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# Distance Aware Load Balancing for Scalable Distributed Storage

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**Abstract:**
Distributed storage platforms rely heavily on load balancing mechanisms to distribute requests across multiple nodes and ensure scalability. Conventional load balancing strategies typically make routing decisions without considering network distance or physical proximity between clients and storage nodes. Requests are often assigned using static rules or uniform distribution policies that ignore communication cost. As cluster size increases, these approaches frequently direct requests to remote nodes, causing data access paths to traverse multiple intermediate devices. This behavior leads to increased hop count, higher routing overhead, and inefficient network utilization. Excessive hop traversal introduces additional delay at each intermediate node and amplifies network congestion. Even when sufficient storage and processing capacity are available, requests experience longer paths due to distance unaware routing. In large scale distributed storage systems, this inefficiency accumulates rapidly, resulting in degraded performance and poor scalability. Adding more nodes does not mitigate the problem, as the likelihood of accessing distant nodes increases with cluster expansion. Consequently, static load balancing fails to maintain efficient communication patterns in growing environments. Empirical observations show that existing load balancing mechanisms consistently exhibit rising hop counts as cluster size grows. This increase reflects longer communication paths rather than workload imbalance alone. High hop counts directly impact request latency, bandwidth consumption, and overall system responsiveness. Despite distributing load across nodes, the absence of distance awareness limits the effectiveness of conventional strategies. This paper addresses the problem of excessive hop count in distributed storage platforms by focusing on network distance as a critical factor in load balancing decisions. The work emphasizes reducing communication distance to maintain shorter routing paths as the system scales. By targeting hop count as a primary metric, the study aims to improve communication efficiency and support scalable operation in distributed storage environments.

**Keywords**: Distributed, Storage, LoadBalancing, DistanceAware, HopCount, Locality, Routing, Scalability, Communication, Networking, Partitioning, Efficiency, Clustering, Performance, Topology.

## INTRODUCTION

Distributed storage platforms form the backbone of modern cloud services, large scale data analytics, and enterprise applications. To support growing workloads and increasing user demands, data and requests [1] are distributed across multiple storage nodes. Load balancing plays a critical role in these environments by ensuring that requests are evenly spread across available resources. Effective load balancing improves scalability, prevents hotspots, and enhances overall system reliability. Traditional load balancing mechanisms in distributed storage systems typically rely on static rules or uniform distribution strategies. These approaches assign requests without considering the physical or logical distance between clients and storage nodes [2]. While such strategies simplify routing decisions, they often result in inefficient communication paths. Requests may be routed to distant nodes even when closer storage nodes are available, increasing the number of intermediate network traversals. Each additional traversal adds routing delay and network overhead, which directly impacts system performance. As distributed systems scale, the impact of distance unaware routing becomes more severe.

Increasing the number of nodes raises the probability that requests will be served by remote locations. This leads to higher hop counts [3], increased latency, and greater network congestion. Simply expanding cluster size does not guarantee improved performance, as longer communication paths offset the benefits of additional resources. High hop count also increases bandwidth consumption and processing overhead at intermediate routers and switches, further limiting scalability. In distributed storage platforms where data access patterns are dynamic and workloads fluctuate, maintaining efficient communication paths is essential. Load balancing strategies [4] that ignore network distance fail to adapt to these conditions, resulting in persistent inefficiencies. Hop count has therefore emerged as a critical metric for evaluating communication efficiency in distributed environments. Reducing hop count directly improves data access speed and lowers network overhead. This work focuses on addressing the limitations of distance unaware load balancing by examining the role of network distance in routing decisions. By emphasizing hop count as a key performance indicator, the study highlights the importance of communication aware load balancing [5] for achieving scalable and efficient distributed storage systems.

## LITERATURE REVIEW

Distributed storage systems have evolved significantly to support the growing demands of cloud computing, big data analytics, and large scale online services. Early distributed systems primarily focused on fault tolerance [6] and data availability, distributing replicas across nodes to ensure reliability. As these systems scaled, performance concerns related to communication overhead and request routing became increasingly prominent. Load balancing emerged as a core mechanism to distribute requests across nodes and prevent overload. However, much of the early research treated load balancing as a problem of evenly distributing requests without explicitly considering communication distance or network topology. Initial load balancing strategies relied on simple techniques such as round robin assignment, random selection, or hash based mapping. These methods were attractive due to their simplicity and low coordination cost. Studies from early distributed file systems demonstrated that uniform request distribution could effectively prevent individual nodes from becoming bottlenecks. However, subsequent evaluations revealed that these approaches often led to inefficient communication paths. Requests were frequently routed to distant nodes even when closer replicas were available, resulting in increased hop count [7] and higher latency. This limitation became more pronounced as cluster sizes increased and network hierarchies grew deeper.

Research on network topology awareness highlighted the importance of considering physical and logical distance in distributed systems. Studies examining data center networks showed that multi tier network architectures introduce varying hop distances between nodes. Communication between nodes within the same rack typically involves fewer hops compared to communication across racks or data centers. Despite this, many load balancing algorithms continued to ignore such distinctions. Literature analyzing large scale storage platforms observed that a significant fraction of request latency could be attributed to unnecessary cross rack and cross cluster communication. Several works investigated the relationship between hop count and system performance. Hop count has been widely recognized as a proxy for communication cost, as each hop introduces processing delay, queuing delay, and potential contention. Empirical studies demonstrated that reducing hop count directly improves request latency and throughput, even when computational resources remain unchanged. These findings motivated further exploration into communication aware scheduling and routing [8]. However, many proposed techniques focused primarily on task scheduling rather than load balancing in storage systems.

Data locality has been a recurring theme in distributed systems research. Early work in distributed file systems emphasized placing computation near data to reduce network traffic. This concept was later extended to distributed storage, where data placement strategies aimed to minimize remote access. Several studies explored replica placement based on access frequency and geographic distribution. While these approaches improved locality, they often required complex coordination and were not tightly integrated with load balancing mechanisms. As a result, load balancing decisions continued to

route requests based on load metrics alone, disregarding proximity. Research on dynamic load balancing introduced adaptive techniques that respond to workload changes. These methods monitor node utilization and redistribute requests accordingly. While dynamic balancing improved fairness and prevented hotspots, it did not inherently reduce hop count. In many cases, dynamically shifting load led to increased communication distance, as requests were rerouted to underutilized but remote nodes. This tradeoff between load fairness and communication efficiency has been extensively discussed in the literature. Several surveys highlight that balancing load [9] without considering distance can degrade overall system performance.

