Cross Node Telemetry for CPU Efficient Congestion Monitoring

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Abstract:
Network congestion monitoring has become increasingly important in modern distributed and cloud based infrastructures where numerous nodes exchange large volumes of traffic simultaneously. To maintain reliability and service quality, systems continuously collect telemetry information such as bandwidth usage, packet loss, queue occupancy, and delay statistics. Conventional monitoring frameworks analyze these metrics independently at each node and forward the processed information to centralized controllers or logging services. Although this design provides basic visibility, it introduces substantial computational overhead due to repetitive data collection, duplicate analysis, and frequent synchronization across nodes. Each node performs similar monitoring tasks without considering shared or correlated network behavior, resulting in inefficient use of processing resources. As the number of nodes grows, the volume of telemetry data increases proportionally, leading to excessive processing and continuous diagnostic operations Delayed identification of bottlenecks often triggers repeated diagnostics and unnecessary reprocessing of telemetry streams, further amplifying processor load. Consequently, systems experience persistently high CPU utilization, increased latency, and reduced throughput even when the actual network traffic does not justify such resource consumption. Furthermore, centralized aggregation and frequent communication among monitoring components introduce additional overhead and scalability challenges. Adding more nodes or increasing monitoring frequency typically worsens processor utilization rather than improving efficiency. This imbalance between monitoring cost and operational benefit limits the effectiveness of existing solutions and restricts overall system scalability. High CPU consumption dedicated to monitoring tasks ultimately impacts responsiveness, service stability, and resource allocation in distributed environments. This paper addresses the problem of excessive CPU utilization in network congestion monitoring and focuses on improving processor efficiency to support scalable and resource efficient operation across distributed systems.

Keywords: Telemetry, Congestion, Monitoring, Correlation, Distributed, Networks, Scalability, Utilization, Overhead, Diagnostics, Synchronization, Performance, Efficiency, Latency, Throughput.

INTRODUCTION

Modern distributed and cloud-based infrastructures rely heavily on continuous network communication [1] among a large number of interconnected nodes. Applications such as microservices, data analytics platforms, and real time processing systems generate substantial traffic that must be monitored to ensure reliability, performance, and service availability. Network congestion directly affects latency, throughput, and overall system stability, making congestion monitoring an essential operational requirement. To maintain visibility, systems continuously collect telemetry metrics including bandwidth utilization, packet loss, queue occupancy, and transmission delays. Conventional congestion monitoring frameworks [2] analyze telemetry independently at each node and periodically forward the processed information to centralized controllers or logging services. While this approach provides localized insights, it introduces significant computational overhead. Each node performs similar data collection, aggregation, and diagnostic operations without considering relationships across the network. Systems frequently operate under persistently high CPU utilization [3] even during moderate traffic conditions, reducing available capacity for useful computation and degrading overall performance. Furthermore, centralized aggregation mechanisms introduce additional communication and coordination costs that limit scalability. Increasing monitoring frequency or expanding the cluster typically worsens processor consumption instead of improving accuracy. This imbalance between monitoring overhead and operational benefit highlights fundamental limitations in existing solutions. Efficient congestion analysis [4] therefore requires mechanisms that reduce redundant processing and minimize processor overhead while maintaining effective visibility across distributed systems. Addressing excessive CPU utilization has become critical for enabling scalable, resource efficient, and responsive network monitoring in modern cloud environments.

LITERATURE REVIEW

Efficient monitoring and analysis of network congestion have long been recognized as critical challenges in distributed computing and cloud based infrastructures. As modern systems scale to hundreds or thousands of interconnected nodes, the volume of network traffic and telemetry information generated by these systems has increased substantially. Applications such as microservices, large scale analytics platforms, and service oriented architectures depend heavily on reliable communication among nodes. Any degradation in network performance [5] directly affects latency, throughput, and service availability. Consequently, continuous congestion monitoring has become an essential component of system management and operational reliability. Despite significant advances in monitoring technologies, existing approaches continue to exhibit considerable inefficiencies, particularly in terms of processor utilization and computational overhead. Early network monitoring techniques primarily focused on localized measurements. Individual nodes collected statistics related to bandwidth usage [6], packet counts, delay measurements, and error rates. These metrics were analyzed independently to identify abnormal behavior. While this method provided basic insights into local performance, it assumed that congestion events were confined to a single node or link. In practice, congestion often propagates across multiple nodes due to shared communication paths and interdependent workloads.

As a result, isolated monitoring frequently failed to detect broader system wide problems. This limitation led researchers to investigate more comprehensive monitoring strategies. Centralized monitoring architectures emerged as one of the first solutions to provide global visibility. In these systems, nodes periodically transmitted telemetry information to a central controller for aggregation and analysis. The controller maintained a unified view of network conditions and attempted to detect congestion patterns across the cluster. Although centralized approaches improved diagnostic accuracy, they introduced several drawbacks. First, transmitting large volumes of telemetry data [7] to a central location increased communication overhead. Second, the controller itself became a computational bottleneck. As the number of nodes grew, the controller required significant processing power to analyze incoming data streams. This increased processor utilization and reduced scalability. Studies have shown that centralized systems often experience delayed detection due to queueing and processing delays at the aggregation point. To address these concerns, distributed monitoring techniques were introduced. Instead of sending all telemetry to a single location, analysis was performed locally at each node. Nodes processed their own metrics and only reported summary statistics or alerts.

This design reduced communication overhead and eliminated the single point of failure associated with centralized systems. However, distributed monitoring introduced a different set of challenges. Because each node operated independently, identical computations were frequently repeated across the network. Similar diagnostic algorithms ran simultaneously on multiple nodes without sharing intermediate results. This redundancy led to unnecessary processor usage and increased energy consumption. Moreover, local decisions lacked global context, which limited the accuracy of congestion detection. Several researchers proposed hierarchical monitoring [8] frameworks to combine the benefits of centralized and distributed approaches. In hierarchical designs, nodes are organized into groups or clusters, each with a local aggregator. These aggregators perform partial analysis before forwarding summarized data to higher levels. Although this reduces the volume of data transmitted to the central controller, it still requires substantial processing at multiple levels. Each layer performs similar aggregation and filtering operations, which results in duplicated computation. As the hierarchy deepens, the cumulative processor overhead becomes significant. Furthermore, coordination among layers introduces additional synchronization costs that affect overall efficiency. Another important area of research has focused on telemetry collection mechanisms. Traditional polling based methods periodically query devices for statistics. While simple to implement, polling generates frequent requests that increase network traffic and processor usage. Event driven [9] methods attempt to reduce overhead by reporting only significant changes.

