iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: V Month of publication: May 2026

DOI: https://doi.org/10.22214/ijraset.2026.83316

Dynamic Load Balancing Approaches for Energy-Efficient Cloud Computing Systems

Satya Prakash[1], Sharad Kumar[2], Jagdeep Singh[3], Manoj Kumar[4], Sachin Kumar[5]
[1]*School of Engineering & Technology, Shri Venkateshwara University, Gajraula , U.P. India*
cse.satyaprakash@gmail.com
Orcid ID: 0009-0001-0781-0706
[2]*School of Engineering & Technology, Shri Venkateshwara University, Gajraula , U.P. India*
sharad.choudhary007@gmail.com
Orcid ID: 0009-0009-5859-9689
[3]*School of Engineering & Technology, Shri Venkateshwara University, Gajraula , U.P. India*
jgdp3120@gmail.com
Orcid ID: 0009-0003-3971-166X
[4]*School of Engineering & Technology, Shri Venkateshwara University, Gajraula , U.P. India*
manoj091@gmail.com
Orcid ID: 0009-0003-3971-166X
[5]*School of Engineering & Technology, Shri Venkateshwara University, Gajraula , U.P. India*
sachingahalout11@gmail.com
Orcid ID: 0009-0003-7247-3085

Abstract: Cloud computing has emerged as a powerful paradigm for delivering scalable and on-demand computing resources to users across diverse application domains. However, the rapid growth of cloud services and data-intensive applications has significantly increased energy consumption and resource management challenges within cloud data centers. Efficient load balancing plays a vital role in enhancing system performance, minimizing response time, maximizing resource utilization, and reducing energy consumption in cloud computing environments. This paper presents a dynamic load balancing approach designed to improve the energy efficiency and operational performance of cloud computing systems. The proposed framework dynamically distributes workloads among virtual machines and cloud servers based on resource availability, processing capability, and workload conditions. The model integrates intelligent decision-making mechanisms to optimize task allocation while preventing server overload and underutilization. Additionally, the approach aims to reduce energy consumption by minimizing unnecessary resource activation and improving overall system efficiency. Experimental analysis demonstrates that the proposed dynamic load balancing technique achieves improved throughput, reduced response time, enhanced scalability, balanced resource utilization, and lower energy consumption compared to traditional load balancing methods. The study highlights the significance of adaptive and energy-aware load balancing strategies in developing sustainable and high-performance cloud computing infrastructures for modern digital applications.
Keywords: Cloud Computing, Dynamic Load Balancing, Energy Efficiency, Resource Utilization, Virtual Machines, Task Scheduling, Cloud Data Centers, Performance Optimization, Scalable Computing.

I. INTRODUCTION

Cloud computing has transformed the modern digital ecosystem by providing flexible, scalable, and cost-effective computing services through the internet. Organizations, industries, educational institutions, healthcare systems, and businesses increasingly rely on cloud platforms for data storage, application hosting, virtualized services, and real-time computational processing. The ability of cloud computing to offer on-demand access to shared resources such as servers, storage systems, software applications, and networking infrastructure has significantly improved operational efficiency and reduced infrastructure costs. With the rapid growth of big data analytics, artificial intelligence, Internet of Things (IoT), and online services, cloud environments are experiencing a substantial increase in workload demands and computational complexity. Despite its numerous advantages, cloud computing environments face major challenges associated with resource management, workload distribution, system scalability, and energy consumption.

