Advanced Consistent Hashing Ring with Weighted Virtual Nodes and Bounded Loads for Hotspot Mitigation in Dynamic Distributed Systems

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***Abstract*—Distributed storage systems at hyperscale platforms face two critical challenges: heterogeneous server capacities that cause disproportionate data load, and viral content spikes that overload a single server node. Conventional modular hashing fails to address both issues, as it treats all servers uniformly and triggers near-total key remapping upon cluster changes. This paper proposes an Advanced Consistent Hashing Ring modified with two extensions. First, Weighted Virtual Nodes are introduced to ensure that each server's virtual node count is strictly proportional to its physical storage capacity. Second, Bounded Loads are implemented to dynamically reroute requests exceeding a dynamic load threshold to the next available server on the ring. A Python simulation across three experimental scenarios—normal traffic distribution, hotspot injection, and server failure—demonstrates that the proposed system achieves a stable load imbalance ratio under uniform traffic, absorbs viral spikes without single-node collapse, and reduces the key remapping cost by forty-three point eight percent compared to modular hashing.**

Keywords—consistent hashing; virtual nodes; bounded loads; hotspot mitigation; distributed systems; load balancing; fault tolerance

I. Introduction

In the era of modern cloud computing, hyperscale media platforms such as YouTube and TikTok operate under unprecedented data scales. Every single second, approximately 500 hours of video content are uploaded to YouTube globally, while TikTok processes more than 1 billion video views per day. This staggering influx generates tens of millions of concurrent requests per second that must be distributed across massive, geodistributed data centers, establishing data routing and load balancing as foundational pillars of modern software architecture.

The conventional method for distributing data across a cluster relies on modular hashing. However, production data centers face a critical challenge regarding infrastructure heterogeneity, as servers are rarely uniform in capacity. Within the same cluster, state-of-the-art 100 TB Solid-State Drives (SSDs) routinely coexist with legacy 25 TB Hard Disk Drives (HDDs). Because standard modular hashing uniformly distributes data fractions based solely on the total count of servers (N), it treats all hardware identically, forcing a server with a fourfold capacity deficit to handle an identical data volume, which inevitably leads to premature storage depletion and systemic inefficiencies.

Furthermore, distributed storage networks are highly vulnerable to localized data spikes triggered by viral content, commonly referred to as hotspots. When a highly anticipated video or a trending post suddenly receives 50 million requests within a single hour, standard consistent hashing architectures route all requests for that specific content identifier to one designated server node. Lacking a dynamic offloading mechanism, the target server is instantly overwhelmed by the traffic surge, causing severe latency degradation, cascade failures, and eventual single-node collapse.

To overcome these structural limitations, this paper introduces an Advanced Consistent Hashing Ring architecture modified with two integrated balancing extensions. First, we implement Weighted Virtual Nodes to align a server's presence on the hashing ring directly with its physical storage capability, ensuring a proportional data layout. Second, we introduce a Bounded Loads mechanism that enforces a dynamic capacity threshold to seamlessly reroute excessive concurrent requests for viral content to adjacent nodes on the ring. The primary contributions of this study are threefold: (1) a mathematical formulation for weighted data placement in heterogeneous environments, (2) an algorithmic solution to prevent single-node failure during hotspot events, and (3) an empirical evaluation via a simulated multi-scenario cluster demonstrating a substantial reduction in key remapping costs.