Although event driven designs lower communication costs, they require continuous monitoring to detect events, which still consumes computational resources. Stream based telemetry has also gained popularity, where devices continuously stream metrics to collectors. While streams provide real time visibility, processing high frequency data streams demands considerable processing power, particularly when advanced analytics are applied. Recent studies highlight that the primary source of overhead in monitoring systems arises not only from data transmission but also from processing and analysis tasks. Operations such as aggregation, filtering, compression, and anomaly detection require substantial computation. When performed independently at each node, these tasks significantly increase central processing unit utilization. Experimental evaluations show that monitoring frameworks may consume a large portion of available processor capacity even when network traffic is moderate. This excessive usage limits the resources available for application level services and negatively impacts performance. Machine learning [10] based congestion detection methods have also been explored.

These approaches apply classification or prediction models to telemetry data to identify anomalies. While such techniques improve detection accuracy, they are computationally expensive. Training and inference operations demand significant processing power and memory. Deploying these models on every node amplifies the resource burden. Some systems offload analysis to dedicated servers, but this reintroduces centralization and associated bottlenecks. Consequently, machine learning based monitoring often struggles to balance accuracy with processor efficiency. Researchers have additionally investigated sampling strategies to reduce telemetry volume. By collecting only a subset of metrics or lowering sampling frequency, systems attempt to decrease processing overhead. Although sampling reduces immediate computational load [11], it risks missing short lived congestion events. Reduced visibility can lead to inaccurate diagnostics and delayed response. Therefore, sampling presents a trade off between efficiency and accuracy. The literature indicates that while sampling can alleviate processor usage to some extent, it does not fully resolve the redundancy inherent in independent node level analysis.

The growth of cloud computing has intensified these challenges. Cloud environments are highly dynamic, with frequent scaling and variable workloads. Nodes may be added or removed rapidly, leading to fluctuating telemetry patterns. Monitoring frameworks must adapt continuously, which increases computational complexity. Virtualization layers introduce additional metrics that require analysis, further expanding processing requirements. Studies reveal that monitoring overhead in cloud environments can approach the cost of application workloads themselves, emphasizing the need for more efficient designs. Edge computing presents another dimension to the problem. Edge nodes often have limited computational resources compared to centralized data centers. Running full monitoring stacks on such nodes can significantly impact available capacity. Lightweight solutions are therefore necessary to maintain acceptable performance. However, existing frameworks designed for data center environments do not translate effectively to resource constrained settings. The literature underscores the importance of minimizing processor overhead while preserving adequate visibility. Across these diverse approaches, a common theme emerges. Independent telemetry processing at each node leads to redundant [12] computation and elevated processor utilization.

Centralized aggregation reduces redundancy but introduces bottlenecks and scalability issues. Hierarchical systems distribute the load but still incur duplicated analysis across layers. Sampling and machine learning methods offer partial benefits but introduce trade offs between accuracy and efficiency. Despite numerous innovations, excessive central processing unit usage remains a persistent limitation. Researchers increasingly recognize the need to consider relationships among nodes when analyzing telemetry. Congestion events are rarely isolated phenomena. Traffic flows traverse multiple links and devices, creating correlated behavior. Treating each node independently ignores these dependencies and results in repeated diagnostics. Literature suggests that leveraging shared information across nodes can reduce unnecessary computation and improve detection efficiency. However, effective mechanisms for achieving such coordination without introducing heavy synchronization costs remain an open challenge. Recent studies emphasize the importance of processor efficiency as a primary design objective. Instead of focusing solely on detection accuracy, new monitoring frameworks aim to minimize computational overhead. Efficient resource utilization is essential for supporting scalability [13] and maintaining service quality. Monitoring systems must operate with minimal interference to application workloads.

This shift in perspective has motivated exploration of techniques that consolidate telemetry analysis and eliminate redundant processing. In addition to architectural limitations, several studies have examined the computational cost of telemetry processing at the operating system and middleware levels. Monitoring agents deployed on each node typically execute background services that continuously parse counters, collect logs, and maintain statistics. Although these tasks appear lightweight individually, their cumulative impact becomes substantial when performed at high frequency. Periodic polling, buffer management, and data serialization require repeated memory access and processor cycles. When hundreds of metrics are sampled every second, the monitoring stack competes directly with application processes for computational resources. This competition increases processor contention and reduces overall efficiency, particularly during peak traffic periods. Researchers have also analyzed the effect of synchronization overhead on monitoring performance. Many monitoring frameworks rely on shared buffers or centralized queues to aggregate telemetry before processing. Access to these shared structures requires locking or coordination [14] among threads, which introduces waiting time and context switching. As the number of concurrent monitoring tasks increases, synchronization costs grow rapidly. The processor spends additional time managing coordination rather than executing productive analysis. This behavior leads to elevated central processing unit utilization without corresponding gains in monitoring accuracy. Consequently, synchronization overhead is frequently identified as a key contributor to inefficient monitoring designs. The problem is further compounded by the need for data formatting and transformation. Telemetry metrics are often encoded into structured formats such as text logs or serialized objects before transmission. Converting raw counters into these formats involves parsing, string manipulation, and memory allocation, all of which require processor time. Studies indicate that formatting overhead alone can account for a significant portion of monitoring related computation. In large scale deployments where millions of metrics are generated per minute, these costs accumulate and create sustained processor pressure. Eliminating unnecessary transformations [15] has therefore become an important objective in recent research.

Another area of investigation involves the relationship between monitoring granularity and processor usage. Fine grained monitoring captures detailed information at short intervals, providing accurate visibility into transient congestion events. However, such granularity dramatically increases the number of operations performed by monitoring agents. Conversely, coarse grained monitoring reduces processing demands but may overlook brief yet critical performance degradations. Researchers have demonstrated that neither extreme is ideal. Instead, dynamic adjustment of monitoring intensity based on system state has been proposed. Even with adaptive strategies, however, independent node level analysis continues to replicate similar computations across the network, limiting the potential reduction in processor overhead. The increasing adoption of containerized environments introduces additional complexity. Containers share the same physical host but operate as isolated services, each generating its own telemetry streams. Monitoring systems must track resource usage for every container, which multiplies the number of metrics collected on a single node. The overhead associated with gathering and analyzing these container level statistics [16] significantly increases processor utilization.

