Computer Fraud and Security
ISSN (online): 1873-7056

Correlated Telemetry Driven Throughput Analysis in Distributed Pipelines

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Abstract

Throughput degradation remains a persistent challenge in distributed data pipelines, particularly as systems scale across multiple nodes and operate under dynamic workload conditions. Modern distributed pipelines rely on parallel execution and shared Input Output resources, making throughput sensitive to coordination overhead, resource contention, and variability in stage level execution behavior. Existing performance analysis approaches commonly depend on isolated monitoring mechanisms such as metrics, logs, or traces analyzed independently. Although these mechanisms provide partial visibility, their separation limits the ability to systematically relate throughput variations to execution flow and resource interactions. A major limitation of current approaches lies in the absence of correlated telemetry across pipeline stages. Metrics capture aggregated system behavior without execution context, logs record discrete events without continuity, and traces expose execution paths without sufficient insight into resource level activity. As cluster size increases, coordination patterns and resource dependencies evolve across nodes, further complicating throughput analysis using isolated signals. This work addresses these limitations by examining a correlated telemetry driven approach to throughput analysis in distributed pipelines. The proposed direction focuses on the structured integration of metrics, logs, and traces using shared execution identifiers and temporal alignment. Through experimental analysis across varying cluster sizes, correlated telemetry is used to examine how execution flow, coordination behavior, and Input Output activity collectively influence throughput. The objective is to establish an analysis framework that supports empirical characterization of throughput dynamics based on observed execution behavior, enabling systematic evaluation of scalability challenges in distributed data pipelines.

Keywords: Throughput, Telemetry, Correlation, Pipelines, Distributed, Observability, Metrics, Logs, Traces, Scalability, Coordination, Contention, Performance, Analysis, Monitoring

INTRODUCTION

Distributed data pipelines [1] form the backbone of modern large scale computing systems, enabling continuous processing of data across multiple interconnected nodes. These pipelines support a wide range of applications including stream processing, data analytics, and real time decision making. As deployment environments grow in size and complexity, achieving stable and predictable throughput becomes increasingly difficult. Throughput in distributed pipelines is influenced by multiple factors such as execution parallelism, coordination overhead, Input Output contention, and variability in stage level processing behavior. Logs capture discrete events and state changes but are difficult to analyze at scale and lack temporal continuity [2]. Traces reveal end to end execution paths but frequently omit fine grained resource level details. When these signals are analyzed independently, the resulting view of system behavior is fragmented, making it difficult to associate throughput variations with specific pipeline stages or resource interactions. The challenge becomes more pronounced as distributed pipelines scale across increasing numbers of nodes. Coordination patterns change as additional nodes are introduced, shared resources experience varying degrees of contention, and execution dependencies [3] evolve dynamically. Under such conditions, throughput degradation may arise from subtle interactions between pipeline structure and Input Output behavior rather than from obvious resource saturation. Existing monitoring approaches struggle to capture these interactions in a unified manner, limiting their effectiveness in diagnosing throughput related issues. Recent advances in observability emphasize the integration of multiple telemetry signals to provide deeper insight into system behavior. Such an approach enables systematic reasoning about how execution flow [4], coordination overhead, and Input Output activity jointly influence throughput across pipeline stages. This work is motivated by the need for structured and correlated telemetry driven analysis of throughput in distributed pipelines. The focus is on establishing a clear relationship between execution behavior and throughput dynamics as systems scale. By addressing the limitations of fragmented observability, this approach aims

to support more precise understanding of throughput behavior and provide a foundation for scalable performance analysis [5] in distributed environments.

LITERATURE REVIEW

Distributed data pipelines have become a fundamental component of modern computing systems, supporting large scale data processing, real time analytics, and continuous service execution. As organizations increasingly rely on distributed infrastructures to meet performance and scalability [6] demands, throughput has emerged as a critical performance metric. Throughput reflects the system's ability to process requests efficiently over time and is directly influenced by execution parallelism, resource availability, coordination mechanisms, and Input Output behavior. Understanding throughput dynamics in distributed pipelines is therefore essential for designing systems that remain performant under varying workloads and cluster sizes. Early research in distributed systems focused primarily on improving parallel execution and fault tolerance, often treating performance analysis as a secondary concern. Traditional approaches emphasized static resource allocation and coarse grained monitoring techniques that provided limited visibility into runtime behavior. Metrics such as CPU utilization, memory usage, and network throughput were commonly collected to provide high level system insights. While useful for identifying obvious resource saturation, these metrics lacked contextual information about how execution flow [7] and coordination overhead affected throughput at the application level.

As distributed systems evolved toward microservices and pipeline oriented architectures, performance analysis became more complex. Pipelines introduced multiple execution stages, each with distinct computational and Input Output characteristics. Throughput in such systems was no longer determined solely by raw resource capacity but also by the interaction between pipeline stages, data dependencies, and synchronization patterns. Researchers began to recognize that isolated monitoring signals were insufficient for understanding these interactions. Metrics alone could indicate throughput fluctuations without revealing their root causes, while logs and traces were often analyzed separately, limiting holistic understanding. Logging mechanisms [8] have long been used to capture application level events and state transitions in distributed systems. Logs provide valuable contextual information, such as request identifiers, error conditions, and execution milestones. However, traditional logging approaches produce large volumes of unstructured or semi structured data, making analysis difficult at scale. Furthermore, logs lack temporal continuity across pipeline stages, which limits their usefulness for understanding throughput behavior over end to end execution paths. As a result, log based analysis has often been reactive, focusing on debugging failures rather than systematically analyzing performance trends.

Distributed tracing emerged as a response to the need for end to end visibility across service boundaries. Tracing techniques enable the reconstruction of execution paths by capturing spans that represent the time spent in different components or pipeline stages. Traces provide valuable insight into latency distribution and execution dependencies, making them particularly useful for diagnosing tail latency [9] and request delays. However, tracing systems often prioritize execution flow over resource level details. As a result, traces may identify where throughput degradation occurs without explaining how resource contention or Input Output behavior contributes to the observed performance patterns. Metrics, logs, and traces each offer distinct perspectives on system behavior, but their independent use has proven insufficient for comprehensive throughput analysis. Metrics provide aggregate views without execution context, logs offer detailed events without continuity, and traces reveal execution paths without resource level insight. The lack of integration among these observability signals has been repeatedly identified as a key limitation in distributed performance analysis. This fragmentation [10] becomes increasingly problematic as systems scale, where throughput degradation may result from subtle interactions across multiple pipeline stages and nodes.

