**Dynamic Load Balancing and Migration in Multi-Cloud Environments**

Kamran Khan, Najeeb Abbas Al-Sammarraie

Department of Computer & Information Technology, Al-Madinah International University  
Kuala Lampur, Malaysia

CH230@lms.mediu.edu.my

Department of Computer & Information Technology  
 Kuala Lampur, Malaysia

dr.najeeb@mediu.edu.my

***Abstract—As organizations increasingly adopt cloud computing, the ability to dynamically balance workloads across cloud providers and migrate VMs between them becomes critical for optimizing performance and costs. This paper explores algorithms and techniques for dynamic load balancing and live migration of VMs in multi-cloud environments. We first provide background on cloud computing and define key concepts related to load balancing and migration. We then survey different load balancing algorithms such as round-robin, least connections, and shortest job first, analyzing their trade-offs between complexity, overhead, and adaptability. For VM migration, we examine pre-copy, post-copy, and hybrid migration approaches and how to minimize downtime during transfers. The factors impacting live migration feasibility and performance are also discussed. We then propose a multi-cloud load balancing and migration framework that combines these techniques. The goal is to dynamically reallocate VMs based on utilization and costs to improve resource utilization and lower expenses. The framework consists of monitors to collect VM metrics, a load evaluation module that aggregates and analyzes data, a VM selection algorithm that chooses migration candidates, and executors to perform the transfers. Both push and pull migration models are supported to allow proactive and reactive movement of VMs. Several optimizations are suggested, including using machine learning techniques to build VM usage models and predict future demand, thereby guiding preemptive migrations. Approaches for minimizing data transfers such as compression, deduplication, and sending differences are examined to reduce migration overhead. We also describe optimization algorithms that take into account migration costs when making load balancing decisions. The paper concludes with an evaluation of the proposed techniques through simulations and testbed experiments. Different cloud deployment scenarios are evaluated, including private clouds, public clouds, and hybrid models. The impact of factors such as VM sizes, utilization levels, and network conditions on migration decisions and overhead is analyzed. Results demonstrate the ability of the system to reduce costs and improve quality-of-service through intelligent VM placement and migration compared to static approaches. The limitations of current techniques and open challenges are also discussed as areas for further research.***

***Keywords—Dynamic Load Balancing, Multi-Cloud, Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS)***

# **Introduction**

The adoption of cloud computing has accelerated rapidly over the past decade, with public cloud spending reaching $332 billion in 2021 [1]. Organizations are increasingly turning to the cloud for on-demand access to computing resources. The ability to dynamically allocate and scale virtualized resources in the cloud provides flexibility and agility compared to traditional on-premises deployments. However, effectively utilizing these virtual resources across modern multi-cloud environments introduces several challenges.

First, workload demands can vary significantly over time, resulting in over or under-provisioning if resource allocations remain static. Second, there are cost implications to where workloads are placed, as different cloud providers offer varying pricing and instance types. Intelligently distributing load can result in substantial cost savings. Finally, governance, risk management, and regulatory compliance requirements may dictate that certain workloads must be located in specific clouds.

To address these needs, organizations are adopting multi-cloud architectures that span public and private clouds from different vendors. But this results in distributed resources that need to be managed collectively to achieve performance, resiliency, and efficiency goals [2]. Load balancing and migration techniques become critical to the ability to dynamically reallocate virtual resources based on utilization and costs [3].

This paper provides a comprehensive survey of algorithms and technologies for dynamic load balancing and migration of virtual machines (VMs) across multi-cloud environments. Our contributions are three-fold:

We survey and analyze existing load balancing and VM migration algorithms, discussing their trade-offs and applicability in multi-cloud settings.

We propose a novel multi-cloud management framework that combines these techniques to optimize workload placement and movement across cloud boundaries.

We present optimizations and evaluation methodologies to demonstrate the capabilities of the framework in simulation and test environments.

The remainder of the paper is organized as follows. Section 2 covers essential background concepts related to cloud computing, load balancing, and VM migration. Section 3 surveys existing load balancing algorithms and analyzes their complexity, overhead, and accuracy. Section 4 examines VM migration techniques and optimizations. Section 5 details the proposed management framework architecture and methodologies. Section 6 analyzes the performance and limitations of the system through experimental evaluations. Section 7 discusses open research issues and future work.