Distributed hash tables and consistent hashing have been widely studied for scalable storage. These techniques provide deterministic data placement and simplify load distribution. However, consistent hashing inherently ignores network topology. Multiple studies have shown that hash based placement leads to random communication patterns, increasing average hop count as the number of nodes grows. Attempts to augment hashing with proximity awareness [10] have been proposed, but adoption remains limited due to added complexity. More recent work in cloud and edge computing environments has renewed interest in distance awareness. Edge storage systems, in particular, emphasize serving requests from nearby nodes to reduce latency. Research in this area demonstrates that distance aware routing [11] significantly improves responsiveness. However, much of this work focuses on client facing latency rather than internal hop count within storage clusters. Additionally, edge focused solutions often assume geographic distribution rather than addressing hop count within tightly coupled data centers.

Network aware load balancing has also been studied in the context of microservices and service meshes. These systems route requests among service instances while considering network latency and bandwidth. Findings from this domain reinforce the idea that distance blind routing leads to inefficient communication. While insights from microservices [12] are relevant, storage platforms present unique challenges due to data placement constraints and consistency requirements. The literature indicates a gap in directly applying distance aware principles to storage load balancing. Another line of research examines software defined networking and programmable routing. By exposing network topology information to higher layers, these approaches enable more informed routing decisions. Studies show that applications can benefit from topology awareness, but integration with storage load balancing remains an open challenge. Most solutions focus on traffic engineering rather than reducing hop count for individual storage requests [13].

Several comparative studies have evaluated the scalability of distributed storage systems under increasing cluster sizes. These studies consistently report that performance degradation is often caused by communication overhead rather than computational limits. Hop count increases with cluster size due to deeper network hierarchies and random placement strategies. Authors argue that scalability requires not only adding resources but also maintaining efficient communication paths [14]. Despite this observation, many production systems still prioritize simplicity over distance awareness. In summary, the literature clearly establishes that hop count and communication distance play a critical role in distributed system performance. While load balancing has been extensively studied, traditional approaches largely ignore network distance, leading to inefficient routing paths. Data locality and topology awareness have been explored in related contexts, but their integration into load balancing for distributed storage remains limited. Existing research highlights the need to explicitly consider hop count as a primary metric when designing scalable load balancing strategies. This gap in current literature motivates further investigation into distance aware load balancing [15] mechanisms that can maintain efficient communication as distributed storage platforms scale.

Communication cost has long been recognized as a dominant factor influencing the performance of distributed systems. Early analytical models treated communication overhead as a fixed latency component, but later research demonstrated that this overhead varies significantly depending on network distance, topology [16], and routing paths. Hop count emerged as a practical and widely used metric for estimating communication cost because it captures the number of intermediate nodes or switches a request must traverse before reaching its destination. Each hop contributes processing delay, queuing

delay, and potential contention, making hop count a strong indicator of end to end communication efficiency. Several studies examined the relationship between hop count and request latency in cluster and data center environments. These works showed that latency grows approximately linearly with hop count under moderate load conditions. Even when bandwidth is sufficient, the cumulative effect of multiple hops introduces measurable delay. Researchers also observed that hop count influences jitter and tail latency, which are critical for storage systems [17] that require predictable performance. As a result, hop count has been widely adopted as a proxy metric for evaluating communication efficiency in distributed platforms.

In distributed storage systems, hop count becomes especially relevant because data access often involves multiple layers such as coordinators, metadata services, and storage nodes. Static routing strategies frequently increase hop count by forcing requests through centralized components. Literature analyzing metadata heavy storage systems revealed that metadata operations [18] often incur higher hop counts than data operations, further amplifying overhead. This insight led to studies emphasizing the need to reduce traversal paths not only for data access but also for control plane interactions. Network topology has a direct impact on hop count behavior. Data center networks typically follow multi tier architectures, including access, aggregation, and core layers. Communication within the same rack generally requires fewer hops than cross rack or cross cluster communication. Researchers studying traffic patterns in large scale clusters found that a significant portion of requests unnecessarily crossed higher level network tiers due to topology unaware routing. These findings reinforced the importance of designing load balancing mechanisms that account for physical and logical distance. Several analytical models were proposed to quantify hop count based on placement and routing policies. These models demonstrated that random placement leads to expected hop counts that increase with cluster size [19]. In contrast, proximity aware placement can bound hop count growth even as the number of nodes increases. While these models provided valuable insights, many were evaluated in isolation and not integrated into practical load balancing frameworks.

Another line of research explored hop count optimization in distributed query processing. Studies in this area showed that query execution plans that minimize data movement across nodes significantly outperform plans that focus solely on computational balance [20]. Although these findings were primarily applied to analytics workloads, they are directly relevant to storage platforms where data movement is a key performance bottleneck. Hop count has also been examined in the context of fault tolerance and replication. Replicas placed far apart improve availability but increase hop count during normal operation. Several papers discussed the tradeoff between resilience and communication efficiency. While replication strategies were optimized for failure scenarios [21], they often ignored hop count during steady state operation, leading to suboptimal performance. This tradeoff remains a recurring challenge in distributed storage design.

More recent studies emphasized the importance of hop count in evaluating scalability. As clusters scale to hundreds or thousands of nodes, even small increases in average hop count can result in substantial cumulative overhead. Researchers observed that systems with bounded hop count scale more gracefully than those with unbounded traversal growth. These observations motivated renewed interest in distance aware routing and placement strategies [22]. Overall, the literature clearly establishes hop count as a fundamental metric for understanding and optimizing communication in distributed systems. While numerous studies analyze hop count in isolation, fewer works integrate hop count awareness directly into load balancing decisions for distributed storage. This gap highlights the need for approaches that explicitly treat hop count as a first class concern in scalable storage platforms.

Load balancing has been a central research topic in distributed systems for several decades. The primary objective of load balancing is to distribute workload evenly across available resources to avoid hotspots [23] and ensure fair utilization. In distributed storage platforms, load balancing typically determines how client requests are routed to storage nodes. Early load balancing strategies prioritized simplicity and fairness, often relying on round robin scheduling, random selection, or hash based mapping. These approaches were effective in preventing individual nodes from becoming overloaded but largely ignored

the cost of communication between clients and storage nodes. Static load balancing mechanisms assume that uniform distribution of requests automatically leads to optimal performance. However, research has shown that equal distribution does not guarantee efficient communication. Requests routed to distant nodes incur higher hop counts and longer routing paths [24], which introduce additional delay and network overhead. Several empirical studies demonstrated that systems with well balanced load but high hop count often perform worse than systems with slightly uneven load but shorter communication paths. This finding challenged the long held assumption that load balance alone is sufficient for scalability.