Recent research has emphasized the importance of observability as a holistic concept that goes beyond traditional monitoring. Observability focuses on understanding system behavior from external outputs rather than relying solely on predefined metrics. This shift has encouraged the integration of multiple telemetry signals to provide richer insights into distributed [11] execution. Structured observability approaches have emerged to standardize how telemetry data is generated and correlated, enabling more systematic analysis of system behavior. By embedding consistent identifiers and timestamps into telemetry data, structured observability facilitates correlation across metrics, logs, and traces. Correlated telemetry approaches aim to unify observability signals by aligning them using shared execution context. This alignment allows analysts to associate throughput changes with specific execution paths, pipeline stages, and resource interactions.

Rather than treating throughput as an isolated metric, correlated telemetry enables throughput to be examined as an emergent property of distributed execution. This perspective is particularly valuable in pipeline [12] oriented systems, where throughput is influenced by coordination overhead, stage level variability, and Input Output contention.

Input Output behavior plays a critical role in determining throughput in distributed pipelines. Shared storage systems, network communication, and disk access patterns introduce variability that can significantly affect pipeline performance. Traditional performance studies have often treated Input Output as a secondary factor, focusing instead on computational efficiency. However, as data volumes and pipeline complexity increase, Input Output bottlenecks have become a dominant source of throughput degradation. Identifying these bottlenecks requires visibility into both execution flow and resource usage, reinforcing the need for integrated observability. Scalability analysis further complicates throughput evaluation. As cluster size increases, the relationship between throughput [13] and resource availability becomes non linear. Additional nodes introduce parallelism but also increase coordination overhead, synchronization costs, and communication complexity. Throughput may initially improve with scale but eventually degrade as coordination and Input Output contention dominate. Capturing this behavior requires observing how execution patterns evolve across different cluster sizes, which cannot be achieved through isolated telemetry signals.

Experimental studies have shown that throughput behavior varies significantly depending on workload characteristics, pipeline structure, and cluster configuration. Fixed monitoring setups often fail to capture these variations because they lack the flexibility to adapt to changing execution dynamics. Correlated telemetry offers a means to empirically analyze throughput across varying conditions by linking observed performance [14] metrics to execution context. This enables systematic comparison of throughput behavior under different cluster sizes and workload intensities. Despite these advances, challenges remain in applying correlated telemetry at scale. The volume of telemetry data generated by distributed pipelines can be substantial, raising concerns about overhead and scalability. Efficient collection, storage, and analysis of telemetry data remain active areas of research. Additionally, correlating telemetry signals across nodes requires precise time synchronization and consistent context propagation, which can be difficult to maintain in heterogeneous environments. These challenges highlight the need for careful system design [15] and experimental validation.

Another limitation in existing literature is the tendency to focus on latency rather than throughput. While latency has received significant attention due to its impact on user experience, throughput is equally important for systems that process large volumes of data or serve high request rates. Throughput analysis requires different methodologies, as it involves sustained system behavior over time rather than individual request performance. Correlated telemetry provides an opportunity to study throughput as a function of execution flow [16] and resource interaction, addressing a gap in existing research. The growing adoption of pipeline based architectures in cloud and data intensive environments underscores the importance of systematic throughput analysis. Distributed pipelines are increasingly deployed in scenarios where predictable performance is critical, such as stream processing and real time analytics. In these contexts, throughput degradation can lead to backlog accumulation, increased latency, and reduced system reliability. Understanding throughput dynamics through empirical analysis is therefore essential for maintaining system stability.

Beyond foundational observability research, recent studies have increasingly focused on understanding how execution variability affects throughput in long running distributed pipelines. Variability arises from multiple sources including heterogeneous hardware, uneven data distribution, transient network delays [17], and fluctuating Input Output performance. These factors introduce non deterministic execution behavior that traditional monitoring approaches struggle to capture. Throughput degradation in such environments often manifests gradually rather than as sudden failures, making early detection difficult without comprehensive execution visibility. This has motivated research into fine grained telemetry collection that captures subtle performance shifts across pipeline stages.

Another important line of research examines pipeline backpressure and its impact on throughput sustainability. Backpressure mechanisms are designed to prevent overload by slowing upstream producers when downstream stages become saturated. While effective for maintaining stability, backpressure can obscure the true causes of throughput degradation by masking bottlenecks. Observability systems that lack correlated telemetry [18] may detect reduced throughput without revealing whether the cause lies in computational imbalance, Input Output delay, or coordination inefficiency. Studies highlight the need for telemetry correlation to distinguish between intentional throttling and unintended performance degradation.

Workload characteristics also play a critical role in shaping throughput behavior. Batch oriented pipelines, stream processing systems, and hybrid workloads exhibit distinct execution patterns and resource usage profiles. Research indicates that throughput analysis techniques optimized for one workload type often fail to generalize across others. For example, steady state batch workloads may tolerate transient delays, while stream processing systems are highly sensitive to sustained throughput drops. Correlated telemetry enables comparative analysis [19] across workload types by providing consistent execution context, allowing throughput behavior to be examined under varying operational conditions.

Recent advances in distributed storage and networking have further complicated throughput analysis. Modern pipelines frequently interact with multiple storage layers including in memory caches, distributed file systems, and object stores. Each layer introduces unique latency and bandwidth characteristics that influence overall throughput. Network level behavior such as congestion, packet loss, and routing variability further contributes to performance complexity. Literature emphasizes that throughput cannot be fully understood without observing how pipeline execution interacts with these underlying subsystems. Integrated telemetry provides the means to associate storage and network behavior with pipeline stage execution. The emergence of cloud native environments has also reshaped throughput analysis challenges. Container orchestration platforms introduce dynamic scheduling [20], resource sharing, and runtime isolation mechanisms that affect execution behavior. Pods may be rescheduled, resources may be throttled, and co located workloads may compete unpredictably. Throughput degradation in such environments often arises from interactions between orchestration policies and application behavior. Observability research increasingly recognizes the importance of correlating application level telemetry with platform level signals to understand these effects.

Another recurring theme in the literature is the temporal dimension of throughput analysis. Throughput is not static and may vary over time due to workload bursts, resource reallocation, or environmental changes. Snapshot based monitoring approaches capture only momentary system states and fail to represent long term throughput trends. Time aligned telemetry enables longitudinal analysis, allowing throughput patterns to be studied across extended execution periods. This temporal perspective is critical for identifying recurring bottlenecks and understanding how throughput evolves under sustained load. Scalability evaluation remains a central concern in distributed systems research. Studies consistently show that throughput scaling behavior differs significantly from linear expectations. Adding nodes may initially increase throughput, but diminishing returns often emerge due to coordination overhead and shared resource contention. Literature highlights the importance of empirically analyzing throughput across incremental cluster sizes to identify scaling thresholds. Correlated telemetry supports such analysis by enabling consistent comparison of execution behavior across different deployment scales.