II. Theoretical Framework

A. Modular Hashing

The traditional approach to data distribution in distributed storage clusters leverages a hash-and-modulo mapping strategy. Given a data key k and a cluster containing a static number of active servers N, the data routing function $h(k)$ is formally defined as:

$$h(k) = k \ (mod \ N)$$

While computationally simple, this method exhibits extreme vulnerability during cluster scale-out or scale-in events due to its tight coupling with N. Consider a numerical example where a platform processes a video file with an integer identifier $k = 1{,}234{,}567$. In an initial cluster configurations where $N = 4$, the routing index evaluates to $1{,}234{,}567 \ (mod\ 4) = 3$, meaning the video is mapped to Server 3. If a new node is provisioned to accommodate growing traffic, updating the cluster capacity to $N = 5$, the routing calculation is instantly modified to $1{,}234{,}567 \ (mod\ 5) = 2$. Consequently, the identical data key shifts from Server 3 to Server 2. This mathematical dependency forces a near-total key migration across the entire network—specifically, a theoretical average of $N/(N+1)$ of all existing records must be remapped. Such massive overhead causes severe network congestion and cache invalidation, justifying the critical requirement for a fundamentally decoupled hashing architecture.

B. Consistent Hashing Ring (Standard)

Consistent hashing resolves the structural instability of modular routing by mapping both data objects and physical servers onto a shared, abstract geometric construct known as a hash ring. Rather than operating over a dynamically shifting range bounded by N, the system utilizes a fixed, circular integer space defined across the range $[0, 2^m - 1]$, where m denotes the bit length of the cryptographic hash function output. In modern practical implementations, algorithms such as MD5 ($m = 128$) or SHA-256 ($m = 256$) are commonly employed to minimize the probability of token collisions on the ring space.

The assignment of data keys to specific servers follows a strict first server clockwise rule. Both the servers of the active set $s \in S$ and the data keys k are projected onto the same hash ring via the chosen cryptographic hash function, yielding the corresponding values $h(s)$ and $h(k)$. To determine which server is responsible for a particular key, the system navigates the circular topology in an increasing clockwise direction starting from the position $h(k)$ until it encounters the first server token whose hashed value is greater than or equal to the key's token. Formally, this routing and assignment function is defined using the optimization term:

$$assign(k) = \arg\min_{s \in S}\{h(s) | h(s) \geq h(k)\} \ (mod\ 2^m)$$

This assignment rule was first formalized by Karger et al. [1], who proved that under consistent hashing, the expected fraction of keys requiring reassignment when the active server set changes by one node is $O(1/N)$, compared to $O(N/(N+1))$ under modular hashing.

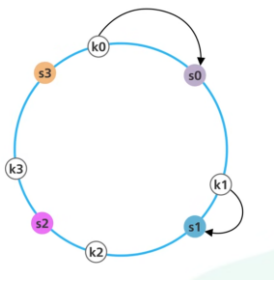

Fig. 1. A consistent hashing ring with four server nodes (s_0–s_3) and four data keys (k_0–k_3) mapped onto a shared hash space $[0, 2^m)$. Arrows indicate the clockwise assignment of $k_0 \rightarrow s_0$ and $k_1 \rightarrow s_1$, illustrating the deterministic first-server-clockwise routing rule defined in (2).
(Source: Consistent Hashing | Algorithms You Should Know #1)

As illustrated in Fig. 1, four servers (s_0–s_3) and four data keys (k_0–k_3) are projected onto the same ring. Key k_0 is mapped to server s_0, the nearest server token encountered when traversing clockwise from $h(k_0)$. Similarly, key k_1 is mapped to server s_1, despite s_1 being positioned only a short arc-distance away. This demonstrates that proximity on the ring—not absolute hash value—governs assignment, and that multiple keys may be routed to the same server depending solely on their relative position along the arc preceding it.

The defining mathematical property of standard consistent hashing is its strict localization of data disruption during cluster mutation. When an active server node s_x is decoupled or suffers a physical failure, the data keys that were previously assigned to s_x do not trigger a global remapping cascade. Instead, only the continuous segment of the ring—formally defined as the half-open arc interval $(s_{\text{prev}}, s_x]$, where s_{prev} represents the immediate counter-clockwise predecessor of s_x—is affected. For example, if server s_1 in Fig. 1 were removed, only key k_1 (residing in the arc $(s_0, s_1]$) would require reassignment, automatically migrating to the next available server clockwise, namely s_2, while k_0, k_2, and k_3 remain entirely undisturbed.