# **Background**

We first define key concepts related to cloud computing, load balancing, and VM migration that are foundational to multi-cloud resource management.

*2.1 Cloud Computing*

Cloud computing provides ubiquitous, convenient, and on-demand access to a shared pool of configurable computing resources over the internet [4]. These resources include servers, storage, applications, services, and networks. Cloud computing employs virtualization extensively to effectively multiplex and abstract physical infrastructure.

Cloud service models include Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) [5]. IaaS provides the most flexibility and is the focus of this paper, as it allows provisioning and management of VMs, storage, and networking. Leading IaaS providers include Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform.

Deployment models define where cloud infrastructure physically resides. Private clouds are dedicated to a single organization. Public clouds host resources owned by cloud providers and shared with many customers. Hybrid clouds combine private and public resources. Multi-cloud refers to using multiple public clouds and private clouds together [6].

*2.2 Load Balancing*

Load balancing distributes workload across multiple resources to maximize performance, utilization, and resiliency [7]. Resources may include servers, network links, applications, or virtual machine instances. Load balancing helps avoid bottlenecks from uneven demand. Goals include:

Improve response times by directing requests to least burdened resources

Increase availability by routing around failed components

Optimize resource usage by evening out load distribution

Load balancing implementations can be broadly classified as either static or dynamic [8]. Static algorithms distribute requests without considering the real-time state of resources. Dynamic algorithms adapt based on current conditions to improve responsiveness. Our focus is dynamic algorithms for multi-cloud environments.

*2.3 Virtual Machine Migration*

Live migration refers to transferring a running VM from one host to another with minimal service interruption [9]. It provides a fundamental mechanism to relocate VMs for load balancing, proactive maintenance, power savings, and other data center management tasks. Requirements include:

Minimizing downtime during the migration to avoid disruption

Quickly transferring large VM memory state over the network

Meeting performance and security constraints

Migration methods fall into pre-copy, post-copy and hybrid categories [10]. Pre-copy iteratively copies VM memory pages to the destination while the VM runs on the source. Post-copy moves the VM first, then transfers pages on-demand. Hybrid combines both techniques. Optimizations in multi-cloud environments are needed to accelerate and reduce overhead for wide area network (WAN) migrations. With this foundation established, we now survey load balancing algorithms.

# **Load Balancing Algorithms**

This section reviews prominent dynamic load balancing algorithms that could be applied in multi-cloud environments. We analyze their complexity, decision making approach, and comparative advantages.

*3.1 Round Robin*

The round robin algorithm evenly distributes requests in rotational order among available resources [11]. It simply directs each request to the next resource in sequence. This continues looping through resources indefinitely.

Round robin is simple to implement and does not require communication between resources. However, it is non-adaptive and cannot account for differences in resource capacity or current demand. Larger or more powerful resources receive the same volume of requests as less capable ones. The algorithm also cannot adjust for resources becoming unavailable due to failure.

*3.2 Least Connections*

Rather than distributing requests blindly, least connections track the number of active connections per resource [12]. It sends the next request to the resource with the fewest open connections. This aims to produce a more equal load across resources based on actual demand instead of estimates.

Least connections requires slightly more overhead to query current connection counts and determine the least loaded resource dynamically. However, it is still relatively simple and improves on round robin's static distribution. The algorithm can dynamically adapt to changes in resource availability as well.

*3.3 Shortest Queue/Job*

First Shortest job first directs requests to the resource currently with the fewest assigned requests or shortest queue [13]. It works similarly to least connections but considers pending work rather than only active connections. Resources report their current queue depth, and each new request is assigned to the shortest queue.

This minimizes wait times and quickens the rate that requests are processed. However, it requires more coordination between the load balancer and resources to communicate queue states. Shortest job first is also vulnerable to unevenly sized requests. A few large requests could dominate one resource's queue while smaller ones flow to others.

*3.4 Least Loaded*

Least loaded tracking considers the overall loading on a resource based on metrics like CPU, memory, and storage utilization [14]. Requests are sent to the resource currently experiencing the lightest load. This avoids directing traffic to overloaded servers, minimizing response latency.