Researchers have also explored the relationship between throughput and reliability. Throughput degradation can precede failures by indicating accumulating backlogs or delayed processing. Observability systems that capture correlated telemetry provide early warning signals by revealing abnormal execution patterns before failures occur. This perspective positions throughput analysis as not only a performance concern but also a reliability indicator. Understanding this relationship requires integrated visibility into execution flow, resource usage, and temporal behavior. The increasing adoption of data driven decision making in system management has further emphasized the need for comprehensive throughput analysis. While automated control mechanisms often rely on simplified metrics, literature suggests that such approaches may overlook complex execution interactions [21]. Empirical analysis based on correlated telemetry provides a richer foundation for understanding system behavior without assuming predictive models. This aligns with experimental methodologies that prioritize observed behavior over inferred outcomes.

Overall, recent literature reinforces the view that throughput analysis in distributed pipelines requires a holistic perspective that integrates execution flow, resource interaction, and temporal dynamics. Fragmented observability approaches fail to capture the complexity of modern distributed systems, particularly as scale and workload diversity increase. Correlated telemetry emerges as a necessary capability for empirically examining throughput behavior and scalability challenges. These insights collectively motivate continued exploration of structured, integrated observability frameworks as a means to advance throughput analysis in distributed pipeline environments.

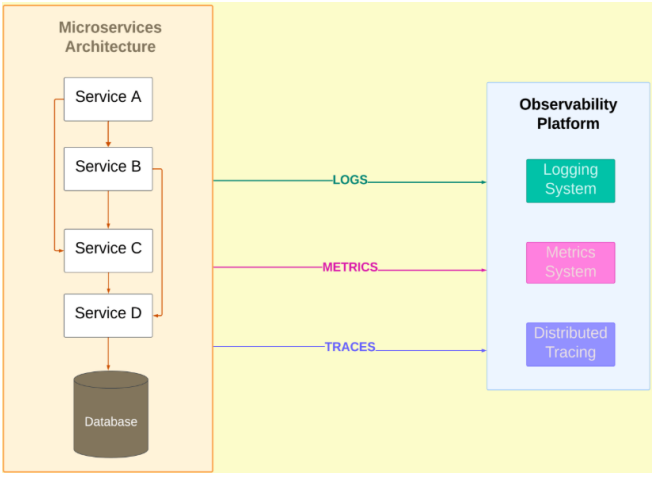


Fig 1. Telemetry Architecture

Fig 1. The illustrated architecture represents a microservices based system integrated with a conventional observability platform. On the left side, the application is structured as a sequence of independent services labeled Service A through Service D. These services interact with each other in a chained execution flow and ultimately communicate with a shared database. Each service operates independently, handling specific functional responsibilities within the overall application workflow.

As requests propagate through the services, operational data is generated in different forms. Logs capture discrete events and execution messages produced by each service. Metrics summarize quantitative measurements such as request rates, resource usage, and response times. Traces record the execution path of a request as it traverses multiple services. These three observability signals are emitted separately from the microservices layer.On the right side, the observability platform receives these signals through distinct pipelines. Logs are forwarded to a logging system, metrics are sent to a metrics collection system, and traces are delivered to a distributed tracing system. Each subsystem stores and processes its respective data independently, without inherent correlation across signals.

While this architecture provides visibility into individual aspects of system behavior, it lacks integrated analysis across logs, metrics, and traces. As a result, understanding performance issues such as throughput degradation or Input Output bottlenecks requires manual cross analysis. This separation limits the ability to systematically associate execution flow with resource behavior, especially as the number of services and request volume increase.

```
type Trace struct {
        ID    int
        Stage string
        Time  time.Duration
}
func stage(name string, in <-chan int, out chan<- int,
        metrics chan<- string, logs chan<- string, traces chan<- Trace) {
        for id := range in {
                start := time.Now()
                time.Sleep(20 * time.Millisecond)
                metrics <- name
                logs <- fmt.Sprintf("req %d at %s", id, name)
                traces <- Trace{ID: id, Stage: name, Time: time.Since(start)}
```

```
                out <- id
        }
}
func main() {
        in := make(chan int)
        a := make(chan int)
        b := make(chan int)
        out := make(chan int)
        metrics := make(chan string)
        logs := make(chan string)
        traces := make(chan Trace)
        go stage("StageA", in, a, metrics, logs, traces)
        go stage("StageB", a, b, metrics, logs, traces)
        go stage("IO", b, out, metrics, logs, traces)
        go func() {
                for {
                        select {
                        case m := <-metrics:
                                fmt.Println("metric", m)
                        case l := <-logs:
                                fmt.Println("log", l)
                        case t := <-traces:
                                fmt.Println("trace", t.ID, t.Stage, t.Time)
                        }
                }
        }()
        for i := 0; i < 5; i++ {
                in <- i
        }
        time.Sleep(time.Second)
}
```

The given Go program demonstrates a simple implementation of an integrated observability pipeline in a distributed processing environment. The application models a request flowing through three sequential stages labeled StageA, StageB, and IO. Each stage represents a processing component that receives input events, performs a fixed duration of work, and forwards the event to the next stage. Communication between stages is handled using channels, enabling concurrent execution and clear separation of processing logic. For each incoming request, the program captures three types of telemetry data. Metrics are generated by recording the stage name, representing stage level activity. Logs are produced as textual messages that indicate the progression of a request through different stages. Traces are represented using a structured data

type that records the request identifier, the stage name, and the execution duration for that stage. This combination of metrics, logs, and traces reflects an integrated observability approach where multiple telemetry signals are collected during execution. A dedicated goroutine continuously listens for telemetry events and outputs them as they are generated.

This design allows telemetry collection to proceed asynchronously without blocking the main execution flow. The main function initiates a small number of requests and allows the system to run long enough for all stages to process the data. Overall, the program illustrates how correlated telemetry can be generated within a pipeline by associating metrics, logs, and traces with a common execution context. It highlights the basic principles of integrated observability, where operational signals are captured together during request execution to support unified analysis of system behavior.

Table I. Reference Configuration Throughput – 1

Nodes	Reference Configuration Throughput (Operations per Second)
3	420
5	560
7	610
9	590
11	540

Table I Under the moderate workload condition, the throughput behavior across different cluster sizes demonstrates how the system responds to increasing parallelism and coordination demands. With 3 nodes, the reference configuration achieves a throughput of 420 operations per second, indicating limited parallel processing capacity. As the cluster size increases to 5 nodes, throughput rises to 560 operations per second, showing effective utilization of additional nodes and improved request handling. The peak throughput is observed at 7 nodes with 610 operations per second, suggesting an optimal balance between parallel execution and coordination overhead under this workload. Beyond this point, throughput begins to decline. At 9 nodes, throughput reduces to 590 operations per second, and further drops to 540 operations per second at 11 nodes. This decline reflects the growing impact of coordination costs, shared resource contention, and communication overhead as the cluster expands. Overall, the moderate workload condition highlights a non linear scalability pattern where throughput improves up to an optimal cluster size and then degrades as system complexity increases.