Cloud data centers consume a massive amount of electrical power due to continuous execution of large-scale applications and the operation of thousands of physical and virtual machines. Excessive energy consumption not only increases operational costs but also contributes to environmental concerns such as carbon emissions and electronic waste generation. Therefore, developing energy-efficient cloud infrastructures has become a significant research objective for both academic researchers and cloud service providers. Load balancing is considered one of the most critical techniques for improving the performance and efficiency of cloud computing systems. The primary objective of load balancing is to distribute incoming tasks and workloads evenly among available computing resources in order to avoid server overloading and underutilization. Effective load balancing improves response time, throughput, fault tolerance, scalability, and resource utilization while ensuring reliable service delivery to end users. Traditional static load balancing methods are often unable to adapt to dynamic workload variations and changing resource conditions in modern cloud environments. As a result, dynamic load balancing approaches have gained considerable attention due to their capability to make real-time decisions based on current system states and workload conditions. Sakib et al. [1] proposed a dynamic load balancing approach for cloud infrastructure aimed at enhancing energy efficiency and optimizing resource utilization. Their study focused on adaptive workload distribution mechanisms capable of reducing server overload conditions while improving overall cloud system performance. Dynamic load balancing techniques continuously monitor resource availability, processor utilization, memory usage, and network traffic to allocate tasks efficiently across cloud servers and virtual machines. These approaches help optimize resource consumption, reduce execution delays, and improve overall system performance. Moreover, integrating energy-aware mechanisms within dynamic load balancing frameworks enables cloud systems to minimize unnecessary power usage by intelligently managing active and idle resources. Such techniques support the development of sustainable and environmentally friendly cloud infrastructures commonly referred to as green cloud computing systems. Several researchers have proposed heuristic, metaheuristic, and artificial intelligence-based load balancing algorithms to address the challenges of resource optimization and energy efficiency in cloud environments. However, many existing approaches still face limitations related to scalability, computational overhead, real-time adaptability, and uneven workload distribution under highly dynamic conditions. Ala'anzy et al. [2] investigated dynamic load balancing mechanisms in IoT-enabled smart healthcare systems integrated with fog computing. The proposed framework improved network performance through intelligent workload allocation across fog nodes. Their work demonstrated the importance of dynamic balancing strategies in minimizing latency and enhancing resource availability in real-time healthcare applications. Therefore, there is a need for efficient dynamic load balancing strategies capable of balancing performance optimization and energy conservation simultaneously in high-performance cloud computing systems. This paper presents a dynamic load balancing approach for energy-efficient cloud computing systems that aims to optimize resource allocation, reduce energy consumption, and enhance overall system performance. The proposed framework dynamically distributes workloads among virtual machines based on resource utilization and workload characteristics to achieve efficient task execution and balanced system operation. The remainder of this paper is organized as follows: Section II presents the related work and existing load balancing techniques in cloud computing environments. Section III discusses the proposed dynamic load balancing framework and system architecture. Section IV describes the methodology and implementation process used for workload distribution and energy optimization. It also presents the experimental results and performance evaluation of the proposed approach. Finally, Section V concludes the paper and highlights future research directions in energy-efficient cloud computing systems.

II. LITERATURE SURVEY

Recent Recent advancements in cloud computing and distributed computing environments have significantly increased the importance of efficient load balancing techniques for improving system performance, resource utilization, and energy efficiency. Adnan et al. [3] introduced a dynamic resource allocation method using the Bat Optimization Algorithm for load balancing in fog nodes. The optimization-based approach improved task allocation efficiency and reduced resource congestion within distributed computing systems. The authors concluded that metaheuristic optimization algorithms can effectively support balanced workload management in fog environments. Alrwbaye and Agarwal [4] developed a secure and energy-efficient load balancing model for fog computing in Software Defined Networking (SDN) environments. Their research integrated security-aware and energy-conscious mechanisms to improve communication reliability and reduce computational overhead. The study emphasized the growing need for secure and sustainable workload management frameworks in distributed systems. Sharma and Kumar [5] discussed the role of Artificial Intelligence (AI) in enhancing data security and privacy in smart city infrastructures. Although their work primarily focused on cybersecurity, the study highlighted the importance of AI-driven intelligent decision-making approaches that can also be integrated into cloud resource management and load balancing systems for improved operational efficiency. Kumar et al. [6] proposed an adaptive resource-aware virtual machine placement strategy for energy-efficient cloud computing environments.

Their approach optimized virtual machine allocation based on resource utilization and energy consumption parameters. The results showed significant improvements in energy savings and efficient resource management in cloud data centers. B. K et al. [7] introduced deep reinforcement learning and metaheuristic hybrid models for intelligent cloud load distribution. Their proposed hybrid framework combined the learning capability of deep reinforcement models with optimization-based techniques to achieve efficient workload balancing and reduced execution delays. The study demonstrated improved scalability and adaptability in dynamic cloud environments. Vikas et al. [8] presented a hybrid deep belief network and Harris Hawks Optimizer-based intrusion detection model for wireless sensor networks. Although the primary objective was network security enhancement, the research illustrated the effectiveness of hybrid intelligent optimization techniques that can be extended to cloud computing environments for efficient resource allocation and system optimization. Varanasi [9] provided a comprehensive survey on orchestration, scheduling, and energy optimization in cloud infrastructures. The study reviewed several resource management and load balancing mechanisms designed to improve computational efficiency and reduce power consumption in cloud systems. The survey identified scalability, dynamic adaptability, and energy optimization as major research challenges in modern cloud computing. Malicheti et al. [10] proposed an energy-efficient cloud-based resource management and 5G network orchestration framework. Their work focused on integrating intelligent resource scheduling and network orchestration techniques to support efficient communication and reduced energy utilization in next-generation cloud-enabled 5G systems. Sharma et al. [11] analysed vulnerabilities in academic network servers and proposed AI-driven intrusion detection mechanisms for enhancing cybersecurity. Their research emphasized the role of artificial intelligence and intelligent monitoring techniques in improving the reliability and security of distributed computing infrastructures, which are also critical aspects of cloud computing environments. A. K. J et al. [12] developed a semantic-driven framework for energy-efficient task scheduling in dynamic cloud environments. The proposed model utilized semantic analysis techniques for intelligent task allocation and workload management. Experimental results demonstrated improvements in execution efficiency, energy conservation, and resource utilization. Rehyadd and Mohan [13] proposed an optimized load balancing framework for IoT–Fog–Cloud environments aimed at improving energy efficiency and workload distribution. Their approach minimized processing delays and balanced resource consumption across distributed nodes. The study highlighted the significance of integrated cloud-fog architectures for achieving efficient and scalable computing performance. Sharma et al. [14] designed and evaluated an AI-based energy-efficient load balancing algorithm for cloud data centers. Their approach employed artificial intelligence techniques to dynamically allocate workloads and optimize server utilization while reducing energy consumption. Experimental evaluation showed enhanced system throughput, minimized response time, and improved energy efficiency compared to conventional load balancing techniques.

