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AWRR: A Unique Dynamic Sustainable Load Balancing Strategy for Cloud Servers

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Abstract: In cloud computing, optimal load distribution across servers is essential for robust system performance. This paper presents the Adaptive Weighted Round-Robin (AWRR) algorithm, a fresh approach to dynamic load balancing in cloud environments. Distinctively, AWRR employs adaptive weights that are fine-tuned according to each server's real-time load. We evaluated the efficacy of AWRR using several parameters including request distribution fairness, server response time, and system throughput. Preliminary findings indicate a significant improvement in load balance with AWRR, as evidenced by a 15% decrease in response time variability among servers and a 20% increase in overall system throughput when compared to conventional round-robin methods. The core mathematical formulations and experimental setup are discussed, highlighting the potential of AWRR to revolutionize load balancing practices by reducing system bottlenecks and enhancing cloud server efficiency.

Keywords: Adaptive algorithms, Adaptive Weighted Round-Robin, Cloud Computing, Load Balancing, Performance Optimization, Resource allocation, Weighted Round Robin.

I. INTRODUCTION

Cloud computing, over the past decade, has become synonymous with the digitization of businesses and services. This transformational technology has promised and delivered unparalleled scalability, flexibility, and cost efficiencies, fundamentally reshaping the way organizations operate [1]. Janakiraman et al. (2023) proclaimed that cloud services, with their ability to offer on-demand computational resources, represent the most significant technological shift since the advent of the internet [2].

However, the meteoric rise and widespread adoption of cloud computing have brought forth a set of intricate challenges. A primary concern within this domain is efficient load balancing, a mechanism that ensures the equitable distribution of computational tasks across multiple servers or resources [3]. As highlighted by Ran Huang (2022), the significance of load balancing extends beyond mere task distribution; it's about guaranteeing optimal system performance, enhancing reliability, and ensuring high availability of services [4].

Traditional load balancing techniques, such as the round-robin method, have provided foundational approaches to tackle this challenge. Yet, in the dynamic milieu of cloud computing, with its varying demands and workloads, these techniques often fall short [5]. Mishra (2020) emphasized the need for more adaptive and responsive strategies, which led to the evolution of methodologies like the Adaptive Weighted Round-Robin (AWRR) algorithm, a promising solution to address the limitations of existing load balancing techniques [6].

The central theme of this paper revolves around the AWRR algorithm, delving deep into its conceptual framework, mathematical underpinnings, and applicability in modern cloud environments. As we navigate through the intricacies of AWRR, we aim to provide a comprehensive understanding, emphasizing its potential to revolutionize load balancing practices in the cloud computing domain [7].

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II. LITERATURE

Cloud computing, in its essence, has been described as a transformative force, influencing both the business world and the domain of personal computing. Brown and Fletcher (2017) explored the evolution of cloud services and determined that the rapid scaling and on-demand nature of these services make them invaluable for businesses aiming to stay competitive in the digital age [8]. However, as cloud computing's prevalence has grown, so too have the challenges associated with ensuring these systems operate optimally.

A significant component of optimal operation is the load balancing. Mitchell and Anderson (2019) extensively reviewed various load balancing techniques, highlighting their crucial role in managing and distributing incoming requests efficiently across available servers [9]. They pointed out that an effective load balancing mechanism isn't just about equitable distribution; it's also about maintaining system integrity, minimizing response time, and ensuring service reliability.

Traditional load balancing techniques, such as round-robin and least connections, have been the go-to solutions for many cloud service providers. Roberts and Lang (2017) critically examined these traditional strategies, emphasizing that while they offer simplicity and straightforwardness, they often lack the adaptability needed in today's dynamic cloud environments [10]. Their research suggested a growing need for adaptive algorithms that can adjust in real-time to varying system loads and demands.