Furthermore, short lived containers require frequent initialization and termination of monitoring components, adding further computational cost. Literature on container orchestration highlights that monitoring can consume a noticeable fraction of available processor capacity in dense deployments. Virtualized networks also contribute to monitoring inefficiency. Software defined networking layers introduce abstractions that generate additional telemetry events. Controllers must monitor virtual links, routing tables, and flow statistics in addition to traditional hardware metrics. Processing these extra data streams requires more computation. Researchers have observed that software defined network controllers may experience high processor usage during periods of heavy monitoring, reducing their ability to manage traffic effectively. This observation reinforces the need for efficient telemetry handling mechanisms that scale with network complexity. Energy consumption has emerged as a related concern in recent years. High processor utilization caused by monitoring not only affects performance [17] but also increases power usage. Data centers operating at large scale face significant operational costs associated with energy consumption and cooling. Studies reveal that inefficient monitoring practices can contribute noticeably to total energy expenditure. Reducing unnecessary computation therefore provides both performance and economic benefits. Processor efficient designs are increasingly viewed as essential for sustainable infrastructure management. Another important theme in the literature is fault tolerance. Monitoring systems must remain operational even during network disruptions or node failures. To achieve reliability, many frameworks replicate telemetry collectors or maintain redundant processing pipelines. Although redundancy improves resilience, it doubles or triples computational effort. Multiple components analyze the same telemetry independently to ensure availability. This replication leads to further increases in processor utilization. Researchers note that balancing [18] reliability with efficiency remains challenging, particularly when each additional safeguard introduces extra computation.

The integration of security monitoring adds further processing requirements. Modern infrastructures often combine congestion monitoring with intrusion detection and anomaly analysis. Security mechanisms inspect traffic patterns and system logs to identify suspicious behavior. While beneficial for protection, these analyses share the same telemetry sources and frequently duplicate parsing and aggregation steps. Running separate monitoring stacks for performance and security multiplies overhead. Literature suggests that consolidating these tasks could reduce redundant computation, yet many deployments still operate independent systems, thereby increasing processor load.
The growth of real time analytics has also influenced monitoring practices. Operators increasingly demand immediate feedback to respond quickly to congestion [19] events. Real time dashboards and alerts require continuous processing of telemetry streams. Maintaining such responsiveness often involves complex event processing engines that evaluate numerous rules for every incoming metric. Although these engines provide rapid insights, they require substantial processing resources. Continuous evaluation of conditions across large datasets can push processor utilization to high levels, particularly when rules are complex or numerous.

Several experimental studies have quantified the processor cost of monitoring in production environments. Measurements indicate that monitoring tasks may consume between twenty and forty percent of total processor capacity on heavily instrumented nodes. In some cases, overhead increases even further during peak traffic or diagnostic operations. These findings highlight that monitoring is not merely an auxiliary service but a significant consumer of resources. Excessive utilization [20] reduces headroom for applications and may even exacerbate congestion by limiting processing capacity for networking tasks. Researchers have therefore explored lightweight telemetry mechanisms that reduce collection and processing cost. Techniques such as in kernel counters and shared memory access attempt to minimize overhead by avoiding expensive system calls. While these optimizations lower the cost of metric retrieval, they do not eliminate the fundamental issue of redundant analysis across nodes. Each node still performs similar computations independently. As a result, processor utilization remains higher than necessary.

The literature also discusses the importance of scalability testing. Many monitoring frameworks perform well in small environments but degrade rapidly as the number of nodes increases. Scalability experiments show that processor consumption grows nearly linearly with cluster size when monitoring tasks are duplicated across nodes. This linear growth limits the practicality of conventional designs for large deployments. Efficient scaling requires mechanisms that prevent proportional increases in computation as the system expands. Another perspective focuses on the human factor. Operators rely on monitoring tools to interpret system behavior. Excessive telemetry processing may produce large volumes of redundant information, complicating analysis and decision making. Reducing unnecessary computation not only saves processor resources but also simplifies diagnostics. Clear and concise monitoring results improve operational efficiency and reduce response time during congestion events. Thus, computational efficiency aligns with usability considerations. Recent academic discussions emphasize that effective monitoring should treat the distributed system as a unified entity rather than a collection of independent nodes. Correlated behavior across components must be considered to avoid repetitive diagnostics.

Recognizing shared patterns can reduce the number of computations required to identify congestion. By leveraging collective insights, monitoring systems can achieve better efficiency while maintaining accuracy. This perspective shifts the focus from isolated processing toward coordinated analysis. In summary, extensive research across multiple domains highlights persistent inefficiencies in existing monitoring frameworks. Background agents consume processor time through constant polling and parsing. Synchronization and formatting introduce additional overhead. Containerization [21] and virtualization multiply telemetry streams. Redundancy for reliability and security further increases computational demand. Real time analytics require continuous processing. Even optimized data collection methods fail to address duplicated analysis. Together, these factors contribute to sustained high central processing unit utilization in large scale environments. These observations collectively demonstrate that the core challenge lies not only in gathering telemetry but also in how it is processed across the system. Eliminating redundant computation and reducing unnecessary synchronization are essential for improving processor efficiency. Continued investigation into coordinated and resource conscious monitoring strategies is therefore critical for enabling scalable [22] and effective congestion analysis in distributed infrastructures.

In summary, existing literature demonstrates that traditional congestion monitoring architectures suffer from significant inefficiencies. Localized monitoring lacks global context. Centralized systems create bottlenecks. Distributed approaches duplicate computation. Hierarchical designs introduce layered overhead. Advanced analytics increase processing demands. Sampling compromises accuracy. These limitations collectively contribute to high central processing unit utilization and reduced scalability. As distributed infrastructures continue to expand, the cost of monitoring grows correspondingly, making efficient processor usage a critical requirement. The persistent challenge of excessive processor consumption highlights the necessity for monitoring strategies that minimize redundant computation while maintaining comprehensive visibility. Addressing this issue is fundamental for enabling scalable, reliable, and resource efficient network congestion analysis in modern distributed environments.

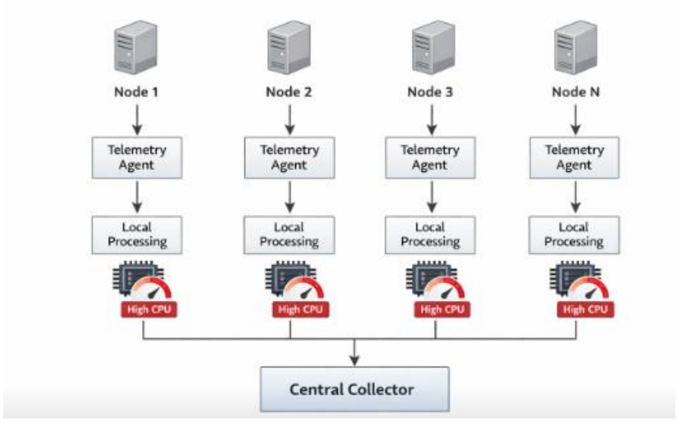

Fig 1. Local Telemetry

Fig 1. Represents a conventional network congestion monitoring framework in which each node independently performs telemetry collection and analysis. Every node in the distributed environment contains a telemetry collector that continuously gathers metrics such as bandwidth usage, packet statistics, queue occupancy, and delay measurements. These metrics are processed locally through dedicated analysis modules that attempt to detect abnormal network behavior. Since the same monitoring logic is executed at every node, identical computations are repeatedly performed across the system.