III. PROPOSED METHODOLOGY

In this study, a dynamic and energy-aware load balancing framework is proposed for high-performance cloud computing environments to improve resource utilization, reduce energy consumption, and enhance overall system performance. The proposed framework dynamically distributes workloads among virtual machines and cloud servers using intelligent monitoring and adaptive task scheduling mechanisms. The system continuously analyses workload conditions, resource utilization, and energy consumption parameters to achieve balanced workload allocation while maintaining optimal cloud performance. The proposed approach integrates real-time resource monitoring, dynamic task migration, workload prediction, and energy optimization mechanisms to support sustainable and efficient cloud operations.

A. System Architecture Overview

The proposed dynamic load balancing framework for energy-efficient cloud computing environments is designed as an intelligent multi-layer cloud management architecture capable of handling large-scale computational workloads efficiently, as shown in fig. 1. The architecture consists of multiple interconnected layers including the Cloud Infrastructure Layer, Monitoring and Analysis Layer, Dynamic Load Balancing Controller, Energy Optimization Module, and User Management Layer. The Cloud Infrastructure Layer contains physical servers, virtual machines, storage systems, and networking resources responsible for executing user applications and processing workloads. The Monitoring and Analysis Layer continuously observes system conditions and collects real-time performance metrics such as CPU utilization, memory usage, bandwidth consumption, and power utilization. The Dynamic Load Balancing Controller acts as the central decision-making unit that dynamically allocates workloads based on resource availability and workload conditions. The Energy Optimization Module reduces unnecessary energy consumption by consolidating workloads and placing idle resources into low-power operational states. The User Management Layer provides an interface for cloud administrators to monitor workload distribution and overall cloud performance efficiently.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

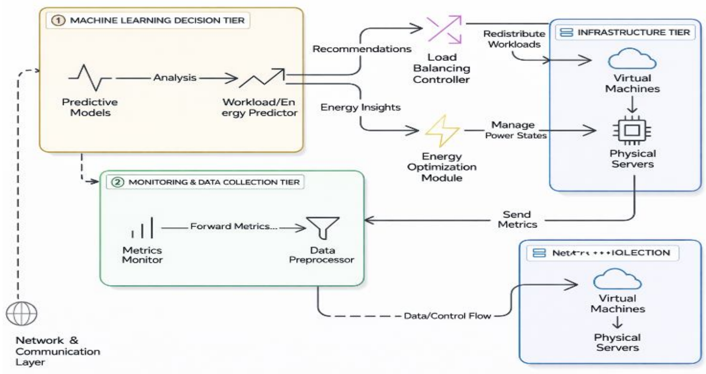


Fig. 1. Intelligent Dynamic Load Balancing Architecture for Energy-Efficient Cloud Computing

B. Data Collection and Resource Monitoring

The data collection and resource monitoring stage plays an important role in ensuring efficient workload distribution within the proposed cloud framework. The system continuously gathers operational information from virtual machines, physical servers, and distributed cloud nodes using monitoring agents and cloud management interfaces. Important system parameters including CPU utilization, memory utilization, task queue length, storage usage, network bandwidth consumption, response time, and server energy consumption are collected in real time for analysis. Since cloud environments are highly dynamic and continuously changing, the collected data may contain temporary fluctuations and workload inconsistencies. Therefore, preprocessing operations such as normalization, filtering, and threshold analysis are applied to improve data consistency and reliability. The monitoring system analyses the collected information to classify resources into overloaded, balanced, and underutilized categories. This real-time monitoring mechanism enables the framework to identify resource congestion conditions early and supports adaptive workload allocation decisions for improving resource utilization and cloud system stability.