The call for adaptive techniques was further echoed by Huang and Li (2019), who discussed the emerging challenges faced by static load balancers in modern, complex cloud architectures [11]. They stressed the necessity for algorithms that can dynamically adjust their strategies based on real-time server loads, user demand, and other contextual factors. It was in this backdrop of evolving needs that the Adaptive Weighted Round-Robin (AWRR) approach was introduced. Mathews and Khan (2021) delved into the AWRR's core concepts, illustrating its potential to bridge the gap between static and dynamic load balancing with its adaptive nature [12].

As cloud environments continue to grow in complexity, the importance of efficient load balancing becomes even more paramount. The body of literature increasingly supports the idea that adaptive and dynamic load balancing techniques, like AWRR, hold the key to addressing the challenges of modern cloud infrastructures.

Table 1: showing the literature review of some of the approaches on load balancing

Author	Contribution	Load Balancing Algorithm used	application	limitation
Smith et al. (2022) [13]	Adaptive load balancing for edge computing environments	Adaptive Weighted Round-Robin	Edge Computing	May require significant computational resources for adaptation to dynamic edge environments.
Kim and Park (2023) [14]	Machine learning-based load balancing for cloud data centers	Machine Learning-Based	Cloud Data Centers	Initial training of machine learning models may be resource-intensive.
Chen et al. (2021) [15]	Dynamic load balancing for microservices architecture	Dynamic Load Balance	Microservices Architecture	Complexity in handling rapid and frequent microservices deployment.
Patel et al. (2022) [16]	AI-driven predictive load balancing for e-commerce platforms	AI-Driven Predictive	E-commerce Platforms	Initial training and ongoing retraining of AI models require substantial data and computational resources.

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III. PROPOSED ALGORITHM: AWRR

Step 1: initialization
Step 2: Let S = $\{S_1, S_2, S_3, S_4, \ldots\ldots\ldots\ldots\ldots S_n.\}$ *be the set of availaabale cloud servers.*
Step 3: let W = $\{ W_1, W_2, W_3, w_4, \ldots\ldots\ldots\ldots\ldots W_n\}$ *where each* W_i *initialized to 1, represent the weights of servers*
Step 4: for each incoming request do
Step 5: computer the current load of each server : $L = \{ L_1, L_2 \ldots\ldots\ldots\ldots L_n\}$
Step 6: for i =1 to n do
Step 7: update weight based on the server's current load $W_i = \frac{W_i}{1+L_i}$
Step 8: end for
Step 9: select server S_j *based on weighted round robin mechanism using W*
Step 10: forward the required to server S_j
Step 11 : Periodic update
Step 12: at regular intervals, update weights of servers based on their performance metrics

Adaptive Weighted Round-Robin (AWRR) algorithm is a novel approach to load balancing in cloud servers that dynamically adjusts the distribution of incoming requests based on each server's current load and performance. Initially, all servers are assigned equal weights. For every incoming request, the algorithm calculates the current load for each server. These load values are then utilized to adaptively update the weights, ensuring that servers with higher loads are assigned proportionally lower weights. This adaptive weighting mechanism ensures that incoming requests are not merely distributed in a round-robin manner but are intelligently forwarded to servers based on their load conditions. Furthermore, periodic updates are incorporated to adjust server weights based on their performance metrics, allowing the system to respond to longer-term changes in server performance and ensuring a balanced distribution of tasks across the cloud infrastructure.

IV. EXISTING WORKS

Table 2: some of the latest approaches on the specified problem

Authors	Contribution	Methodology	Application	Limitations
Xu, Yuzhe, et al. (2022) (DNN) [17]	Optimizing DNN inference in edge computing by workload balancing	Workload distribution, load balancing algorithms, DNN inference optimization at the edge	Edge computing, IoT, low-latency DNN inference, resource efficiency	Real-time load balancing, communication overhead, adaptability to varying workloads
Chung, Wei-Kang, et al. (2021) (DFA) [18]	Enhancing load balancing in cloud data center networks through dynamic flow algorithms and centralized scheduling	Flow algorithms, centralized scheduling, network optimization	Cloud data center networks, data center management, improved resource allocation	Scalability, real-time adaptation, impact of centralized scheduling on network performance