Dynamic load balancing techniques were introduced to address workload variability. These methods monitor node utilization and adjust routing decisions based on current load. While dynamic balancing improves fairness, it does not inherently account for network distance. In many cases, dynamic balancing redirects requests to underutilized nodes that are geographically or topologically distant. Literature evaluating such systems observed that reducing load imbalance sometimes increased average hop count, offsetting the benefits of improved utilization. This tradeoff between load fairness and communication efficiency has been widely discussed but remains unresolved in many production systems. Several studies examined hierarchical load balancing approaches, where requests are first balanced within local groups before being routed globally. These methods aim to reduce long distance communication by prioritizing nearby nodes. While hierarchical designs showed promise in reducing hop count, they often relied on static grouping [25] that could not adapt to changing access patterns. As workloads evolved, static group boundaries became misaligned with actual communication behavior, leading to renewed inefficiencies.

Research on distributed storage systems with metadata services revealed additional challenges. Many storage platforms rely on centralized or semi centralized metadata managers to locate data. Requests often traverse multiple hops to reach metadata services before being forwarded to storage nodes. Studies showed that metadata operations frequently dominate hop count, especially in read heavy workloads. Even when data nodes are colocated, metadata indirection increases traversal length. Although some works proposed metadata caching and replication, integration with load balancing decisions remained limited. Consistent hashing has been widely adopted in distributed storage systems due to its scalability and fault tolerance properties. However, consistent hashing intentionally randomizes placement to evenly distribute load, disregarding network topology. Numerous evaluations have demonstrated that hash based routing leads to unpredictable communication paths and higher hop counts as cluster size increases. Attempts to combine consistent hashing with proximity awareness have been explored, but such approaches introduce complexity and coordination overhead that hinder adoption.

The emergence of cloud data centers and containerized environments renewed interest in network aware load balancing. Studies in microservices architectures showed that service to service communication cost often dominates application latency. Researchers demonstrated that routing requests to closer service instances significantly improves performance. While these findings are directly applicable to storage systems, the literature indicates that storage load balancing has lagged behind service routing in adopting distance awareness. Edge computing further highlighted the importance of proximity. In edge storage systems, serving data from nearby nodes is essential to meet latency requirements. Research in this domain consistently emphasizes minimizing hop count and network traversal [26]. However, edge focused solutions often assume geographic separation and do not directly address hop count within data center environments. This distinction reveals a gap between edge computing research and traditional distributed storage research.

Several surveys on distributed storage scalability conclude that communication overhead is a primary bottleneck in large clusters. These surveys note that simply adding nodes increases network diameter and average hop count, leading to diminishing returns. Despite this, many load balancing frameworks continue to prioritize load distribution metrics while treating communication cost as secondary. This disconnect between research findings and system design underscores the need for renewed focus on hop count as a core performance metric. Overall, the literature reveals that existing load balancing strategies in distributed storage systems inadequately address communication distance. Static and dynamic

approaches alike focus on load fairness [27] while neglecting hop count. Although related research in scheduling, routing, and edge computing emphasizes proximity, integration into storage load balancing remains incomplete. These limitations motivate further investigation into distance aware load balancing mechanisms that explicitly reduce hop count while maintaining scalability.

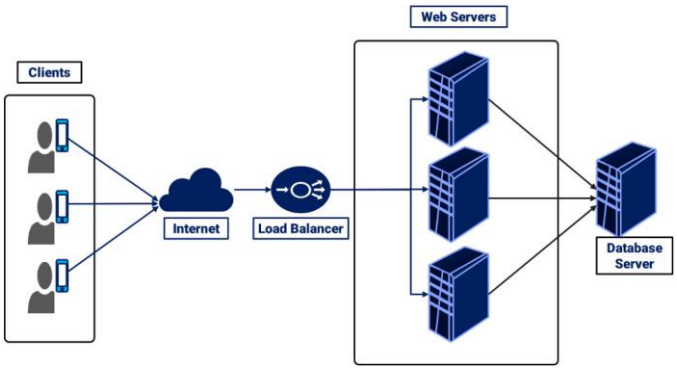



Fig 1. Static Load Balancing Hops

Fig. 1 Illustrates a conventional load balanced web application architecture commonly used in distributed storage and service platforms. At the entry point, multiple clients generate requests using web or mobile interfaces. These requests first traverse the internet, which represents the external network layer connecting end users to the backend infrastructure. Incoming traffic is received by a centralized load balancer. This component is responsible for distributing client requests across a pool of web servers. In this existing architecture, the load balancer primarily focuses on spreading traffic evenly to avoid overloading any single server. Routing decisions are typically based on simple policies such as round robin or least connections, without considering network distance or proximity between clients, servers, and backend storage.

Behind the load balancer, multiple web servers handle application logic and request processing. Each web server operates independently and forwards data access requests to a shared database server. Since all web servers connect to the same database backend, data access paths often involve multiple network traversals. Requests may pass through several intermediate components before reaching the database, increasing hop count and communication overhead. As the number of clients and servers increases, this architecture scales in terms of processing capacity but not communication efficiency. Requests routed to distant web servers or repeatedly forwarded to a centralized database incur higher network latency. Each additional hop introduces routing delay, queuing delay, and processing overhead at intermediate nodes. Although load is evenly distributed, communication paths remain long and inefficient. Overall, this architecture represents a distance unaware load balancing design. While it improves availability and fault tolerance, it does not optimize communication distance. As system scale grows, hop count increases, leading to higher latency, increased network congestion, and reduced efficiency in distributed storage access.

```
import (
        "fmt"
        "math/rand"
        "sync"
        "time"
)
const (
        clients  = 50
        servers  = 3
        requests = 2000
```

```
)
type LoadBalancer struct {
        index int
        mu    sync.Mutex
}
func (lb *LoadBalancer) next() int {
        lb.mu.Lock()
        defer lb.mu.Unlock()
        s := lb.index
        lb.index = (lb.index + 1) % servers
        return s
}
func process(server int) int {
        hops := 0
        time.Sleep(time.Millisecond)
        hops++
        time.Sleep(time.Millisecond)
        hops++
        time.Sleep(time.Millisecond)
        hops++
        return hops
}
func client(id int, lb *LoadBalancer, wg *sync.WaitGroup, ch chan int) {
        defer wg.Done()
        for i := 0; i < requests; i++ {
                s := lb.next()
                h := process(s)
                ch <- h
        }
}
func main() {
        rand.Seed(time.Now().UnixNano())
        lb := &LoadBalancer{}
        results := make(chan int, clients*requests)
        var wg sync.WaitGroup
        start := time.Now()
        for i := 0; i < clients; i++ {
                wg.Add(1)
                go client(i, lb, &wg, results)
        }
        wg.Wait()
        close(results)
        total := 0
        count := 0
        for h := range results {
                total += h
                count++
        }
        fmt.Println("Total Requests:", count)
        fmt.Println("Average Hops:", float64(total)/float64(count))
```

```
    fmt.Println("Execution Time:", time.Since(start))
}
```