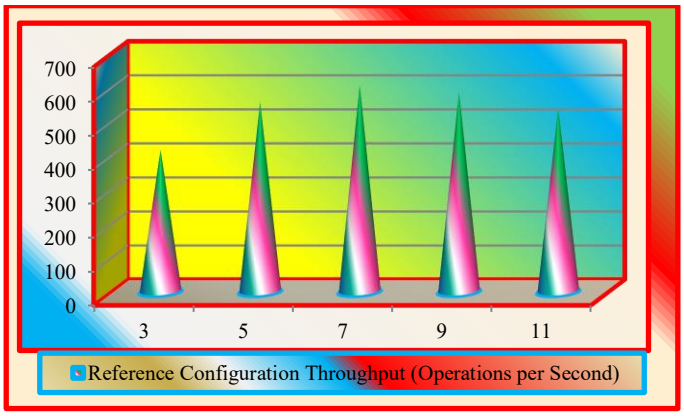


Fig 2. Reference Configuration Throughput - 1

Fig 2. The graph illustrates throughput variation under a moderate workload condition across increasing cluster sizes. Throughput increases from 420 operations per second at 3 nodes to 560 at 5 nodes, indicating improved parallelism. The highest throughput of 610 operations per second is observed at 7 nodes, representing an optimal operating point. Beyond this size, throughput declines to 590 at 9 nodes and further to 540 at 11 nodes. This downward trend reflects the growing influence of coordination overhead and shared resource contention as more nodes participate. Overall, the graph highlights

a non linear scalability pattern, where performance gains from additional nodes diminish beyond a certain cluster size under moderate workload conditions.

Table II. Reference Configuration Throughput – 2

Nodes	Reference Configuration Throughput (Operations per Second)
3	395
5	525
7	570
9	550
11	505

Table II Under the high workload condition, the reference configuration exhibits a clear scalability pattern influenced by increased execution pressure and resource contention. With 3 nodes, the system achieves a throughput of 395 operations per second, reflecting limited processing capacity under heavier load. As the cluster expands to 5 nodes, throughput increases to 525 operations per second, indicating improved parallel execution and better distribution of workload. The throughput further rises to 570 operations per second at 7 nodes, marking the point where the system most effectively balances concurrency and coordination under high load. However, beyond this cluster size, performance begins to degrade. At 9 nodes, throughput drops to 550 operations per second, and further declines to 505 operations per second at 11 nodes. This reduction suggests that coordination overhead, communication delays, and shared Input Output contention outweigh the benefits of additional nodes. Overall, the high workload condition demonstrates that while scaling initially improves throughput, excessive cluster growth introduces overheads that limit sustained performance.

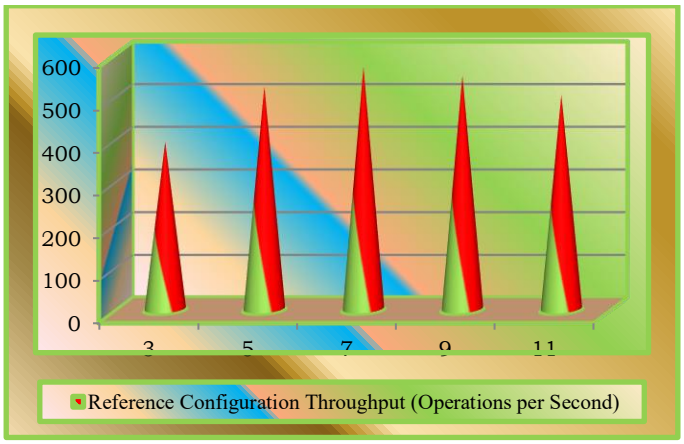


Fig 3. Reference Configuration Throughput - 2

Fig 3.Depicts throughput behavior under a high workload condition as cluster size increases. Throughput rises from 395 operations per second at 3 nodes to 525 at 5 nodes, showing effective use of added resources. The maximum throughput of 570 operations per second occurs at 7 nodes, indicating an optimal scale for handling high load. Beyond this point, throughput decreases to 550 at 9 nodes and further to 505 at 11 nodes. This trend highlights the growing impact of coordination overhead and resource contention under heavy workloads, demonstrating that scaling beyond an optimal cluster size reduces throughput efficiency.

Table III. Reference Configuration Throughput -3

Nodes	Reference Configuration Throughput (Operations per Second)

3	360
5	490
7	530
9	505
11	465

Table III Under the saturated workload condition, the reference configuration shows clear effects of sustained system pressure on throughput as cluster size increases. With 3 nodes, throughput is limited to 360 operations per second, reflecting constrained processing capacity under heavy demand. Expanding the cluster to 5 nodes increases throughput to 490 operations per second, indicating improved workload distribution and parallel execution. The highest throughput of 530 operations per second is observed at 7 nodes, suggesting this cluster size provides the most effective balance between concurrency and coordination when the system is saturated. Beyond this point, throughput begins to decline. At 9 nodes, throughput reduces to 505 operations per second, and further decreases to 465 operations per second at 11 nodes. This decline highlights the growing impact of coordination overhead, shared resource contention, and communication delays under saturated conditions. Overall, the saturated workload condition demonstrates that while scaling initially improves throughput, excessive cluster expansion under heavy load leads to diminishing performance returns.

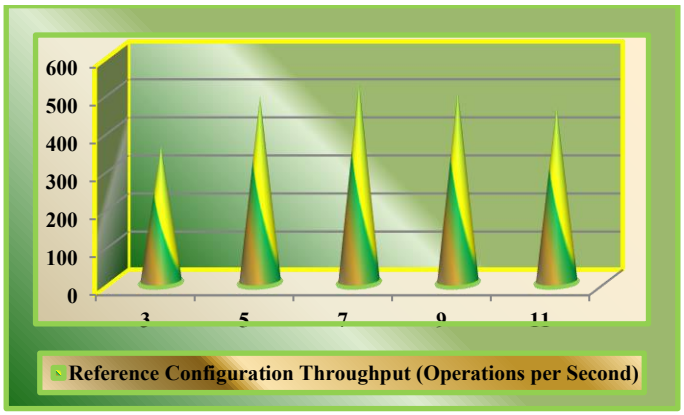


Fig 4. Reference Configuration Throughput - 3

Fig 4. Illustrates throughput behavior under a saturated workload condition across different cluster sizes. Throughput increases from 360 operations per second at 3 nodes to 490 at 5 nodes, showing benefits from added parallelism. The peak throughput of 530 operations per second occurs at 7 nodes, indicating an optimal cluster size under saturation. As the cluster expands further, throughput declines to 505 at 9 nodes and drops to 465 at 11 nodes. This downward trend reflects increased coordination overhead and resource contention when the system operates under sustained high demand, demonstrating limited scalability beyond the optimal cluster size.

