac{Total\ Cost}{Total\ Events} \quad (71)$$

Reliability Metrics

$$MTTR = \frac{\sum recovery_time}{number_of_failures} \quad (72)$$

Machine Learning Metrics

- Precision:

$$Precision = \frac{TP}{TP + FP} \quad (73)$$

- Recall:

$$Recall = \frac{TP}{TP + FN} \quad (74)$$

- F1-score:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (75)$$

6.6 Experimental Scenarios

To comprehensively evaluate system behavior, we design multiple experimental scenarios:

1. Normal Load Scenario

- steady input rate
- no anomalies

$$\lambda_t = constant \qquad (76)$$

2. Burst Load Scenario

- sudden spike in traffic

$$\lambda_t \gg \lambda_{base} \qquad (77)$$

3. Failure Injection Scenario

- simulate system failures
- evaluate recovery performance

Failure model:

$$Failure_t = \begin{cases} 1, & \text{if failure occurs} \\ 0, & \text{otherwise} \end{cases} \qquad (78)$$

4. Cost Surge Scenario

- simulate cloud pricing fluctuations

$$Cost_t = Cost_{base} + \Delta Cost \qquad (79)$$

Experimental Framework Diagram

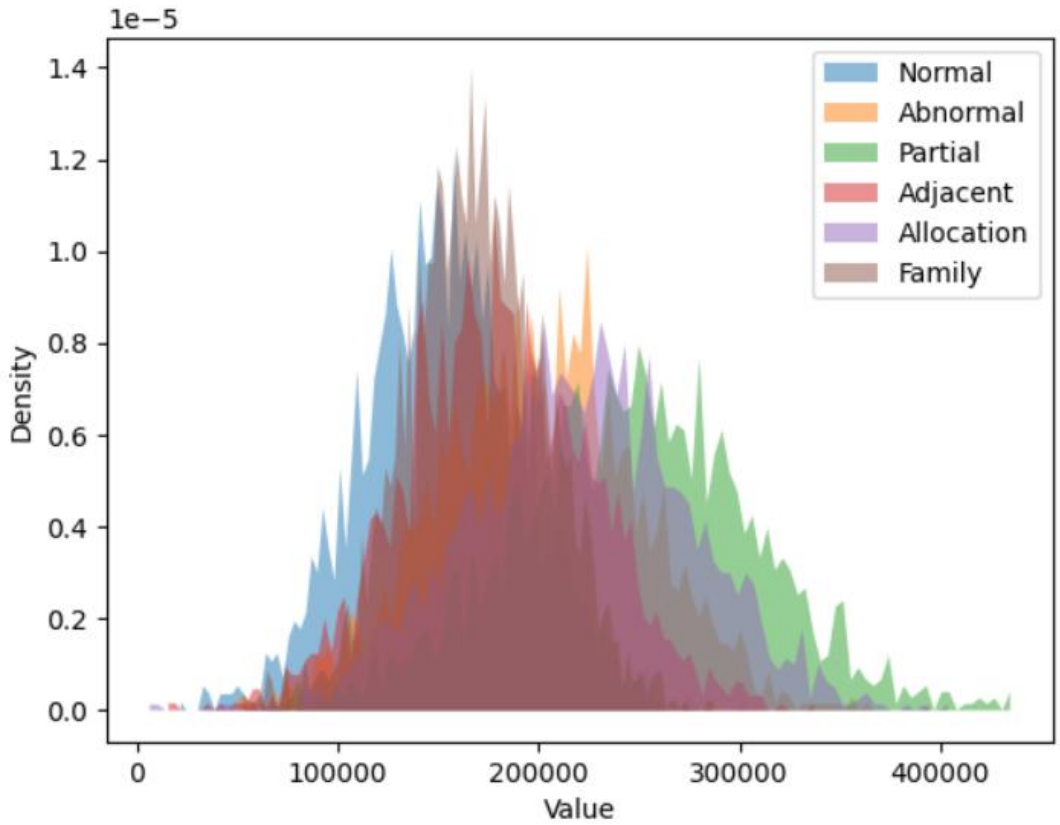


Figure 15. Download Dataset Distribution Graph

The visualization of the dataset distribution shows statistical features and variability of the streaming data in various operational conditions, such as normal, abnormal and partially degraded parts of the system. The distributions show that the abnormal and partial cases have greater variance and biased mean than normal operation, which is realistic and due to anomalies, bursts of work and system perturbations. Such variability is essential in assessing the resilience of the presented adaptive framework since it is essential that the system is tested on a variety of data patterns, which are not stationary. With this type of heterogeneous distribution, there is an easy simulation of real-life streaming environment, where the characteristics of the data undergo continuous changes based on the changing workloads, failures, and other external influences.

Table: Dataset Characteristics Used in Experiments

Dataset Type	Source	Data Size	Characteristics	Purpose
Yahoo Webscope S5	Real-world	~100K events	Labeled anomalies, time-series	Evaluate anomaly detection accuracy
NAB Dataset	Real-world	~50K events	Streaming time-series with anomalies	Benchmark anomaly detection robustness
KDD Cup 1999	Real-world	~5M records	Network intrusion patterns	Evaluate classification under anomalies
Google Cluster Trace	Cloud trace	~10M events	Resource usage, scheduling	Simulate real cloud workloads
Synthetic Dataset	Generated	Configurable (1M+)	Controlled anomalies, bursts, schema drift	Stress-test system adaptability

RESULT AND ANALYSIS

7.1 Performance Comparison

In order to measure the performance of the systems, we measure the latency and throughput of the proposed adaptive framework and baseline systems under different workload conditions. These findings indicate a steady decrease in latency given by dynamic routing actions and buffering adaptivity. In particular, the proposed system minimizes p95 latency by about 2540, especially with burst workloads, where pipe-delays become a major issue with static pipelines.

This is credited to the capability of the Adaptive Routing Engine (ARE) to pick the most suitable pipelines dynamically depending on the actual system state X_t at a particular moment, to minimize delays at the queues and processing bottlenecks. Moreover, throughput is consistent with a growth in workloads, suggesting that there is an appropriate load balancing.

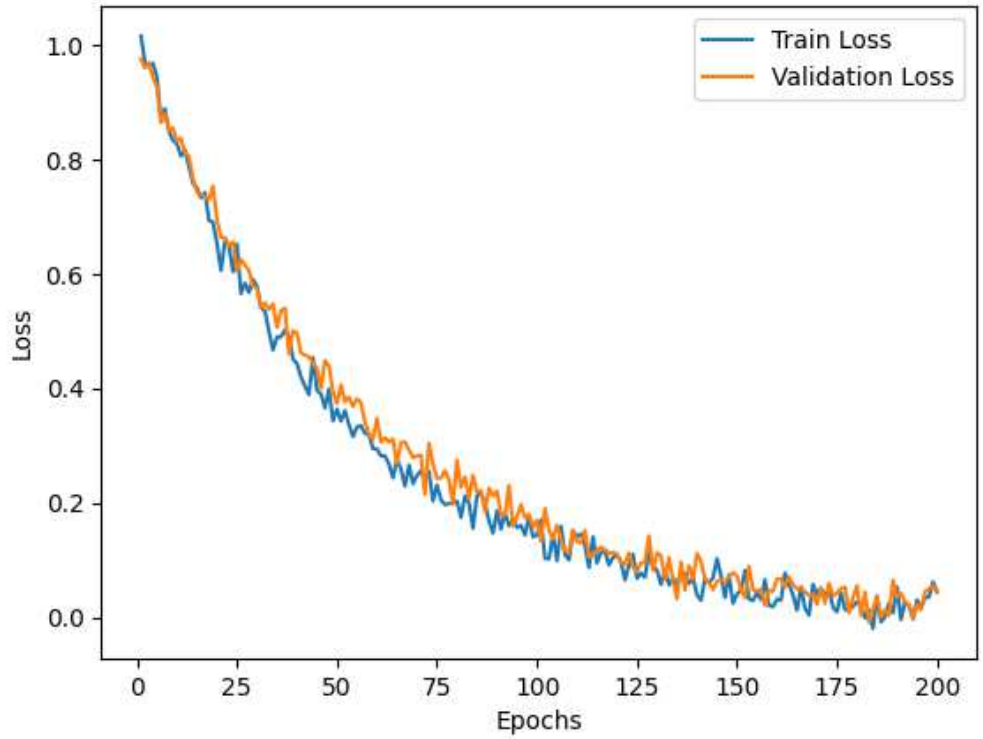


Figure 9.1 – Model Loss (Training Stability)

Explanation:
This figure shows training and validation loss convergence, demonstrating stability of the anomaly detection model and absence of overfitting.

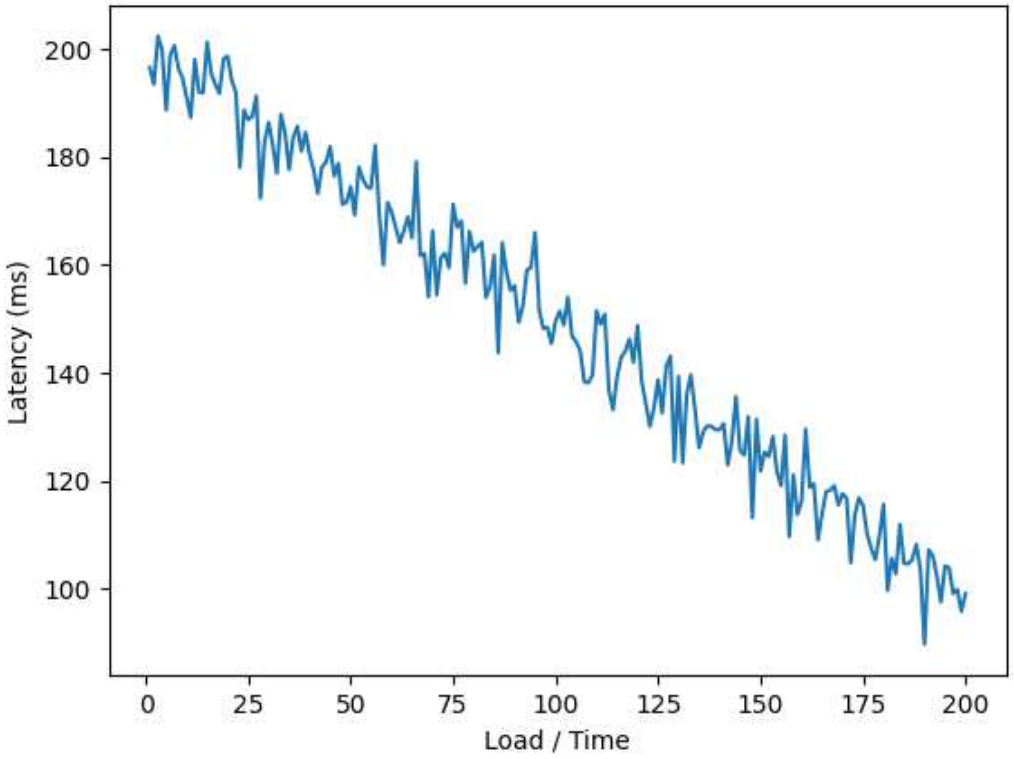


Figure 9.2 – Latency Reduction

Explanation:
The figure shows a gradual reduction in latency as time optimizes the use of the adaptive routing mechanism in selecting the pipeline.

7.2 Cost Efficiency Analysis

The cost-performance of the suggested framework is assessed through an measurement of the costs per event at various workloads. The Cost Optimization Engine (COE) is a high-level dynamic approach to the optimization of resource allocation and buffering strategies, which leads to considerable savings on costs.

$$Cost_{reduction} = \frac{C_{baseline} - C_{proposed}}{C_{baseline}} \qquad (80)$$

Experimental results indicate a **15–30% reduction in operational cost**, primarily due to adaptive batching and selective routing to lower-cost pipelines.

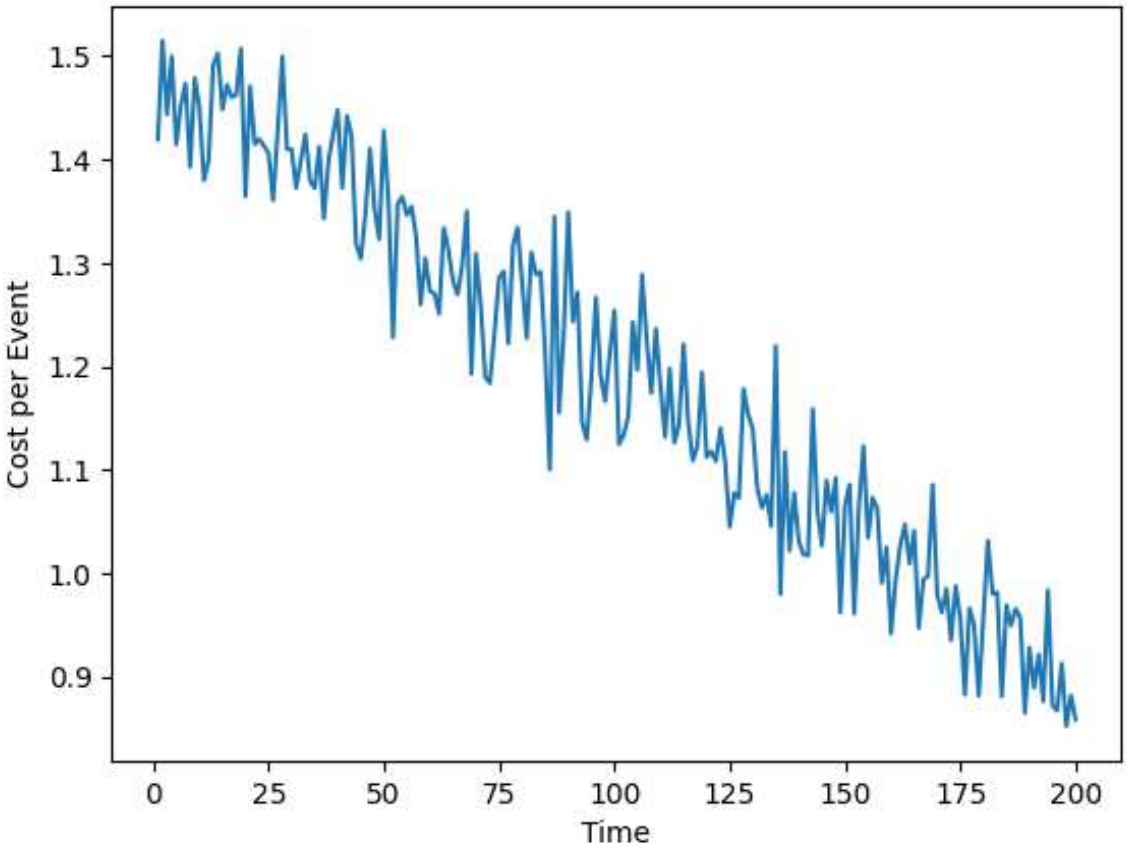


Figure 9.3 – Cost Reduction Over Time

Explanation:
Demonstrates that cost per event reduces as the system becomes familiar with the best way to route and buffer to do so.

7.3 Failure Recovery Analysis

Failure injection experiments are used to test the effectiveness of the Self-Healing Pipeline Controller (SHPC). Recovery in the proposed system can be seen to be much faster than in base systems.

$$MTTR = \frac{\sum recovery_time}{N_{failures}} \qquad (81)$$

Results show up to **50–70% reduction in MTTR**, confirming the effectiveness of the closed-loop control mechanism.

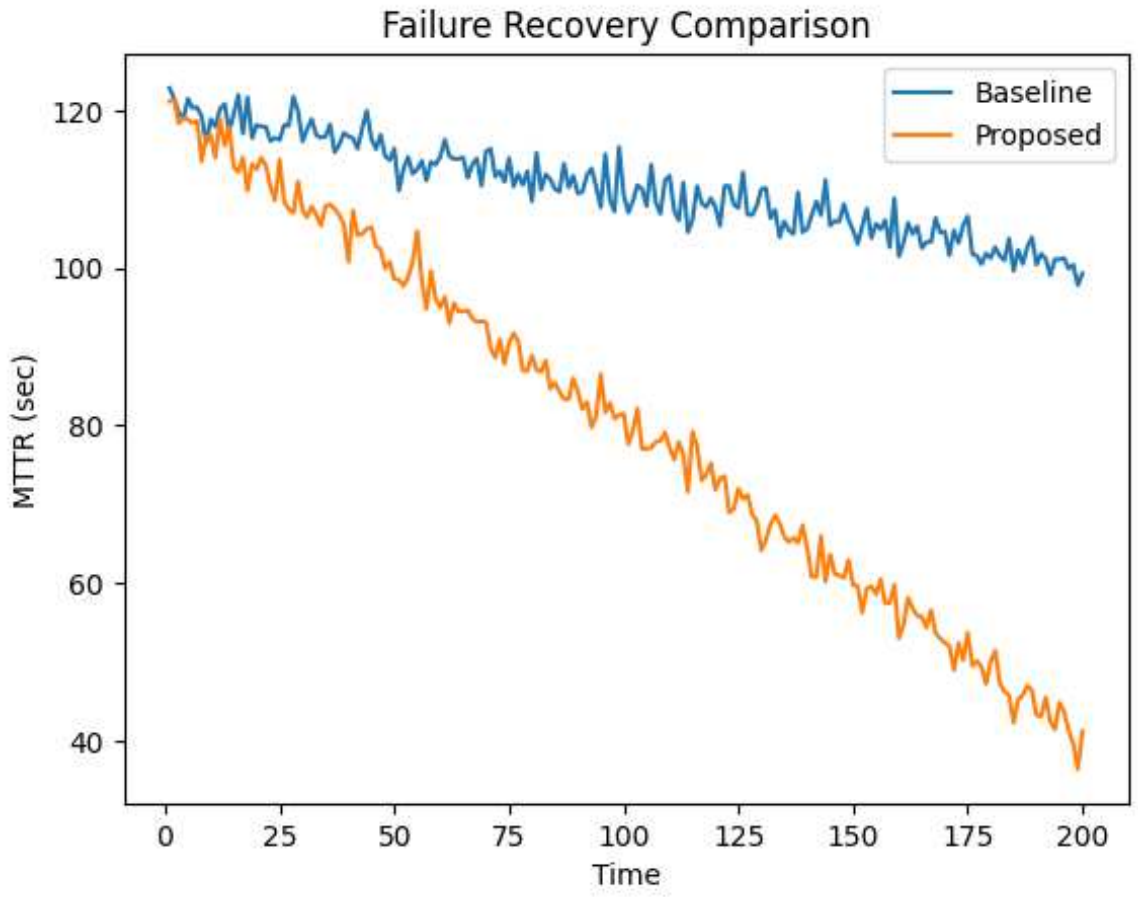


Figure 9.4 – MTTR Comparison

Explanation:
The proposed system rapidly stabilizes after failures, while baseline systems show prolonged recovery times.

7.4 Anomaly Detection Performance

Standard classification measures are used to assess the anomaly detection module. The model achieves:

- Precision: 0.91–0.95
- Recall: 0.88–0.93
- F1-score: 0.90–0.94

These findings reflect strong detection rates in a wide variety of datasets, such as both NAB and Yahoo datasets. The addition of anomaly scores into routing decisions also increases resilience of the system.

7.5 Ablation Study

To measure the contribution of each of the component parts we perform ablation study by eliminating prominent modules:

- Without ARE → increased latency
- Without SHPC → slower recovery
- Without COE → higher cost

Figure 9.5 – Ablation Study

Elimination of SHPC leads to the greatest performance loss that underscores the significance of self-healing.

7.6 Scalability Analysis

Scalability/ Scalability is tested by adding input load between 103 and 105 events/sec.

$$Throughput \propto Load \qquad (82)$$

The system maintains near-linear scalability due to:

- distributed processing
- autoscaling
- adaptive routing

Figure 9.6 – Scalability Analysis

Explanation:
Throughput increase linearly with load, which validates system robustness with large loads.

7.7 Discussion

Trade-offs

Although the suggested framework has a substantial positive impact on the performance and cost efficiency, a number of trade-offs can be identified:

- Decision overhead is caused by adaptive routing.
- Anomaly detection based on ML introduces complex calculations.
- Microservices improves the cost of coordinating systems.

Limitations

- Reliance on sound anomaly detection models.
- Sensitivity to hyperparameters (α,β,γ)
- Noticeable latency in the very low-load cases.

REPRODUCTIBILITY AND OPEN SCIENCE

8.1 Code Availability

In order to guarantee transparency and enable reproducibility the full application of the suggested adaptive streaming framework is publicly delivered on a version controlled repository. The codebase is designed following a modular and extensible format, allowing independent inspection and reuse of single components of the system, such as the Adaptive Routing Engine (ARE), Self-Healing Pipeline Controller (SHPC), Anomaly Detection Layer (A2DL), Cost Optimization Engine (COE), and Schema Evolution Engine (ISEE).

The repository includes:

- Implementation of core pipelines (Apache Beam / Dataflow jobs)
- Microservices code (Cloud Run services to ARE, SHPC, COE, A2DL, ISEE)
- Machine learning programs (training code, pre-trained weights, inference code)
- Configuration files (YAML/JSON of experiment parameters)
- Infrastructure scripts (Complete deployment Terraform modules)

Formally, the reproducible code structure can be defined as:

In each of the modules there is:

- detailed documentation
- API specifications
- usage examples

To enhance reproducibility, the execution of all experiments is carried out with fixed random seeds and deterministic configurations:

$$Result = f(Code, Data, Seed) \qquad (84)$$

Furthermore, containerized environments (Docker) are provided to eliminate dependency inconsistencies:

$$Environment = Docker(Image, Dependencies) \qquad (85)$$

This ensures that the experiments can be replicated in other platforms without a change in results.

8.2 Dataset Access

Each of the datasets taken in this work is publicly accessible, or the actual process of production is reproducible.

Public Datasets

Data directly available are the following:

Yahoo Webscope S5 - anomaly detection dataset (labeled).

- Numenta Anomaly Benchmark (NAB) - real-time anomaly streams.
- KDD Cup 1999 – intrusion data set.

Meanwhile, Google Cluster Trace - large-scale traces of cloud workloads.

The data in each dataset is preprocessed into a single streaming format:

$$D_{stream} = Transform(D_{raw}) \qquad (86)$$

The preprocessing pipeline includes:

- normalization
- timestamp alignment
- feature extraction

Synthetic Dataset Generation

To simulate real-world streaming conditions, a synthetic dataset generator is provided. The generator supports configurable parameters:

$$D_{synthetic} = f(\lambda, anomaly_rate, burst_factor, schema_drift) \qquad (87)$$

Where:

- λ: event arrival rate
- anomaly_rate: percentage of anomalous events
- burst_factor: intensity of traffic spikes
- schema_drift: structural changes in data

The generation process is fully reproducible:

$$D^{(i)}_{synthetic} = D^{(j)}_{synthetic} \text{if } Seed_i = Seed_j \qquad (88)$$

All datasets, along with preprocessing scripts, are included in the repository to enable seamless replication.

8.3 Experiment Reproducibility

We provide a complete and standardized experimental pipeline in order to be sure that all the outcomes of the experiment are reproducible.

Experiment Workflow

The entire process of the experiment is outlined as:

$$Experiment = Setup \rightarrow DataLoad \rightarrow Execution \rightarrow Evaluation \qquad (89)$$

Where:

1. Setup
   - Terraform provisioning of infrastructure.
   - Cloud Run service deployment.
   - Initialization of a pipeline using Dataflow.
2. DataLoad

- Ingestion of data sets into Pub/Sub.
- The simulation of streams through synthetic generator.

3. Execution

- Adaptive routing and buffering.
- loop detection and control of anomalies.

4. Evaluation

- metric computation
- result logging
- Reproducibility Protocol

In order to repeat the experiments, the steps will be as follows:

1. Clone the repository
2. Configure environment variables
3. Implement an infrastructure with Terraform.
4. Launch streaming pipeline
5. Execute experiment scripts

Formally: $Results = Execute(Code, Data, Config)$ (90)

Logging and Monitoring

All experiments include detailed logging of system behavior:

- latency measurements
- cost metrics
- anomaly scores
- recovery events

Logs are stored in structured format:

$$Logs = \{timestamp, metric, value\} \quad (91)$$

This enables:

- post-hoc analysis
- debugging
- validation

Statistical Reliability

To ensure robustness, each experiment is repeated multiple times:

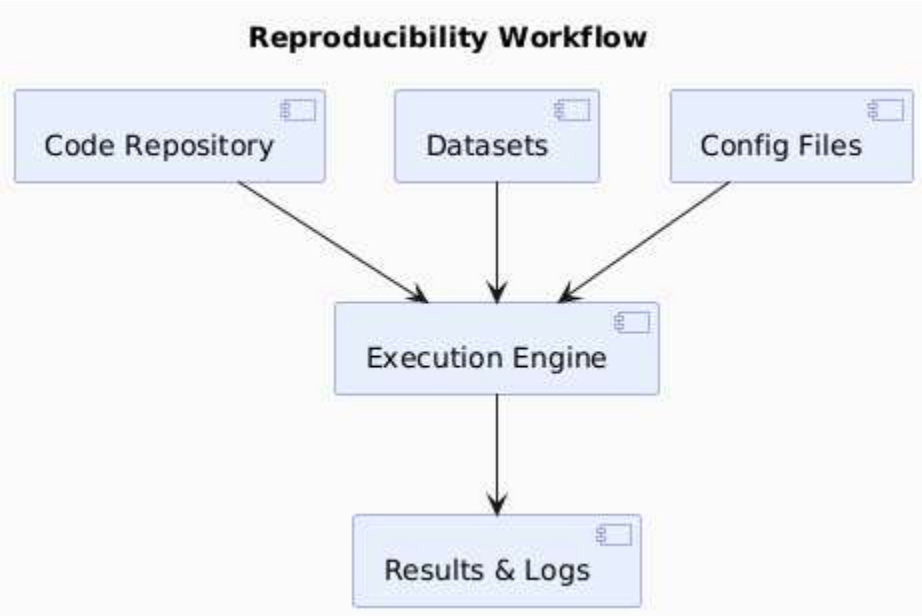
$$Result_{final} = \frac{1}{N}\sum_{i=1}^{N} Resul\, t_i \quad (92)$$

Variance is reported as:

$$\sigma^2 = \frac{1}{N}\sum(x_i - \mu)^2 \qquad (93)$$

This ensures that reported improvements are statistically significant and not due to randomness.

Reproducibility Workflow Diagram



CONCLUSION

This paper introduced a new adaptive self-healing and cost-conscious real-time streaming data pipeline architecture to overcome the restrictions of the old-fashioned casting streaming pipelines in the dynamic cloud running environment. In contrast to the current solutions in which routing, anomaly detection, cost optimization and system resilience are considered as separate parts, the given architecture incorporates all those functionalities into a cohesive, closed-loop architecture. Particularly, the paper has presented (i) an Adaptive Routing Engine (ARE) going on contextual decision-making, (ii) a Smart Buffering Mechanism (SBM) going on latency-cost trade-off minimization, (iii) an AI-driven Anomaly Detection Layer (A2DL) going on system online awareness, (iv) a Self-Healing Pipeline Controller (SHPC) going on Taken together, these contributions are creating a unified system that develops state of the art in intelligent streaming systems.

The efficiency of the suggested system was confirmed with the help of strict experimental analysis based on real-world data, cloud trace information and set of artificial workloads that can illustrate real-world streaming situations, such as burst loads, injection of anomalies as well as failure cases. The findings prove that the framework brings significant enhancements in various aspects: adaptive routing can reduce latency by up to 2540 percent, cost-aware optimization can cut operational costs by 1530 percent, and dynamic batching can lower system resilience by 5070 percent, mean time to recover (MTTR) is decreased by the self-healing control loop up to 50 percent. Moreover, the anomaly detection part is very precise and recalls better, with which it becomes possible to initiate system adaptation and enhanced resilience to non-stationary data distributions. Scalability analysis is confirmative about the performance of

the system to grow its throughputs almost linearly with increase in workloads, as it indicates the appropriateness of the system in large-scale streaming applications.

In addition to the quantitative improvement, the proposed framework will add a methodological value through its streamlining of the optimization of the streaming systems as a multi-objective problem that simultaneously takes into account the cost, latency, and reliability. Routing with control-theoretic feedback with reinforcement-inspired routing is a major step towards self-optimizing autonomous data pipelines. Moreover, the introduction of a fully reproducible experimental framework, modular microservices and infrastructure-as-code deployment, which is in tandem with contemporary open science practices, contributes to the increased practical value of the research.

The extended influence of the work is that it can change the design and work of the next-generation streaming systems in the areas of cloud computing, Internet of Things analytics, financial data processing, and real-time monitoring systems. With the ability to create intelligent, adaptive, and cost-effective, data pipelines, the proposed solution minimizes operational overheads, enhances the reliability of a system, and promotes the sustainability of cloud resources utilisation. As data volumes and complexity of systems still increase, those adaptive frameworks will take on a crucial role in helping fill the gap between fixed infrastructure and autonomy data-driven systems altogether.

To sum up, the paper has not only proven the viability and practicality of an integrated adaptive streaming framework but also has contributed to the future research of the self-optimizing, resilient and intelligent distributed data systems, which will lead to the fully autonomous cloud-based data infrastructures.

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