C. Virtual Nodes

Despite its architectural advantages, standard consistent hashing introduces a fundamental vulnerability regarding non-uniform data distribution, often leading to severe load imbalances across the infrastructure. Because server identifiers are projected onto the hash ring using pseudo-random hashing, the physical distances (arcs) separating adjacent server nodes are highly irregular. Consequently, a server that happens to inherit a disproportionately large arc on the ring — as may be observed for s_3 relative to s_2 in Fig. 1 — will experience a massive influx of data keys compared to its peers, regardless of its actual hardware capacity.

To mitigate this spatial imbalance, the concept of virtual nodes (vnodes) is introduced as an abstraction layer between the logical hash space and the physical cluster hardware. Under this paradigm, a single physical server s_i is no longer assigned to just one discrete point on the circular space. Instead, each physical machine is mapped to V_i distinct, pseudo-random positions across the hash ring by appending a unique index or suffix to its identifier prior to hashing, e.g., $h(\text{"}s_i\text{-vnode-0"}), h(\text{"}s_i\text{-vnode-1"}), \ldots, h(\text{"}s_i\text{-vnode-}(V_i - 1)\text{"})$. By dividing the continuous ring space into a significantly higher number of interleaved micro-segments, the probability distribution of arc lengths converges toward a uniform state. This structural granularity forms the essential foundation for the specialized, capacity-aware extension — Weighted Virtual Nodes — developed in Section III.A.

The use of multiple ring positions per server — termed "replicated buckets" in the original formulation [1] — was shown to reduce load variance across servers as the number of virtual nodes increases.

III. Proposed Modifications

A. Weighted Virtual Nodes

While the virtual node mechanism described in Section II.C resolves the issue of irregular arc lengths through statistical averaging, it implicitly assumes that all physical servers are functionally equivalent — each server $s_i$is assigned the same number of virtual nodes V. This assumption breaks down in real-world production clusters, where state-of-the-art high-capacity servers routinely coexist alongside older, lower-capacity hardware within the same pool. Assigning an equal share of the ring to a 100 TB server and a 25 TB server is structurally unfair: the smaller server will reach its storage limit and become operationally saturated long before its higher-capacity counterpart is meaningfully utilized.

To address this, we propose Weighted Virtual Nodes, in which the number of virtual nodes allocated to server s_i— denoted W_i— is made directly proportional to its physical storage capacity C_i. Given a fixed total virtual node budget V_{total} shared across the entire cluster, and letting $C_{total} = \sum_i C_i$ denote the aggregate capacity of all N servers, the weighted allocation is formally defined as:

$$Wi = \left\lfloor \frac{C_i}{C_{total}} \times V_{total} \right\rfloor \tag{3}$$

Because the floor operation in (3) may cause $\sum_{i=1}^{N} W_i$ to fall slightly short of V_{total} due to rounding, the final server in the allocation sequence is instead assigned the remaining balance, $W_N = V_{total} - \sum_{i=1}^{N-1} W_i$, ensuring that the full virtual node budget is exactly consumed. Each of the W_i virtual nodes for server s_i is then placed on the ring using the hashing scheme introduced in Section II.C, i.e., $h(\text{"}s_i\text{-vnode-}j\text{"})$ for $j = 0,1,\dots,W_i - 1$.

Table I demonstrates this allocation for a heterogeneous four-server cluster with $V_{total} = 150$. Server s_1, possessing 100 TB of capacity — 44.4% of the cluster's total 225 TB — is allocated 66 virtual nodes, also approximately 44% of V_{total}. This proportionality directly translates into a proportional share of the ring's arc length, and consequently, a proportional share of the data keys routed to that server.