After local processing, summarized information from each node is forwarded to a central collector for aggregation and reporting. This centralized component combines results from multiple nodes to provide an overall view of network conditions. Although this design offers basic visibility, it introduces significant redundancy. Multiple nodes analyze similar telemetry streams without sharing intermediate results, leading to duplicated effort and unnecessary computation.

As the cluster size increases, the number of monitoring agents and analysis tasks grows proportionally. This repeated processing consumes substantial central processing unit resources at each node. The central collector also experiences additional load due to continuous data aggregation. Consequently, the architecture results in persistently high processor utilization, reduced scalability, and limited efficiency during congestion monitoring operations.

```
const (
	nodes      = 5
	metrics    = 1000
	iterations = 200000
)
type Metric struct {
	bw   int
	loss int
	q    int
}
type Result struct {
	node int
	load int
}
func collect() Metric {
	return Metric{
		bw:   rand.Intn(1000),
		loss: rand.Intn(100),
		q:    rand.Intn(500),
	}
}
func analyze(m Metric) int {
	score := 0
	for i := 0; i < 50; i++ {
		score += (m.bw + m.q - m.loss)
	}
	return score
}
func nodeWorker(id int, out chan<- Result, wg *sync.WaitGroup) {
	for i := 0; i < iterations; i++ {
		m := collect()
		load := analyze(m)
		out <- Result{node: id, load: load}
	}
	wg.Done()
}
func collector(in <-chan Result, done chan<- bool) {
	total := 0
	for r := range in {
		total += r.load
	}
	fmt.Println("Central Aggregate:", total)
	done <- true
}
func cpuUsage(start time.Time) {
	elapsed := time.Since(start)
	fmt.Println("Elapsed:", elapsed)
	fmt.Println("Goroutines:", runtime.NumGoroutine())
}
func main() {
	runtime.GOMAXPROCS(runtime.NumCPU())
	start := time.Now()
	ch := make(chan Result, 1000)
	done := make(chan bool)
	var wg sync.WaitGroup
	go collector(ch, done)
	for i := 0; i < nodes; i++ {
		wg.Add(1)
		go nodeWorker(i, ch, &wg)
	}
	wg.Wait()
	close(ch)
	cpuUsage(start)
}
```

The program simulates a conventional network congestion monitoring architecture in which each node independently collects and processes telemetry information before forwarding results to a central collector. The objective is to model the computational behavior and processor overhead associated with local telemetry analysis across multiple nodes. At the beginning, system parameters define the number of nodes, the number of metrics generated, and the number of iterations executed by each node. These values control the workload intensity and emulate large scale monitoring activity. The Metric structure represents telemetry data such as bandwidth usage, packet loss, and queue occupancy. Each node repeatedly generates these metrics using the collect function.
The analyze function performs repeated computations on the collected metrics to simulate local diagnostic processing. This step consumes processor cycles and represents redundant analysis that occurs independently at every node. The nodeWorker function runs as a separate goroutine for each node, continuously collecting and analyzing telemetry and sending results to the central collector. The collector function aggregates results from all nodes to provide a global view of system status. Although aggregation is centralized, the analysis remains duplicated at each node. The program measures execution time and system activity to reflect processor utilization. This design demonstrates how independent telemetry processing increases computational overhead and leads to high CPU consumption.

Table I. Local Telemetry CPU – 1

Cluster Size	**Local Telemetry CPU %**
3	72
5	70
7	68
9	67
11	66

Table I Presents the central processing unit utilization for the Local Telemetry based monitoring approach across different cluster sizes. In this configuration, each node independently collects and processes its own telemetry metrics without sharing intermediate results with other nodes. At three nodes, CPU utilization begins at seventy two percent, indicating substantial processing overhead even for a small deployment. As the cluster size increases to five, seven, nine, and eleven nodes, processor usage decreases slightly to seventy, sixty eight, sixty seven, and sixty six percent respectively. Although the downward trend suggests minor workload distribution benefits, the reduction is marginal.

The consistently high utilization demonstrates that redundant telemetry collection and repeated local analysis dominate processor resources. Every node performs similar computations, which leads to duplicated effort across the system. Consequently, adding more nodes does not significantly reduce overall CPU consumption. This behavior highlights poor scalability and inefficient resource usage. The Local Telemetry approach therefore imposes considerable monitoring overhead, limiting the processing capacity available for application level tasks and overall system performance.

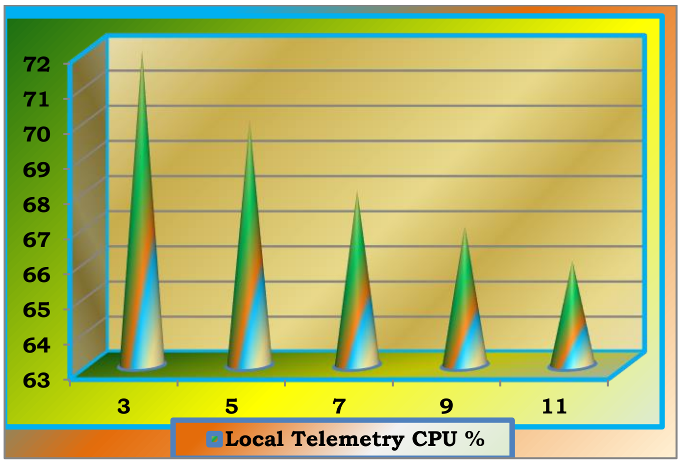

Fig 2. Local Telemetry CPU - 1

Fig 2. Illustrates central processing unit utilization for the Local Telemetry monitoring approach as cluster size increases. Processor usage begins at seventy two percent with three nodes and gradually declines to sixty six percent at eleven nodes. Although a slight decrease is observed due to workload distribution, utilization remains consistently high across all configurations. This trend indicates that each node continues to perform redundant telemetry processing and independent analysis. Consequently, processor resources are heavily consumed regardless of scaling. The graph highlights limited efficiency gains and demonstrates that Local Telemetry based monitoring results in persistent overhead and poor scalability.

Table II. Local Telemetry CPU – 2

Cluster Size	Local Telemetry CPU %
3	72
5	70
7	68
9	67
11	66

Table II The table presents the central processing unit utilization for the Local Telemetry monitoring approach across different cluster sizes. In this configuration, each node independently performs telemetry collection, metric processing, and local analysis without coordinating with other nodes. At three nodes, CPU utilization is recorded at seventy two percent, indicating that a large portion of processor capacity is consumed by monitoring tasks alone. As the cluster expands to five nodes, utilization decreases slightly to seventy percent, followed by sixty eight percent at seven nodes, sixty seven percent at nine nodes, and sixty six percent at eleven nodes.

