Vol 8, Issue 11, 2025 **Impact Factor: 8.535** DOI: https://doi.org/10.31426/ijamsr.2025.8.11.8921

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

An Intelligent Non-Cooperative Game Theory Approach for Cloud Resource Allocation

Jitender

Research Scholar, Ph.D. - Department of Computer Science and Engineering,
Sunrise University, Alwar, Rajasthan.

Email: jitender.kathuria@gmail.com

Dr. Gulshan Kumar

Department of Computer Science and Engineering, Sunrise University, Alwar, Rajasthan.

ABSTRACT

This study presented a game theory-based resource allocation model for optimizing cloud computing environments. The proposed model aimed to improve resource utilization, Quality of Service, SLA compliance, energy efficiency, and system stability. A non-cooperative game theory approach was adopted, where cloud users and service providers acted as rational agents to maximize their utilities. The model was evaluated using a Python Notebook-based simulation framework and compared with traditional methods such as FCFS and Round Robin. Results showed improved resource utilization, reduced latency, higher throughput, better task completion rate, fewer SLA violations, and lower energy consumption. Although direct allocation cost increased, the improved performance justified the cost. The study concludes that game theory offers an intelligent and adaptive solution for cloud resource allocation.

Keywords: *Cloud Computing, Game Theory, Resource Allocation.*

I. INTRODUCTION

Cloud computing has emerged as one of the most significant technological advancements in the modern digital world. It has changed the traditional way of storing data, running applications, managing servers, and accessing computing resources. In earlier computing systems, organizations had to maintain their own physical infrastructure, including servers, storage devices, networking equipment, software platforms, and security systems. This required large investment, continuous maintenance, technical manpower, and regular upgrades. However, cloud computing has reduced these limitations by providing computing services through the internet on a flexible and on-demand basis. Users can access servers, storage, databases, applications, and other computing services without owning the physical infrastructure directly. This has made cloud computing highly useful for business organizations, educational institutions, healthcare systems, banking sectors, e-commerce platforms, research organizations, and government services. The major features of cloud computing

IJAMSR
**International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**

include scalability, flexibility, cost-effectiveness, resource sharing, virtualization, and on-demand service delivery. Scalability allows users to increase or decrease resources according to their requirements. Flexibility helps users access cloud services from any location through the internet. Cost-effectiveness is achieved because users pay only for the resources they use instead of investing in expensive physical infrastructure. Resource sharing enables multiple users to use the same cloud infrastructure efficiently. Virtualization allows physical resources to be divided into several virtual resources so that different users can use them independently. These features have made cloud computing one of the most important foundations of digital transformation. As the number of cloud users continues to increase, the efficient management of cloud resources has become a major concern for cloud service providers and researchers.

Resource allocation is one of the most important issues in cloud computing. It refers to the process of assigning available computing resources such as CPU, memory, storage, bandwidth, and virtual machines to different users, applications, and tasks according to their needs. In a cloud environment, many users access the same shared infrastructure at the same time. These users may have different requirements related to performance, cost, response time, reliability, availability, and quality of service. Therefore, cloud service providers must allocate resources in such a way that the available infrastructure is used efficiently and users receive satisfactory service. If resources are not allocated properly, several problems may occur, such as low resource utilization, high operational cost, increased response time, service delay, energy wastage, low throughput, and violation of Service Level Agreements. The cloud computing environment is highly dynamic because user demands change continuously. At one time, the workload may be very low, while at another time, the system may experience heavy traffic and high demand for computing resources. For example, e-commerce websites may experience more traffic during festival sales, educational platforms may face higher load during online examinations, and healthcare systems may require quick data processing during emergencies. In such situations, fixed or static resource allocation techniques are not sufficient because they do not respond effectively to real-time workload changes. Static methods may lead to over-provisioning or under-provisioning of resources. Over-provisioning means allocating more resources than required, which results in wastage and higher cost. Under-provisioning means allocating fewer resources than required, which causes slow performance, service delays, and user dissatisfaction. Therefore, intelligent and adaptive resource allocation methods are needed to manage cloud resources effectively.

Traditional resource allocation techniques such as First-Come First-Serve, Round Robin, and priority-based scheduling are simple and easy to implement. However, these methods have several limitations in complex cloud environments. First-Come First-Serve allocates resources according to the order of request arrival, but it does not always consider task priority or resource demand. Round Robin distributes resources in a cyclic manner, but it may not be suitable for tasks with different processing requirements. Priority-based scheduling gives preference to high-priority tasks, but it may ignore fairness among users. These traditional approaches are not always capable of handling dynamic workloads, competitive user behaviour, cost optimization, and quality of service requirements. Hence, there is a need for more advanced approaches that can manage the strategic and

IJAMSR
International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

competitive nature of cloud computing. Cloud computing is not only a technical environment but also a strategic environment. In a cloud system, different users compete for limited resources. Each user wants to obtain maximum resources at minimum cost, while cloud service providers aim to increase revenue, improve resource utilization, reduce energy consumption, and maintain service quality. These objectives may conflict with one another. For example, users may demand high performance at low cost, while providers need to balance performance with profitability and infrastructure limitations. This creates a decision-making situation where the action of one participant affects the outcome of others. Therefore, resource allocation in cloud computing can be understood as a strategic interaction among different decision-makers.

Game theory provides a powerful mathematical framework for studying strategic decision-making problems. It deals with situations where multiple rational participants, known as players, choose strategies to maximize their own benefits or utility. In the context of cloud computing, the players may be clouding users, service providers, virtual machines, applications, or data centers. Their strategies may include requesting resources, selecting service plans, bidding for resources, setting prices, adjusting workload distribution, or sharing infrastructure. The payoff or utility may be measured in terms of cost reduction, better performance, improved response time, higher resource utilization, energy saving, or increased revenue. By applying game theory, cloud resource allocation can be modeled as an interaction among multiple decision-makers. One of the most important concepts in game theory is Nash Equilibrium. It represents a stable condition in which no player can improve its benefit by changing its strategy alone while the strategies of other players remain unchanged. In cloud resource allocation, Nash Equilibrium can help achieve a balanced allocation pattern where users receive appropriate resources and providers maintain efficient utilization of infrastructure. It also helps reduce unnecessary competition among users and prevents the misuse or monopolization of resources. Non-cooperative game models are especially useful in public cloud environments where users act independently and compete for limited resources. These models can control selfish user behaviour through pricing mechanisms, utility functions, and allocation rules.

Cooperative game theory is another important approach for cloud resource management. Unlike non-cooperative games, cooperative game models encourage participants to work together for collective benefit. In cloud computing, users, virtual machines, data centers, or service providers may form coalitions to share resources, balance workload, reduce cost, and improve system performance. Fairness mechanisms such as the Shapley value can be used to distribute benefits among participants according to their contribution. Cooperative models are especially useful in federated cloud, hybrid cloud, and multi-cloud environments where collaboration among different cloud entities can improve efficiency and reduce operational expenses. Stackelberg game models are also useful in cloud resource allocation. In this type of game, one player acts as a leader and other players act as followers. Usually, the cloud service provider acts as the leader by setting resource prices, service policies, or allocation limits. Users act as followers and respond by selecting resources according to their requirements and budgets. This model is highly suitable for pricing-based resource allocation because it helps providers influence user behaviour while maintaining profitability and service efficiency. Stackelberg game theory can be applied in Infrastructure-as-a-Service platforms, where pricing decisions and user demand directly affect resource utilization.

Vol 8, Issue 11, 2025 **Impact Factor: 8.535** DOI: https://doi.org/10.31426/ijamsr.2025.8.11.8921

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Auction-based game models are another effective method for cloud resource allocation. In these models, users submit bids based on their resource requirements and willingness to pay. The cloud provider allocates resources according to auction rules. Auction-based allocation is useful in dynamic cloud environments because it allows resources to be distributed according to real-time demand and market conditions. It also encourages users to reveal their actual resource needs and supports transparent allocation. Such models help in improving resource utilization, reducing wastage, and maintaining economic balance between users and service providers. In recent years, the integration of game theory with artificial intelligence and machine learning has created new opportunities for cloud resource allocation. Machine learning techniques can predict future workload patterns, user behavior, and resource demand. These predictions can be combined with game-theoretic models to make resource allocation more accurate and adaptive. Reinforcement learning can help the system learn from previous allocation results and improve decision-making over time. AI-enhanced game-theoretic models can support real-time allocation, reduce response time, improve energy efficiency, and maintain Quality of Service under uncertain and changing conditions.

Quality of Service is a major concern in cloud computing. Users expect cloud services to be fast, reliable, secure, and affordable. Important QoS parameters include response time, latency, throughput, availability, task completion rate, reliability, and service continuity. Cloud service providers usually define these requirements through Service Level Agreements. If the provider fails to meet the agreed performance standards, it may face penalties, loss of customer trust, and reduced market reputation. Therefore, an effective resource allocation model must ensure that resources are distributed in a way that satisfies SLA conditions and improves user experience. Energy efficiency is also an important issue in modern cloud computing. Large data centers consume a huge amount of electricity for operating servers, cooling systems, storage devices, and networking equipment. Inefficient resource allocation may keep many servers active even when they are underutilized. This increases energy consumption and operational cost. Game theory-based allocation can help reduce energy wastage by balancing workloads, consolidating tasks, and minimizing idle resources. It also supports green computing by reducing carbon emissions and promoting sustainable use of computing infrastructure.

Although game theory offers many advantages, its application in cloud resource allocation also faces certain challenges. One major challenge is computational complexity. In large-scale cloud environments, thousands of users and multiple types of resources may be involved, making it difficult to find equilibrium solutions quickly. Another challenge is incomplete information, because users and providers may not always know the strategies, demands, or preferences of others. The heterogeneous nature of cloud resources also increases complexity, as CPU, memory, storage, and bandwidth have different characteristics and costs. Security, privacy, and truthful behavior are additional concerns, especially in competitive environments where users may try to manipulate the system for personal benefit. The present study focuses on optimizing resource allocation in cloud computing environments using game theory-based approaches. The study aims to examine how strategic interaction among cloud users and service providers can improve resource utilization, cost efficiency, Quality of Service, SLA satisfaction, and energy efficiency. It considers the competitive and dynamic nature of cloud systems and attempts to achieve a balanced and fair allocation of resources. By comparing game theory-based methods with traditional resource allocation techniques, the study evaluates whether game theory can provide a more intelligent, adaptive, and efficient solution for cloud resource management.

In conclusion, cloud computing has become an essential part of modern digital infrastructure. However, the efficient allocation of computing resources remains a major challenge due to dynamic workloads, increasing user demand, multi-user competition, cost limitations, and quality requirements. Traditional allocation techniques are often insufficient to manage these challenges effectively. Game theory provides a suitable framework for modelling the strategic behaviour of cloud users and service providers. Through non-cooperative, cooperative, Stackelberg, auction-based, and AI-enhanced models, game theory can improve fairness, efficiency, scalability, and sustainability in cloud resource allocation. Therefore, this research explores the role of game theory in optimizing cloud computing resources and highlights its potential for developing reliable, cost-effective, and sustainable cloud systems.

II. REVIEWS OF LITERATURE

Rawat et al. (2025) were reported to have emphasized that cloud computing had transformed the way businesses and individuals accessed and utilized computing resources. They highlighted that efficient virtual machine placement was crucial for optimizing resource utilization, reducing operational costs, energy consumption, service level agreement violations, and virtual machine migrations, as well as minimizing execution time and ensuring overall cloud service performance. Their study was described as introducing a novel approach that combined human brainstorming with the computational capabilities of Artificial Neural Networks (ANN) to tackle the virtual machine placement problem in cloud environments. It was explained that the hybrid technique leveraged the collective intelligence of brainstorming to generate diverse placement strategies, which were then evaluated and refined using an ANN trained on historical cloud resource allocation data. The authors were noted to have argued that integrating human creativity with ANN's predictive power could overcome limitations of traditional placement algorithms that struggled with dynamic workloads and changing resource demands. The manuscript reportedly detailed the process of generating strategies through brainstorming, data collection and preprocessing, ANN model development, and the integration of these components into an efficient placement system. Experimental results were claimed to demonstrate improvements in resource allocation, service performance, energy consumption, execution time, SLA compliance, and migration reduction compared to static and meta-heuristic methods. The proposed BSO-ANN hybrid technique was observed to outperform existing approaches across performance metrics, combining human ingenuity with data-driven insights to adapt to evolving cloud workloads. Overall, the study was recognized as contributing practical solutions to cloud resource management and offering guidance for service providers to enhance the efficiency and quality of cloud-based services.

Wang and Yang (2025) highlighted that resource scheduling optimization in edge-cloud collaborative computing had been a critical challenge due to dynamic workloads, latency constraints, and limited edge resources. They proposed a deep reinforcement learning (DRL)-based scheduling

IJAMSR

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

approach, which aimed to enhance task processing efficiency, minimize overall processing time, optimize resource utilization, and control task migrations. Their experimental results indicated that the DRL model had outperformed traditional scheduling algorithms, reportedly reducing total processing time by up to 18% and improving resource utilization by 12% under high task loads. Additionally, the study noted that DRL effectively balanced task allocation, resulting in approximately 30% fewer task migrations compared to priority-based and load-balancing methods. However, they acknowledged that issues remained regarding learning efficiency, training overhead, and convergence stability, and suggested that future research should focus on improving algorithm fault tolerance and accelerating training convergence to better manage large-scale and uncertain scheduling environments.

Alozie et al. (2024) argued that capacity planning had been essential for optimizing resource allocation in cloud computing environments, ensuring efficient resource utilization to meet demand while minimizing costs. They noted that Site Reliability Engineering (SRE) provided a systematic approach to capacity planning by integrating reliability, scalability, and operational efficiency into cloud resource management. The study examined how SRE principles and practices could be applied to enhance capacity planning, particularly in optimizing resource allocation and maintaining system performance. It highlighted the definition and significance of capacity planning in cloud computing, emphasizing its role in balancing supply and demand. By applying SRE methodologies, the authors suggested that organizations were able to implement robust capacity planning strategies aligned with business objectives and operational requirements. Key SRE practices, such as monitoring, forecasting, and automated scaling, were reviewed for their effectiveness in predicting and addressing capacity needs. The paper discussed how SRE approaches enhanced capacity planning through metrics and data-driven insights to guide resource allocation decisions, stressing the importance of real-time monitoring and predictive analytics in identifying bottlenecks and proactively adjusting resources. Additionally, the integration of automation tools was described as improving responsiveness to changing demand patterns. Case studies of successful SRE implementations were presented, illustrating practical benefits such as improved resource utilization, cost savings, and enhanced system reliability. The authors concluded that adopting an SRE-driven capacity planning strategy enabled organizations to achieve optimal resource allocation, reduce operational overhead, and maintain high levels of performance and availability.

Zhang et al. (2024, April) discussed the widespread adoption of cloud computing in recent years, explaining that it involved centralized computing resources through which users could perform computations, with the cloud computing center returning the results of program processing. They noted that cloud computing served not only individual users but also enterprises, highlighting that purchasing cloud servers allowed users to avoid buying large numbers of computers, thereby reducing computing costs. According to a report cited by China Economic News Network, they mentioned that the scale of cloud computing in China had reached 209.1 billion yuan. The authors emphasized the importance of rational resource allocation in cloud computing, describing how cloud computing centers, with limited resources, managed sequential user requests, each requiring a specific number of cloud resources at designated times.

IJAMSR

International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Lekkala (2024) highlighted that the advancement in cloud computing had created a growing need for effective resource management, emphasizing the dynamic allocation of computing, storage, and network resources to meet evolving workloads. The study discussed how machine learning (ML) and deep learning (DL) approaches could be applied to develop predictive algorithms for resource allocation in cloud systems. Lekkala proposed an AI-based method to forecast workloads, resource usage, and real-time objectives, aiming to optimize resource allocation and enhance clients' Quality of Service while significantly reducing overall costs. The experimental evaluation, conducted using realistic cloud traces, indicated that the proposed solution outperformed traditional rule-based and heuristic-based approaches, achieving approximately 25% higher resource utilization and 30% fewer quality-of-service violations. The paper concluded that the presented dynamic resource allocation framework had the potential to substantially improve the efficiency, effectiveness, and competitiveness of cloud computing systems.

Chen (2023) discussed cloud computing as one of the most successful technologies for providing on-demand services via the Internet, highlighting its advantages of hyperscale, modernization, reliability, universality, high scalability, and pay-on-demand model. The author noted, however, that with the rapid growth of content distribution and interactive computing services, such as social networking and online scientific processes, the capacity of cloud data centers had become limited and could not meet business demands during peak hours. To address the resulting challenges of handling large data volumes, Chen mentioned that multiple cloud systems had been introduced to pool clouds together, offering a unified set of services collaboratively. The study focused on the resource allocation problem in cloud environments and proposed a multi-objective task optimization scheduling method based on dynamic programming. Chen described how the method first outlined the resource allocation process in a multi-cloud environment, then established a progress model for multi-user tasks, formalized the multi-user task optimization problem, and designed a solution algorithm using dynamic programming. Simulation experiments were conducted to evaluate the method, and the results indicated that it could effectively optimize both time and cost in multi-user task scheduling.

Lyu et al. (2023) were reported to have highlighted that unmanned aerial vehicle (UAV) communications had emerged as a significant technology for enhancing emergency communication networks. Their study was said to have investigated computing offloading and resource allocation in nonorthogonal multiple access (NOMA)-based UAV emergency communication scenarios, aiming to reduce the computational overhead of terminal devices. It was indicated that they formulated a joint task offloading and resource allocation problem, where the computation overhead of marine Internet of Things (IoT) devices was measured as a weighted combination of task completion time and energy consumption. The authors were described as having modeled the optimization of IoT device transmission, UAV computing resource allocation, task offloading, and carrier assignment as an NP-hard mixed-integer nonlinear programming problem. To address its complexity, the problem was reportedly decomposed into two subproblems: resource optimization and task offloading. The resource allocation problem was reportedly solved by decoupling it and applying quasi-convex and convex optimization techniques, while a low-complexity task offloading algorithm was designed using a coalition game approach to achieve a Nash-stable solution. Their numerical results were noted to have validated the effectiveness of the proposed algorithm, demonstrating improvements compared with other schemes in the literature.

Wang et al. (2022) investigated task offloading and resource allocation as critical components of edge computing. They noted that an effective task offloading strategy combined with a proper resource allocation scheme could reduce task processing time and lower system energy consumption. They observed that most existing studies on task migration in edge computing focused primarily on resource allocation between terminals and edge servers, often neglecting the substantial computing resources available in cloud centers. To address this, they proposed a coarse-grained task offloading strategy alongside an intelligent resource matching scheme under Cloud-Edge collaboration. They took into account the heterogeneity of mobile devices and inter-channel interference, and formulated task offloading decisions for multiple end-users as a game-theory-based task migration model aimed at maximizing system utility. Furthermore, they introduced an improved game-theory-based particle swarm optimization algorithm to determine optimal task offloading strategies. Their experimental results indicated that the proposed approach outperformed existing schemes in terms of latency and energy consumption and maintained scalability as the number of mobile devices increased.

Zeng (2022) conducted a game-theoretic optimization study on IoT energy efficiency. The study addressed the problem of selecting suitable backbone access points for wireless sensor nodes to optimize energy consumption. Zeng first established a mathematical model for system-level energy optimization in the free-choice access point scenario and then proposed a cooperative game model with an associated utility function. The study noted that over 30% of future connections could be supported by cellular networks, presenting significant challenges for mobile operators. The paper also examined mainstream IoT technologies in mobile network development, particularly NB-IoT, analyzing its application principles, key technologies, and role in industrial promotion and commercialization. Zeng demonstrated that the optimal access point allocation corresponded to the equilibrium of the proposed game and introduced a non-correlated parallel learning algorithm that allowed the system to converge to this equilibrium with very low probability of failure. Compared with other models, the approach improved efficiency by about 12% and accuracy by about 8%, showing practical applicability.

III. RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research methodology adopted for the study entitled “Game Theory-Based Approaches for Optimizing Resource Allocation in Cloud Computing Environments.” The methodology explains the systematic procedure followed to design, develop, simulate, and evaluate the proposed resource allocation model. Since cloud computing environments involve multiple users, applications, virtual machines, and service providers sharing limited resources, the allocation of resources becomes a critical task. Efficient allocation of CPU, memory, storage, and bandwidth is necessary to improve system performance, reduce operational cost, maintain Quality of Service, satisfy Service Level Agreement conditions, and minimize energy consumption.

Cloud computing systems are dynamic because user requirements change continuously according to workload, application type, time, and service demand. Traditional resource allocation techniques such as First-Come First-Serve, Round Robin, and priority-based scheduling are simple and useful in basic computing environments, but they often fail to handle the competitive and strategic behavior of users in modern cloud systems. Therefore, this study adopts a game theory-based approach in which cloud users and service providers are considered rational decision-makers. The proposed methodology provides a clear framework for problem identification, system modeling, data generation, model implementation, simulation analysis, and performance evaluation. The study used a Python Notebook-based simulation environment to test and compare the proposed model with traditional approaches.

3.2 Research Design

The research design of this study is experimental and analytical in nature. The experimental part includes the creation of a simulated cloud computing environment where users submit resource requests and service providers allocate resources according to the proposed game theory-based strategy. The analytical part focuses on evaluating the performance of the proposed model using different performance parameters such as resource utilization, response time, throughput, latency, cost, SLA compliance, task completion rate, and energy consumption.

The study does not depend on a live commercial cloud platform because real cloud workload data is often difficult to access due to privacy, security, and infrastructure limitations. Therefore, synthetic simulation data was generated to represent realistic cloud computing workload conditions. The generated data included resource demand, user requests, available resources, allocation values, task execution time, cost factors, and system performance indicators. This helped in testing the proposed model under different workload conditions in a controlled environment.

The research design followed a step-by-step process. First, the problem of inefficient resource allocation in cloud computing was identified. Second, the objectives of the study were defined. Third, a simulation-based cloud model was developed. Fourth, game theory was applied to model the strategic interaction between users and service providers. Fifth, the proposed model was implemented using Python. Finally, the results were compared with traditional methods to evaluate the effectiveness of the proposed approach.

3.3 Problem Identification

Resource allocation is one of the major challenges in cloud computing. In a cloud environment, many users access the same infrastructure at the same time. Each user may demand different amounts of CPU, memory, bandwidth, and storage. If resources are not allocated properly, the cloud system may suffer from underutilization, overloading, poor response time, low throughput, high energy consumption, and SLA violations.

Traditional allocation methods often fail to respond effectively to changing workloads. For example, First-Come First-Serve allocates resources according to request arrival order, but it does not consider resource priority or user utility. Round Robin distributes resources equally, but it may not be suitable for tasks with different sizes and execution requirements. Priority-based scheduling gives preference

IJAMSR
International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

to high-priority tasks, but it may reduce fairness for normal users. Due to these limitations, there is a need for an intelligent and adaptive resource allocation approach.

The main problem addressed in this study is how to allocate limited cloud resources among multiple users in a fair, efficient, and cost-effective manner. The study considers cloud resource allocation as a strategic decision-making problem where users and providers interact with each other. Users aim to maximize their benefit by obtaining required resources at minimum cost, while providers aim to maximize revenue, improve utilization, and reduce energy consumption. Game theory is suitable for solving this problem because it provides a mathematical framework for analyzing competition, cooperation, pricing, and equilibrium among rational decision-makers.

3.4 Proposed Methodology Framework

The proposed methodology follows a structured framework consisting of different stages. These stages include problem analysis, system model development, dataset generation, preprocessing, game theory model formulation, simulation execution, performance evaluation, and comparative analysis.

In the first stage, the problem of cloud resource allocation was studied. The major issues considered included low resource utilization, increased response time, high latency, poor throughput, SLA violation, and energy wastage. In the second stage, the cloud system model was developed. The system consisted of cloud users, service providers, virtual machines, and available resources such as CPU, memory, and bandwidth.

In the third stage, synthetic workload data was generated using Python. This data represented different user demands and resource availability conditions. In the fourth stage, preprocessing was performed to remove duplicate values, missing values, and inconsistent records. In the fifth stage, the game theory-based allocation model was formulated by defining players, strategies, utility functions, and payoff values. In the sixth stage, the simulation was executed for multiple iterations until a stable allocation pattern was obtained. In the final stage, the results were analyzed and compared with traditional methods such as FCFS and Round Robin.

3.5 System Model

The system model represents the cloud computing environment used in the simulation. It consists of cloud users, cloud service providers, resource pool, virtual machines, and allocation mechanism. Cloud users submit requests for resources based on their application requirements. These requests may include CPU demand, memory demand, bandwidth demand, and task execution requirements. The cloud service provider manages the available infrastructure and allocates resources to users according to the proposed game theory-based strategy.

The resource pool contains limited computing resources. Since the resources are shared among multiple users, efficient allocation is necessary to avoid wastage and overloading. Virtual machines are used to provide isolated computing environments to users. Each virtual machine receives a certain amount of CPU, memory, and bandwidth according to the allocation decision.

International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

The system model assumes that all users are rational and try to maximize their own benefit. Similarly, the provider also acts rationally and attempts to improve revenue, resource utilization, and energy efficiency. The interaction between users and providers is modeled as a non-cooperative game. In this game, each participant selects a strategy based on its own objective. The allocation process continues until the system reaches a stable state where no participant can improve its utility by changing its strategy alone.

3.6 Game Theory Model Formulation

Game theory is used in this study to model the interaction between cloud users and service providers. The basic elements of the game include players, strategies, utility functions, and equilibrium. The players in the proposed model are cloud users and cloud service providers. Users submit resource requests and attempt to obtain maximum service benefit at minimum cost. Providers allocate resources and aim to maximize revenue while maintaining system performance and energy efficiency. The strategies of users include selecting resource demand, choosing service level, and deciding willingness to pay. The strategies of providers include deciding allocation quantity, setting resource price, and managing resource distribution. The utility of a user is calculated by considering the performance benefit received from allocated resources and the cost paid for those resources. If the allocated resources improve task execution and reduce response time, the user utility increases. However, if the cost is high or resources are insufficient, the utility decreases. The provider utility is calculated by considering revenue generated from resource allocation and cost related to energy consumption and infrastructure usage. A provider receives higher utility when resources are utilized efficiently and SLA requirements are satisfied. The objective of the game is to reach an equilibrium condition where allocation becomes stable and no user or provider can improve its benefit by changing strategy independently.

3.7 Dataset Generation

Since real-time cloud datasets are difficult to obtain, synthetic datasets were generated for simulation. The dataset was designed to represent realistic cloud workload conditions. It included user IDs, task IDs, CPU demand, memory demand, bandwidth demand, execution time, cost value, allocation value, response time, latency, throughput, and energy consumption.

The dataset was generated using Python libraries. Randomized values were used within controlled limits to represent different workload conditions. For example, some users were assigned low resource demand, while others were assigned medium or high demand. This helped in testing the proposed model under different cloud traffic situations. The generated dataset was stored in tabular form using Pandas DataFrames. Each row represented a user request or task, while each column represented a resource or performance parameter. This structured format made data processing and analysis easier. The dataset was later used to compare the proposed game theory-based model with FCFS and Round Robin methods.

3.8 Data Preprocessing

Data preprocessing was an important step in the methodology. The raw simulation data was checked and cleaned before applying the allocation model. Missing values, duplicate records, irrelevant entries, and inconsistent values were removed. Data normalization was also performed where required so that different variables could be compared on a common scale.

Preprocessing helped in improving the accuracy and reliability of the simulation results. If raw data contains errors or inconsistencies, the final output may become misleading. Therefore, the dataset was carefully organized before analysis. After cleaning, the data was divided into different categories such as resource demand data, allocation data, cost data, QoS data, SLA data, and energy consumption data.

3.9 Implementation Tools

The proposed model was implemented using Python 3.9 in a Jupyter Notebook environment. Python was selected because it provides powerful libraries for numerical computation, data analysis, simulation, and visualization. The major libraries used in this study included NumPy, Pandas, Matplotlib, and Seaborn.

NumPy was used for numerical calculations and array-based operations. Pandas was used for dataset creation, storage, cleaning, and tabular analysis. Matplotlib and Seaborn were used for graphical representation of results. These tools helped in generating bar graphs, line graphs, comparison charts, and result tables.

The Jupyter Notebook environment was useful because it allowed step-by-step execution of code, visualization of results, and easy interpretation of simulation outputs. It also helped in documenting the model implementation process clearly.

3.10 Performance Evaluation Metrics

The performance of the proposed model was evaluated using several important metrics. These metrics were selected to measure the effectiveness of resource allocation from different perspectives.

- **Resource Utilization** was used to measure how efficiently CPU, memory, and bandwidth were used. Higher utilization indicates better use of available infrastructure.
- **Response Time** was used to measure the time taken by the system to respond to user requests. Lower response time indicates better system performance.
- **Throughput** measured the number of tasks completed successfully within a given time. Higher throughput indicates better processing capacity.
- **Latency** measured the delay experienced during task execution or communication. Lower latency is important for real-time cloud applications.
- **Cost Efficiency** measured the relationship between resource usage and allocation cost. An efficient model should provide good performance without unnecessary expenditure.
- **SLA Compliance** measured whether the system satisfied predefined service requirements. Higher SLA compliance indicates better reliability and user satisfaction.
- **Energy Consumption** measured the amount of power used by the cloud system. Lower energy consumption supports green and sustainable cloud computing.
- **Task Completion Rate** measured the percentage of tasks completed successfully. A higher task completion rate indicates better reliability and resource management.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

3.11 Comparative Analysis Method

The proposed game theory-based model was compared with two traditional resource allocation methods: First-Come First-Serve and Round Robin. FCFS allocates resources according to the order in which requests arrive. It is simple but may not be suitable for dynamic workloads. Round Robin allocates resources in a cyclic manner and provides equal opportunity to tasks, but it may not consider resource demand variation.

The same dataset and workload conditions were applied to all three methods. This ensured fair comparison. The results were compared using resource utilization, cost, response time, throughput, latency, task completion rate, SLA compliance, and energy consumption. The comparison helped in identifying whether the proposed model performed better than traditional allocation approaches.

IV. SIMULATIVE ANALYSIS AND RESULT

This chapter presents the simulative analysis and results of the proposed Game Theory-Based Resource Allocation Model in Cloud Computing Environments. The main aim of this chapter is to evaluate how effectively the proposed model allocates limited cloud resources such as CPU, memory, bandwidth, and storage among multiple users. In cloud computing, several users request resources at the same time, and each user expects better performance, minimum cost, low delay, and reliable service. Therefore, an efficient allocation technique is required to improve resource utilization, Quality of Service, SLA satisfaction, and energy efficiency.

The proposed model is based on game theory, where users and service providers are treated as rational decision-makers. Each user tries to maximize personal benefit by obtaining suitable resources at minimum cost, while the cloud provider attempts to maximize resource utilization, revenue, and service quality. The simulation was carried out using a Python Notebook environment. The output data was generated, processed, and analysed through tables and graphs. The performance of the proposed model was compared with traditional allocation methods such as First-Come First-Serve and Round Robin. The analysis was performed using important parameters such as resource utilization, allocation cost, response time, throughput, latency, task completion rate, SLA compliance, and energy consumption.

The chapter also includes tables and figure representations to present the results in a clear and systematic manner. These results help in understanding whether the proposed game theory-based model provides better performance than existing traditional methods. The findings show that the proposed model performs better in terms of resource utilization, response time, throughput, latency, SLA compliance, and energy efficiency. Although the direct allocation cost of the proposed model is higher, this cost is justified because the model provides better resource usage and improved service quality.

4.1 Simulation Environment and Data Processing

The simulation environment was developed using Python Notebook. The main purpose of the simulation was to create a cloud computing scenario where several users compete for limited resources. The resources considered in this study were CPU, memory, bandwidth, and storage. Each

IJAMSR

**International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**

user submitted resource demands according to task requirements, while the cloud service provider allocated available resources using different allocation techniques.

The proposed game theory-based model was compared with FCFS and Round Robin methods. In FCFS, resources are allocated according to the order in which requests arrive. In Round Robin, resources are distributed in a cyclic manner among users. However, both methods have limitations because they do not fully consider strategic behaviour, dynamic workload changes, and utility maximization. The proposed model overcomes these limitations by considering user utility, provider utility, resource demand, cost, and system constraints.

The raw simulation output contained user requests, allocation values, cost records, delay values, utilization percentage, and payoff values. These values were cleaned and arranged into structured tabular form using Python data-handling tools. Missing values, duplicate records, and irrelevant entries were removed before analysis. After preprocessing, the data was used to generate tables and graphs for interpretation.

User Requests

↓

Resource Demand Identification

↓

Game Theory-Based Decision Process

↓

Resource Allocation by Cloud Provider

↓

Performance Measurement

↓

Comparison with FCFS and Round Robin

↓

Result Analysis and Interpretation

Figure 4.1: Simulation Workflow of Proposed Resource Allocation Model

Figure 4.1 shows the workflow of the proposed simulation model. First, users submit resource requests. Then, the system identifies resource requirements such as CPU, memory, and bandwidth. After this, the game theory-based decision process is applied to determine suitable allocation. Finally, performance metrics are measured and compared with traditional methods. This workflow shows that the proposed approach follows a systematic and logical process for cloud resource allocation.

4.2 Resource Utilization Results

Resource utilization is one of the most important performance indicators in cloud computing. It shows how efficiently the available resources are being used. Higher utilization means that fewer resources are idle and the cloud infrastructure is being used effectively. In this study, CPU utilization, memory utilization, and bandwidth utilization were analysed.

The results showed that the proposed model achieved better CPU utilization compared to FCFS and Round Robin. The proposed model dynamically allocated resources according to user demand and system availability. This helped in reducing resource wastage and improving the overall efficiency of the cloud system.

Table 4.1: Sample Resource Utilization Data

Iteration	CPU Proposed (%)	Memory Proposed (%)	Bandwidth Proposed (%)	CPU FCFS (%)	CPU RR (%)
1	41	41	88	40	54
2	84	82	64	64	54
3	93	49	68	58	46
4	49	91	85	51	42
5	45	84	69	41	58

Table 4.1 presents the sample utilization values for the first five simulation iterations. The proposed model shows strong utilization of CPU, memory, and bandwidth in most iterations. For example, in the third iteration, CPU utilization reached 93%, which is higher than FCFS and Round Robin. This indicates that the proposed model allocates processing resources more efficiently. Similarly, memory utilization reached 91% in the fourth iteration, showing better memory management. Bandwidth utilization also remained strong, which indicates effective network resource allocation.

Table 4.2: Average Resource Utilization Summary

Model	CPU Utilization (%)	Memory Utilization (%)	Bandwidth Utilization (%)
Proposed Model	82.16	75.08	72.44
FCFS	61.48	55.18	51.16
Round Robin	63.34	59.88	54.22

Table 4.2 clearly shows that the proposed model achieved the highest average utilization in CPU, memory, and bandwidth. The average CPU utilization of the proposed model was 82.16%, while FCFS and Round Robin achieved only 61.48% and 63.34%, respectively. This improvement shows that the game theory-based model is more adaptive and efficient than traditional methods. Better utilization also means that the cloud provider can serve more users without unnecessary wastage of infrastructure.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

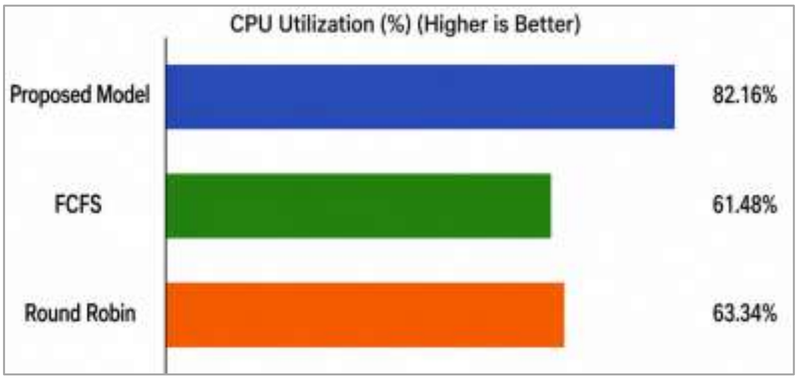


Figure 4.2: Resource Utilization Comparison

Figure 4.2 shows that the proposed model has the highest CPU utilization. This confirms that the game theory-based allocation strategy improves processing capacity and reduces idle CPU time. FCFS and Round Robin show lower utilization because they do not dynamically adjust resources according to user demand.

4.3 Cost Optimization Results

Cost is an important factor in cloud computing because users expect affordable services, while providers aim to maintain profitability. In this study, cost was analysed in terms of total allocation cost and average cost per user or task. The proposed model showed higher direct cost compared to FCFS and Round Robin. However, this higher cost is linked with better resource utilization and improved service quality.

Table 4.3: Sample Cost Data

Iteration	Cost - Proposed Model	Cost - FCFS	Cost - Round Robin
1	410.9	338.8	333.0
2	434.4	354.1	310.2
3	456.3	296.2	349.0
4	463.3	330.9	328.2
5	421.5	329.9	326.8

Table 4.3 shows that the proposed model has higher allocation cost in all five iterations. This is because the proposed model uses more resources effectively to provide better performance. FCFS and Round Robin show lower costs, but their lower cost is mainly due to underutilization of resources. In practical cloud environments, lower cost is not always beneficial if it results in high delay, low throughput, and SLA violations.

Table 4.4: Total Allocation Cost Summary

Model	Total Allocation Cost	Average Cost per User/Task
Proposed Model	21343.6	42.45
FCFS	15458.3	31.52
Round Robin	16439.9	33.48

IJAMSR
International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Table 4.4 indicates that the proposed model recorded the highest total allocation cost and average cost per task. However, this cost is justified because the proposed model delivers better Quality of Service, higher task completion rate, lower latency, and stronger SLA compliance. FCFS has the lowest cost, but it also provides poor resource utilization and lower performance. Round Robin performs moderately but still does not match the proposed model.

Average Cost per Task

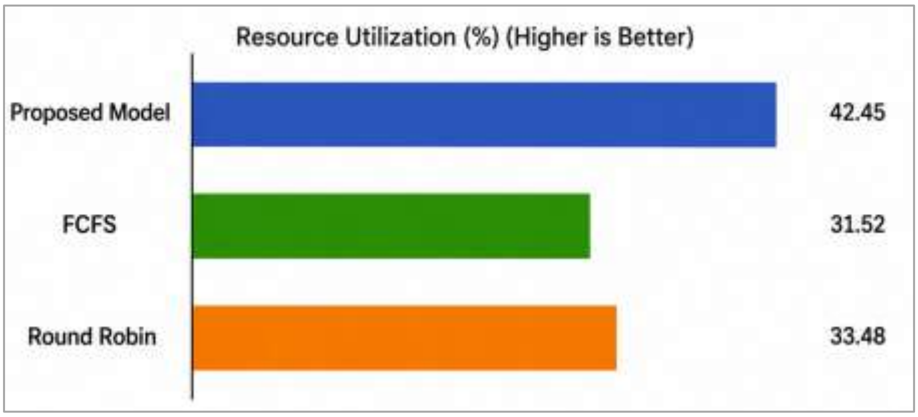


Figure 4.3: Average Cost Per Task Comparison

Figure 4.3 shows that the proposed model has the highest average cost per task. This indicates that more resources are actively allocated to complete tasks efficiently. The higher cost should be understood as a performance-oriented investment rather than a weakness. Better allocation reduces hidden costs such as delay, SLA penalties, and user dissatisfaction.

4.4 Quality of Service Results

Quality of Service is an important measure of cloud system performance. Users expect cloud services to be fast, reliable, and efficient. In this study, QoS was evaluated using response time, throughput, latency, and task completion rate.

Table 4.5: Sample QoS Data

Iteration	Response Proposed	Response FCFS	Response RR	Throughput Proposed	Throughput FCFS	Throughput RR
1	2.44	5.41	2.68	104.41	44.26	68.83
2	3.42	5.14	4.13	90.99	54.52	41.55
3	3.04	5.63	3.35	88.62	59.85	85.53
4	2.82	5.51	3.82	94.24	81.96	69.51
5	2.04	4.64	4.48	109.64	43.19	65.08

Table 4.5 shows that the proposed model achieved lower response time and higher throughput compared to FCFS and Round Robin. Lower response time means that user requests were processed faster. Higher throughput means that more tasks were completed within a given time. The proposed model performed better because it allocated resources dynamically according to demand and system condition.

Vol 8, Issue 11, 2025 **Impact Factor: 8.535** DOI: https://doi.org/10.31426/ijamsr.2025.8.11.8921

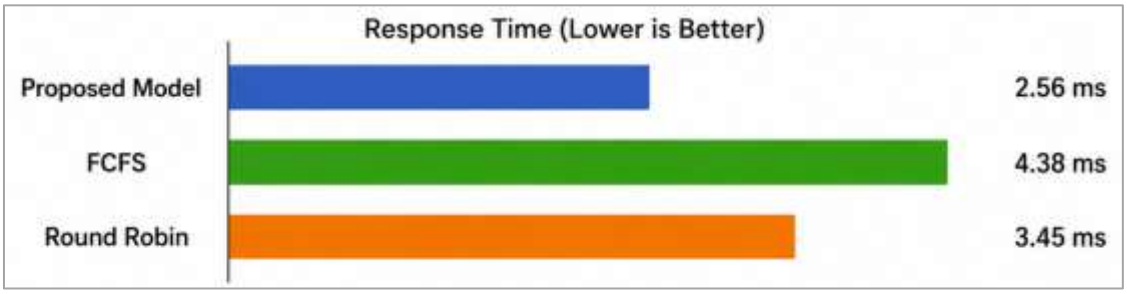
International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Table 4.6: QoS Summary Table

Model	Avg Response Time (ms)	Avg Throughput	Avg Latency (ms)	Avg Task Completion Rate (%)
Proposed Model	2.56	94.93	1.35	94.43
FCFS	4.38	40.48	3.16	80.43
Round Robin	3.45	45.54	2.51	82.24

Table 4.6 presents the overall QoS performance. The proposed model achieved the lowest average response time of 2.56 ms, while FCFS and Round Robin recorded 4.38 ms and 3.45 ms, respectively. The proposed model also achieved the highest throughput of 94.93 and the highest task completion rate of 94.43%. This confirms that the game theory-based model provides faster and more reliable service.

Response Time (Lower is Better)



Throughput (Higher is Better)

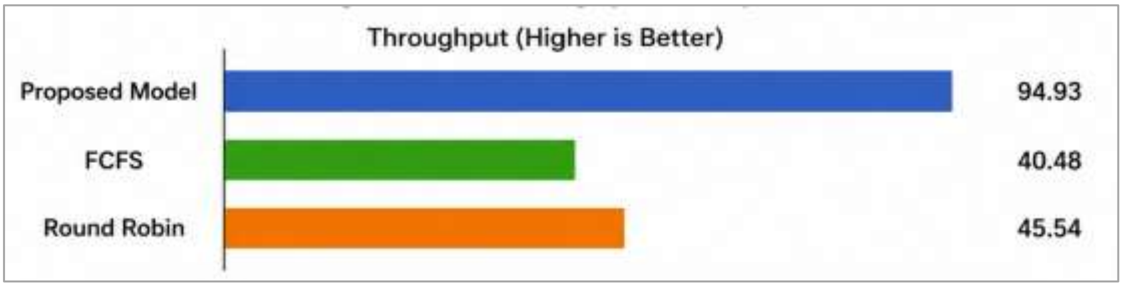


Figure 4.4: QoS Performance Comparison

Figure 4.4 shows that the proposed model has the best QoS performance. It has the lowest response time and highest throughput. This means that the proposed model can process user requests quickly and complete more tasks successfully. FCFS shows poor performance because it follows a rigid allocation order. Round Robin performs better than FCFS but still lacks optimization capability.

4.5 SLA Satisfaction Results

Service Level Agreement satisfaction is a critical factor in cloud computing. SLA defines the expected level of service between the user and cloud provider. It includes requirements such as response time, availability, throughput, reliability, and task completion rate. If the provider fails to meet SLA conditions, it may face penalties and loss of user trust.

The simulation results showed that the proposed model achieved very high SLA compliance. It reduced SLA violations by allocating resources more effectively. FCFS showed the highest number of SLA violations because it does not consider dynamic workload requirements. Round Robin performed better than FCFS but still showed more violations than the proposed model.

Table 4.7: SLA Satisfaction Comparison

Model	SLA Violations	SLA Compliance (%)
Proposed Model	Very Low / Near Zero	99.80
FCFS	High	22.00
Round Robin	Moderate	42.00

Table 4.7 shows that the proposed model achieved almost complete SLA compliance. This means that most user requests were completed within the required performance limits. FCFS had poor SLA compliance because many tasks experienced delay and inefficient allocation. Round Robin showed moderate compliance but still failed to match the proposed approach.

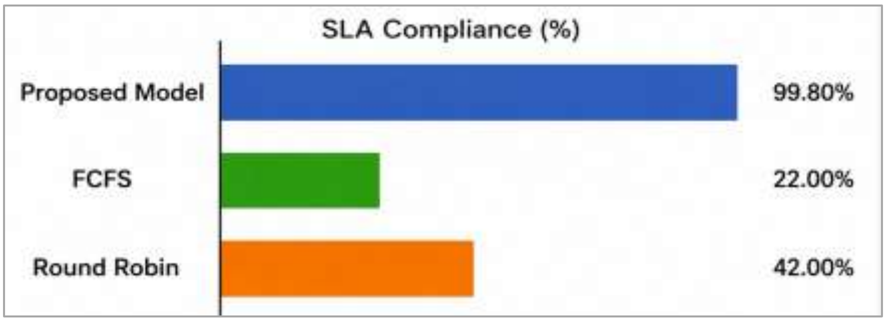


Figure 4.5: SLA Compliance Comparison

Figure 4.5 clearly shows that the proposed model provides the highest SLA compliance. This result proves that the game theory-based allocation method is more reliable for cloud computing environments. Higher SLA compliance improves user satisfaction and reduces penalty risks for cloud service providers.

4.6 Energy Efficiency Results

Energy efficiency is an important concern in cloud computing because large data centers consume a huge amount of electricity. Servers, cooling systems, networking devices, and storage units require continuous power. Inefficient resource allocation may keep many servers active even when they are underutilized. This increases energy consumption and operational cost.

The proposed model reduced energy consumption by improving workload distribution and minimizing idle resources. It allocated resources according to demand and utility, which helped in avoiding unnecessary resource activation. As a result, the proposed model supported green and sustainable cloud computing.

IJAMSR

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Table 4.8: Energy Consumption Summary

Model	Total Energy Consumption (kWh)	Energy Efficiency
Proposed Model	13,300	High
FCFS	18,800	Low
Round Robin	14,400	Moderate

Table 4.8 shows that the proposed model consumed the least energy. The total energy consumption of the proposed model was approximately 13,300 kWh, while FCFS consumed 18,800 kWh and Round Robin consumed 14,400 kWh. This result shows that the proposed model is more energy-efficient than both traditional methods.

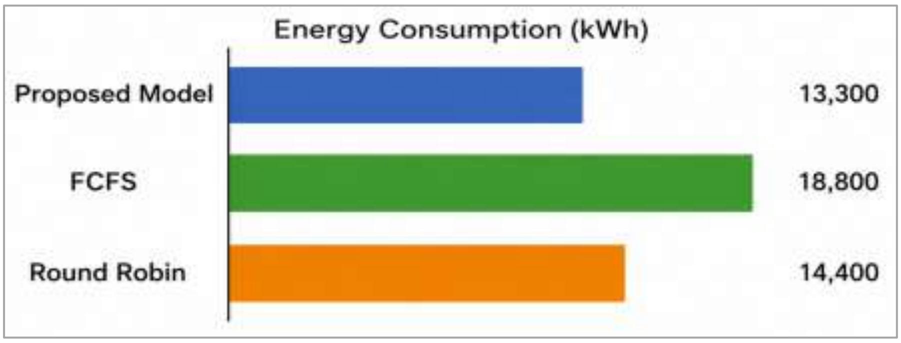


Figure 4.6: Total Energy Consumption Comparison

Figure 4.6 shows that FCFS has the highest energy consumption, while the proposed model has the lowest. The lower energy consumption of the proposed model is due to better resource planning, reduced idle time, and balanced workload distribution. This makes the proposed model suitable for sustainable cloud computing systems.

4.7 Comparative Discussion

The comparative analysis of all results shows that the proposed game theory-based resource allocation model performs better than FCFS and Round Robin in most performance areas. The proposed model achieved higher CPU utilization, better QoS, lower response time, higher throughput, lower latency, improved task completion rate, better SLA compliance, and reduced energy consumption.

FCFS is simple and easy to implement, but it performs poorly in dynamic cloud environments. It allocates resources according to arrival order and does not consider system optimization. As a result, it leads to poor resource utilization, higher delay, and more SLA violations. Round Robin provides better fairness than FCFS, but it still does not consider user demand, pricing, utility, and system conditions effectively. Therefore, its performance remains moderate.

The proposed model performs better because it considers strategic interaction between users and service providers. It uses utility-based decision-making to allocate resources more efficiently. It balances user requirements and provider objectives. The model also adapts to changing workload conditions, which makes it more suitable for modern cloud computing environments.

IJAMSR

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Table 4.9: Overall Comparative Performance

Performance Metric	Proposed Model	FCFS	Round Robin	Best Model
CPU Utilization (%)	82.16	61.48	63.34	Proposed
Response Time (ms)	2.56	4.38	3.45	Proposed
Throughput	94.93	40.48	45.54	Proposed
Latency (ms)	1.35	3.16	2.51	Proposed
Task Completion Rate (%)	94.43	80.43	82.24	Proposed
SLA Compliance (%)	99.80	22.00	42.00	Proposed
Energy Consumption (kWh)	13,300	18,800	14,400	Proposed

Table 4.9 confirms that the proposed model is the best-performing model in almost all major metrics. It provides better utilization, faster response, higher throughput, lower latency, better task completion, stronger SLA compliance, and lower energy consumption. Therefore, the proposed model is more efficient, reliable, and suitable for dynamic cloud computing environments.

4.8 Summary

This chapter presented the simulative analysis and results of the proposed game theory-based resource allocation model. The simulation was performed using Python Notebook, and the results were analysed through tables and graphical representations. The proposed model was compared with traditional methods such as FCFS and Round Robin.

The results showed that the proposed model achieved higher resource utilization and improved Quality of Service. It reduced response time and latency while increasing throughput and task completion rate. The model also achieved near-complete SLA compliance, which indicates better reliability and user satisfaction. In terms of energy efficiency, the proposed model consumed less energy than FCFS and Round Robin, making it suitable for sustainable cloud computing.

Although the proposed model had higher direct allocation cost, this cost was justified by improved performance and better resource utilization. Lower cost in FCFS and Round Robin was mainly due to underutilization, which can create hidden losses such as poor service quality, SLA violations, and inefficient infrastructure usage.

Overall, the findings confirm that game theory is an effective approach for optimizing resource allocation in cloud computing environments. The proposed model supports intelligent, adaptive, and efficient allocation of resources and provides a strong foundation for improving cloud service performance. The next chapter presents the conclusion and future scope of the study.

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This research presented a game theory-based resource allocation model for optimizing cloud computing environments. The main aim of the study was to improve resource utilization, Quality of Service, SLA compliance, energy efficiency, and overall system stability. Cloud computing systems involve multiple users competing for limited computational resources such as CPU, memory, bandwidth, and storage. Traditional allocation methods such as First-Come First-Serve and Round

IJAMSR

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

Robin are simple but often fail to manage dynamic workloads effectively. Therefore, this study adopted a non-cooperative game theory approach, where cloud users and service providers were considered rational agents who attempt to maximize their respective utilities.

The proposed model was evaluated using a Python Notebook-based simulation framework. The simulation generated different cloud workload conditions and tested the performance of the proposed model against traditional techniques. The results showed that the proposed game theory-based model achieved better resource utilization by reducing idle resources and distributing workload more efficiently. It also improved Quality of Service by reducing response time and latency while increasing throughput and task completion rate. These improvements indicate that the proposed model is more suitable for handling dynamic and competitive cloud computing environments. The study also found that the proposed model achieved higher SLA satisfaction compared to FCFS and Round Robin. The number of SLA violations was significantly reduced, which shows that the model can maintain service reliability and user satisfaction. In terms of energy efficiency, the proposed model reduced total energy consumption by minimizing unnecessary resource usage and improving workload distribution across nodes. Although the proposed model showed higher direct allocation cost, this cost was justified by better performance, improved utilization, reduced delay, and enhanced service quality. Overall, the findings confirm that game theory provides an intelligent and adaptive solution for cloud resource allocation.

5.2 Future Scope

Although the proposed model produced effective results, there is still scope for further improvement. Future research can integrate machine learning and artificial intelligence with game theory to predict workload patterns and make more accurate allocation decisions. Reinforcement learning can also be used to improve the model through continuous learning from previous allocation results. The proposed model can further be tested in real cloud platforms such as AWS, Microsoft Azure, or Google Cloud to validate its practical performance. Future studies may also extend the model to multi-cloud, hybrid cloud, fog computing, and edge computing environments. These extensions can improve resource sharing, reduce latency, and support Internet of Things applications. Dynamic pricing, auction-based mechanisms, blockchain-based resource management, and security-aware allocation can also be included in future work. In addition, the model can be tested with large-scale datasets involving thousands of users to examine its scalability. Thus, the proposed game theory-based model provides a strong foundation for future research in intelligent, sustainable, and efficient cloud computing resource management.

REFERENCES

1. Rawat, P. S., Gaur, S., Barthwal, V., Gupta, P., Ghosh, D., Gupta, D., & Rodrigues, J. J. C. (2025). Efficient virtual machine placement in cloud computing environment using BSO-ANN based hybrid technique. *Alexandria Engineering Journal*, *110*, 145-152.
2. Wang, Y., & Yang, X. (2025, March). Research on edge computing and cloud collaborative resource scheduling optimization based on deep reinforcement learning. In *2025 8th International Conference on Advanced Algorithms and Control Engineering (ICAACE)* (pp. 2065-2073). IEEE.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

3. Alozie, C. E., Akerele, J. I., Kamau, E., & Myllynen, T. (2024). Capacity planning in cloud computing: A site reliability engineering approach to optimizing resource allocation. *International Journal of Management and Organizational Research*, *3*(1), 49-61.
4. Zhang, Y., Liu, B., Gong, Y., Huang, J., Xu, J., & Wan, W. (2024, April). Application of machine learning optimization in cloud computing resource scheduling and management. In *Proceedings of the 5th international conference on computer information and big data applications* (pp. 171-175).
5. Lekkala, C. (2024). Ai-driven dynamic resource allocation in cloud computing: Predictive models and real-time optimization. *J Artif Intell Mach Learn & Data Sci*, *2*.
6. Chen, X. (2023, July). Multi-objective optimization task scheduling method based on dynamic programming for multi-cloud environment. In *2023 4th International Conference on Information Science, Parallel and Distributed Systems (ISPDS)* (pp. 278-283). IEEE.
7. Lyu, T., Xu, H., Liu, F., Li, M., Li, L., & Han, Z. (2023). Computing offloading and resource allocation of noma-based uav emergency communication in marine internet of things. *IEEE internet of things journal*, *11*(9), 15571-15586.
8. Wang, S., Hu, Z., Deng, Y., & Hu, L. (2022). Game-theory-based task offloading and resource scheduling in cloud-edge collaborative systems. *Applied Sciences*, *12*(12), 6154.
9. Zeng, X. (2022). Game theory-based energy efficiency optimization model for the Internet of Things. *Computer communications*, *183*, 171-180.