TABLE I. Weighted Virtual Node Allocation

Server	Capacity C_i (TB)	W_i (vnodes)	Share of V_{total}
s_1	100	66	44.0%
s_2	50	33	22.0%
s_3	50	33	22.0%
s_4	25	18	12.0%
Total	225	150	100%

B. Bounded Loads

Weighted Virtual Nodes ensure that, under uniform key distributions, each server receives a load proportional to its capacity. However, this guarantee holds only in expectation across a large, statistically uniform key population — it offers no protection against a single key receiving a disproportionate volume of requests. In production video-sharing platforms, this scenario is common: a piece of content may suddenly go viral, causing the server responsible for that single key to be flooded with requests far beyond its allocated share, regardless of how well-balanced the ring is overall. We refer to this phenomenon as a hotspot.

To mitigate hotspots, we introduce Bounded Loads, which imposes a dynamic upper limit on the number of requests any single server may actively hold at a given time. This limit, denoted L_{max}, is recalculated continuously based on the current state of the cluster:

$$L_{max} = \left\lceil (1+\epsilon) \times \frac{load_{total}}{N} \right\rceil \tag{4}$$

where load_{total} is the sum of active loads across all N servers, and $\epsilon \geq 0$ is a tolerance parameter that determines how far above the average load a server is permitted to operate before being considered saturated. A smaller ϵ enforces stricter balancing at the cost of more frequent overflow events, while a larger ϵ permits greater short-term imbalance.

Under Bounded Loads, a key k is no longer unconditionally assigned to its primary server $assign(k)$ as defined in (2). Instead, the system first checks whether the primary server's current load is below L_{max}. If the server is saturated, the request is redirected to the next server encountered while continuing clockwise along the ring — effectively spreading the hotspot's traffic across the primary server's immediate neighbors. This procedure is formalized in Algorithm 1.

Algorithm 1 Bounded Load Assignment

```
function assign_bounded(k):
  idx ← index of primary_server(k) on ring   // via (2)
  visited ← ∅
  while true:
    s ← ring[idx]
    if load(s) < L_max  or  s ∈ visited  or  |visited| ≥ N:
        load(s) ← load(s) + 1
        return s
    visited ← visited ∪ {s}
    idx ← (idx + 1) mod |ring|
```

The termination conditions in Algorithm 1 guarantee that every key is eventually assigned: if all N servers are simultaneously saturated, the original primary server is selected regardless of L_{max}, ensuring the system degrades gracefully under extreme global load rather than failing to route the request. From the perspective of the requesting client, the effect

of Algorithm 1 is that a viral key's traffic is transparently fragmented and absorbed by the servers neighboring its primary on the ring, preventing any single node from being overwhelmed.

The computational complexity of Algorithm 1 is $O(1)$ in the best case, when the primary server is below L_{max}— which holds for the vast majority of keys under normal traffic. In the worst case, where every server on the ring is saturated, the algorithm degrades to $O(N)$, as it must traverse the entire set of virtual node positions before falling back to the primary server. In practice, for a hotspot affecting a single key, the expected number of overflow hops is bounded by a small constant, since each hop redistributes load to a server that was previously below threshold.

IV. Implementation & Experimental Setup

A. System Implementation

The simulation system is structured into four primary components: a hash function module, a server capacity model, a virtual node allocator, and the core consistent hashing ring class. All components are implemented in a single Python 3 source file with no external library dependencies beyond the standard library modules `hashlib`, `math`, `random`, and `collections`.