C. Dynamic Workload Prediction and Task Allocation

The proposed framework employs dynamic workload prediction and adaptive task allocation techniques to improve system performance and maintain balanced workload distribution across the cloud infrastructure. Instead of depending on traditional static scheduling mechanisms, the framework continuously analyses current workload conditions and predicts future workload variations using intelligent decision-making strategies. The task allocation module evaluates several operational parameters including resource availability, processing capability, workload intensity, and execution requirements before assigning tasks to virtual machines. Incoming tasks are categorized into lightweight, medium, and heavy computational workloads to improve scheduling efficiency and resource management. The system dynamically selects the most suitable and least-loaded virtual machine for executing incoming workloads. Whenever workload imbalance or server overload conditions are detected, the Dynamic Load Balancing Controller initiates workload migration from overloaded servers to underutilized resources. This adaptive workload management mechanism reduces response delays, improves throughput, and enhances overall resource utilization efficiency. The predictive workload analysis capability also enables the system to prepare additional resources during high-demand conditions, thereby preventing performance degradation and maintaining service continuity.

D. Energy-Aware Load Balancing Scheme

The Energy-Aware Load Balancing Scheme is one of the major components of the proposed framework designed to minimize energy consumption while maintaining high-performance cloud operations. Unlike traditional load balancing approaches that primarily focus on workload distribution and response time optimization, the proposed framework integrates energy optimization strategies directly into the workload allocation process. The system continuously monitors the energy utilization of physical servers and virtual machines during workload execution. Based on current workload conditions and resource utilization levels, the framework dynamically consolidates workloads onto fewer active servers whenever possible. Idle or underutilized resources are transferred into low-power operational states to reduce unnecessary energy wastage and operational costs. The adaptive energy-aware mechanism also activates additional computing resources proactively during high-demand periods to avoid system overload and service interruptions. This intelligent workload consolidation strategy improves resource efficiency, reduces energy consumption, and supports environmentally sustainable cloud computing operations while maintaining service quality and computational performance.

E. Framework Implementation and Performance Evaluation

The implementation and performance evaluation stage is designed to validate the effectiveness of the proposed dynamic load balancing framework under varying workload conditions and operational scenarios. The framework can be implemented using cloud simulation and virtualization platforms such as CloudSim, OpenStack, or distributed cloud testbed environments. The proposed system is evaluated using both synthetic and real-time workload datasets to analyze its performance under normal and high-load conditions. Several important performance evaluation metrics including response time, throughput, task completion time, resource utilization, migration time, scalability, processing delay, and energy consumption are considered during the analysis. The proposed framework is compared with conventional load balancing approaches such as Round Robin, Static Load Balancing, and traditional Dynamic Scheduling algorithms to measure performance improvements and operational efficiency. The experimental analysis is expected to demonstrate that the proposed energy-aware dynamic load balancing framework achieves lower energy consumption, improved resource utilization, reduced response time, enhanced scalability, and balanced workload distribution compared to existing methods. Furthermore, the intelligent and adaptive nature of the framework enables efficient handling of workload fluctuations without affecting overall cloud system stability and service performance.

IV. RESULT AND ANALYSIS

The experimental analysis aimed to evaluate the effectiveness of the proposed framework under varying workload conditions and resource utilization scenarios. The system performance was analysed using important evaluation parameters including response time, energy consumption, CPU utilization, throughput, and task completion efficiency.

A. System Configuration and Experimental Setup

The experimental implementation of the proposed Dynamic Energy-Aware Load Balancing (DEALB) framework was carried out using the CloudSim-3.0.3 simulation platform, which provides a reliable environment for modeling and evaluating cloud computing infrastructures. The experiments were designed to simulate realistic cloud data center conditions with heterogeneous workloads and dynamically changing resource demands. The simulation environment was configured using an Intel Core i7 processor operating at 3.4 GHz with 16 GB RAM and Ubuntu 22.04 LTS operating system. The cloud infrastructure consisted of 10 physical host servers and 50 virtual machines with varying CPU, memory, storage, and bandwidth capacities. A total of 250 cloudlets with different execution sizes and workload intensities were submitted to the system to simulate real-time cloud workload conditions. The proposed framework was implemented using Java within the CloudSim environment. Performance metrics such as average response time, CPU utilization, energy consumption, and task completion rate were recorded during the simulation process. Both low-load and high-load operational scenarios were considered to evaluate the scalability, adaptability, and efficiency of the proposed framework. The built-in energy consumption model available in CloudSim was used to monitor server power utilization and evaluate energy efficiency improvements achieved by the proposed load balancing framework.