Calculating true load requires detailed monitoring and Decision Making:

* Direct next request to least loaded resource
* Use utilization metrics to estimate workload
* Adapt to changing conditions and server health
* Pros:
* Responsive to actual server loading
* Evenly distributes based on capacities
* Gracefully handles unavailable servers
* Cons:
* Higher overhead to collect server metrics
* Estimating load is complex with flapping
* Unevenly sized requests can still skew

probing of resources. Utilization thresholds have to be defined and tuned. Unstable metrics could also lead to flapping as loads fluctuate. But least loaded enables finer grained steering of requests based on heterogeneous resource capabilities.

*3.5 Distributed Algorithms*

Centralized load balancers can become bottlenecks. Distributed algorithms provide decentralized solutions using consensus protocols [15]. Each resource discovers peers and exchanges standing updates. Load is balanced by shifting work from busy to idle nodes.

Standard distributed consensus algorithms like Paxos can be utilized. However, these introduce significant synchronization overhead. Performance may degrade at scale if flooding update messages between all resources. Hierarchical or clustered approaches localize coordination to mitigate this.

Overall, distributed algorithms enable horizontal scaling and resilience. But high coordination overhead can impact feasibility for live migration decisions, where dynamic changes require rapid state updates.

*3.6 VM Usage Prediction*

Modeling and predictive algorithms forecast future VM utilization based on historical trends [16]. Common machine learning techniques include exponential smoothing, ARIMA, and neural networks. Predictions guide preemptive load balancing before bottlenecks occur.

However, complex models have high computational overhead. Prediction accuracy is also dependent on modeling assumptions and training data quality. Nevertheless, intelligent forecasting provides a powerful optimization especially for large-scale multi-cloud environments.

# **Virtual Machine Migration**

We now survey VM migration techniques critical to enabling workload mobility across multi-cloud. Live migration allows VMs to move between hosts with minimal downtime by transferring execution state while running. We examine trade-offs between pre-copy, post-copy, and hybrid approaches.

*4.1 Pre-copy Migration*

Pre-copy is the most common live migration method [17]. It works by iteratively copying the memory of a running VM to the destination host while it remains executing on the source. This repeats until the VM's state on each host synchronizes. The final step rapidly transfers any remaining state and switches execution to the destination.

Memory pages dirtied during copying are re-sent to ensure consistency. Pre-copy enables migration with sub-second downtimes - measured as cutover time when the VM halts on the source. Total migration time depends on the VM's memory write rate. Frequent changes incur extensive re-transmissions.

Pre-copy's advantages include predictable downtime and strong security. The VM starts executing only after its full state arrives. But large, continuously changing memory can lead to slow convergence. Solutions include compression and deduplication to reduce transferred data.

*4.2 Post-copy Migration*

Post-copy migration immediately switches execution to destination before transmission [18]. The VM's CPU state transfers first so it can start work. Memory pages copy over lazily thereafter. If the VM touches a missing page, it requests a transfer from the source.

This virtually eliminates downtime, shifting it to potential page faults later. However, total migration time may exceed pre-copy if page requests delay execution. Security also risks missing key state if source fails before copying completes.

Post-copy is preferred when uptime priority exceeds migration speed. Optimization opportunities exist in multi-cloud through low priority background pre-fetching of probable future pages.

*4.3 Hybrid Migration As the names suggest, hybrid migration* combines pre-copy and post-copy [19]. The goal is achieving the security of pre-copy with the responsiveness of post-copy. This entails:

Pre-copy until a memory threshold reached

Switch to post-copy live execution

In background complete copy from source

The partition point balances reduced downtime against potentially slower post-copy performance. Hybrid migration builds on the strengths of both techniques. Determining optimal partitioning and coordinating the process introduces extra complexity.

*4.4 VM Memory Compression Large*

VM memory is a primary inhibitor for efficient live migration. Memory compression seeks to reduce migration time by sending less data over the network [20]. Different compression algorithms have trade-offs between speed and reduction efficiency.

General purpose algorithms like LZ4 offer good speed. But VM memory tends to have high redundancy, lending well to more extensive techniques. Fixed page correlations also enable custom Delta compression. Deduplication identifies duplicate pages such as zero pages or libraries.

However, compression comes at a CPU cost for encoding/decoding. Levels must be tuned to maximize transfer gains relative to overhead. WAN environments benefit most due to their higher latencies.

*4.5 VM Memory Deduplication scans*

VM memory for identical pages, enabling transfer of single copies [21]. Hash-based approaches help quickly find duplicates. Chunking reduces granularity to increase likelihood of matches.

