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Original Article

AI-Assisted Resource Scheduling in Multi-Cloud Computing Environments

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ABSTRACT

Cloud computing has evolved significantly, with multi-cloud environments becoming popular for improving scalability, reliability, fault tolerance, and cost efficiency. However, resource scheduling in multi-cloud systems remains challenging due to heterogeneous infrastructures, dynamic workloads, varying pricing models, network latency, and SLA requirements. Traditional scheduling methods such as Round Robin and FCFS often fail to adapt effectively to these complexities. Artificial Intelligence (AI) offers an advanced solution through intelligent resource scheduling. By leveraging machine learning, reinforcement learning, and predictive analytics, AI-based schedulers can forecast workloads, optimize resource allocation, and make autonomous scheduling decisions. This research proposes an AI-driven resource scheduling framework that integrates workload prediction, resource classification, intelligent scheduling, and continuous feedback mechanisms. The framework aims to optimize multiple objectives, including cost reduction, execution efficiency, energy consumption, and SLA compliance. Performance evaluation using metrics such as resource utilization, makespan, response time, throughput, and energy consumption demonstrates that AI-assisted scheduling outperforms traditional approaches. The results indicate improved resource utilization, better workload balancing, reduced operational costs, and enhanced service quality, highlighting the potential of AI-driven scheduling for next-generation multi-cloud resource management systems.

KEYWORDS

Artificial Intelligence, Multi-Cloud Computing, Resource Scheduling, Machine Learning, Reinforcement Learning, Cloud Resource Management, Sla Optimization, Intelligent Scheduling, Predictive Analytics, Cloud Computing.

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1. INTRODUCTION

1.1. Multi-Cloud Computing Architecture

Multi-cloud computing architecture is a sophisticated approach to cloud computing that leverages services and resources from various cloud service providers to provide enhanced performance, reliability, and flexibility. Organizations move their applications and workloads to various public, private and hybrid clouds based on their business and technical needs, rather than relying on a single cloud platform. Public clouds provide scalable and cost-effective resources, private clouds offer enhanced security and control over sensitive data and hybrid clouds offer the benefits of both. Using multiple cloud platforms helps organizations avoid vendor lock-in, bolsters fault tolerance, and guarantees service availability even if one cloud platform fails. Multi-cloud architecture also facilitates intelligent workload distribution whereby tasks can be run on the most appropriate cloud service depending on, among other things, cost, performance, security, and the availability of resources. This method allows for efficient use of resources, business continuity, and scalability to meet the demands of a changing workload in the modern distributed computing landscape.

1.2. Challenges in Resource Scheduling

Resource scheduling is a key function in cloud computing that involves the assignment of computing resources to various tasks and applications. Cloud-based environments are becoming larger and more intricate, and with multiple users, different applications and fluctuating resource needs, it becomes hard to schedule. An efficient scheduling system should be able to schedule resources efficiently, with a high performance level, low cost and satisfy the Quality of Service (QoS) requirements. This process, however, is complicated by a number of technical issues. A big challenge is that of dynamic workloads. The demand of the users and application may fluctuate quickly over time and it will be difficult to accurately predict future resource requirements. A sudden rise in workload can cause resource congestion and a sudden drop can cause resources to go unused. Another important challenge is resource heterogeneity. Cloud environments are made up of cloud resources of different kinds and capacities, all with different processing speeds, memory, storage space, and network bandwidths. This is a complex scheduling problem of matching these resources with application requirements efficiently. Service Level Agreement (SLA) management is also an important issue. Cloud providers should adhere to the specifications of the cloud tasks in terms of their expected performance, including response time, availability, and reliability. If it's not scheduled properly, SLA violations occur and customers get upset and monetary losses are incurred. Load balancing is necessary to ensure that not all servers are overloaded, and not all of them are idle. Inappropriate workload distribution may lead to lower performance of the system and longer execution times. An effective scheduling system would assign tasks in such a manner that it is evenly spread across the resources available to it to ensure maximal efficiency. A second challenge is the optimization of energy. Consumption of massive quantities of electricity in large cloud data centers demands a lot of energy, which translates into higher operational costs and environmental impact. Energy should be used efficiently in resource scheduling by reducing unnecessary energy

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consumption by the use of the available servers appropriately. In fact, resource scheduling is impacted by security and privacy considerations, particularly in multi-cloud scenarios involving data and applications spread across cloud providers. Sensitive information should be safe from unauthorized access, cyber threats and data breaches while ensuring efficient resource allocation. Last but not least, cost optimization is an important challenge faced by cloud service providers and users alike. Scheduling algorithms need to prioritise performance and operational costs to ensure they leverage cost-effective resources without impacting service quality. These issues must be overcome to develop intelligent and efficient cloud resource scheduling systems that can support modern distributed computing environments.