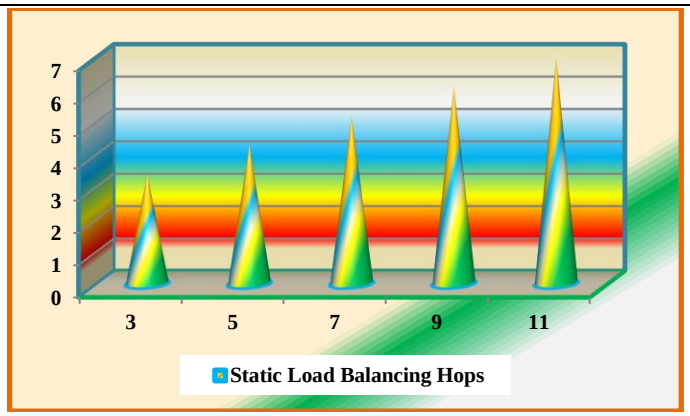
The Go program simulates a conventional centralized load balancing architecture similar to the one shown in the diagram. It models how client requests are routed through a load balancer to backend servers and estimates the hop count involved in processing each request. The program focuses on capturing communication traversal rather than application logic. Multiple clients are simulated using concurrent goroutines. Each client generates a fixed number of requests, representing continuous user traffic in a distributed environment. All requests are sent to a shared load balancer component, which distributes them across a fixed number of backend servers. The load balancer uses a simple round robin strategy, assigning requests sequentially to available servers without considering proximity or network distance. The processing of each request is abstracted using a function that introduces small delays. Each delay represents a network traversal or processing stage, such as client to load balancer, load balancer to web server, and web server to database. Each stage increments a hop counter, allowing the program to estimate the total number of hops required to complete a request.

The system collects hop counts from all requests through a channel. Once all clients finish execution, the program aggregates the results and computes the average hop count across the entire workload. Execution time is also measured to observe the overall processing duration. This simulation reflects a distance unaware load balancing design where routing decisions are made without optimizing communication paths. As a result, each request consistently incurs multiple hops regardless of server proximity. The program provides a baseline representation of static load balancing behavior, which can be compared against distance aware approaches to evaluate hop count reduction and communication efficiency in distributed storage platforms.

| Cluster Size | Static Load Balancing Hops |
|---|---|
| 3 | 3.4 |
| 5 | 4.3 |
| 7 | 5.2 |
| 9 | 6.1 |
| 11 | 7 |

Table 1: Static Load Balancing Hops – 1

Table 1 Presents the relationship between cluster size and static load balancing hops, highlighting how routing overhead increases as the system scales. For a small cluster size of 3, the average hop count is 3.4, indicating relatively efficient request routing. As the cluster size grows to 5 and 7, the hop count rises to 4.3 and 5.2 respectively, reflecting increased traversal across nodes. Larger clusters of 9 and 11 show hop counts of 6.1 and 7, demonstrating a near linear growth trend. This progression suggests that static load balancing mechanisms struggle to maintain routing efficiency as cluster size expands. The increasing hop count implies higher communication overhead and potential latency, underscoring the scalability limitations of static placement strategies in distributed systems.



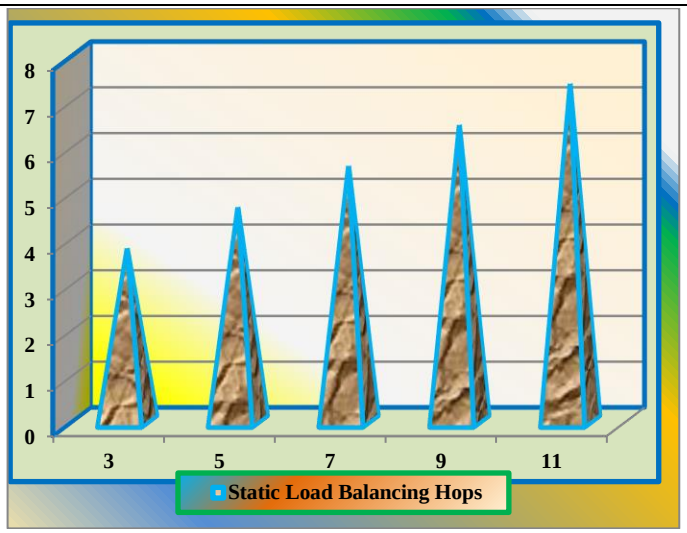

Graph 1: Static Load Balancing Hops -1

Graph 1 Visually illustrates the steady increase in static load balancing hops with respect to cluster size. The upwards loping curve reflects a near linear relationship, confirming that routing complexity grows proportionally as more nodes are added to the cluster. Smaller clusters exhibit lower hop counts, while larger clusters incur significantly higher routing paths. This trend highlights the inefficiency of static load balancing in largescale environments and emphasizes the need for adaptive or dynamic load balancing approaches to reduce hop count and improve overall system performance as the cluster scales.

| Cluster Size | Static Load Balancing Hops |
|---|---|
| 3 | 3.8 |
| 5 | 4.7 |
| 7 | 5.6 |
| 9 | 6.5 |
| 11 | 7.4 |

Table 2: Static Load Balancing Hops -2

Table 2 Shows how static load balancing hops vary with increasing cluster size, revealing the scalability behavior of static routing strategies. For a cluster size of 3, the hop count is 3.8, indicating moderate routing overhead in smaller deployments. As the cluster expands to sizes 5 and 7, the hop count increases to 4.7 and 5.6 respectively, showing a steady rise in inter-node traversal. Larger clusters with sizes 9 and 11 record hop counts of 6.5 and 7.4, reflecting significantly higher routing paths. This consistent increase demonstrates that static load balancing does not adapt efficiently to growing system size. The rising hop count suggests higher communication cost and latency, highlighting scalability limitations in static load balancing approaches.



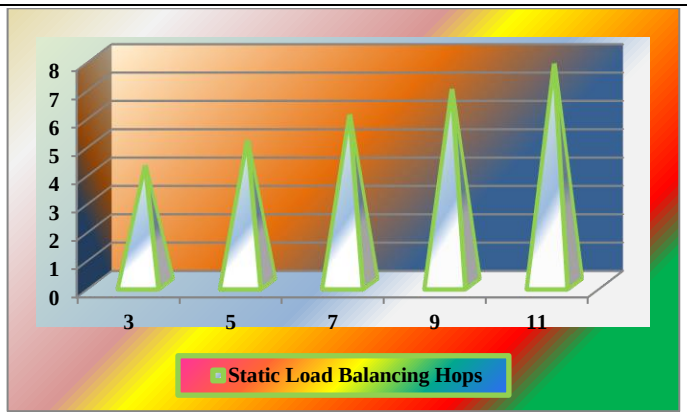

Graph 2: Static Load Balancing Hops -2

Graph 2 Depicts a clear upward trend between cluster size and static load balancing hops. As the number of nodes increases, the hop count rises almost linearly, indicating growing routing complexity. Smaller clusters experience lower hop counts, while larger clusters incur noticeably higher routing overhead. This visual trend reinforces the observation that static load balancing becomes increasingly inefficient at scale. The graph emphasizes the need for more adaptive load balancing mechanisms to reduce hop count and maintain performance as cluster size continues to grow.