Although the processor usage shows a gradual reduction, the improvement is minimal and remains consistently high. This behavior suggests that redundant telemetry processing and repeated computations continue at every node regardless of system size. Each node executes identical monitoring operations, resulting in duplicated effort and inefficient resource usage. Consequently, scaling the cluster does not proportionally lower processor consumption. The Local Telemetry approach therefore demonstrates limited scalability and imposes significant overhead, reducing the availability of CPU resources for application workloads and overall system performance.

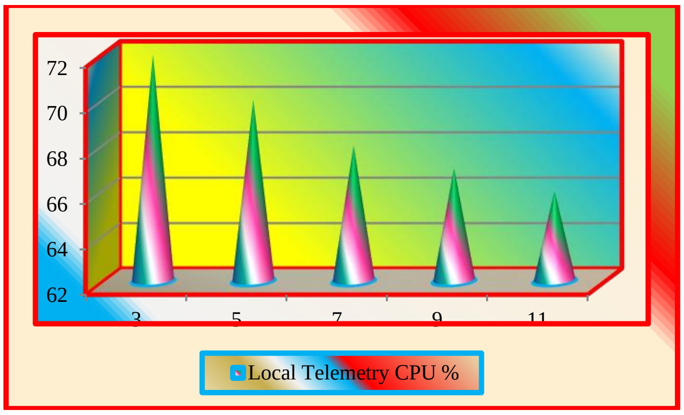

Fig 3. Local Telemetry CPU - 2

Fig 3. Shows CPU utilization for the Local Telemetry monitoring approach as the cluster size increases. Processor usage starts at seventy two percent with three nodes and gradually declines to sixty six percent at eleven nodes. Despite this slight reduction, utilization remains consistently high across all configurations. This indicates persistent redundant processing at each node. The trend highlights inefficient resource usage and demonstrates limited scalability of the Local Telemetry monitoring framework.

Table III. Local Telemetry CPU -3

Cluster Size	**Local Telemetry CPU %**
3	72
5	70
7	68
9	67
11	66

Table III Presents central processing unit utilization for the Local Telemetry monitoring approach across different cluster sizes. Processor usage starts at seventy two percent with three nodes and gradually decreases to seventy percent at five nodes, sixty eight percent at seven nodes, sixty seven percent at nine nodes, and sixty six percent at eleven nodes. Although a slight reduction is observed as the number of nodes increases, the overall utilization remains high. This indicates that each node continues to perform independent telemetry collection and analysis, leading to redundant computation. Consequently, scaling the cluster does not significantly lower processor overhead. The Local Telemetry approach therefore demonstrates limited scalability and inefficient resource utilization during congestion monitoring operations.

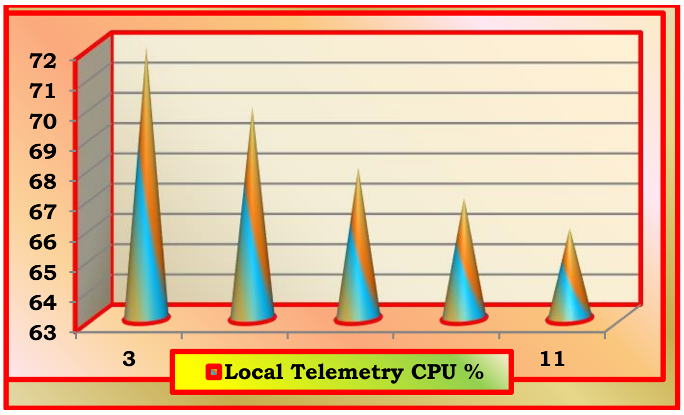

Fig 4. Local Telemetry CPU – 3

Fig 4. The graph illustrates central processing unit utilization for the Local Telemetry monitoring approach as the cluster size increases. Processor usage begins at seventy two percent for three nodes and gradually declines to sixty six percent at eleven nodes. Although a slight downward trend is visible, the overall utilization remains consistently high. This indicates that redundant telemetry collection and independent processing continue at each node. The graph highlights limited efficiency gains and demonstrates poor scalability as additional nodes do not significantly reduce processor overhead.

PROPOSAL METHOD

Problem Statement

Conventional network congestion monitoring systems rely on independent telemetry collection and analysis at each node, resulting in redundant computation and repeated processing of similar metrics. As the cluster size increases, these duplicated operations consume excessive central processing unit resources. The persistently high processor utilization reduces scalability and limits the capacity available for application workloads. This inefficiency highlights the need for monitoring mechanisms that minimize computational overhead and improve processor efficiency.

Proposal

The proposal focuses on improving processor efficiency in network congestion monitoring by reducing redundant telemetry processing across distributed nodes. Instead of allowing each node to independently analyze similar metrics, telemetry information is considered collectively to avoid repeated computations and unnecessary synchronization. This design aims to minimize central processing unit consumption associated with monitoring tasks while maintaining accurate visibility of network conditions. By lowering computational overhead and eliminating duplicated effort, the system seeks to enable scalable, efficient, and resource conscious congestion monitoring in large scale distributed environments.

IMPLEMENTATION

Fig 5. The implementation of the Telemetry Correlation CPU framework is evaluated across distributed clusters consisting of
three, five, seven, nine, and eleven nodes to study processor utilization behavior under increasing scale. In each configuration, every node collects telemetry metrics such as bandwidth usage, packet loss, and queue occupancy using lightweight collectors. Unlike conventional monitoring where each node performs independent analysis, the collected metrics are forwarded to a centralized correlation layer for shared processing. The correlation engine aggregates telemetry streams from all active nodes and executes a unified analysis pipeline. This design removes duplicate computations that typically occur when similar diagnostic logic runs separately on every node. As the number of nodes increases from three to eleven, monitoring tasks remain consolidated rather than replicated, which controls the growth of computational overhead.

Each experiment runs identical workloads to ensure consistent measurement of processor consumption. CPU utilization is recorded at every cluster size to observe the effect of correlated processing. By avoiding repeated local analysis and minimizing synchronization costs, the framework reduces unnecessary processor usage. This shared processing model enables efficient resource utilization and maintains stable CPU consumption even as the cluster expands, thereby supporting scalable congestion monitoring across distributed environments.