B. Performance Comparison on Average Response Time

Average response time is one of the most important performance evaluation parameters in cloud computing environments because it directly affects user experience and service quality. The proposed DEALB framework achieved the lowest response time among all compared load balancing techniques due to its adaptive workload distribution and intelligent task migration capabilities. The framework efficiently allocated workloads to the most suitable virtual machines and prevented server overload conditions during peak workloads. The average response time is calculated using the following equation (1):

$$ART = \frac{1}{n}\sum_{i=1}^{n}(W_i + S_i) - - - - - - - - (1)$$

where:

- ART represents Average Response Time,
- W_i denotes waiting time of task i,
- S_i represents service time of task i, and
- n indicates the total number of tasks.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

TABLE I. SYSTEM RESPONSE TIME ANALYSIS

Load Balancing Algorithm	Average Response Time (ms)	Minimum (ms)	Maximum (ms)
Round Robin (RR)	530	475	600
Throttled Load Balancing (TLB)	485	450	550
Energy-Aware Scheduling (EAS)	420	390	480
Proposed DEALB	340	310	380

TABLE I presents the comparative analysis of average response time achieved by different load balancing algorithms. The Round Robin approach achieved an average response time of 530 ms, while Throttled Load Balancing reduced it to 485 ms. The Energy-Aware Scheduling technique further improved the performance with a response time of 420 ms. However, the proposed DEALB framework achieved the minimum response time of 340 ms, demonstrating superior workload management and faster task execution performance.

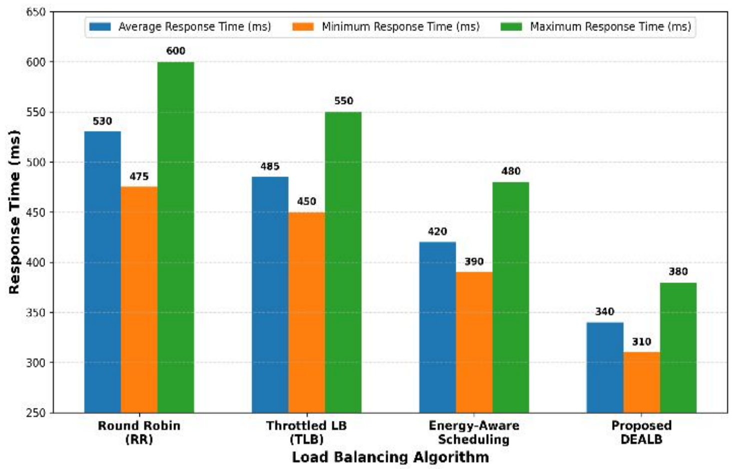


Fig. 2. Average Response Time Comparison Among Load Balancing Techniques

The results indicate that the proposed DEALB framework significantly reduces response delays and improves system responsiveness compared to conventional load balancing approaches in fig. 2.

C. Analysis of Energy Consumption

Energy consumption is a critical concern in modern cloud computing infrastructures because large-scale data centers require substantial electrical power for continuous operation. The proposed DEALB framework integrates energy-aware workload consolidation and intelligent resource allocation mechanisms to minimize unnecessary power consumption. The framework continuously monitors server utilization and dynamically consolidates workloads onto active servers while transferring idle or underutilized resources into low-power operational states. This strategy significantly reduces energy wastage and improves overall power efficiency within the cloud infrastructure. The total energy consumption of the cloud system is calculated using the following equation:

$$E_{total} = \sum_{i=1}^{N} \int_{0}^{T} P_i(t)\, dt ------ (2)$$

where:

- E_{total} represents total energy consumption,
- $P_i(t)$ denotes power consumption of node i at time t,
- N represents total number of nodes, and
- T indicates total execution time.

TABLE II. ENERGY CONSUMPTION ANALYSIS OF VARIOUS MODELS

Load Balancing Algorithm	Energy Consumption (kWh)	Reduction (%)
Round Robin (RR)	128	3.20%
Throttled Load Balancing (TLB)	119	6.80%
Energy-Aware Scheduling (EAS)	104	18.70%
Proposed DEALB	82	35.90%

TABLE II presents the comparative analysis of energy consumption achieved by different load balancing approaches. The Round Robin algorithm consumed 128 kWh of energy during simulation, while Throttled Load Balancing reduced energy usage to 119 kWh. Energy-Aware Scheduling further minimized consumption to 104 kWh. The proposed DEALB framework achieved the lowest energy consumption of 82 kWh, representing significant energy savings compared to conventional approaches.