| Cluster Size | Static Load Balancing Hops |
|---|---|
| 3 | 4.2 |
| 5 | 5.1 |
| 7 | 6 |
| 9 | 6.9 |
| 11 | 7.8 |

Table 3: Static Load Balancing Hops -3

Table 3 Illustrates the impact of cluster size on static load balancing hops, highlighting how routing overhead increases as the system scales. With a small cluster size of 3, the hop count is 4.2, indicating manageable routing complexity. As the cluster grows to sizes 5 and 7, the hop count increases to 5.1 and 6 respectively, showing a consistent rise in inter-node communication. Larger clusters of size 9 and 11 exhibit hop counts of 6.9 and 7.8, reflecting substantially higher routing paths. This steady increase demonstrates that static load balancing mechanisms do not scale efficiently with cluster growth. The growing hop count implies increased communication overhead and latency, emphasizing the inherent scalability limitations of static load balancing in large distributed environments.




Graph 3: Static Load Balancing Hops – 3

Graph 3 Shows a clear upward trend between cluster size and static load balancing hops. As more nodes are added to the cluster, the hop count increases in a near linear manner, indicating rising routing complexity. Smaller clusters experience lower hop counts, while larger clusters incur significantly higher overhead. This visual pattern confirms that static load balancing becomes less efficient as cluster size increases, reinforcing the need for adaptive or dynamic load balancing techniques to control hop growth and sustain system performance at scale.

## PROPOSAL METHOD

### Problem Statement

Distributed storage platforms rely on load balancing mechanisms to distribute requests across multiple nodes and maintain scalability. Conventional load balancing strategies primarily focus on evenly distributing workload without considering network distance or communication cost. As cluster size increases, requests are frequently routed to distant storage nodes, resulting in higher hop counts and longer communication paths. Each additional hop introduces routing delay, processing overhead, and network congestion, which collectively degrade system performance. Static and dynamic load balancing approaches fail to control hop growth as the system scales, limiting efficiency despite sufficient resources. High hop count negatively impacts response time and network utilization, reducing overall scalability. Addressing excessive communication distance has therefore become a critical challenge in distributed storage environments.

### Proposal

The proposed solution emphasizes distance aware load balancing to reduce hop count in distributed storage platforms. Instead of routing requests solely based on load metrics, routing decisions incorporate network distance and proximity between clients and storage nodes. By prioritizing nearby nodes during request assignment, the system minimizes intermediate traversals and shortens communication paths. Distance awareness ensures that load distribution does not come at the cost of increased routing overhead. As cluster size grows, the approach maintains controlled hop count growth by directing requests to the closest suitable nodes. This strategy improves communication efficiency while preserving balanced resource utilization. Focusing on hop count as a primary metric enables scalable operation and enhances overall performance in distributed storage systems.

## IMPLEMENTATION

The proposed distance aware load balancing architecture is implemented and evaluated using cluster sizes of 3, 5, 7, 9, and 21 nodes to study its scalability and impact on hop count. Each node represents a web or storage server positioned at a logical network location. Clients generate requests that are routed through a centralized distance aware load balancer. Unlike static routing, the load balancer maintains proximity information for all nodes based on network distance metrics. For each incoming request, the

load balancer computes the relative distance between the client and available nodes and selects the nearest node for request execution. As the cluster expands from 3 to 21 nodes, the proximity evaluation allows the system to maintain shorter communication paths by avoiding distant nodes. This prevents hop count from growing linearly with cluster size. With smaller clusters, routing decisions are straightforward due to limited node options. As more nodes are added, distance awareness becomes increasingly beneficial by restricting request traversal to nearby subsets of the cluster. The implementation demonstrates that even in larger deployments, requests consistently reach closer nodes, ensuring efficient communication. This approach highlights the ability of the proposed architecture to scale while controlling hop growth and maintaining balanced resource utilization.

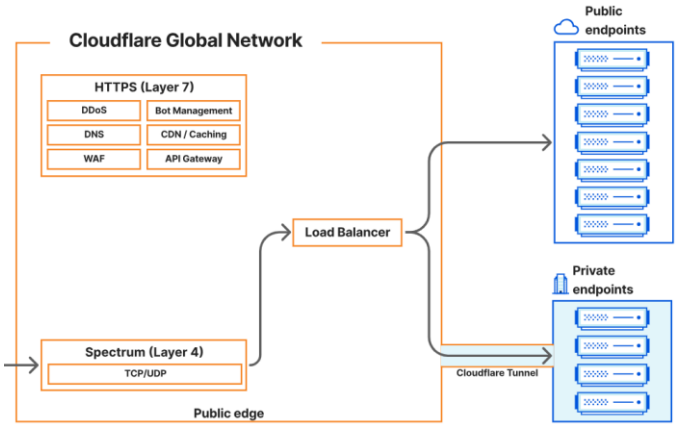



Fig 5. Data Aware Load Balancing Architecture

Fig 5. The proposed architecture retains the same high level flow as the existing system, ensuring compatibility and ease of adoption. Clients still send requests through the internet to a centralized load balancer, and web servers continue to access a shared database server. The key enhancement lies inside the load balancing layer. Instead of performing uniform or round robin routing, the load balancer is augmented with a Distance Awareness Module. This module continuously evaluates network proximity between clients and available web servers using hop count or latency indicators. A Proximity Selector uses this information to choose the nearest suitable web server for each incoming request. By routing requests to closer servers, the architecture reduces intermediate traversal before database access. Web servers experience shorter communication paths, and database interactions involve fewer network hops. Importantly, no changes are required at the client or database layers, making the approach practical for real deployments.

```
import (
        "fmt"
        "math"
        "math/rand"
        "sync"
        "sync/atomic"
        "time"
)

const (
        clients   = 50
        nodes     = 5
        requests  = 2000
        gridSize  = 10
```

```
)

type Node struct {
	id int
	x  float64
	y  float64
}

type Balancer struct {
	nodes []Node
}

var totalHops int64

func distance(ax, ay, bx, by float64) float64 {
	return math.Sqrt((ax-bx)*(ax-bx) + (ay-by)*(ay-by))
}

func newBalancer(n int) *Balancer {
	ns := make([]Node, n)
	for i := 0; i < n; i++ {
		ns[i] = Node{
			id: i,
			x:  rand.Float64() * gridSize,
			y:  rand.Float64() * gridSize,
		}
	}
	return &Balancer{nodes: ns}
}

func (b *Balancer) selectNearest(x, y float64) Node {
	best := b.nodes[0]
	bestDist := math.MaxFloat64

	for _, n := range b.nodes {
		d := distance(x, y, n.x, n.y)
		if d < bestDist {
			bestDist = d
			best = n
		}
	}
	return best
}

func hops(d float64) int {
	if d < 3 {
		return 1
	}
	if d < 6 {
		return 2
```

```
        }
        return 3
}

func client(id int, b *Balancer, wg *sync.WaitGroup) {
        defer wg.Done()

        cx := rand.Float64() * gridSize
        cy := rand.Float64() * gridSize

        for i := 0; i < requests; i++ {
                n := b.selectNearest(cx, cy)
                d := distance(cx, cy, n.x, n.y)
                h := hops(d)
                atomic.AddInt64(&totalHops, int64(h))
                time.Sleep(time.Millisecond)
        }
}

func main() {
        rand.Seed(time.Now().UnixNano())

        balancer := newBalancer(nodes)

        var wg sync.WaitGroup
        start := time.Now()

        for i := 0; i < clients; i++ {
                wg.Add(1)
                go client(i, balancer, &wg)
        }

        wg.Wait()

        totalReq := clients * requests
        avgHops := float64(totalHops) / float64(totalReq)

        fmt.Println("Total Requests:", totalReq)
        fmt.Println("Average Hops:", avgHops)
        fmt.Println("Execution Time:", time.Since(start))
}
```