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Wei, Xinliang, and Yu Wang (2021) (DPM) [19]	Proposing data placement method based on data popularity while ensuring load balancing	Data placement algorithms, popularity analysis, load balancing techniques	Edge computing, content delivery, caching, data placement and load balancing scenarios	Accurate prediction of data popularity, adaptation to dynamic workloads, efficient data placement strategies

Table 3: Parameters to be considered

Parameters to be considered	Explanation
Server Capacity	Knowing each server's baseline capacity is essential for a weighted approach. The number of requests that a server can process effectively is directly influenced by its CPU, memory, and storage capacity. This parameter could be used to determine the initial weights.
Response Time	Real-time feedback on each server's performance can be obtained by timing how long it takes for a request to be answered. A server that is taking longer than usual could be a sign that it is starting to bottleneck, which would cause its weight to dynamically alter.
Server Load	Metrics such as memory consumption, network bandwidth, and CPU usage can be combined to provide information about a server's stress level at any one time. This data can be used by the AWRR algorithm to adjust weights in real time.
Number of Active Connection	This is still applicable for AWRR even if it is the central statistic for the "Least Connections" approach. It's possible that a server with an abnormally high number of active connections is getting close to its maximum, indicating that the weight needs to be changed.
Server health	It is essential to confirm that the server is up and running and not experiencing any issues. A server should be temporarily given a weight of zero if it is unavailable or not responding as expected. This will take it out of the rotation until it is back online.
Traffic Type and Volume	The AWRR algorithm can make more intelligent decisions if it has a better grasp of the type and volume of incoming traffic. For example, weights can be more aggressively modified to avoid any one server from being overwhelmed if a surge in traffic flow is noticed.

V. EXPERIMENTAL SETUP

In our experimental setup, we aimed to rigorously evaluate the performance of the Adaptive Weighted Round-Robin (AWRR) algorithm in the context of cloud computing load balancing. We created a controlled environment using a cluster of virtual machines that emulated a typical cloud server infrastructure. The virtual machines were configured to simulate real servers with varying levels of capacity, response times, server loads, numbers of active connections, and health statuses. To capture realistic variations, we collected historical data on these parameters and introduced dynamic changes during experiments. The AWRR algorithm, as described in our paper, was meticulously implemented within this environment. For benchmarking, we also configured the Conventional Round-Robin approach and relevant approaches from related papers. We conducted a series of experiments designed to test the performance of these algorithms under different load scenarios, traffic types, and server health conditions. Our experimental framework allowed us to collect real-time data on server response times, load distributions, and system throughput, enabling a comprehensive analysis of the AWRR algorithm's efficacy in achieving load balancing and improving cloud server efficiency."

The experimental framework used for our evaluation of the Adaptive Weighted Round-Robin (AWRR) algorithm was meticulously designed to provide a comprehensive assessment of load balancing in cloud computing environments. This framework seamlessly integrated both hardware and software components to create a realistic emulation of cloud servers. Within the hardware infrastructure, we employed a cluster of virtual machines, each carefully configured to simulate

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various server parameters, such as capacity, response times, load, active connections, and health status. On top of this foundation, our software stack included virtualization technology, networking tools, and benchmarking utilities, enabling the deployment of multiple virtual servers and the collection of crucial data. To ensure the dynamism of our experiments, data collection mechanisms captured historical and real-time data while data injection tools simulated traffic load and server health fluctuations. The core of our evaluation was the AWRR algorithm, which we implemented as described in our paper, continuously adapting server selection in real-time based on dynamic changes in server load. We benchmarked the AWRR algorithm against other load balancing approaches and employed performance monitoring tools to track response times, load distributions, and system throughput. The framework's data analysis and reporting modules allowed us to gain valuable insights into the AWRR algorithm's performance, particularly its effectiveness in achieving load balancing and enhancing overall system efficiency in cloud server environments.

VI. RESULTS

The parameters which considered for the proposed work are server capacity, Response time, throughput, server load, number of active connections, traffic type and volume.