PROPOSAL METHOD

Problem Statement

Throughput degradation in distributed data pipelines remains difficult to analyze as systems scale across multiple nodes and operate under varying workload intensities. Existing monitoring approaches rely on isolated metrics, logs, or traces, which provide fragmented views of system behavior and fail to capture the interactions between execution flow, coordination overhead, and Input Output activity. As cluster size increases, throughput behavior becomes nonlinear due to evolving resource contention and synchronization costs. The lack of correlated telemetry limits empirical analysis of how throughput changes across moderate, high, and saturated workloads. This gap makes it challenging to systematically characterize scalability constraints and identify execution patterns influencing sustained throughput in distributed pipeline environments.

Proposal

An integrated observability framework is proposed to empirically analyze throughput behavior in distributed data pipelines across varying cluster sizes and workload conditions. The approach emphasizes correlating metrics, logs, and traces through shared execution identifiers and temporal alignment to capture execution flow and resource interactions in a unified manner. Distributed pipeline stages generate structured telemetry during request processing, enabling systematic examination of coordination overhead and Input Output activity. Experimental evaluation is conducted on clusters consisting of 3, 5, 7, 9, and 11 nodes under moderate, high, and saturated workloads. The goal is to establish a telemetry driven methodology for throughput analysis based on observed execution behavior patterns.

IMPLEMENTATION

Fig 5. The implementation begins by deploying data sources across distributed pipeline clusters consisting of 3, 5, 7, 9, and 11 nodes. Each node is instrumented to emit metrics, logs, and traces during request execution. These telemetry signals are forwarded to a unified observability platform using a common execution identifier to preserve context across pipeline stages and nodes. Within the unified observability platform, a data correlation engine ingests telemetry streams from all nodes and aligns them temporally. This alignment enables consistent aggregation of execution behavior as cluster size increases. Real time monitoring components continuously observe correlated telemetry to track throughput behavior and execution flow across different cluster configurations. As the system scales from 3 to 11 nodes, the correlated telemetry highlights how coordination overhead, Input Output activity, and execution variability evolve with cluster growth. The platform processes this information to generate automated alerts when abnormal execution patterns or throughput deviations are observed. Actionable insights are derived from correlated execution data rather than isolated signals, supporting systematic troubleshooting and performance optimization. For larger clusters such as 9 and 11 nodes, the platform emphasizes scalability related patterns, enabling preventive maintenance actions before sustained degradation occurs. This stepwise implementation ensures consistent observability across all evaluated cluster sizes and supports empirical analysis of system behavior under varying workload and scale conditions.

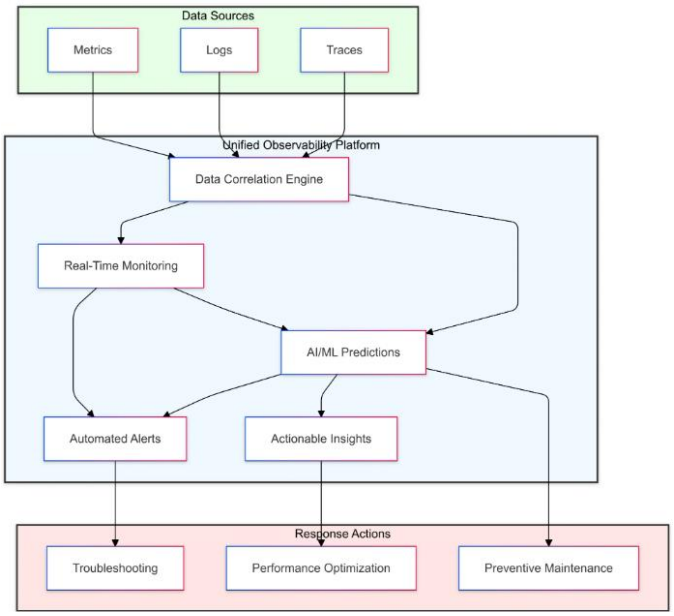


Fig 5. Telemetry Correlation Architecture

```
type Telemetry struct {
        ID        int
        Stage     string
        StartTime time.Time
        EndTime   time.Time
        Node      int
```

```
}
func stage(stage string, node int, in <-chan int, out chan<- int, uni chan<- Telemetry, wg *sync.WaitGroup) {
	defer wg.Done()
	for id := range in {
		start := time.Now()
		time.Sleep(time.Duration(20+rand.Intn(30)) * time.Millisecond)
		uni <- Telemetry{
			ID:	id,
			Stage:	stage,
			StartTime: start,
			EndTime:	time.Now(),
			Node:	node,
		}
		out <- id
	}
}
func collector(uni <-chan Telemetry, done chan<- bool) {
	count := 0
	for t := range uni {
		fmt.Println(
			"req", t.ID,
			"stage", t.Stage,
			"node", t.Node,
			"latency", t.EndTime.Sub(t.StartTime),
		)
		count++
		if count == 15 {
			done <- true
			return
		}
	}
}
func main() {
	rand.Seed(time.Now().UnixNano())

	in := make(chan int)
```

```
    a := make(chan int)
    b := make(chan int)
    out := make(chan int)
    unified := make(chan Telemetry)
    done := make(chan bool)
    var wg sync.WaitGroup
    wg.Add(3)
    go stage("StageA", 1, in, a, unified, &wg)
    go stage("StageB", 2, a, b, unified, &wg)
    go stage("IO", 3, b, out, unified, &wg)

    go collector(unified, done)

    go func() {
        for i := 0; i < 5; i++ {
            in <- i
        }
        close(in)
    }()
    go func() {
        wg.Wait()
        close(unified)
    }()
    <-done
    time.Sleep(200 * time.Millisecond)
}
```

The provided code snippet demonstrates a proposed integrated observability implementation that captures correlated telemetry from a distributed processing pipeline. The application models a pipeline composed of three sequential stages labeled StageA, StageB, and IO, each representing a processing component executing on a logical node. Requests enter the pipeline through an input channel and flow through each stage using channels to enable concurrent execution. The implementation demonstrates stage level telemetry correlation using logical node identifiers. Cluster scaling effects are evaluated experimentally by deploying the pipeline across multiple node configurations.