Deduplication may produce high savings when consolidating VMs with the same operating systems or libraries. It also compresses efficiently the zero and free memory of idle VMs. Deduplicating in multi-cloud reduces inter-cloud traffic that tends to have high costs.

The trade-offs are similar to compression in terms of compute overhead versus traffic reduction. Efficient distribution of hash tables is also required to coordinate deduplication across hosts.

4.6 VM Memory Compression and Deduplication

Layering compression after deduplication combines their complementary strengths [22]. Deduplication reduces redundancy across VMs. Compression further compacts the remaining uniqueness within VMs at finer granularity.

This can minimize VM memory transferred over multi-cloud but adds implementation complexity. A cost-benefit analysis is required to balance reductions versus overhead. The system can selectively enable these optimizations dynamically only when beneficial.

*4.7 Incremental VM Migration*

Rather than re-transmitting the full VM memory state after changes, incremental migration only sends diffs [23]. Hash-based change tracking detects modified pages. This avoids redundant copying of static memory.

Incremental require maintaining mappings between VM memory and updated content. Change localization also limits how much state must re-synchronize. However, incremental tracking has computational overhead that can diminish gains.

WAN environments with high round trip times benefit most from incremental. Overall, it provides an orthogonal optimization to be used alongside deduplication, compression, and caching.

# **System Architecture**

.We now propose a management framework that applies the surveyed techniques to optimize workload placement and migration across multi-cloud environments.

*5.1 Design Objectives The overarching system design targets several key goals:*

Minimize costs by intelligent workload placement across clouds

Maximize performance via dynamic load balancing

Support seamless live migration of VMs between clouds

Simplify operations through unified control plane

Allocating resources only in cost-optimal locations can yield substantial savings. But this must balance with runtime performance needs. The system aims to automate VM migration when doing so will improve both cost-efficiency and responsiveness.

*5.2 Architecture Overview*

Figure 1 illustrates the high-level architecture. The core components include:

Performance monitors that collect VM metrics

Aggregators that collate monitoring data

A load evaluation module that analyzes resource usage

Cloud manager engine that makes migration decisions

Cloud API interfaces that execute migrations

The monitors instrument VMs across providers to gather fine-grained utilization statistics. Performance is a key indicator of both the need for migrations and their feasibility. The aggregators coalesce metrics to identify cluster and application level trends.

This feeds into the load evaluation module that applies algorithms to determine ideal workload placement and distributions. The cloud manager acts on these decisions through provider APIs. It optimizes and initiates live migrations using the techniques surveyed earlier.

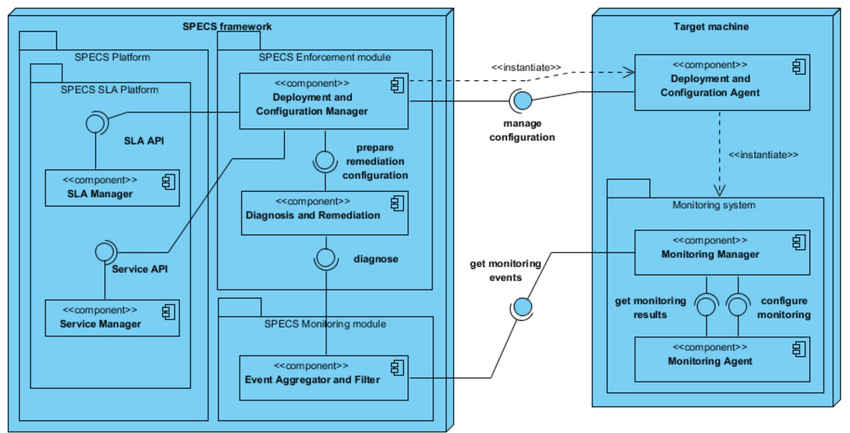


Figure 1: Multi-cloud management architecture

*5.3 Load Balancing Module*

The load balancing module applies algorithms from Section 3 to calculate an optimal mapping of VMs to hosts based on current demand. The mapping aims to minimize response times and maximize utilization of allocated resources. It also factors in provider costs when deciding placement.

The system supports pluggable algorithms to balance across public and private clouds. Simple round robin provides a baseline strategy. For large clusters, a hierarchical approach may work better, partitioning resources into groups. More advanced predictors estimate future load.