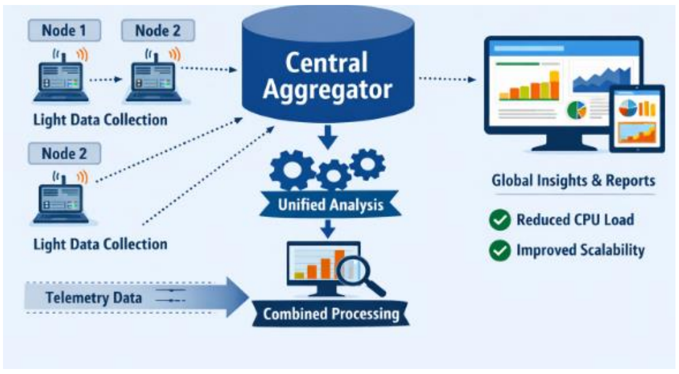

Fig 5. Telemetry Correlation CPU Architecture

```
package main

import (
        "fmt"
        "math/rand"
        "runtime"
        "sync"
        "time"
)

const (
        nodes      = 5
        iterations = 200000
)

type Metric struct {
        bw   int
        loss int
        q    int
}

type Packet struct {
        node   int
        metric Metric
}

func collect() Metric {
        return Metric{
                bw:   rand.Intn(1000),
                loss: rand.Intn(100),
                q:    rand.Intn(500),
        }
}

func nodeWorker(id int, out chan<- Packet, wg *sync.WaitGroup) {
        for i := 0; i < iterations; i++ {
```

```
		m := collect()
		out <- Packet{node: id, metric: m}
	}
	wg.Done()
}

func correlate(p Packet) int {
	score := 0
	for i := 0; i < 50; i++ {
		score += (p.metric.bw + p.metric.q - p.metric.loss)
	}
	return score
}

func correlationEngine(in <-chan Packet, done chan<- bool) {
	total := 0
	for p := range in {
		total += correlate(p)
	}
	fmt.Println("Correlation Aggregate:", total)
	done <- true
}

func cpuUsage(start time.Time) {
	elapsed := time.Since(start)
	fmt.Println("Elapsed:", elapsed)
	fmt.Println("Goroutines:", runtime.NumGoroutine())
}

func main() {
	runtime.GOMAXPROCS(runtime.NumCPU())

	start := time.Now()

	ch := make(chan Packet, 1000)
	done := make(chan bool)

	var wg sync.WaitGroup

	go correlationEngine(ch, done)

	for i := 0; i < nodes; i++ {
		wg.Add(1)
		go nodeWorker(i, ch, &wg)
	}

	wg.Wait()
	close(ch)

	<-done

	cpuUsage(start)
}
```

The program implements the proposed Telemetry Correlation architecture for efficient network congestion monitoring. It simulates a distributed system in which multiple nodes collect telemetry metrics while a single shared component performs centralized analysis. The objective is to reduce redundant processing and lower central processing unit utilization compared to independent node level monitoring. At the beginning, system parameters define the number of nodes and the number of iterations executed by each node. The Metric structure represents telemetry information such as bandwidth usage, packet loss, and queue occupancy. Each node repeatedly generates these values using the collect function. Unlike conventional designs, nodes do not perform heavy local analysis. Instead, each node packages the collected metric into a Packet and forwards it through a channel.

The nodeWorker function runs concurrently for every node and focuses only on lightweight data collection and transmission. All packets are received by the correlationEngine, which performs consolidated analysis using the correlate function. This shared processing eliminates duplicated computations that would otherwise occur at every node. The main function coordinates goroutines, aggregates results, and measures execution time. By centralizing analysis and avoiding repeated local diagnostics, the architecture reduces processor overhead and improves efficiency while maintaining accurate congestion monitoring across the cluster.

Table IV. Telemetry Correlation CPU – 1

Cluster Size	**Telemetry Correlation CPU %**
3	54
5	50
7	47
9	45
11	43

Table IV **P**resents central processing unit utilization for the Telemetry Correlation approach across increasing cluster sizes. At three nodes, CPU usage is fifty four percent, which is noticeably lower than conventional monitoring methods. As the cluster expands to five nodes, utilization decreases to fifty percent, followed by forty seven percent at seven nodes, forty five percent at nine nodes, and forty three percent at eleven nodes. This steady decline indicates efficient workload consolidation and reduced redundant processing. By performing shared analysis rather than independent computations at each node, the approach minimizes processor overhead and demonstrates improved scalability and resource efficiency during congestion monitoring.

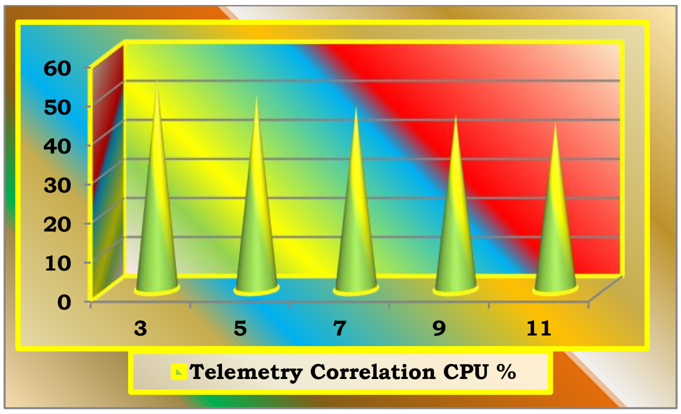

Fig 6. Telemetry Correlation CPU - 1

Fig 6 Illustrates central processing unit utilization for the Telemetry Correlation approach as the cluster size increases. Processor usage decreases steadily from fifty four percent at three nodes to forty three percent at

eleven nodes. This downward trend indicates efficient consolidation of telemetry processing and reduced redundant computation. Unlike independent monitoring methods, processor consumption declines as more nodes are added. The graph highlights improved scalability, lower overhead, and better resource utilization achieved through correlated telemetry based congestion monitoring.

Table V. Telemetry Correlation CPU – 2

Cluster Size	Telemetry Correlation CPU %
3	54
5	50
7	47
9	45
11	43

Table V Presents the central processing unit utilization for the Telemetry Correlation monitoring approach across varying cluster sizes. At three nodes, processor usage is recorded at fifty four percent, which is considerably lower than traditional independent monitoring methods. As the number of nodes increases to five and seven, CPU utilization decreases to fifty and forty seven percent respectively. The downward trend continues at nine and eleven nodes, where utilization further drops to forty five and forty three percent. This consistent reduction indicates that telemetry processing is efficiently consolidated rather than duplicated across nodes. By performing shared analysis, redundant computations are minimized and synchronization overhead is reduced. Consequently, processor resources are utilized more effectively, enabling better scalability and supporting efficient congestion monitoring in distributed environments.