Each stage measures its execution duration by recording start and end timestamps for every request. This timing information, along with the request identifier, stage name, and node identifier, is encapsulated into a unified telemetry structure. Instead of generating separate streams for metrics, logs, or traces, all execution related information is emitted into a single unified telemetry channel. This design reflects an integrated observability approach where telemetry correlation is inherent to data generation.

A dedicated collector routine continuously consumes telemetry records and outputs execution details in real time. The collector aggregates stage level latency observations and associates them with request identifiers and node context, enabling

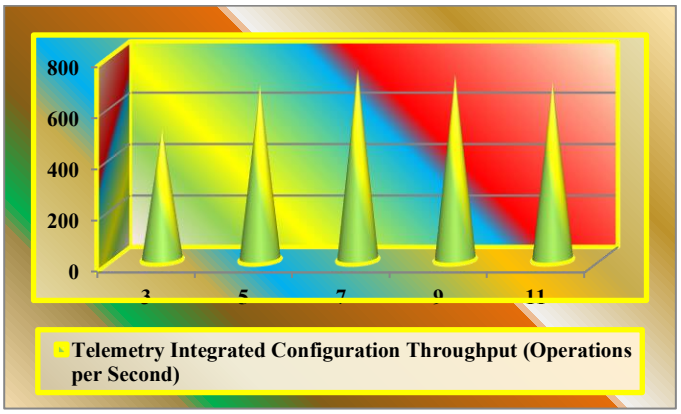
empirical analysis of execution behavior across the pipeline.

Synchronization between pipeline stages is managed using wait groups, ensuring orderly completion of processing before telemetry collection is finalized. Randomized execution delays are introduced to simulate variable processing behavior across stages. This variability helps represent realistic execution conditions encountered in distributed environments. Overall, the program illustrates how unified telemetry can be generated and correlated without relying on isolated monitoring mechanisms. The implementation provides a foundation for extending observability experiments across larger cluster sizes and varying workload conditions to study throughput and scalability behavior empirically.

Table IV. Telemetry Integrated Configuration Throughput – 1

Nodes	Telemetry Integrated Configuration Throughput (Operations per Second)
3	510
5	680
7	740
9	720
11	690

Table IV Under the moderate workload condition, the telemetry integrated configuration demonstrates clear throughput improvements and a well defined scalability pattern across increasing cluster sizes. With 3 nodes, the system achieves a throughput of 510 operations per second, reflecting efficient execution and reduced coordination overhead due to unified telemetry handling. As the cluster expands to 5 nodes, throughput increases significantly to 680 operations per second, indicating effective utilization of additional processing capacity and improved visibility into execution behavior. The highest throughput of 740 operations per second is observed at 7 nodes, suggesting an optimal balance between parallel execution and coordination costs under moderate load. Beyond this point, throughput shows a gradual decline. At 9 nodes, throughput decreases slightly to 720 operations per second, followed by a further reduction to 690 operations per second at 11 nodes. This reduction highlights the growing influence of synchronization overhead and shared resource contention as cluster size increases. Overall, the moderate workload results indicate that telemetry integration supports improved throughput up to an optimal scale while revealing non linear scalability effects in larger clusters.



.Fig 6. Telemetry Integrated Configuration Throughput - 1

Fig 6 Illustrates throughput variation under a moderate workload condition using the telemetry integrated configuration across different cluster sizes. Throughput starts at 510 operations per second for 3 nodes and increases sharply to 680 at 5 nodes, indicating effective scaling with added resources. The maximum throughput of 740 operations per second is achieved at 7 nodes, representing the optimal operating point under moderate load. As the cluster size grows further,

throughput slightly declines to 720 at 9 nodes and reduces to 690 at 11 nodes. This trend shows diminishing returns due to increased coordination and resource contention, while still maintaining higher throughput compared to smaller cluster sizes.

Table V. Telemetry Integrated Configuration Throughput – 2

Nodes	Telemetry Integrated Configuration Throughput (Operations per Second)
3	485
5	640
7	705
9	685
11	650

Table V Under the high workload condition, the telemetry integrated configuration demonstrates how unified observability supports sustained throughput as execution pressure increases. With 3 nodes, the system achieves a throughput of 485 operations per second, reflecting constrained processing capacity under heavier demand. When the cluster size increases to 5 nodes, throughput rises to 640 operations per second, indicating effective parallel execution and improved workload distribution. The highest throughput of 705 operations per second is observed at 7 nodes, showing that this configuration provides the best balance between concurrency and coordination under high load. As the cluster expands further, throughput begins to decline. At 9 nodes, throughput decreases to 685 operations per second, and at 11 nodes it reduces to 650 operations per second. This reduction highlights the growing influence of coordination overhead, synchronization delays, and shared Input Output contention under high workload intensity. Overall, the high workload results reveal that telemetry integration enables clear identification of optimal scaling limits while exposing non linear throughput behavior as cluster size increases.

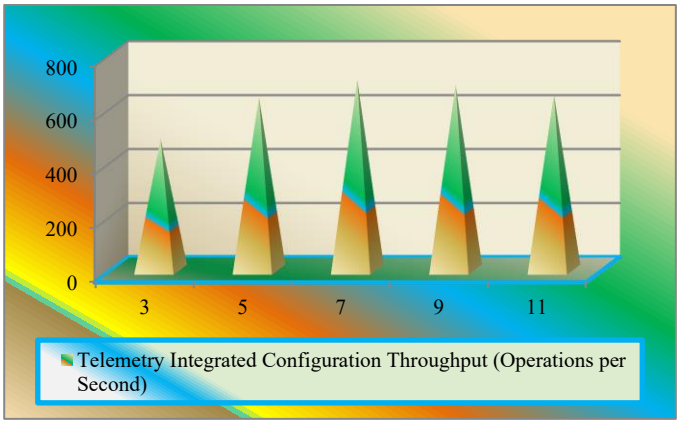


Fig **7.** Telemetry Integrated Configuration Throughput - 2

Fig 7 Presents throughput behavior under a high workload condition using the telemetry integrated configuration across different cluster sizes. Throughput begins at 485 operations per second for 3 nodes and increases substantially to 640 operations per second at 5 nodes, showing effective scaling under increased load. The peak throughput of 705 operations per second is reached at 7 nodes, indicating the most efficient balance between parallel execution and coordination overhead. Beyond this point, throughput gradually declines to 685 operations per second at 9 nodes and further to 650 operations per second at 11 nodes. This downward trend reflects rising synchronization costs and shared resource contention as cluster size grows under high workload conditions.