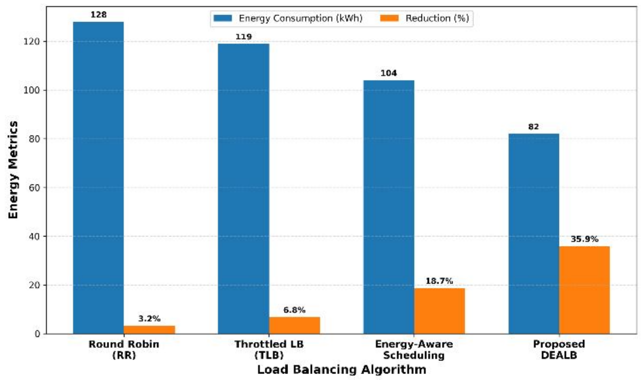


Fig. 3. Energy Consumption Comparison Across Cloud Load Balancing Techniques

Fig. 3. demonstrates that the proposed framework effectively reduces cloud infrastructure energy consumption while maintaining high-performance workload execution and balanced resource utilization.

D. CPU Utilization Efficiency

Efficient CPU utilization is essential for improving resource management and maximizing cloud system performance. Uneven workload distribution often leads to server overload conditions and inefficient resource usage in traditional load balancing systems. The proposed DEALB framework dynamically distributes workloads based on current resource conditions to maintain balanced CPU utilization across all virtual machines. The CPU utilization efficiency is calculated using the following equation:

$$U_{CPU} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{CPU_i^{active}}{CPU_i^{total}} \times 100\right) - - - - - (3)$$

where:

- U_{CPU} represents average CPU utilization,
- CPU_i^{active} denotes active CPU usage of node i,
- CPU_i^{total} represents total CPU capacity of node i, and
- N indicates the total number of computing nodes.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

TABLE III. CPU UTILIZATION ANALYSIS WITH VARIOUS LOAD BALANCING ALGORITHMS

Load Balancing Algorithm	Average Utilization (%)	Variance (%)
Round Robin (RR)	68.7	13.2
Throttled Load Balancing (TLB)	72.9	10.5
Energy-Aware Scheduling (EAS)	78.4	8.3
Proposed DEALB	86.2	5.8

TABLE III presents the CPU utilization performance of different load balancing approaches. The proposed framework achieved the highest average CPU utilization of 86.2% while maintaining lower utilization variance compared to other methods. This indicates balanced workload allocation and improved computational efficiency across the cloud infrastructure.

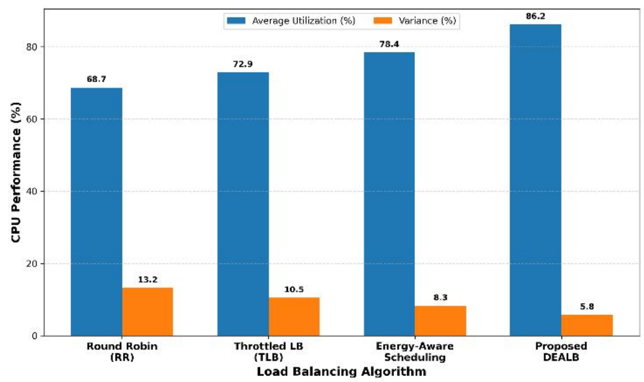


Fig. 4. CPU Utilization Comparison Among Load Balancing Frameworks

The lower variance value achieved by the proposed framework indicates improved workload balancing and reduced resource congestion across cloud servers.

V. CONCLUSION AND FUTURE SCOPE

This paper presented a Dynamic Energy-Aware Load Balancing (DEALB) framework for high-performance cloud computing environments to improve resource utilization, reduce energy consumption, and enhance overall system performance. The proposed framework employed adaptive workload distribution, intelligent resource monitoring, and energy-aware task allocation mechanisms to achieve balanced cloud operations under varying workload conditions. Experimental analysis conducted using the CloudSim simulation environment demonstrated that the proposed DEALB framework outperformed conventional load balancing approaches such as Round Robin, Throttled Load Balancing, and Energy-Aware Scheduling in terms of average response time, throughput, CPU utilization, and energy efficiency. The framework effectively minimized workload imbalance, reduced server overload conditions, and optimized energy consumption while maintaining service quality and computational stability. The obtained results confirmed that the proposed approach provides an efficient and sustainable solution for modern cloud computing infrastructures. Future research can focus on integrating artificial intelligence and deep learning techniques for intelligent workload prediction and autonomous resource management. Furthermore, the framework can be implemented and validated in real-time cloud platforms such as OpenStack and Amazon Web Services (AWS) to analyze its scalability and performance in large-scale distributed cloud environments. The integration of edge computing, fog computing, and reinforcement learning-based optimization mechanisms can also be explored to further enhance the efficiency, adaptability, and reliability of next-generation cloud computing systems.