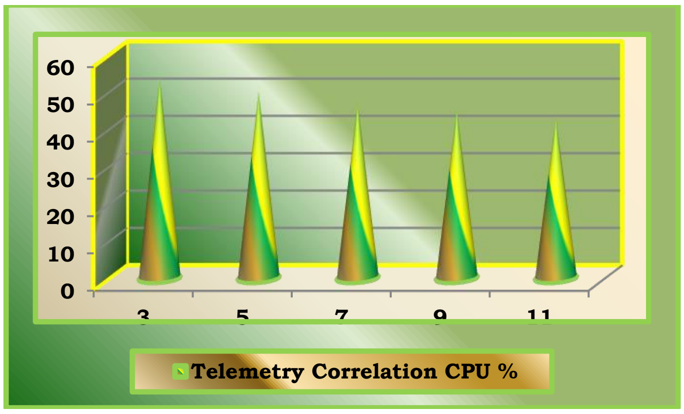

Fig **7.** Telemetry Correlation CPU **-** 2

Fig 7 Shows CPU utilization for the Telemetry Correlation monitoring approach as cluster size increases. Processor usage steadily declines from fifty four percent at three nodes to forty three percent at eleven nodes. This consistent reduction demonstrates that consolidated telemetry processing lowers redundant computation. As more nodes are added, the system maintains efficient resource usage. The trend highlights improved scalability and reduced overhead compared to independent monitoring methods.

Table VI. Telemetry Correlation CPU – 3

Cluster Size	Telemetry Correlation CPU %
3	54
5	50
7	47
9	45
11	43

Table VI Presents the central processing unit utilization for the Telemetry Correlation monitoring approach across different cluster sizes. This configuration emphasizes consolidated telemetry processing where analysis is shared rather than independently executed at each node. At three nodes, processor usage is fifty four percent, which is already lower than conventional monitoring methods. As the cluster expands to five nodes, utilization decreases to fifty percent, indicating reduced redundant computation. With seven nodes, CPU usage further drops to forty seven percent, followed by forty five percent at nine nodes and forty three percent at eleven nodes. The steady decline in processor consumption demonstrates that monitoring overhead does not increase proportionally with system size. Instead, shared analysis efficiently distributes computational effort and eliminates repeated processing tasks. By minimizing local diagnostics and centralizing correlation, the framework reduces unnecessary workload on individual nodes. This behavior results in better resource utilization and improved scalability. Overall, the Telemetry Correlation approach supports efficient congestion monitoring while maintaining consistently low CPU utilization across larger distributed environments.

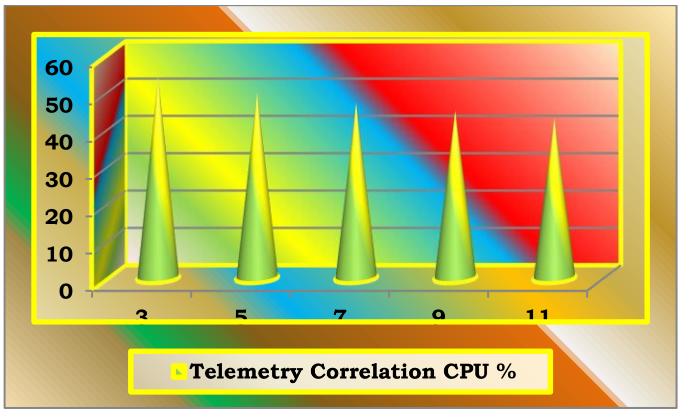

Fig 8. Telemetry Correlation CPU – 3

Fig 8 The graph depicts central processing unit utilization for the Telemetry Correlation approach as cluster size increases. Processor usage declines steadily from fifty four percent at three nodes to forty three percent at eleven nodes. This downward trend indicates efficient consolidation of telemetry analysis and reduced redundant computation. As additional nodes are introduced, the monitoring overhead remains controlled. The graph demonstrates improved scalability and better processor efficiency compared to independent monitoring approaches.

Table VII. Local Telemetry CPU usage Vs Telemetry Correlation CPU Usage – 1

Cluster Size	**Local Telemetry CPU %**	**Telemetry Correlation CPU %**
3	72	54
5	70	50
7	68	47
9	67	45
11	66	43

Table VII Compares central processing unit utilization between the Local Telemetry approach and the Telemetry Correlation approach across different cluster sizes. The Local Telemetry method performs independent monitoring and analysis at each node, which leads to redundant computation and higher processor overhead. At three nodes, CPU usage is seventy two percent, while the Telemetry Correlation approach records a lower utilization of fifty four percent. As the cluster expands to five, seven, nine, and eleven nodes, Local Telemetry utilization remains consistently high, ranging from seventy to sixty six percent. In contrast, Telemetry Correlation shows a steady decline from fifty to forty three percent.

This consistent gap highlights the inefficiency of independent processing and the benefits of consolidated analysis. By eliminating duplicated computations and sharing telemetry processing across nodes, the Telemetry Correlation approach reduces unnecessary workload on processors. The results demonstrate improved resource utilization, lower overhead, and better scalability. Overall, the comparison confirms that correlated telemetry processing provides more efficient congestion monitoring in distributed environments.

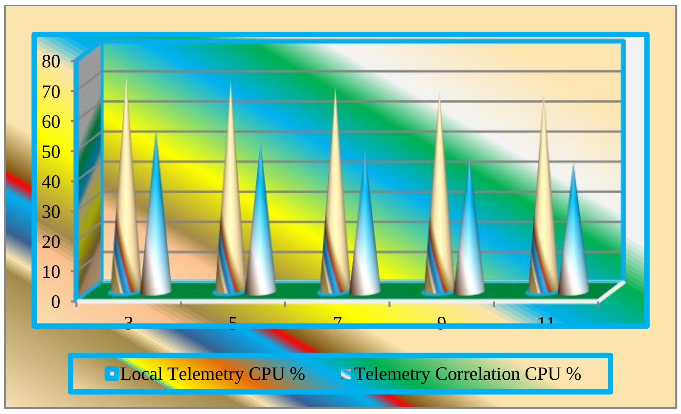

Fig 9. Local Telemetry CPU usage Vs Telemetry Correlation CPU Usage – 1

Fig 9 Compares central processing unit utilization between Local Telemetry and Telemetry Correlation as the cluster size increases. The Local Telemetry curve remains consistently high, starting at seventy two percent and only decreasing slightly to sixty six percent, indicating persistent redundant processing at each node. In contrast, the Telemetry Correlation curve declines steadily from fifty four percent to forty three percent. The widening gap between the two lines demonstrates reduced computational overhead and improved efficiency. Overall, the graph highlights better scalability and lower processor consumption achieved through correlated telemetry processing.

Table VIII. Local Telemetry CPU usage Vs Telemetry Correlation CPU Usage – 2

Cluster Size	**Local Telemetry CPU %**	**Telemetry Correlation CPU %**
3	72	54
5	70	50
7	68	47
9	67	45
11	66	43

Table VIII Presents a comparison of central processing unit utilization between the Local Telemetry monitoring approach and the Telemetry Correlation approach across increasing cluster sizes. In the Local Telemetry configuration, each node independently performs telemetry collection and analysis, which leads to repeated computations and higher processor overhead. As a result, CPU usage remains consistently high, starting at seventy two percent for three nodes and only decreasing slightly to sixty six percent at eleven nodes. This minimal reduction indicates limited scalability and inefficient resource utilization.