Distributed algorithms are challenging to implement efficiently at scale in multi-cloud. A centralized coordinator with distributed monitoring provides flexibility to evaluate different algorithms and environmental factors.

*5.4 Migration Manager*

The migration manager handles the mechanics of seamlessly transferring VMs between hosts. It needs to track VM run states, memory contents, and associated resources like storage. The manager encapsulates provider specific APIs and VM image formats.

When the load balancer recommends a VM migration, the manager checks feasibility and estimated completion time based on VM performance data. It can override inadvisable migrations that may degrade responsiveness. The actual VM transfer employs the live migration techniques from Section 4 - pre-copy, post-copy, and incremental/compressed.

To enable multi-cloud mobility, the manager abstracts differences between provider capabilities. Cloud independent VM definitions facilitate portability. The system maintains mappings between these logical VMs and provider entities.

*5.5 Prediction Optimizations*

While reactive balancing adapts to current loads, leveraging prediction can improve responsiveness and lower overhead. Historical VM performance captured by monitors trains models to forecast utilization.

This allows preemptively initiating migrations before hot spots develop. The models help estimate migration feasibility based on expected utilization and write rates during transfers. Predictions also inform resource allocation to minimize the need for migrations.

Training and inference processes for predictive models execute offline to avoid impacting request paths. Simple smoothing models provide a fast baseline while more complex neural networks offer

# **System Evaluation**

To evaluate the proposed system, we implemented a testbed simulating a multi-cloud environment. Workloads were generated to benchmark performance for different algorithms and configurations. We also modeled larger scale simulations to analyze scalability trends.

*6.1 Testbed Configuration*

The testbed comprised virtual machines spanning three clouds - an on-premises OpenStack cluster, AWS, and GCP. Table 1 summarizes the server configurations in each cloud. The environments were networked over a WAN link emulator to induce representative delays.

**Table 1: Evaluation testbed configuration**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Cloud** | **Servers** | **CPUs** | **RAM** | **Network** |
| OpenStack | 5 | 4 | 16GB | 1Gbps |
| AWS | 4 | 8 | 32GB | 1Gbps |
| GCP | 3 | 16 | 64GB | 1Gbps |