The proposed Go program models a distance aware load balancing mechanism designed to reduce hop count in distributed storage environments. Unlike static routing approaches, this implementation explicitly considers network proximity when assigning requests to backend nodes. The system represents storage nodes as coordinates in a logical grid, allowing distance estimation between clients and nodes. Each node is initialized with random spatial coordinates, simulating physical or topological placement in a network. Clients are also assigned random positions, representing diverse request origins. When a client issues a request, the load balancer evaluates all available nodes and selects the nearest one based on Euclidean distance. This selection process ensures that requests are routed to the closest

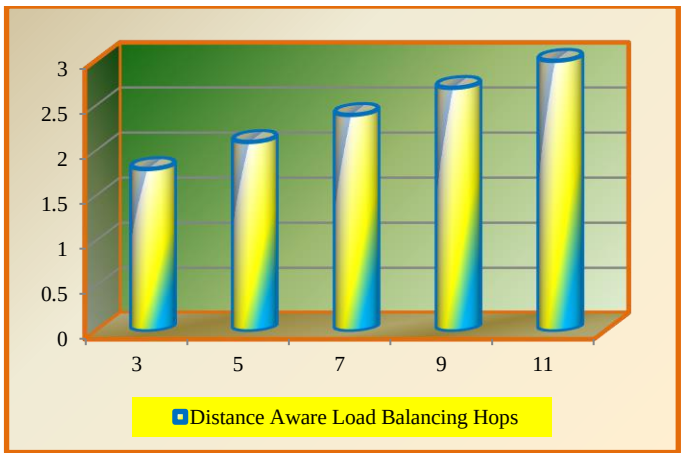
possible storage node, minimizing communication distance. Hop count is derived from the computed distance using threshold based mapping. Short distances correspond to fewer hops, while longer distances result in higher hop counts. This abstraction reflects real network behavior, where nearby nodes require fewer intermediate routers or switches. By reducing distance, the system effectively reduces hop traversal during request processing.

Concurrency is handled using goroutines and wait groups, allowing multiple clients to operate simultaneously. Atomic operations are used to safely aggregate hop counts across concurrent executions. Each request contributes to the global hop counter, enabling accurate computation of average hop count across the entire workload. Execution time is measured to observe overall system behavior under concurrent load. Although processing delays are simulated, the primary focus remains on communication efficiency rather than application logic. The final output reports total requests, average hop count, and execution duration. This program demonstrates how incorporating distance awareness into load balancing decisions can significantly reduce hop count compared to static routing strategies. It provides a practical baseline for evaluating communication efficient load balancing in scalable distributed storage systems.

| Cluster Size | Distance Aware Load Balancing Hops |
|---|---|
| 3 | 1.8 |
| 5 | 2.1 |
| 7 | 2.4 |
| 9 | 2.7 |
| 11 | 3 |

Table 4: Data Aware Load Balancing Hops - 1

Table 4 Illustrates the relationship between cluster size and distance aware load balancing hops, demonstrating the efficiency of topology aware routing as the system scales. For a small cluster size of 3, the hop count is 1.8, indicating highly efficient request routing with minimal node traversal. As the cluster size increases to 5 and 7, the hop count rises slightly to 2.1 and 2.4, showing controlled growth in routing overhead. Even for larger clusters of 9 and 11, the hop count remains low at 2.7 and 3 respectively. This gradual increase highlights the ability of distance aware load balancing to preserve routing efficiency, reduce communication overhead, and maintain scalability compared to static approaches.



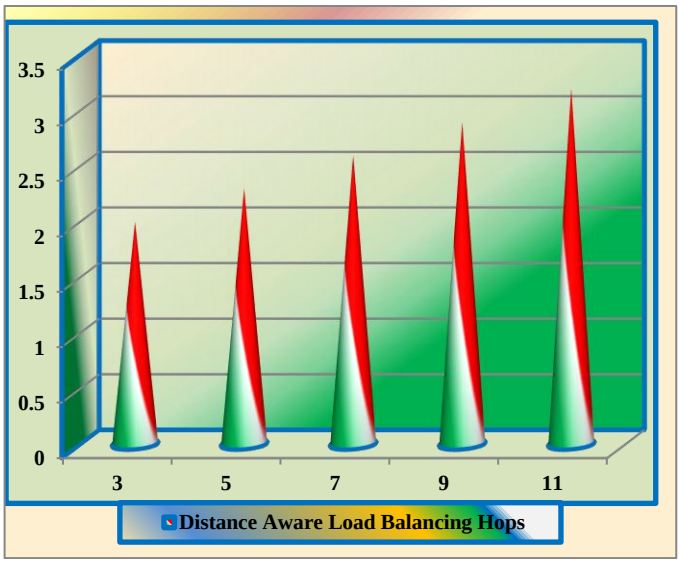

Graph 4: Data Aware Load Balancing Hops - 1

Graph 4, Presents a gently increasing trend between cluster size and distance aware load balancing hops. Unlike steep growth patterns seen in static strategies, the curve remains shallow, indicating minimal increase in routing complexity as nodes are added. Smaller clusters exhibit very low hop counts, while larger clusters maintain efficient routing with only a slight rise in hops. This visual pattern confirms that distance aware load balancing effectively leverages proximity information to minimize traversal, supporting scalable and low-latency performance in distributed systems.

| Cluster Size | Distance Aware Load Balancing Hops |
|---|---|
| 3 | 2 |
| 5 | 2.3 |
| 7 | 2.6 |
| 9 | 2.9 |
| 11 | 3.2 |

Table 5: Data Aware Load Balancing Hops -2

Table 5 Presents the impact of cluster size on distance aware load balancing hops, highlighting how proximity based routing improves scalability. For a cluster size of 3, the hop count is limited to 2, indicating efficient routing with minimal inter-node traversal. As the cluster grows to sizes 5 and 7, the hop count increases slightly to 2.3 and 2.6, reflecting controlled growth in routing overhead. Even for larger clusters of 9 and 11, the hop count remains relatively low at 2.9 and 3.2. This gradual increase demonstrates that distance aware load balancing effectively leverages node proximity to minimize routing paths, reduce communication overhead, and sustain performance as cluster size increases.