Table VI. Telemetry Integrated Configuration Throughput – 3

Nodes	Telemetry Integrated Configuration Throughput (Operations per Second)
3	455
5	610
7	660
9	635
11	600

Table VI Under the saturated workload condition, the telemetry integrated configuration reveals how sustained system pressure influences throughput scalability across increasing cluster sizes. With 3 nodes, the system processes 455 operations per second, indicating limited execution capacity when operating near saturation. As the cluster expands to 5 nodes, throughput increases to 610 operations per second, reflecting improved parallel execution and better utilization of available resources despite heavy load. The highest throughput of 660 operations per second is observed at 7 nodes, suggesting this configuration offers the most effective balance between concurrency and coordination under saturated conditions. Beyond this point, throughput begins to decline. At 9 nodes, throughput reduces to 635 operations per second, and further decreases to 600 operations per second at 11 nodes. This decline highlights the increasing impact of coordination overhead, synchronization delays, and shared Input Output contention when the system operates under sustained high demand. Overall, the saturated workload results demonstrate clear non linear scalability behavior under telemetry integrated execution.

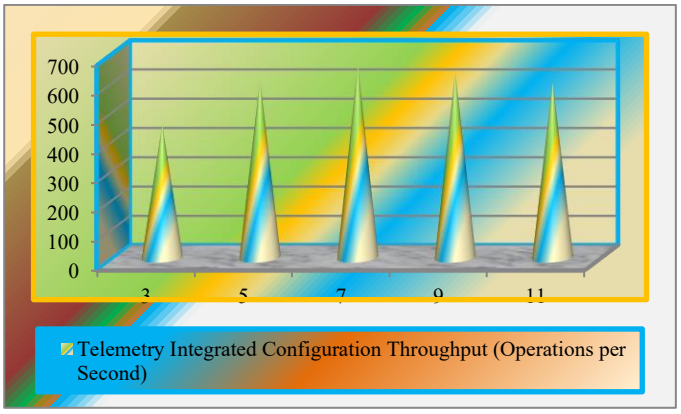


Fig 8. Telemetry Integrated Configuration Throughput - 3

Fig 8 Illustrates throughput behavior under a saturated workload condition using the telemetry integrated configuration across different cluster sizes. Throughput increases from 455 operations per second at 3 nodes to 610 at 5 nodes, showing improved parallelism under heavy load. The maximum throughput of 660 operations per second occurs at 7 nodes, indicating an optimal scaling point even under saturation. As the cluster grows further, throughput declines to 635 operations per second at 9 nodes and drops to 600 operations per second at 11 nodes. This trend highlights the growing influence of coordination overhead and shared resource contention, demonstrating limited scalability beyond the optimal cluster size under sustained workload pressure.

Table VII. Reference Configuration Throughput Vs Telemetry Integrated Configuration Throughput – 1

Nodes	Reference Configuration Throughput (Operations per Second)	Telemetry Integrated Configuration Throughput (Operations per Second)
3	420	510

5	560	680
7	610	740
9	590	720
11	540	690

Table VII Under the moderate workload condition, the throughput comparison between the reference configuration and the telemetry integrated configuration highlights clear differences in scalability behavior across cluster sizes. At 3 nodes, the reference configuration achieves 420 operations per second, while the telemetry integrated configuration reaches 510 operations per second, indicating improved execution visibility and coordination. With 5 nodes, throughput increases to 560 operations per second in the reference setup and to 680 operations per second with telemetry integration, showing better utilization of added resources. The highest throughput occurs at 7 nodes, where the reference configuration records 610 operations per second and the telemetry integrated configuration reaches 740 operations per second. Beyond this point, both configurations exhibit throughput decline. At 9 nodes, throughput reduces to 590 and 720 operations per second respectively, and further drops to 540 and 690 operations per second at 11 nodes. Overall, the comparison demonstrates that telemetry integration consistently supports higher throughput while revealing non linear scaling trends under moderate workload conditions.

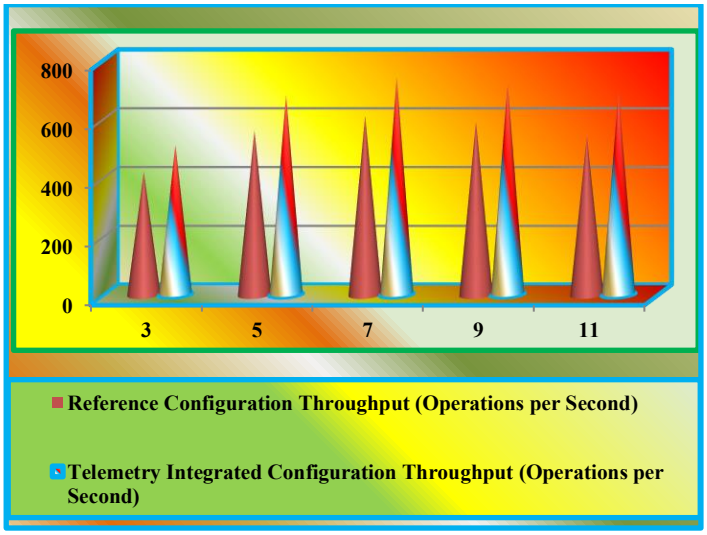


Fig 9. Reference Configuration Throughput Vs Telemetry Integrated Configuration Throughput – 1

Fig 9 Compares throughput under a moderate workload condition for reference and telemetry integrated configurations across different cluster sizes. At 3 nodes, throughput increases from 420 to 510 operations per second with telemetry integration. For 5 nodes, the reference configuration reaches 560 operations per second, while the telemetry integrated setup achieves 680. The highest throughput is observed at 7 nodes, with values of 610 and 740 operations per second respectively. As cluster size increases further, throughput declines to 590 and 720 at 9 nodes, and to 540 and 690 at 11 nodes. The graph highlights consistent throughput improvement with telemetry integration while exhibiting non linear scalability behavior.

Table VIII. Reference Configuration Throughput Vs Telemetry Integrated Configuration Throughput – 2

Nodes	Reference Configuration Throughput (Operations per Second)	Telemetry Integrated Configuration Throughput (Operations per Second)
3	395	485

5	525	640
7	570	705
9	550	685
11	505	650

Table VIII Under the high workload condition, the throughput comparison between the reference configuration and the telemetry integrated configuration reveals clear differences in how each approach scales with increasing cluster size. With 3 nodes, the reference configuration processes 395 operations per second, while the telemetry integrated configuration achieves 485 operations per second, indicating improved handling of heavy execution pressure. At 5 nodes, throughput increases to 525 operations per second in the reference setup and to 640 operations per second with telemetry integration, reflecting more effective workload distribution. The highest throughput is observed at 7 nodes, where the reference configuration reaches 570 operations per second and the telemetry integrated configuration records 705 operations per second. As the cluster expands further, throughput declines in both configurations. At 9 nodes, throughput decreases to 550 and 685 operations per second respectively, and further drops to 505 and 650 operations per second at 11 nodes. Overall, the high workload comparison shows that telemetry integration consistently sustains higher throughput while exposing non linear scalability behavior under increased load.