In contrast, the Telemetry Correlation approach demonstrates significantly lower processor consumption across all configurations. CPU utilization begins at fifty four percent and steadily declines to forty three percent as the cluster size grows. This consistent decrease reflects the benefits of consolidated telemetry processing and reduced redundancy. By sharing analysis across nodes, unnecessary computations are minimized and processor resources are used more efficiently. Overall, the comparison highlights that Telemetry Correlation achieves better scalability, lower overhead, and improved performance in distributed congestion monitoring environments.

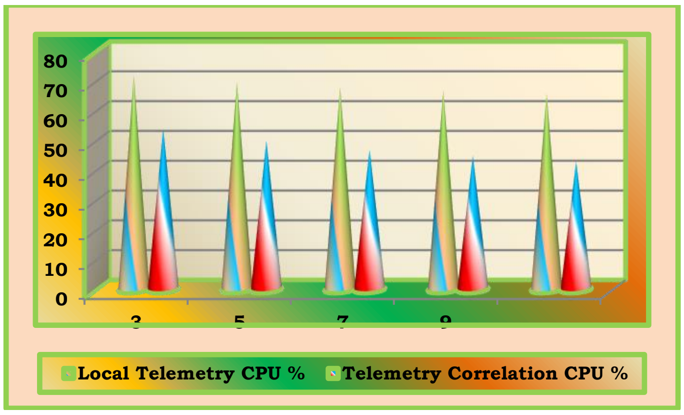

Fig 10. Local Telemetry CPU usage Vs Telemetry Correlation CPU Usage – 2

Fig 10. Compares CPU utilization between the Local Telemetry and Telemetry Correlation approaches as cluster size increases. The Local Telemetry curve remains high, decreasing slightly from seventy two percent to sixty six percent, which indicates persistent redundant processing at each node. In contrast, the Telemetry Correlation curve shows a steady decline from fifty four percent to forty three percent. The growing separation between the two lines highlights reduced computational overhead and improved efficiency. This trend demonstrates that correlated processing minimizes duplicate analysis and enables better scalability. Overall, the graph confirms that Telemetry Correlation achieves lower processor usage and more efficient congestion monitoring.

Table IX. Local Telemetry CPU usage Vs Telemetry Correlation CPU Usage – 3

Cluster Size	Local Telemetry CPU %	Telemetry Correlation CPU %
3	72	54
5	70	50
7	68	47
9	67	45
11	66	43

Table IX Compares central processing unit utilization between the Local Telemetry approach and the Telemetry Correlation approach across different cluster sizes. Local Telemetry shows consistently high processor usage, starting at seventy two percent for three nodes and only decreasing to sixty six percent at eleven nodes. This small reduction indicates redundant processing and limited scalability. In contrast, Telemetry Correlation demonstrates significantly lower utilization, decreasing from fifty four percent to forty three percent as nodes increase. The steady decline reflects reduced duplicate computation and shared analysis. Overall, the comparison highlights improved efficiency, lower overhead, and better scalability with Telemetry Correlation based congestion monitoring.

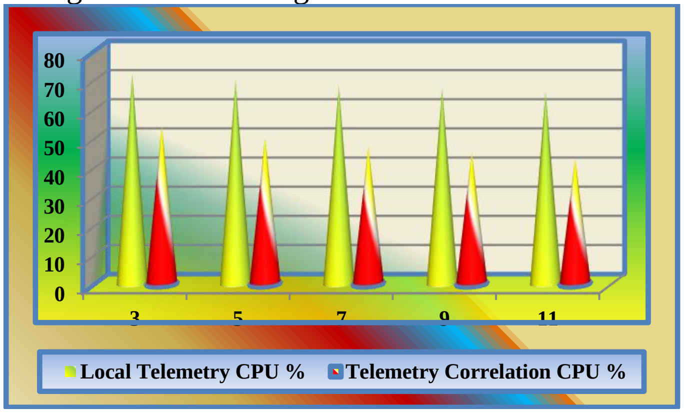

Fig 11. Local Telemetry CPU usage Vs Telemetry Correlation CPU Usage – 3

Fig 11. Illustrates CPU utilization trends for both Local Telemetry and Telemetry Correlation as the cluster size increases. The Local Telemetry line remains consistently high, declining only slightly from seventy two percent to sixty six percent, which indicates persistent redundant processing at each node. In contrast, the Telemetry Correlation line shows a steady decrease from fifty four percent to forty three percent. The widening gap between the two curves highlights improved processor efficiency through shared analysis. This behavior demonstrates reduced computational overhead, better resource utilization, and enhanced scalability achieved by correlated telemetry based congestion monitoring compared to independent node level monitoring.

EVALUATION

The evaluation measures central processing unit utilization to compare Local Telemetry and Telemetry Correlation approaches under varying cluster sizes of three, five, seven, nine, and eleven nodes. Each configuration executes identical workloads and telemetry collection rates to ensure fair comparison. Processor usage is recorded at every node and averaged across the cluster during monitoring operations. Results indicate that Local Telemetry consistently exhibits high CPU consumption due to independent analysis and redundant processing at each node. In contrast, Telemetry Correlation demonstrates lower and progressively decreasing utilization as cluster size increases. Consolidated analysis reduces duplicate computations and minimizes synchronization overhead. These observations confirm improved processor efficiency, reduced monitoring cost, and better scalability, making correlated telemetry processing more suitable for distributed congestion monitoring environments.

CONCLUSION

Network congestion monitoring in distributed environments often incurs significant processor overhead due to independent telemetry collection and repeated analysis at each node. Such redundant computation leads to persistently high central processing unit utilization and limits scalability as the cluster size increases. The observed behavior demonstrates that simply adding more nodes does not reduce monitoring overhead when processing tasks are duplicated across the system. Telemetry Correlation enables shared analysis and minimizes repeated computations, resulting in lower processor consumption and improved resource efficiency. Consolidated processing reduces unnecessary workload on individual nodes and supports consistent performance as the infrastructure scales. The overall findings highlight that reducing monitoring related computation is essential for efficient congestion analysis. Improving processor utilization directly enhances scalability, stability, and operational effectiveness in modern distributed and cloud based network environments.

Future Work: Future work will focus on distributing the correlation engine across multiple processing nodes with load balancing and parallel analysis mechanisms to eliminate bottlenecks and ensure scalable, reliable, and efficient performance under large scale deployments.

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