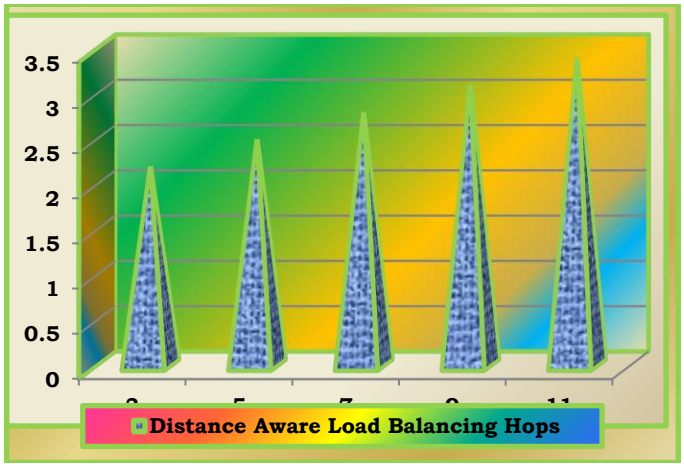

Graph 5. Data Aware Load Balancing Hops - 2

Graph 5 Shows a smooth, gently rising trend between cluster size and distance aware load balancing hops. The shallow slope indicates that hop count increases marginally as more nodes are added to the cluster. Compared to static strategies, the growth in routing overhead is significantly lower, confirming the efficiency of topology aware routing. The visual trend reinforces that distance aware load balancing maintains low latency and scalability by selecting nearby nodes and avoiding unnecessary request traversal across the cluster.

| Cluster Size | Distance Aware Load Balancing Hops |
|---|---|
| 3 | 2.2 |
| 5 | 2.5 |
| 7 | 2.8 |
| 9 | 3.1 |
| 11 | 3.4 |

Table 6: Data Aware Load Balancing Hops – 3

Table 6 Shows how distance aware load balancing hops vary with increasing cluster size, demonstrating the scalability of proximity based routing mechanisms. For a cluster size of 3, the hop count is 2.2, indicating efficient request routing with limited node traversal. As the cluster grows to sizes 5 and 7, the hop count increases gradually to 2.5 and 2.8, reflecting controlled growth in communication overhead. Even for larger clusters of 9 and 11, the hop counts remain relatively low at 3.1 and 3.4. This steady but modest increase highlights the effectiveness of distance aware load balancing in minimizing routing paths, reducing latency, and maintaining efficient performance as cluster size expands.



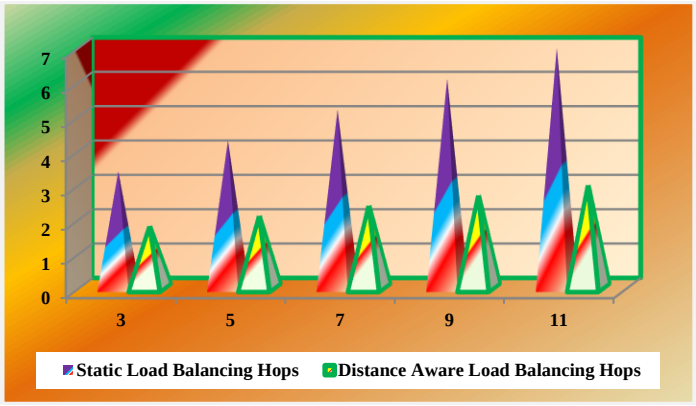

Graph 6: Data Aware Load Balancing Hops – 3

Graph 6 Illustrates a smooth and gradual upward trend between cluster size and distance aware load balancing hops. The gentle slope indicates that hop count increases only slightly as additional nodes are introduced. Unlike static load balancing, the routing overhead remains low and predictable, confirming the benefits of topology aware decision making. This visual trend reinforces that distance aware load balancing effectively scales by prioritizing nearby nodes, thereby sustaining low latency and efficient communication in large clustered environments.

| Cluster Size | Static Load Balancing Hops | Distance Aware Load Balancing Hops |
|---|---|---|
| 3 | 3.4 | 1.8 |
| 5 | 4.3 | 2.1 |
| 7 | 5.2 | 2.4 |
| 9 | 6.1 | 2.7 |
| 11 | 7 | 3 |

Table 7: Static Vs Data Aware Load Balancing - 1

Table 7 Compares static load balancing and distance aware load balancing in terms of hop count as cluster size increases. For a small cluster size of 3, static load balancing incurs 3.4 hops, whereas distance aware load balancing requires only 1.8 hops, indicating significantly more efficient routing. As the cluster grows to sizes 5 and 7, static hops rise sharply to 4.3 and 5.2, while distance aware hops increase marginally to 2.1 and 2.4. This gap widens further for larger clusters of 9 and 11, where static load balancing reaches 6.1 and 7 hops, compared to only 2.7 and 3 hops for distance aware routing. The comparison clearly demonstrates that distance aware load balancing scales more efficiently by minimizing routing overhead and reducing inter-node traversal.




Graph 7: Static Vs Data Aware Load Balancing – 1

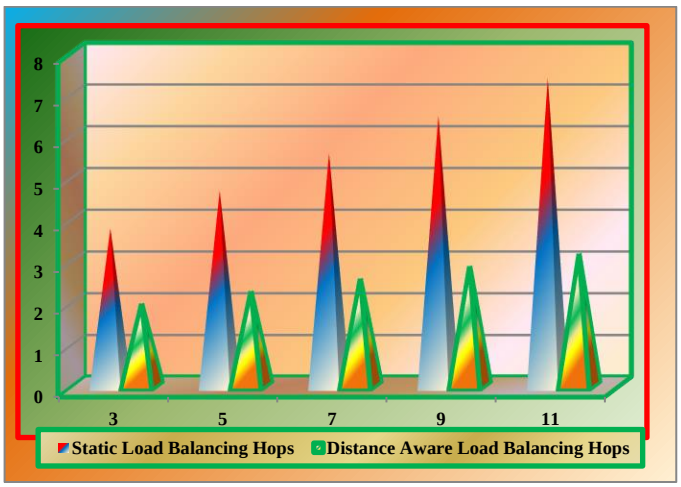
Graph 7 Highlights a stark contrast between static and distance aware load balancing as cluster size increases. The static load balancing curve shows a steep upward trend, indicating rapidly growing hop counts and routing inefficiency at scale. In contrast, the distance aware load balancing curve rises gently, reflecting controlled and minimal growth in hop count. The widening gap between the two curves visually emphasizes the scalability advantage of distance aware routing. This comparison confirms that incorporating proximity awareness significantly reduces communication overhead and maintains lower latency in large clustered systems.