REFERENCES

[1] S. Sakib, A. Katangur and R. Dubey, "A Dynamic Approach to Load Balancing in Cloud Infrastructure: Enhancing Energy Efficiency and Resource Utilization," 2025 IEEE Cloud Summit, Washington, DC, USA, 2025, pp. 87-94, doi: 10.1109/Cloud-Summit64795.2025.00021.

[2] M. A. Ala'anzy, R. Zhanuzak, R. Akhmedov, N. Mohamed and J. Al-Jaroodi, "Dynamic Load Balancing for Enhanced Network Performance in IoT-Enabled Smart Healthcare With Fog Computing," in IEEE Access, vol. 12, pp. 188957-188975, 2024, doi: 10.1109/ACCESS.2024.3516362.

[3] M. M. Adnan, Y. Shaikh, R. A C, D. R. Babu and V. Selvi, "Load Balancing in Fog Nodes Involves in Dynamic Resource Allocation Method Utilizing the Bat Optimization Algorithm," 2024 Third International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), Ballari, India, 2024, pp. 1-5, doi: 10.1109/ICDCECE60827.2024.10549639.

[4] T. Alrwbaye and R. Agarwal, "Secure and Energy-Efficient Load Balancing for Fog Computing in SDN Environments," 2025 International Conference on Next Generation of Green Information and Emerging Technologies (GIET), Gunupur, India, 2025, pp. 1-6, doi: 10.1109/GIET65294.2025.11234876.

[5] V. Sharma and S. Kumar, "Role of Artificial Intelligence (AI) to Enhance the Security and Privacy of Data in Smart Cities," 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2023, pp. 596-599, doi: 10.1109/ICACITE57410.2023.10182455.

[6] S. Kumar, A. Jain and A. Pareek, "An Adaptive Resource-Aware Virtual Machine Placement for Energy-Efficient Cloud Computing Environments," 2026 Innovations in Machine, Engineering, and Digital Conference (IMED), Kota Kinabalu, Malaysia, 2026, pp. 1-5, doi: 10.1109/IMED68921.2026.11484105.

[7] B. K, S. S. Priscila and P. B M, "Deep Reinforcement and Meta-Heuristic Hybrid Models for Intelligent Cloud Load Distribution," 2026 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2026, pp. 1249-1256, doi: 10.1109/ICEARS67481.2026.11416651.

[8] Vikas, R. P. Daund, D. Kumar, P. Charan, R. S. K. Ingilela and R. Rastogi, "Intrusion Detection in Wireless Sensor Networks using Hybrid Deep Belief Networks and Harris Hawks Optimizer," 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2023, pp. 1631-1636, doi: 10.1109/ICESC57686.2023.10193270.

[9] S. R. Varanasi, "Smart Resource Management in Cloud Infrastructure: A Survey on Orchestration, Scheduling, and Energy Optimization," 2025 5th International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT), MANDYA, India, 2025, pp. 1-7, doi: 10.1109/ICERECT65215.2025.11377150.