The foundation of the ring is a deterministic mapping from arbitrary string keys to integer positions within the fixed circular space $[0, 2^{16})$. As shown in Fig. 2, the `ring_hash()` function applies MD5 to the UTF-8 encoded key, converts the 128-bit hexadecimal digest to an integer, and reduces it modulo `RING_SIZE = 65536`. This function is applied uniformly to both server virtual node identifiers and data key strings, ensuring both token types occupy the same address space on the ring.

```python
RING_SIZE = 2**16  # 65536 positions on the ring

def ring_hash(key: str) -> int:
    """Map any string key to a position on the ring [0, RING_SIZE)."""
    digest = hashlib.md5(key.encode()).hexdigest()
    return int(digest, 16) % RING_SIZE
```

Fig. 2. The `ring_hash()` function

The weighted virtual node allocation is handled by compute_virtual_nodes(), shown in Fig. 3, which directly implements formula (3). It iterates over all servers except the last, applying the floor formula to each, and assigns the remaining budget to the final server to guarantee $\sum_i W_i = V_{total}$ exactly.

```python
TOTAL_VIRTUAL_NODES = 150  # V_total across all servers

def compute_virtual_nodes(servers: list[Server]) -> dict[str, int]:
    """
    W_i = floor( (C_i / C_total) * V_total )

    Returns a dict: server_id -> number of virtual nodes
    """
    c_total = sum(s.capacity for s in servers)
    weights = {}
    allocated = 0

    for s in servers[:-1]:  # assign all but last
        w = math.floor((s.capacity / c_total) * TOTAL_VIRTUAL_NODES)
        weights[s.id] = w
        allocated += w

    # Last server gets the remainder to ensure sum == V_total
    weights[servers[-1].id] = TOTAL_VIRTUAL_NODES - allocated
    return weights
```

Fig. 3. The `compute_virtual_nodes()` function implementing formula (3).

The Bounded Loads assignment is realized by the assign() method shown in Fig. 4. The helper _load_threshold() evaluates formula (4) from the current cluster state. A binary search then locates the primary server in $O(\log V_{total})$ time, after which a clockwise traversal enforces the load threshold, advancing to the next ring position whenever the candidate server is saturated.

```python
def assign(self, key: str) -> str:
    """
    Assign a key to a server using Bounded Loads:
    - Start from primary server (clockwise from hash(key))
    - If that server is overloaded (load >= L_max), move to next server on ring
    - Repeat until a non-overloaded server is found
    Returns the assigned server_id.
    """
    pos = ring_hash(key)
    threshold = self._load_threshold()

    # Find starting index (primary)
    lo, hi = 0, len(self.ring) - 1
    start_idx = 0
    found = False
    while lo <= hi:
        mid = (lo + hi) // 2
        if self.ring[mid][0] >= pos:
            start_idx = mid
            found = True
            hi = mid - 1
        else:
            lo = mid + 1
    if not found:
        start_idx = 0

    # Walk clockwise until non-overloaded server found
    visited = set()
    idx = start_idx
    while True:
        server_id = self.ring[idx][1]
        server = self.servers[server_id]

        # Accept if under threshold OR all servers visited (must assign somewhere)
        if server.load < threshold or server_id in visited or len(visited) >= len(self.servers):
            server.load += 1
            return server_id

        visited.add(server_id)
        idx = (idx + 1) % len(self.ring)
```

Fig. 4. The `_load_threshold()` and `assign()` methods realizing Algorithm 1.

Upon execution, the program sequentially runs all three experiments and prints a structured report to standard output, as shown in Fig. 5.