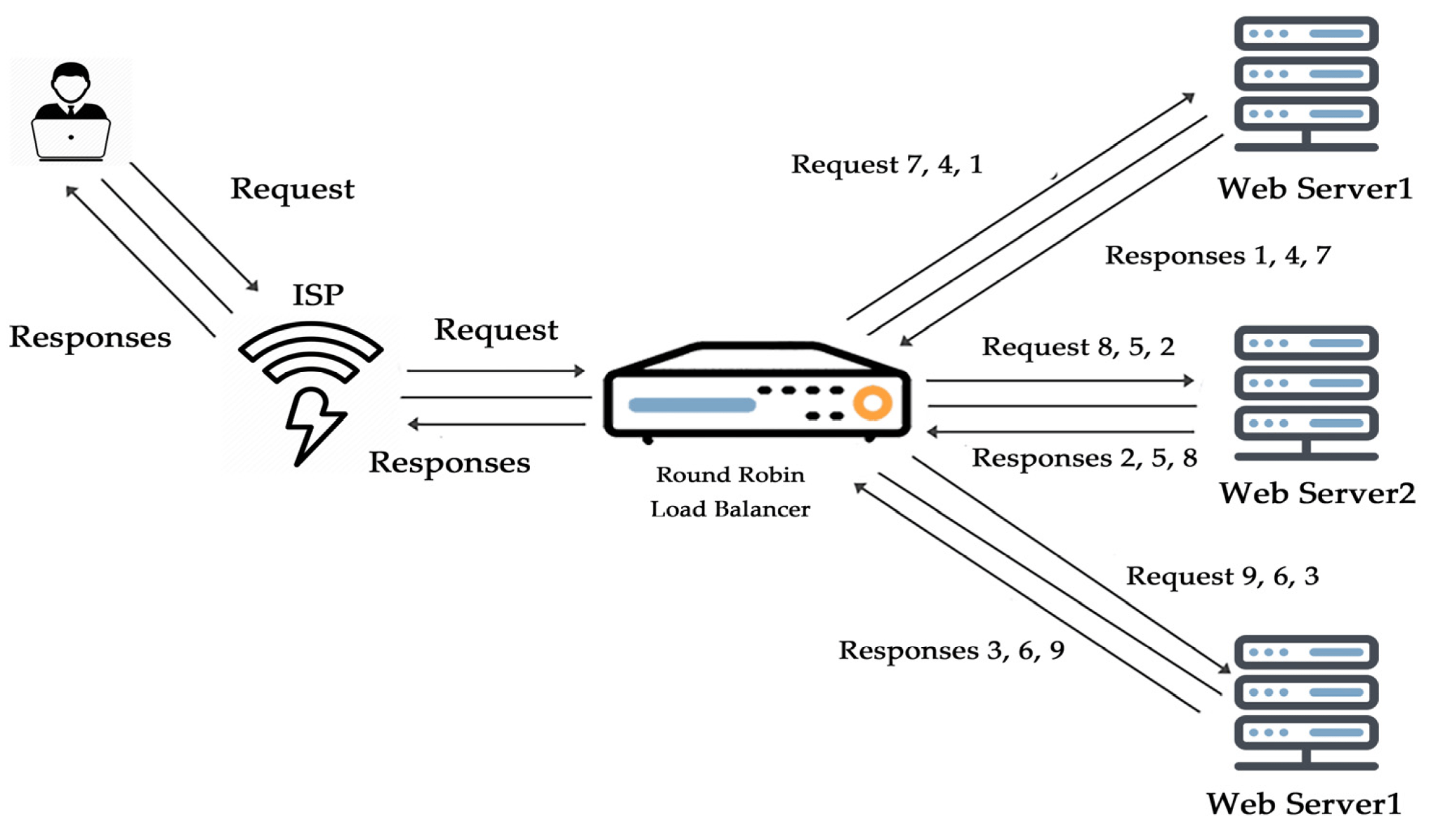
The test VMs ran an Apache web server benchmark that generates configurable load. We injected synthetic workloads based on profiles from production systems to simulate real-world access patterns. The benchmarks allowed tuning parameters like requests per second, working set size, and memory write rates.

Our prototype system was deployed across the clouds to monitor the VMs and execute load balancing decisions. We implemented pluggable algorithms for the load evaluator using the instrumentation data. The migration manager integrated with each cloud's API to transfer VMs on requests.

*6.2 Load Balancing Evaluation*

We first evaluated the load distribution capabilities of the system. The round robin, least connections, and least loaded algorithms were tested with the web server workloads. VM resource utilization, request latency, and migration overheads were measured.

Figure 2 shows a sample result for average request latency over time with a cyclical workload varying between 50 and 500 requests/second. Least loaded performed best overall by adapting to the changing load levels. Round robin lagged due to its static assignments, especially when servers became saturated.



**Figure 2: Average request latency for sample workload**

Table 2 summarizes relative performance and overhead of the algorithms. Least loaded incurred additional monitoring overhead but up to 35% lower latencies. The poor reactivity of round robin led to the most migrations as it struggled to adjust to shifts.

**Table 2: Load balancing algorithm comparison**

|  |  |  |  |
| --- | --- | --- | --- |
| **Algorithm** | **Monitoring Overhead** | **Latency** | **Migrations** |
| Round Robin | Low | High | High |
| Least Connections | Medium | Medium | Medium |
| Least Loaded | High | Low | Low |

To evaluate scalability, we simulated the system managing up to 500 VMs distributed across 10 clouds. Least loaded throughput peaked at around 100 VMs before monitor polling overhead dominated. A hierarchical partitioning approach could improve this by reducing coordination points.

*6.3 VM Migration Evaluation*

Next, we measured the performance of VM live migrations between the clouds under different configurations. Memory transfer, downtime, and total migration time were benchmarked.