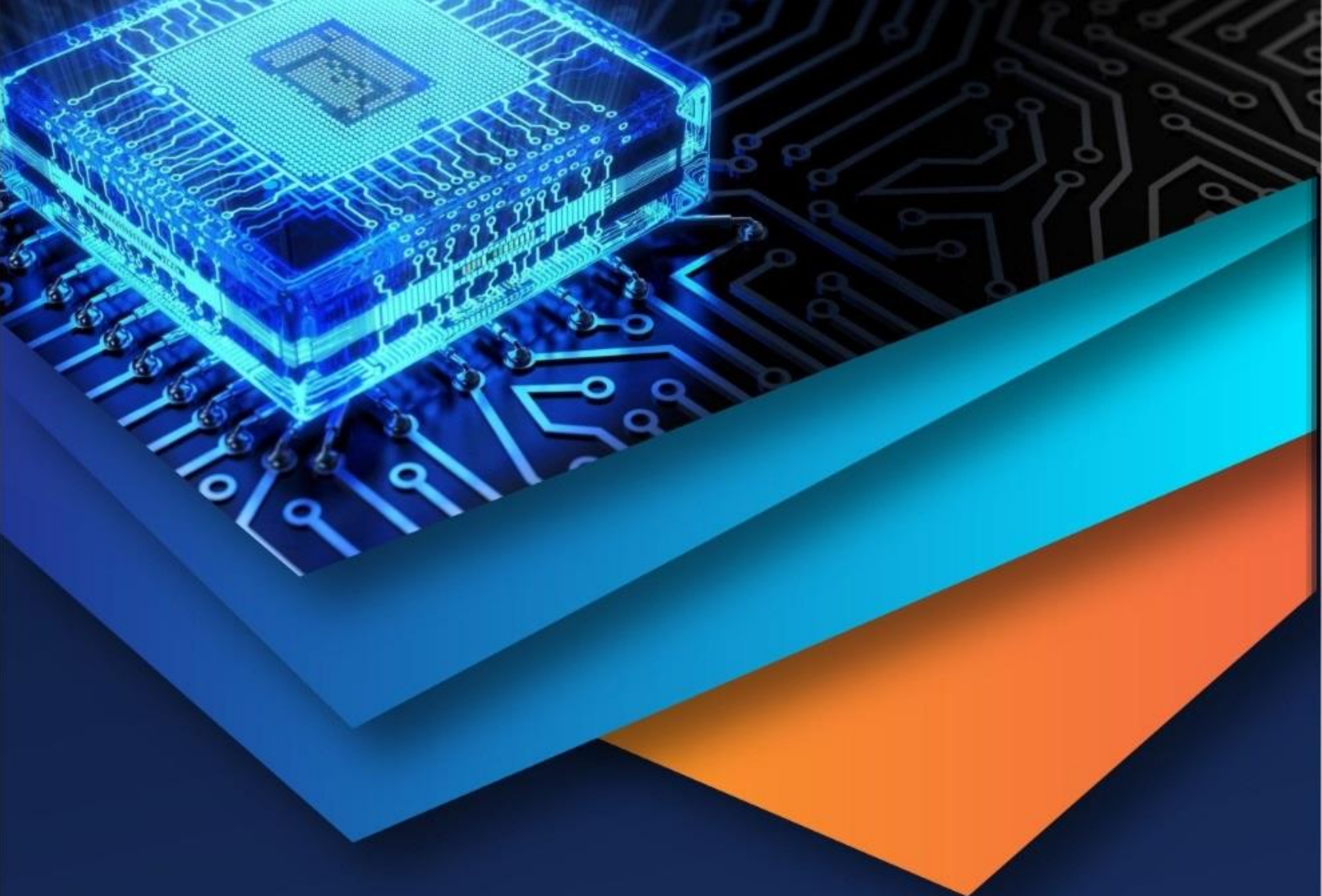
[10] A. Malicheti, A. Papuri, A. Cheguri, N. Kumar, V. Satyakumar and S. Yoon, "Energy Efficient Cloud-based Resource Management and 5G Network Orchestration," 2025 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bengaluru, India, 2025, pp. 1-6, doi: 10.1109/CONECCT65861.2025.11306607.

[11] V. Sharma, P. Chauhan, T. K. Vashishth, S. Kaushik, P. Rana and K. Chaudhary, "Analyzing Vulnerabilities in Academic Network Servers: A Foundation for AI-Driven Intrusion Detection Systems," 2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS), Mohali, India, 2025, pp. 1093-1098, doi: 10.1109/IETACS68750.2025.11385339.

[12] A. K. J, R. S. Amshavalli, V. R. D, V. S. V. Varma and G. Kavitha, "A Semantic Driven Framework for Energy Efficient Task Scheduling in Dynamic Cloud Environment," 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL), Bhimdatta, Nepal, 2025, pp. 274-281, doi: 10.1109/ICSADL65848.2025.10933265.

[13] R. Rehyadd and D. S. Mohan, "Optimised Load Balancing for Energy Efficiency in IoT–Fog–Cloud Frameworks," 2025 International Conference on Next Generation of Green Information and Emerging Technologies (GIET), Gunupur, India, 2025, pp. 1-6, doi: 10.1109/GIET65294.2025.11234807.

[14] V. Sharma, A. Chaudhary, S. Kumari, T. K. Vashishth, K. Choudhary and P. Chauhan, "Design and Evaluation of AI-Based Energy-Efficient Load Balancing Algorithm in Cloud Data Centers," 2025 IEEE 1st International Conference on Recent Trends in Computing and Smart Mobility (RCSM), Bhopal, India, 2025, pp. 1-6, doi: 10.1109/RCSM67767.2025.11506712.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR:
7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY