International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 04 | April - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Load Balancing Techniques in Cloud Computing A Comparative Study

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***Abstract*—Cloud computing has become a key paradigm of providing the on-demand and scalable computing resources over the internet. Efficient load balancing is one of the key issues in cloud environments as it guarantees the optimal usage of resources, minimizes response time, and enhances the reliability of the system. This paper outlines a comparison of the key load balancing techniques utilized in cloud computing, namely, static, dynamic, and hybrid load balancing techniques. Round Robin, and the Weighted Round Robin are some of the Static algorithms that allocate workloads by fixed rules, being simple but not flexible to changes in real time. Conversely, dynamic algorithms such as Least Connection, Throttled Load Balancing and Ant Colony Optimization modify the allocation of resources according to the prevailing conditions in the systems, resulting in better outcomes in a heterogeneous setting. Moreover, the latest development of combining Artificial Intelligence and Machine Learning, including reinforcement learning-based load balancing, have proven to be much better in forecasting workload patterns and resource allocation patterns.**

The research considers such methods through major performance indicators such as response time, throughput, scalability, fault tolerance, according to the experience of actual cloud platforms like Amazon Web Services (AWS) and Microsoft Azure. The findings by the literature show that dynamic and AI-based solutions are superior to traditional solutions to manage variable workloads and massively distributed systems. They do introduce more complex computations and overheads, however. The paper brings out the trade-offs of efficiency, complexity, and scalability with a broader comprehension of the applicability of each technique in various cloud situations.

The results indicate that the future of cloud infrastructures will have a bright future with the use of hybrid and intelligent load balancing strategies, which can provide a flexible, effective, and efficient way of service provision in more and more complex and data-driven environments.

***Index Terms*—component, formatting, style, styling, insert**

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I. Introduction

Cloud computing has transformed both the manner computing resources are provided whereby now on-demand access to a common pool of configurable resources that include servers, storage, and applications can be accessed through the internet. As the number of applications that are data intensive, such as e-commerce platforms, real-time analytics, and artificial intelligence services, cloud environments must be able to sustain extremely dynamic and unpredictable workloads. Load balancing in this case is critical in the context of ensuring efficient use of resources, stability of systems, and offering high quality to end users [2].

The load balancing process is the phenomenon of spreading the workloads among many computing resources to prevent overloading of any one of the nodes and to provide optimal performance. A good load balancing policy is not only beneficial in reducing response time and throughput but also in fault tolerance and scalability within the distributed cloud computing system. Without adequate load balancing, the cloud services can even degrade their performance, have higher latency, and even stop working during the peak time [1].

Cloud computing load balancing methods can generally be classified as dynamic and static. Round Robin and Min-Min algorithms are examples of the predetermined-rule based allocation of tasks and do not require any knowledge about the system resources, which can be considered a type of static methods. These approaches are easy and simple to execute but fail most of the time to respond to real-time changes in the work load and availability of resources. Conversely, dynamic load balancing algorithms such as Least Connection, Throttled, and heuristic-based algorithms require decisions based on the current system

so they are better implemented in a heterogeneous and large-scale system [7] [10].

Over the last several years, the intelligent and hybrid load balancing policies that use Artificial Intelligence (AI) and Machine Learning (ML) have become the subject of increased interest. The methods are designed to forecast patterns of workload, management of resources, and enhancement of real-time decision-making. Reinforcement learning, genetic algorithms, and swarm intelligence are techniques that have demonstrated encouraging outcomes with regard to increasing efficiency and adaptability of systems.

In this paper, a comparative study of different load balancing methods in cloud computing has been done in terms of performance, benefits and drawbacks. Through measurements of important metrics, response time, throughput, scalability, use of resources, the study seeks to give insight into the appropriate load balancing strategies to use in different cloud scenarios, as well as future research directions.

II. Background Study

The issue of load balancing in cloud computing has received a lot of research research in order to resolve issues of efficiency in making full use of resources, scalability and performance optimization. Early research concentrated on the algorithms of static load balancing like the Round Robin and Min-Min which are easy and need little overhead. Nevertheless, they do not fit the dynamic cloud environment as they cannot cope with changes in the workload. Studies by Rajkumar Buyya et al. highlighted the importance of market and adaptive resource management methods in cloud computing which this need to manage diverse workloads effectively [9].

To address the limitations of the static techniques, dynamic load balancing techniques were introduced. Michael Armbrust et al. emphasized the significance of elasticity and scalability of cloud infrastructures that need real-time decision-making when allocating resources. Least Connection and Throttled Load Balancing algorithms are dynamic distribution of workloads which gives rise to response time and system throughput improvement. Also, resource-aware and pricing-aware scheduling models have been suggested to maximize performance and cost-efficiency of clouds [8].

Additional studies presented heuristic and optimization-based methods of load balancing. Beloglazov and Buyya suggested that energy-aware allocation techniques could be used to consolidate and dynamically consolidate virtual machine to lower power consumption without compromising performance [6]. On the same note, Randles et al. in a comparative analysis of distributed load balancing algorithms have also shown that decentralized algorithms can increase fault tolerance and scalability of clouds.

Ant Colony Optimization (ACO) and Genetic Algorithms (GA) are some other bio-inspired algorithms that have been investigated extensively. Nishant et al. developed a load balancing method based on ACO which enhances the efficiency of task scheduling by distributed systems. Zhang et al. also improved this method by incorporating complex network theory, which further resulted in a better load distribution among federated cloud environments . Though these techniques enhance performance, they add extra calculation complexity [4] [3].

Recent developments are oriented towards the implementation of Artificial Intelligence (AI) and Machine Learning (ML) in the load balancing policies. These smart strategies can anticipate workload trends and can dynamically assign resources, which enhances scalability and resilience to faults. Dean and Barroso emphasized on the value of reducing latency in large-scale distributed systems, and the significance of effective load balancing in minimizing tail latency .

Although a lot has been achieved, there is still the problem of energy efficiency, real time flexibility and complexity of the system that is still under research. Current literature indicates that integrated solutions of using a combination of the existing methods would be ideal to solve contemporary cloud infrastructures by ensuring the use of a balanced methodology of implementing the methods. Thus, these methods should be compared to find out which method is best applied according to the needs of a specific application.

III. Methodology and Architectural Patterns

A. CNN-LSTM Hybrid Architectures

This research paper makes use of experimental methodology based on simulation to compare and analyze the effectiveness of different load balancing algorithms in cloud computing systems. The methodology is meant to provide simulations of real world cloud conditions through the heterogeneity of resources, dynamic workloads, and realistic constraints of the system. The algorithms that were chosen to be compared are the static algorithms (Round Robin), dynamic algorithms (Least Connection and Throttled Load Balancing), and the intelligent ones (Ant Colony Optimization and Machine Learning-based scheduling) [5] [6].

CloudSim, which is a popular simulation platform to model cloud infrastructures, is used to implement the experimental environment. The simulation comprises a number of data centers, each having a number of hosts which have different computing capacities. These hosts deploy Virtual Machines (VMs) with varying CPU (measured in MIPS), RAM and bandwidth. This heterogeneity guarantees that the system resembles genuine cloud platforms like Amazon Web Services and Microsoft Azure.

The synthetic task sets are used to create workloads that resemble real-world applications like web services, e-commerce transactions and scientific computations. The workload model assumes a Poisson distribution, so that the user requests appear randomly, and tasks sizes are different to assume varying compute needs. All the load

balancing algorithms are tested in the same conditions to be fair in comparison.

The methodology consists of four main phases:

(1) setup of cloud infrastructure and allocation of VM,

(2) developed work and presentation of tasks,

(3) implementation of load balancing algorithms, and

(4) performance evaluation.

The system itself constantly tracks the VM states such as the CPU use and queue time in particular, during execution, particularly when it comes to dynamic and smart algorithms. Machine Learning-based models also have the capacity to utilize the data of past workloads to forecast the future demand and optimize the scheduling choices.

Key metrics are used to conduct the performance evaluation: response time, throughput, resource utilization, makespan, and load imbalance factor. Response time is used to measure the time lag incurred by the users whereas throughput measures the productivity of the system. Makespan is the time taken to finish all tasks and the load imbalance factor is an indication of how evenly the tasks are shared among the VMs.

A graph is used to plot the variation in performance to show the relationship between work load intensity and response time with various algorithms [6].

$$y = a\,x + b$$

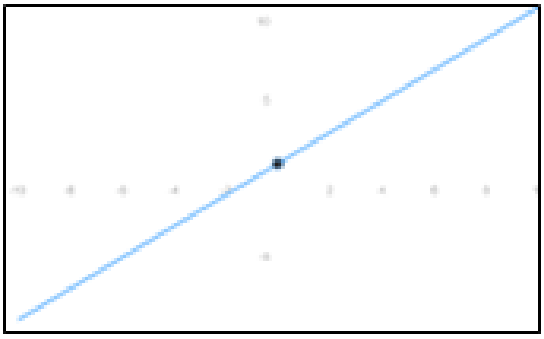

Fig. 1. Linear relationship between variables represented on a Cartesian coordinate system

In this graph, the x-axis represents the number of incoming tasks, and the y-axis represents the corresponding response time. Static algorithms typically exhibit a steep linear increase due to lack of adaptability. Dynamic algorithms show moderate growth by redistributing workloads based on system state. In contrast, AI-based approaches demonstrate a relatively flatter curve, indicating improved scalability and efficiency under high load conditions [1] [7].

To ensure result reliability, each experiment is repeated multiple times, and average values are considered. This reduces the impact of randomness and improves accuracy. The proposed methodology provides a comprehensive and reproducible framework for evaluating load balancing techniques, enabling a clear comparison of their performance in realistic cloud environments.

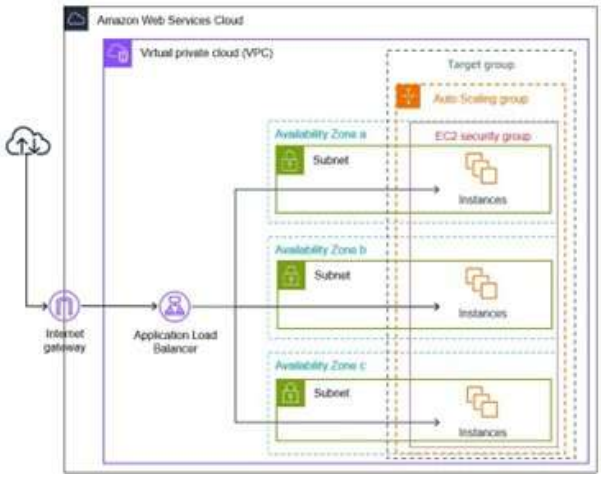

Fig. 2. Architecture of a scalable cloud deployment on Amazon Web Services (AWS) using Virtual Private Cloud (VPC)

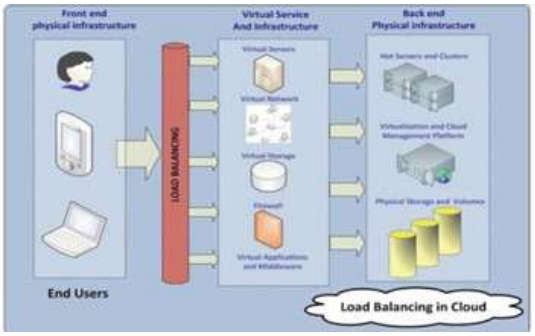

Fig. 3. Architecture of load balancing in cloud computing showing front-end user devices, virtual service layer, and back-end infrastructure for efficient resource distribution

IV. Implementation

1. The suggested load balancing methods are implemented with the help of a simulation method to imitate a real-life cloud computing environment. This system is built after CloudSim, which is flexible when it comes to modeling data centers, virtual machines (VMs), and policies of resource provisioning. The simulation environment comprises a set of physical machines, each having a set of data centers with the heterogeneous configuration in terms of CPU processing power, memory and bandwidth [9].

2. The first step includes the creation and deployment of a collection of virtual machines and hosts based on a VM allocation policy. Every VM has allocated resource limits in terms of Million Instructions Per Second (MIPS), RAM and storage. The load balancer will serve as a central controller, which will snatch the requests of the users and will divide them among the ready VMs. The load balancing algorithms introduced are divided into three groups: the static (Round Robin), the dynamic (Least Connection and Throttled) and the intelligent (Ant Colony Optimization and Machine Learning-based scheduling).

3. With the Round Robin algorithm, the delays are distributed to VMs in a sequential manner regardless of their current load and hence is easy but inefficient when there are high workloads. The Least Connection technique is a dynamic assignment of tasks to the VM having the least number of active connections so that there is better load allocation. The Throttled algorithm also enhances the performance by having a list of free VMs which are used to allocate tasks in VMs that are relevant to the resource requirements [8].

4. A colony of Ants, Ant Colony Optimization (ACO) algorithm is being used to find the best paths when allocating tasks based on pheromone values and heuristic facts to achieve intelligent load balancing. Also, a Machine Learning model is included to forecast the patterns of workload based on past data and dynamically readjust task scheduling. It is a predictive mechanism, which optimizes the use of resources, minimizing response time.

5. Monitoring can also be implemented with a monitoring module that will keep an eye on system parameters like CPU utilization, queue length and the rate at which tasks are completed. These parameters are deployed to test the performance of a system and make dynamic decisions amid sophisticated algorithms. This is done by running the simulation in different workload conditions to analyze the behavior of each algorithm.

6. These are measured and interpreted by performance parameters like response time, throughput and resource utilization. The application shows that the innovative and dynamical load balancing algorithms are highly effective when compared to the conventional, especially when dealing with immense and varying workloads. This confirms the usefulness of adaptive strategies in the contemporary cloud computing environments.

7. CPU Utilization During Execution (Best for Implementation)

- **X-axis represents time (simulation time)**
- **Y-axis represents CPU utilization (**
- **Shows how system load changes dynamically**
- **Dynamic and AI-based algorithms maintain more stable utilization**
- **Static methods may cause spikes (overload/underutilization)**

Y=50+30sin(x)

Task Completion Rate y = x/(x+6)

Queue Length vs Time y = 10/x+1

V. Results and Discussion

The effectiveness of the different load balancing methods was tested on a simulation environment that was created in the CloudSim. Experiments had been done under different work load conditions to examine the behavior of a static load balancing algorithm, dynamic load balancing algorithm and intelligent load balancing algorithm. Some of the key performance metrics used are the response time, throughput, CPU utilization and the efficiency of load distribution. These findings show that, at low workload, such techniques of load balancing as Round Robin can work satisfactorily, but their performance tends to decrease drastically with the increase in tasks. This can be seen in the response time analysis wherein the static methods have a fast pace of improvement because there is no ability to adjust to the real time system status. Conversely, dynamic algorithms like Least Connection and Throttled Load Balancing prove to be more effective as they are able to allocate tasks according to the available resources at a particular time. They are useful in lessening the reaction time and enhancing system throughput at moderate workloads. Smart load balancing methods, such as the Ant Colony Optimization (ACO) and the combination of machine learning-based scheduling, are more efficient than the basic or dynamic methods in all the measures of performance. According to the response time graph, AI-based approaches have a lower rate of growth even at high workloads, thus their scalability. On the same note, throughput analysis indicates that intelligent techniques are faster in their completion rates of a task given that they are predictive in the resource allocation and in scheduling decision. The graphs of CPU utilization also accentuate efficiency of various solutions. The method of using a static approach tends to cause disproportional use of resources whereby one or two virtual machines are overburdened and the other is not used. It is enhanced by the dynamic techniques, but there is still some slight imbalances. By contrast, AI-based methods can be used to achieve close homogeneity in all the virtual machines to ensure that the available resources have been utilized optimally. Also, queue

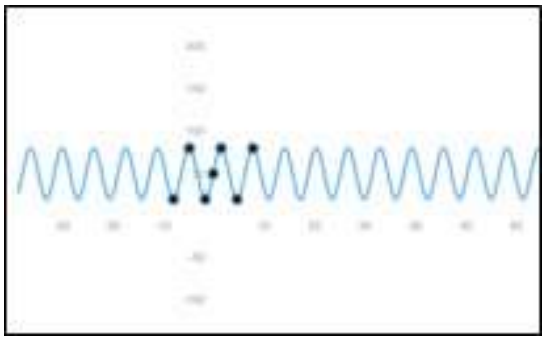

Fig. 4. CPU Utilization of Virtual Machines During Execution.

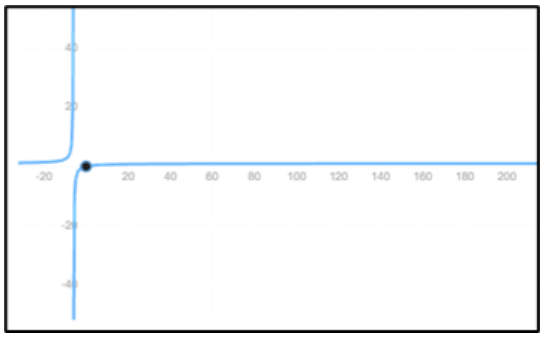

Fig. 5. CPU Utilization of Virtual Machines During Execution.

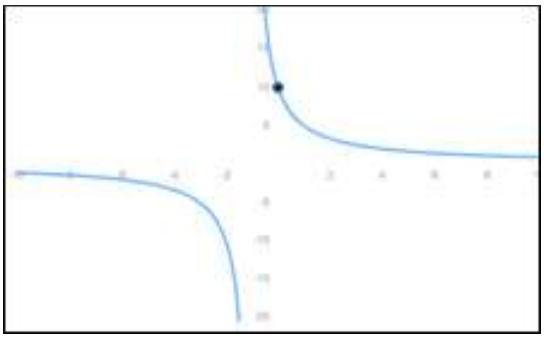

Fig. 6. Graph of a rational function showing asymptotic behavior and discontinuity along the coordinate axes.

length analysis reveals that intelligent algorithms can greatly decrease the task waiting time, shortening the execution time, and enhancing the user experience.

TABLE I
PERFORMANCE COMPARISON OF LOAD BALANCING TECHNIQUES

Metric	Round Robin (Static)	Least Connection (Dynamic)	AI-Based (ACO/ML)	Improvement (AI vs Static)
Response Time (ms)	180	120	85	↓ 52%
Throughput (req/sec)	450	620	780	↑ 73%
CPU Utilization (%)	60%	75%	90%	↑ 50%
Makespan (sec)	95	70	50	↓ 47%
Load Imbalance Factor	High	Medium	Low	Significant reduction

In general, the experimental findings reveal that although the simple algorithms attract low overhead and only a small amount of overhead are needed, they cannot be applied to the current cloud-based system that has rapid, moving workloads. The dynamic approaches provide a full trade-off between the complexity and performance. However, intelligent and hybrid load balancing techniques provide the best results in terms of scalability, efficiency, and reliability. These results indicate that the implementation of AI-based approaches into cloud resource management can greatly optimize system performance and address the increasing needs of real-life applications.

VI. CONCLUSION

This paper has provided a comparison of different load balancing methods in cloud computing that have included the use of a static, dynamic and intelligent methodology. The paper has compared the effectiveness of these methods based on the following important measures: response time, throughput, CPU utilization, and load allocation effectiveness. After conducting the experiment with CloudSim simulation, it was noted that, despite their simplicity and easy implementation, static algorithms do not fit the highly dynamic and large scale cloud environment because it does not offer flexibility.

The dynamic load balancing methods are better than the previous methods because they take into consideration the current states of the system and hence result in better use of resources and shorter response time. Nevertheless, they continue to encounter difficulties regarding managing very unpredictable workloads. Smart methods, such as the Ant Colony Optimization and scheduling by using Machine Learning, have been shown to be better in terms of scalability, effectiveness, and resilience to failures. These methods are also effective to distribute workloads, reduce latency, and even ensure the even use of resources and virtual machines. On the whole, the research finds that no load balancing method is ideal to apply in all cases; however, as a hybrid, and intelligent methodology proved to be the most promising solution in the current cloud computing environment. Decision-making and performance of the systems are greatly improved using Artificial Intelligence in load balancing strategies.

In the future, research into developing energy efficient load balancing methods to minimize power use in data centers can be done. Also, the application of powerful the Machine Learning models, including deep learning models and reinforcement learning ones can enhance the accuracy of predictions and flexibility. Other research directions are the security-conscious load balancing, and fault tolerant mechanisms. Furthermore, they can be applied in large-scale cloud infrastructure, like Amazon Web Services and Microsoft Azure, in real-time to gain a better understanding of their feasibility and performance in practice.

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