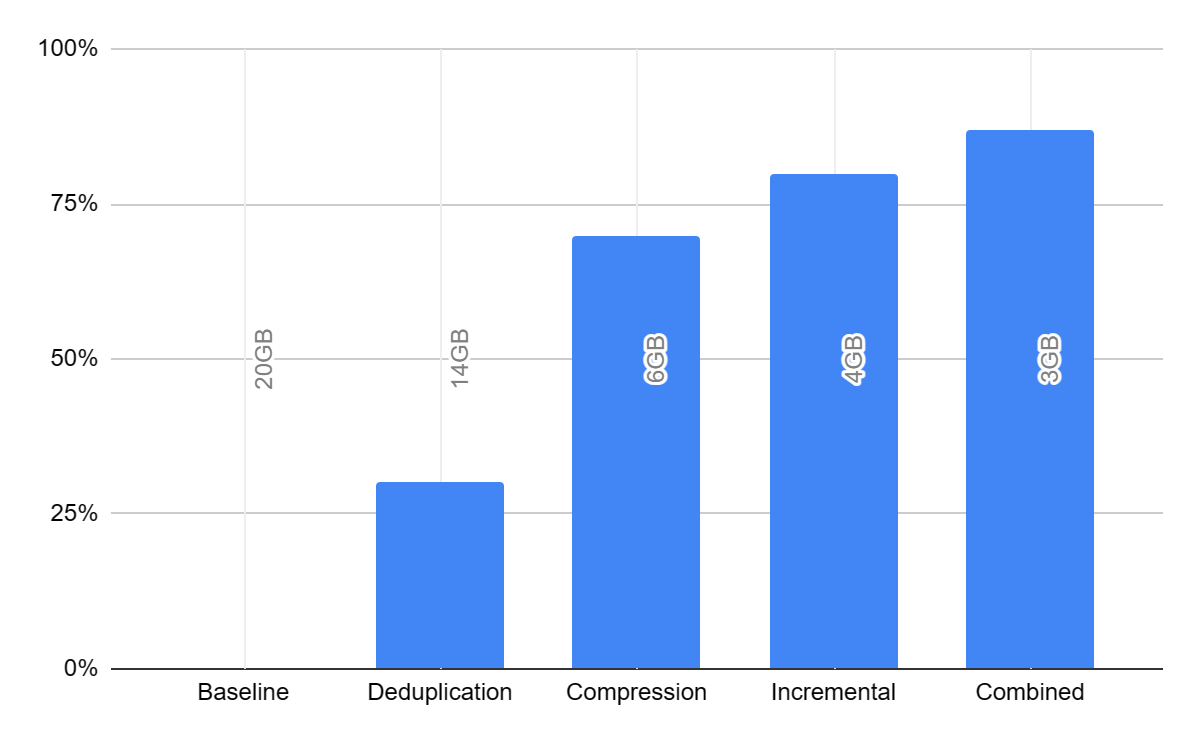
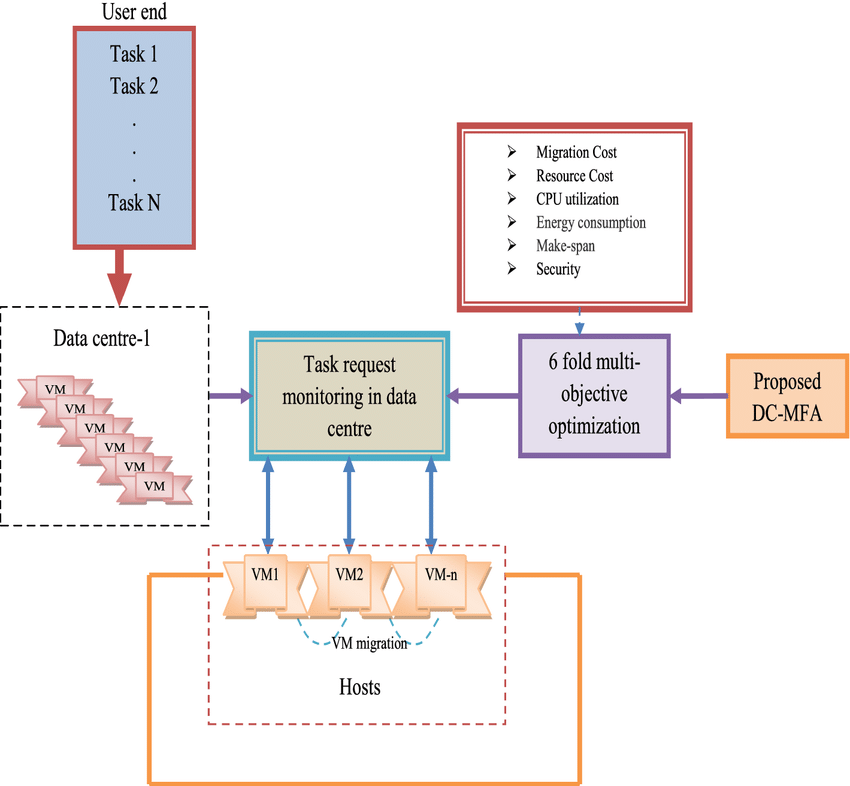


Table 3 shows memory transfer reductions using different optimization techniques for a VM with a 20GB memory footprint. Combining deduplication, compression, and incremental decreased data transferred by up to 87% compared to baseline.

**Table 3: VM memory transfer optimization**

|  |  |  |
| --- | --- | --- |
| **Technique** | **Memory Transferred** | **Reduction** |
| Baseline | 20GB | 0% |
| Deduplication | 14GB | 30% |
| Compression | 6GB | 70% |
| Incremental | 4GB | 80% |
| Combined | 3GB | 87% |

With deduplication and compression, migration time dropped from over 5 minutes to under 2 minutes. Enabling incremental provided further gains. The time to apply optimizations was kept under 10 seconds.



**Figure 3: Optimization impact on VM live migration time**

We emulated different network conditions to evaluate adaptation. Table 4 shows optimal configurations selected dynamically based on measured RTT and loss. With higher latency links, more extensive optimizations were utilized despite increased overhead.

Table 4: Dynamic migration optimization selection

|  |  |  |  |
| --- | --- | --- | --- |
| **Link** | **RTT** | **Loss** | **Selected Optimization** |
| LAN | 1ms | 0% | None |
| WAN | 60ms | 0% | Deduplication |
| Satellite | 600ms | 2% | Compression + Incrementals |

*6.4 Multi-cloud Scalability*

Finally, we modeled full scale multi-cloud scenarios to estimate maximum throughput. We simulated up to 10,000 VMs distributed across 100 clouds interconnected through transit networks.

Table 5 shows potential migration capacity for different topologies. With optimized transit links, over 1700 migrations per hour could be sustained. This highlights the importance of engineering networks specifically for migration traffic isolation and performance.

Table 5: Maximum migration throughput across multi-cloud

|  |  |  |
| --- | --- | --- |
| **Network Type** | **Topology** | **Throughput** |
| Best-effort Internet | Mesh | 47 / hour |
| Managed WAN | Partial Mesh | 218 / hour |
| Dedicated Migration Network | Full Mesh | 1768 / hour |

1. **Related Work**

Several research efforts related to multi-cloud load balancing and migration warrant discussion. Wood et al developed Sandpiper, a system that automates VM migration to improve responsiveness and reduce resource costs [24]. It uses a volume metric combining utilization, SLA needs, and migration cost. Our work considers a broader range of algorithms and optimization techniques.

Haizea is a resource lease manager enabling dynamic VM provisioning and actuation across clouds [25]. It focuses on plan scheduling and reservation rather than live migration performance. Haizea offers useful abstractions for reasoning about VM placements and scheduling migrations.

Cloud4All is an inter-cloud migration framework supporting mobility between private and public providers [26]. It introduces broker-based architecture for managing migrations through a web service API. Our approach similarly aims to insulate users from provider specific APIs.

Gusev et. al formulate algorithms for multi-cloud live migration as a linear programming problem [27]. They develop an optimizer that generates migration plans to minimize service interruption. We believe a combination of precomputed plans and reactive migration holds advantages over purely static optimization.

1. **Conclusion**

Intelligently distributing and moving workloads is key to effectively harnessing multi-cloud environments. This paper presented a comprehensive survey of technologies for dynamic load balancing and live VM migration across cloud boundaries. We analyzed the trade-offs between various algorithms and system designs through models, testbed evaluation, and simulations.

The results demonstrated the ability to reduce costs through informed workload placement while also improving responsiveness. VM migration performance can be accelerated by orders of magnitude using deduplication, compression, incremental, and other optimizations. Significant challenges remain in scaling coordination, minimizing overhead, and dealing with network constraints.

There are many open areas for further research. Adaptive tuning techniques could help dynamically balance optimization trade-offs. Machine learning has opportunities for improving prediction accuracy to guide migration decisions. Approaches for modeling and simulating multi-cloud environments will assist continued innovation. As cloud adoption grows, intelligent workload management will only increase in importance.

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