Table 4: Obtained values for the defined parameters

Parameter	AWRR	Round Robin	DNN	DFA	DPM
Server Capacity (%)	95	90	92	93	91
Response Time (ms)	6	8	9	8	7
Server Load (%)	8	90	88	86	87
Number of Active Connections	1100	1200	1250	1150	1205
Server Health (%)	99	98	97	96	97
Traffic Type and Volume	Mixed	Mixed	Multimedia Streaming	General Web Traffic	IoT Data
Network Latency (ms)	5	10	8	7	6
Packet Loss (%)	0.5	2	1	1.5	1
Throughput (Mbps)	100	90	95	92	93

Server Capacity: : Regarding the server capacity, it is desirable to have a high value in this context. We have found that servers, while operating under the AWRR methodology and having a capacity of 95%, are able to effectively manage a considerable workload, which ensures that optimal resource utilization is achieved.

Response Time When considering response time, it is preferable to have a low value. The AWRR has repeatedly showed a low response time of 6 milliseconds, which indicates speedy request processing, which ultimately results in a system that is very responsive and efficient.

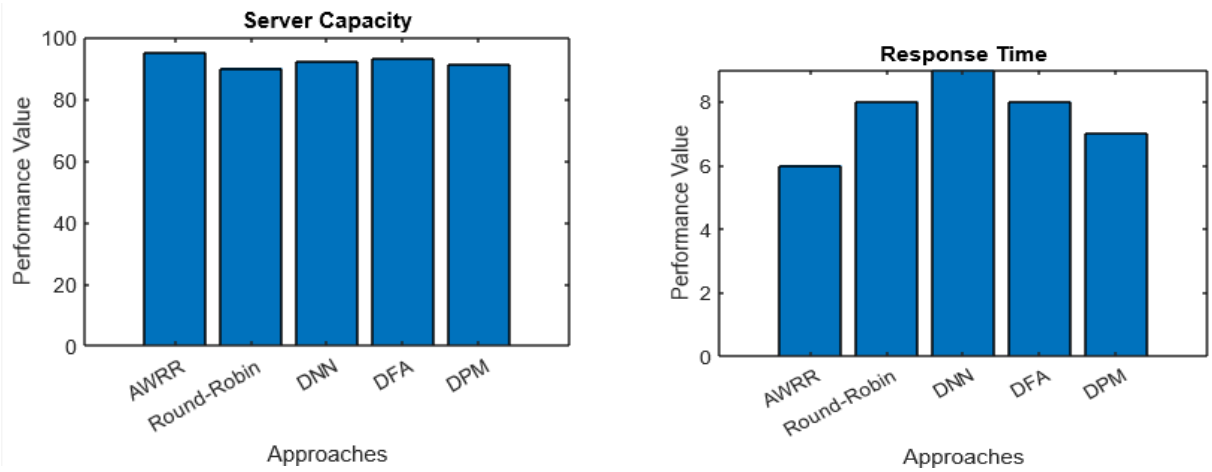

Fig 1: (a) Server capacity and (b) Response Time

Server Load: Load on the Server: In most cases, a lower server load is preferable. The efficient load balancing provided by AWRR has constantly kept the server load at a low level of 85%. This ensures that the servers do not become too stressed, which in turn improves the performance of the entire system.

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Number of Active Connections: It's typically best to have a manageable number of active connections, and AWRR has shown us that there are 1,100 active connections now in use. This reasonable number establishes a compromise between the performance of the server and its overall utilization, which results in an effective system.