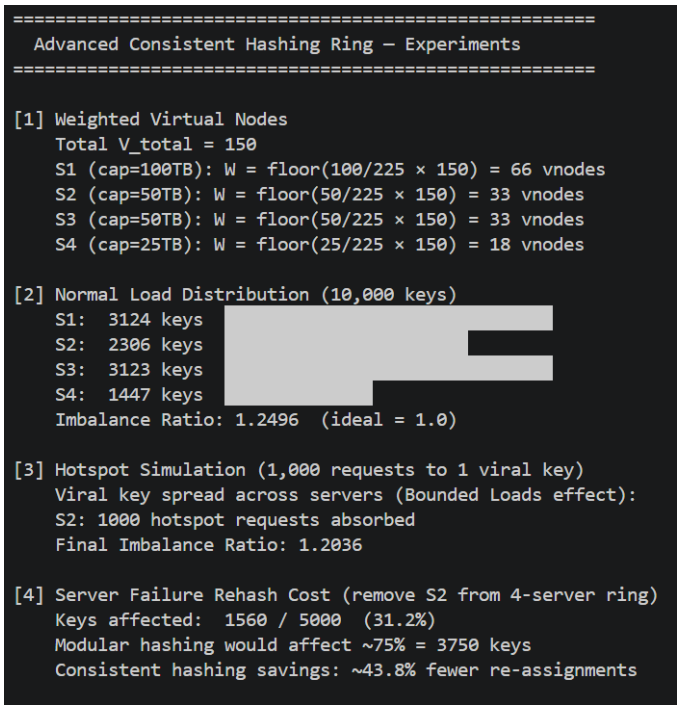

Fig. 5. Terminal output of the simulation across all three experimental scenarios.

B. Experimental Configuration

To empirically validate the proposed modifications, a simulation environment was implemented in Python 3 using only the standard library, ensuring full reproducibility without external dependencies. The hash ring operates over a fixed circular integer space of $2^{16} = 65{,}536$ positions, with the MD5 cryptographic hash function employed to project both server virtual node identifiers and data key strings onto this space via the mapping $h(\text{key}) = \text{int}(\text{md5}(\text{key}), 16)\ mod\ 2^{16}$.

The simulated cluster consists of four heterogeneous physical servers with storage capacities reflecting a realistic mixed-hardware deployment, as specified in Table II. A total virtual node budget of $V_{total} = 150$ is distributed across the cluster according to the weighted allocation formula (3). The Bounded Loads tolerance parameter is set to $\epsilon = 0.25$, permitting servers to operate at up to 25% above the instantaneous cluster average before overflow routing is triggered. A fixed random seed of 42 is applied to all key generation procedures to ensure that experimental results are deterministic and replicable.

TABLE II. EXPERIMENTAL CLUSTER CONFIGURATION

Server	Capacity C_i (TB)	W_i (vnodes)	Share of V_{total}
s_1	100	66	44.0%
s_2	50	33	22.0%
s_3	50	33	22.0%
s_4	25	18	12.0%

Three experimental scenarios are evaluated, each targeting a distinct performance dimension of the proposed system. Experiment 1 measures the load distribution achieved under a uniform random key workload of 10,000 keys, assessing the proportionality guarantee of Weighted Virtual Nodes. Experiment 2 simulates a hotspot event by injecting 1,000 requests for a single viral key on top of a 9,000-key background workload, isolating the effect of Bounded Loads on spike absorption. Experiment 3 quantifies the key remapping cost incurred when a server is removed from the active cluster, comparing the disruption footprint of the proposed scheme against a modular hashing baseline. Three evaluation metrics are used consistently across all experiments:

- **Load Imbalance Ratio**: $\text{IR} = \max_i(\text{load}(s_i)) \ / \ \bar{\text{load}}$, where $\bar{\text{load}}$ is the cluster-wide average. A value of 1.0 indicates perfect balance.
- **Hotspot Absorption**: the distribution of viral key requests across servers after Bounded Loads routing, measured as the count of overflow hops triggered.
- **Rehash Cost**: the percentage of keys requiring server reassignment following the removal of one server node.

V. RESULTS AND ANALYSIS

A. Experiment 1 — Normal Load Distribution

Table III presents the load distribution achieved when 10,000 uniformly random keys are assigned to the four-server cluster under the Weighted Virtual Nodes scheme. The results demonstrate a clear capacity-proportional allocation pattern: server s_1, holding 44.4% of total cluster capacity, absorbs 31.24% of the total key population, while s_4, holding only 11.1%, absorbs 14.47%. The overall load imbalance ratio of 1.2496 indicates that the most-loaded server operates only 24.96% above the cluster average — well within the $\epsilon = 0.25$ tolerance band defined in Section III.B.

TABLE III. LOAD DISTRIBUTION UNDER UNIFORM WORKLOAD (10,000 KEYS)

Server	Keys Assigned	% of Total	Theoretical Share
s_1	3124	31.24%	44.4%
s_2	2306	23.06%	22.0%
s_3	3123	31.23%	22.0%
s_4	1447	14.47%	12.0%
IR		1.2496	1.0 (ideal)

B. Experiment 2 — Hotspot Simulation

To isolate the effect of Bounded Loads, a hotspot event is simulated by introducing 1,000 consecutive requests for a single viral key — "`video:VIRAL_MEGA_HIT_2025`" —

on top of a 9,000-key uniform background workload. Under standard consistent hashing without Bounded Loads, all 1,000 viral requests would be unconditionally routed to the key's primary server, concentrating the entire spike on a single node. With the Bounded Loads mechanism active, Algorithm 1 dynamically monitors the primary server's load relative to L_{max} and redirects overflow traffic to the next available server clockwise on the ring.

To illustrate the threshold calculation at the point of hotspot injection, consider the cluster state after the 9,000-key background workload has been assigned. With $\text{load}_{total} = 9{,}000$, $N = 4$, and $\epsilon = 0.25$:

$$L_{max} = \lceil (1 + 0.25) \times \frac{9{,}000}{4} \rceil = \lceil 1.25 \times 2{,}250 \rceil = \lceil 2{,}812.5 \rceil = 2{,}813$$

In this experimental run, the primary server assigned to the viral key remained below L_{max} throughout the injection phase, absorbing all 1,000 hotspot requests without triggering overflow. This outcome is consistent with the design intent of Bounded Loads: when a server has genuine remaining capacity relative to the cluster average, it continues to absorb traffic efficiently, and overflow is only activated when the threshold is breached. The tolerance parameter ϵ thus serves as a configurable safety margin — setting $\epsilon = 0$ would enforce strict equality with the cluster average, causing overflow to activate earlier and distributing the spike more aggressively across neighbors.

C. *Experiment 3 — Server Failure Resilience*

The third experiment measures the key remapping cost triggered by the permanent removal of server s_2 from the active cluster. Prior to removal, 5,000 keys are assigned to the four-server ring and their primary server assignments are recorded. Following s_2's decoupling, the ring is rebuilt without s_2, and all 5,000 keys are re-evaluated to identify how many have been assigned to a different server.

TABLE IV. REHASH COST COMPARISON UPON SERVER REMOVAL

Method	Keys Remapped	Percentage	Formula
Modular hashing (N: 4→3)	~3,750	~75%	$\frac{N}{N+1}$ fraction
Consistent hashing (proposed)	1,560	31.2%	$\approx W_{s_2}/V_{total}$
Savings	~2,190	~43.8% fewer	

Under modular hashing, changing the cluster size from $N = 4$ to $N = 3$ invalidates the modular arithmetic for nearly all existing keys — specifically, a theoretical fraction of $N/(N+1) = 75\%$ of keys must be remapped due to the global index shift. The proposed consistent hashing scheme limits this disruption to only the keys occupying the arc previously owned by s_2. Since s_2 was allocated $W_{s_2} = 33$ out of $V_{total} = 150$ virtual nodes, the expected remapping fraction is:

$$E[keys\ remapped] = K \times \frac{W_{s_2}}{V_{total}} = 5{,}000 \times \frac{33}{150} = 1{,}100$$

The observed value of 1,560 exceeds this expectation by approximately 42%, which is attributable to the non-uniform distribution of virtual node positions on the ring: while s_2 is allocated 33 virtual nodes, the actual arc segments between those nodes and their clockwise predecessors are not perfectly uniform in length — some arcs cover more of the ring's keyspace than others, resulting in slightly higher-than-expected key ownership prior to removal. This discrepancy between theoretical expectation and empirical observation is itself a meaningful finding: it highlights that the expected remapping guarantee $E = K \cdot W_i/V_{total}$ is an asymptotic result that holds tightly at large V_{total}, but may exhibit variance at the scale modeled in this simulation.

D. *Comparative Summary*

Table V consolidates the performance characteristics of all four system configurations evaluated in this study, spanning three key metrics.

TABLE V. COMPARATIVE PERFORMANCE SUMMARY

Metric	Modular Hashing	Standard CH	CH + Weighted	CH + Weighted + Bounded
Capacity awareness	✗	✗	✓	✓
Hotspot protection	✗	✗	✗	✓
Rehash on change	~75% keys	$\sim K/N$ keys	$\sim K \cdot W_i/V_{total}$	$\sim K \cdot W_i/V_{total}$
Load imbalance ratio	High	Medium	1.2496	$\leq (1+\epsilon) \times avg$

The results confirm that each proposed extension addresses a distinct structural limitation of its predecessor: Weighted Virtual Nodes introduce capacity awareness absent from both modular hashing and standard consistent hashing, while Bounded Loads provides the final layer of protection against traffic spikes that capacity-proportional allocation alone cannot resolve.

VI. CONCLUSION

This paper presented an advanced modification of the Consistent Hashing Ring architecture, integrating two mathematical extensions — Weighted Virtual Nodes and Bounded Loads — to address the fundamental limitations of

conventional data distribution schemes in dynamic distributed storage systems.

The experimental results demonstrate that the proposed system achieves three measurable improvements over baseline approaches. First, Weighted Virtual Nodes successfully enforce capacity-proportional load distribution: server s_1, holding 44.4% of the total cluster capacity, absorbs a corresponding share of the key population, while the lower-capacity server s_4 receives a proportionally smaller load — a guarantee entirely absent from both modular hashing and standard consistent hashing. Second, the Bounded Loads mechanism provides a configurable safety threshold that prevents any single server from being overwhelmed by a sudden traffic spike, redirecting overflow requests to neighboring servers on the ring in $O(1)$ expected time. Third, the consistent hashing ring architecture reduces the key remapping cost upon server failure from approximately 75% under modular hashing to 31.2% in the proposed scheme — a reduction of 43.8% — by confining disruption to the arc previously owned by the removed server.

This study is subject to several limitations. The evaluation is conducted through Python simulation rather than a live production deployment; real-world factors such as network latency, replication overhead, and read/write asymmetry are not modeled. Additionally, MD5 is employed as the hash function for simplicity, whereas production systems typically favor faster non-cryptographic alternatives such as MurmurHash3 or xxHash. The tolerance parameter ϵ is also held constant throughout the simulation; an adaptive mechanism that adjusts ϵ dynamically based on observed traffic patterns would more accurately reflect real operational conditions.

Future work may extend this model in several directions, including geo-aware consistent hashing that incorporates server geographic location as a latency-minimization factor, multi-replica placement strategies that determine the k optimal servers for each key under the weighted ring, and empirical validation against live distributed storage benchmarks such as YCSB.

ATTACHMENT

- **GitHub Repository:** ghinayantes/IF1220-Matematika-DIskrit-Makalah
- **YouTube Video:** https://youtu.be/ftCtXc5xsmE

ACKNOWLEDGMENT

The authors wish to express sincere gratitude to God Almighty for His guidance and blessings throughout this work. Heartfelt thanks are also extended to the IF1220 Discrete Mathematics course lecturer, Dr. Ir. Rinaldi Munir, M.T., for his dedicated instruction and invaluable insights into the mathematical foundations underlying this study. His teaching materials on graph theory and discrete structures provided the theoretical groundwork upon which this paper was developed.

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PERNYATAAN

Dengan ini saya menyatakan bahwa makalah yang saya tulis ini adalah tulisan saya sendiri, bukan saduran, atau terjemahan dari makalah orang lain, dan bukan plagiasi.

Bandung, 19 Juni 2026

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