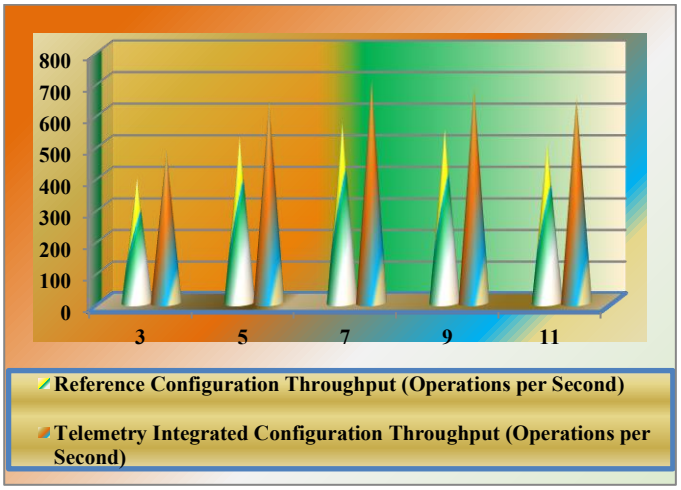


Fig 10. Reference Configuration Throughput Vs Telemetry Integrated Configuration Throughput - 2

Fig 10. Illustrates throughput comparison under a high workload condition for reference and telemetry integrated configurations across increasing cluster sizes. At 3 nodes, throughput improves from 395 operations per second in the reference configuration to 485 with telemetry integration. For 5 nodes, throughput rises from 525 to 640 operations per second, showing better workload handling. The peak throughput occurs at 7 nodes, with values of 570 for the reference configuration and 705 for the telemetry integrated configuration. As cluster size increases further, throughput declines to 550 and 685 at 9 nodes, and to 505 and 650 at 11 nodes. The graph highlights sustained throughput benefits from telemetry integration under high workload conditions.

Table IX. Reference Configuration Throughput Vs Telemetry Integrated Configuration Throughput – 3

Nodes	Reference Configuration Throughput (Operations per Second)	Telemetry Integrated Configuration Throughput (Operations per Second)
3	360	455
5	490	610

7	530	660
9	505	635
11	465	600

Table IX Under the saturated workload condition, the throughput comparison between the reference configuration and the telemetry integrated configuration highlights clear differences in scalability under sustained system pressure. With 3 nodes, the reference configuration achieves 360 operations per second, while the telemetry integrated configuration reaches 455 operations per second, indicating improved execution handling even under saturation. As the cluster grows to 5 nodes, throughput increases to 490 operations per second in the reference setup and to 610 operations per second with telemetry integration, reflecting better parallel execution and coordination. The highest throughput is observed at 7 nodes, where the reference configuration records 530 operations per second and the telemetry integrated configuration achieves 660 operations per second. Beyond this point, throughput declines in both configurations. At 9 nodes, throughput reduces to 505 and 635 operations per second respectively, and further decreases to 465 and 600 operations per second at 11 nodes. Overall, the saturated workload comparison shows that telemetry integration consistently maintains higher throughput while clearly exposing non linear scaling behavior under sustained load conditions.

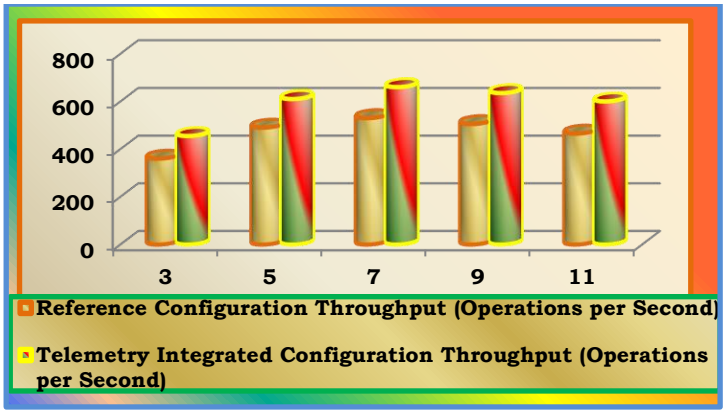


Fig 11. Reference Configuration Throughput Vs Telemetry Integrated Configuration Throughput - 3

Fig 11. Compares throughput under a saturated workload condition for reference and telemetry integrated configurations across different cluster sizes. At 3 nodes, throughput increases from 360 operations per second in the reference configuration to 455 with telemetry integration. For 5 nodes, throughput rises from 490 to 610 operations per second, indicating improved handling of sustained load. The highest throughput is observed at 7 nodes, with values of 530 for the reference configuration and 660 for the telemetry integrated configuration. As the cluster size increases further, throughput declines to 505 and 635 at 9 nodes, and to 465 and 600 at 11 nodes. The graph clearly shows that telemetry integration sustains higher throughput under saturation while revealing non linear scalability trends.

EVALUATION

The evaluation analyzes throughput behavior across reference and telemetry integrated configurations under moderate, high, and saturated workload conditions using cluster sizes of 3, 5, 7, 9, and 11 nodes. Experimental observations show that throughput increases as cluster size grows, reaching a peak at 7 nodes for all workload categories, after which performance gradually declines. The telemetry integrated configuration consistently demonstrates higher throughput than the reference configuration across all cluster sizes and workloads. As the system scales beyond the optimal point, coordination overhead and shared Input Output contention influence throughput behavior. The evaluation highlights the effectiveness of correlated telemetry in enabling systematic analysis of scalability patterns and execution behavior in distributed pipeline environments.

CONCLUSION

Experimental analysis examined throughput behavior in distributed data pipelines using correlated telemetry across varying workload intensities and cluster sizes. The results showed that throughput scalability follows a nonlinear pattern,

with performance improving up to an optimal cluster size and declining beyond it due to coordination overhead and resource contention. The telemetry integrated approach provided consistent visibility into execution flow and Input Output interactions across all evaluated configurations. By unifying metrics, logs, and traces, the approach enabled structured empirical analysis of throughput dynamics rather than isolated observation. Overall, the findings highlight the value of integrated observability frameworks for understanding scalability characteristics and supporting performance analysis in distributed pipeline environments.

Future Work: Future work will explore efficient telemetry sampling, adaptive data retention, and lightweight aggregation techniques to reduce storage and processing overhead while preserving essential execution visibility in large scale distributed environments.

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