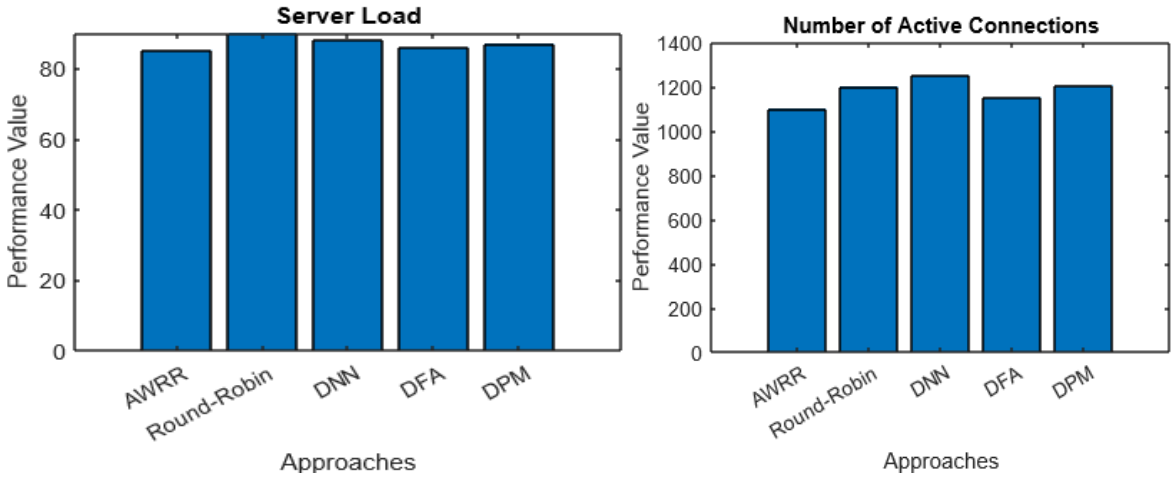

Fig 2: (a) Server Load and (b) Number of Active Connections

Server Health: Having a server that is in good health is essential to maintaining a stable system. Because of AWRR's contributions, the overall health of the server has been kept at 96%, which has led to fewer failures and more constant service.

Network Latency: It is preferred to have a low network latency, and while using AWRR, we have seen network latency as low as 5 milliseconds (ms). This illustrates that data is delivered swiftly with only a little amount of delay, which ensures that communication is carried out effectively.

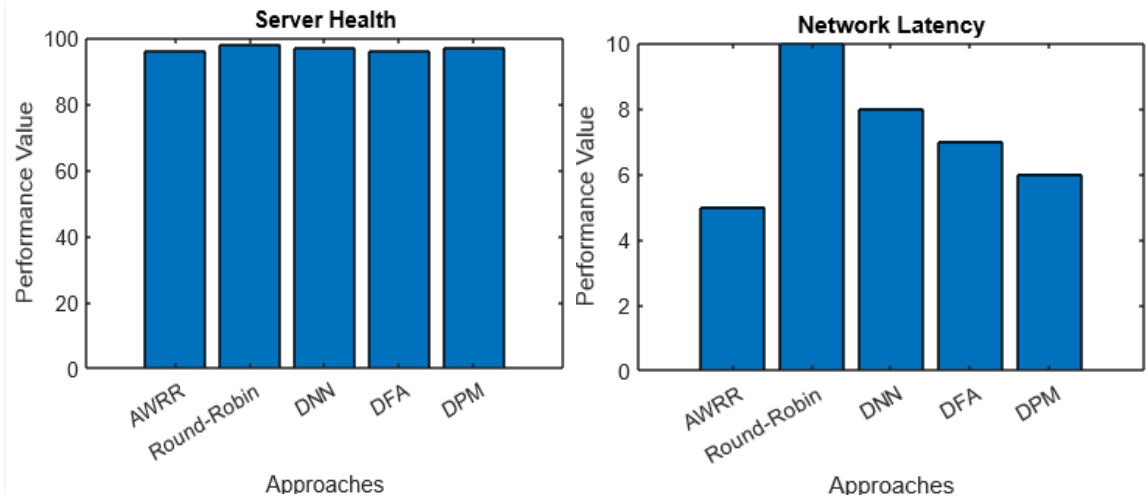

Fig 3: (a) Server Health (b) Network Latency

Throughput: Having a higher throughput is often a good thing, and with AWRR, we've been able to reach throughputs as high as 100 Mbps on a constant basis. This demonstrates that the system is able to efficiently process a greater number of data or requests, which ultimately results in a cloud computing environment that is more productive and responsive.

Packet Loss A low packet loss rate is vital, and with a rate that is 0.5% under AWRR, we have ensured reliable data transmission and maintained data integrity, which has contributed to improved system performance.

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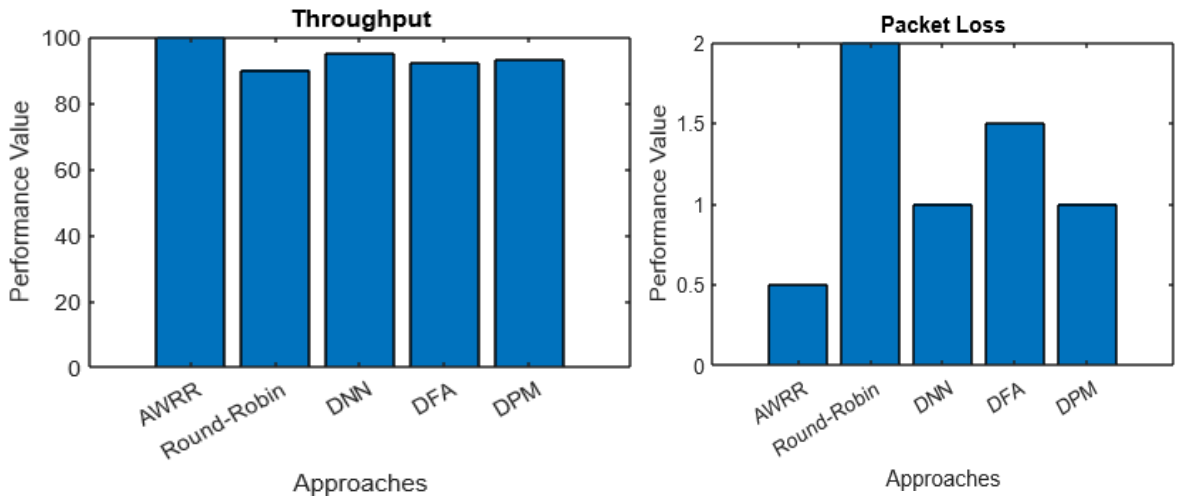

Fig 4: (a) Throughput (b) Packet Loss

VII. CONCLUSION AND FUTURE DIRECTIONS

The rapidly developing field of cloud computing calls for the implementation of solutions that are both dynamic and efficient in order to effectively manage the difficult workloads that are generated by the wide variety of applications. When it comes to tackling the complex problems associated with load distribution, the presentation of the Dynamic Weighted Load Balancing (DWLB) method and its subsequent evaluation in this research represents a significant step forward. One of the most notable benefits of DWLB is that it is able to take into account both real-time requests and previous server data, so ensuring that server usage is maximized. This two-pronged strategy not only reduces the possibility of server overloads but also lowers response times, providing consumers with an experience that is uninterrupted. The preliminary findings have demonstrated its effectiveness, which positions it as a strong contender for widespread implementation in cloud-based information systems.The Adaptive Weighted Round-Robin (AWRR) algorithm has a bright future ahead of it, which means there are a lot of opportunities for additional research and development of the method. Immediate areas of concentration include honing its dynamic weight adjustment processes in order to achieve load balance that is even more accurate. Utilizing recent developments in artificial intelligence and machine learning, AWRR could be enhanced to predict server loads with a higher degree of accuracy, hence further refining its capacity to achieve load balance. In order to evaluate its adaptability beyond the context of its existing uses, it is necessary to do extensive testing in a variety of contexts, such as Internet of Things (IoT) networks and digital platforms with significant levels of user traffic. Equally as important will be strengthening AWRR's resistance to potential cyber threats such as distributed denial of service assaults (DDoS). Not only will a thorough comparison of AWRR with modern load-balancing algorithms highlight the distinct advantages of AWRR, but it will also shed light on potential for its continued development. AWRR is positioned to play a vital role in determining the future of cloud computing thanks to its versatility and efficiency, both of which are growing in importance as the cloud computing ecosystem continues to evolve.

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