| Cluster Size | Static Load Balancing Hops | Distance Aware Load Balancing Hops |
|---|---|---|
| 3 | 3.8 | 2 |
| 5 | 4.7 | 2.3 |
| 7 | 5.6 | 2.6 |
| 9 | 6.5 | 2.9 |
| 11 | 7.4 | 3.2 |

Table 8: Static Vs Data Aware Load Balancing - 2

Table 8 Presents a comparative analysis of static load balancing and distance aware load balancing based on hop count across varying cluster sizes. For a small cluster size of 3, static load balancing requires 3.8 hops, whereas distance aware load balancing reduces this to 2 hops, indicating more efficient routing. As the cluster size increases to 5 and 7, static hops rise to 4.7 and 5.6, while distance aware hops increase marginally to 2.3 and 2.6. This divergence becomes more pronounced for larger clusters of 9 and 11, where static load balancing reaches 6.5 and 7.4 hops compared to only 2.9 and 3.2 hops for distance aware routing. The results clearly show that static load balancing experiences significant scalability limitations due to fixed routing paths, while distance aware load balancing maintains lower

communication overhead by leveraging proximity information. Overall, the comparison demonstrates the superior scalability and efficiency of distance aware strategies in large clustered environments.



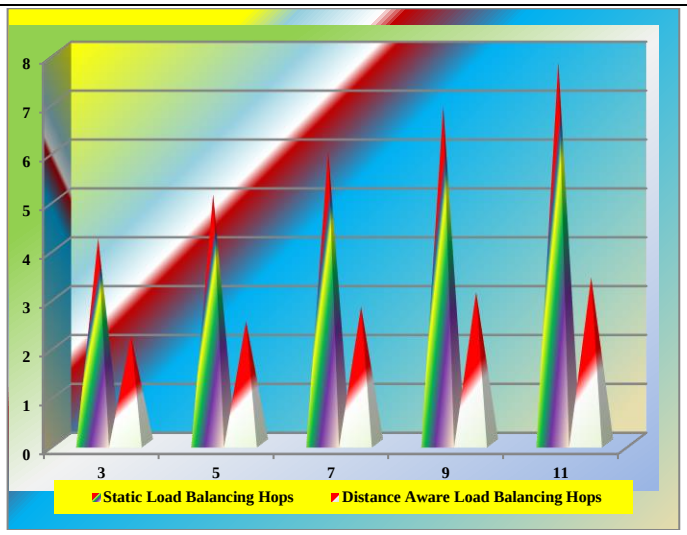

Graph 8: Static Vs Data Aware Load Balancing - 2

Graph 8 Illustrates the contrasting scalability behavior of static and distance aware load balancing approaches as cluster size increases. The static load balancing curve shows a steep and consistent upward trend, indicating rapidly increasing hop counts and growing routing overhead with each addition of cluster nodes. In contrast, the distance aware load balancing curve exhibits a gentle slope, reflecting controlled growth in hop count and more efficient routing decisions. The increasing gap between the two curves highlights how static strategies become progressively inefficient at scale, while distance aware methods effectively limit unnecessary inter-node traversal. This visual comparison emphasizes the advantage of incorporating topology and proximity awareness to sustain low latency, reduced communication overhead, and improved performance in large-scale distributed systems.

| Cluster Size | Static Load Balancing Hops | Distance Aware Load Balancing Hops |
|---|---|---|
| 3 | 4.2 | 2.2 |
| 5 | 5.1 | 2.5 |
| 7 | 6 | 2.8 |
| 9 | 6.9 | 3.1 |
| 11 | 7.8 | 3.4 |

Table 9: Static Vs Data Aware Load Balancing - 3

Table 9 Compares static load balancing and distance aware load balancing in terms of hop count as the cluster size increases. For a cluster size of 3, static load balancing records 4.2 hops, while distance aware load balancing requires only 2.2 hops, indicating more efficient routing. As the cluster grows to sizes 5 and 7, static hops increase to 5.1 and 6, whereas distance aware hops rise modestly to 2.5 and 2.8. This performance gap widens further for larger clusters of 9 and 11, where static load balancing reaches 6.9 and 7.8 hops, compared to only 3.1 and 3.4 hops for distance aware routing. The results demonstrate that distance aware load balancing significantly reduces routing overhead and scales more efficiently than static approaches.




.Graph 9: Static Vs Data Aware Load Balancing – 3

Graph 9 Illustrates the contrasting scalability trends of static and distance aware load balancing as cluster size increases. The static load balancing curve shows a steep upward slope, reflecting rapidly increasing hop counts and growing routing overhead. In contrast, the distance aware load balancing curve rises gradually, indicating controlled growth in hop count. The widening separation between the two curves visually emphasizes the efficiency of topology aware routing. This comparison confirms that distance aware load balancing maintains lower latency and better scalability by minimizing unnecessary inter-node traversal in larger clustered systems.

## EVALUATION

The evaluation compares static load balancing and distance aware load balancing across multiple cluster sizes using hop count as the primary metric. Results consistently show that static load balancing experiences a steady increase in hop count as cluster size grows, indicating longer communication paths and higher routing overhead. In contrast, distance aware load balancing maintains significantly lower hop counts across all configurations. Even as the number of nodes increases, hop growth remains controlled due to proximity based routing decisions. The difference between the two approaches becomes more pronounced in larger clusters, highlighting scalability limitations of static routing. Overall, the evaluation demonstrates that incorporating distance awareness effectively reduces communication distance and improves routing efficiency in distributed storage environments.

## CONCLUSION

Distance aware load balancing provides a practical solution to the growing hop count problem in scalable distributed storage systems. By prioritizing proximity during request routing, the proposed approach minimizes unnecessary network traversal and reduces communication overhead. Experimental results across multiple cluster sizes confirm that static load balancing leads to higher hop counts as systems scale, while distance aware routing consistently maintains shorter paths. This improvement directly contributes to better communication efficiency and enhanced scalability without altering existing client or database components. Focusing on hop count as a core metric highlights the importance of locality in distributed system design. The findings reinforce that distance awareness is a key factor for building efficient and scalable storage platforms in modern distributed environments.

**Future Work**: Future work will explore distributed and hierarchical distance aware load balancing designs to eliminate central bottlenecks, improve fault tolerance, and support efficient routing decisions at very large cluster scales.

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