1.3. Role of Artificial Intelligence

In cloud computing environments, Resource Scheduling and Management is a critical aspect of technology that AI has become a vital part of improving. AI can help cloud systems process vast amounts of information, understand the patterns of workload usage, and make informed decisions without requiring frequent manual input. AI-powered scheduling methods can adjust to varying circumstances and dynamically optimize resources, whereas conventional scheduling algorithms are based on predetermined rules. This can help to optimize system performance, lower operational expenses, and improve the quality of cloud services.

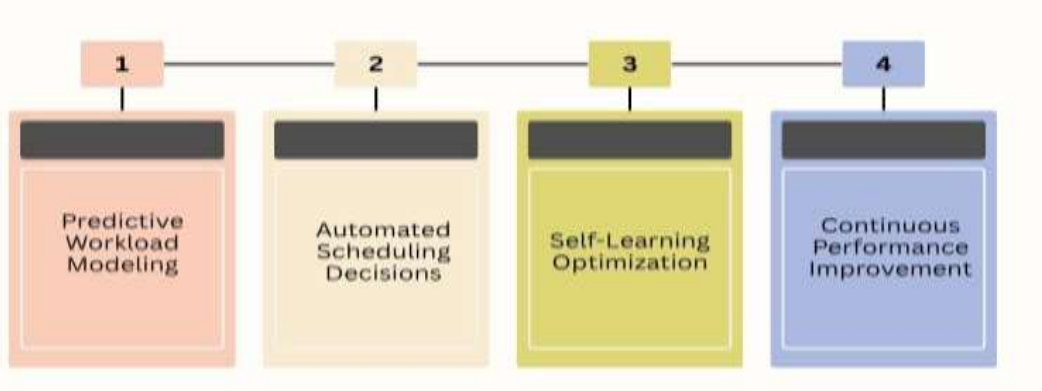

Fig 1 - Role of Artificial Intelligence

1.3.1. Predictive Workload Modeling

One of the major use cases of AI in the cloud is predictive workload modeling. Historical workload data and system conditions are used by AI algorithms to predict future resource requirements. The forecasting system can forecast the periods of high and low workloads by analyzing the usage patterns and trends. This enables cloud service providers to anticipate and proactively allocate resources, avoid shortages and prevent performance bottlenecks in the future.

1.3.2. Automated Scheduling Decisions

AI can perform automated scheduling decisions, automatically allocating the most appropriate cloud resources to incoming tasks. The AI scheduler considers CPU usage, memory

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allocation, network bandwidth, storage space and workload priority in its decision making process. This smart automation cuts down scheduling delays, better use of resources and optimizes resource allocation.

1.3.3. Self-Learning Optimization

Self-learning optimization enables AI systems to learn from past experiences and make better decisions for future scheduling. The scheduler makes use of machine learning and reinforcement learning methods to learn from past decisions and optimize its policies for future ones. Over time, the system is able to become more efficient in resource management by continuously learning from all its interactions, whether with users or with the cloud.

1.3.4. Continuous Performance Improvement

AI's role in cloud computing is not limited to just these aspects; continuous performance improvement is another crucial function. An AI-driven system keeps a close watch on resources, runtime, energy consumption, and Service Level Agreement (SLA) adherence on an ongoing basis. The information is used by the system to update its scheduling models and optimize the allocation of resources in the future. This continuous improvement process helps to optimize cloud performance, improve reliability, decrease operational costs, and deliver high-quality services to users.

2. LITERATURE SURVEY

In cloud computing systems, several researchers have studied the resource scheduling mechanisms to increase resource utilization, decrease run time and meet the Quality of Service (QoS) requirements. In cloud environments, scheduling is critical because there are many users and applications vying for scarce computing resources. Traditional heuristic methods, metaheuristic optimization techniques and Artificial Intelligence (AI) based scheduling models are the broadly categorized existing scheduling approaches. While each category has their own pros and cons, there is still room for further research.

2.1. Traditional Scheduling Approaches

Traditional scheduling algorithms are one of the earliest algorithms applied in resource allocation in cloud computing. These are commonly used: First Come First Serve (FCFS), Round Robin (RR), Priority Scheduling and Shortest Job First (SJF). FCFS is based on the first come first served principle, that is, it allocates resources based on the order in which the tasks arrive; this is easy but can result in long wait times. Priority Scheduling executes tasks based on a pre-defined priority whereas Round Robin distributes CPU time equally among tasks, in order to achieve fairness. SJF chooses the tasks that can be executed in the shortest time to minimise the average waiting time. These algorithms are simple but don't adapt to dynamic clouds and may not scale effectively with fluctuating workloads.

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2.1.1. Limitations of Traditional Scheduling Approaches

While traditional scheduling methods are simple, they have several drawbacks when applied to modern cloud infrastructures. They do not scale well and are not able to deal with large numbers of diverse resources and user requests. Such algorithms may result in high makespan and thus high overall task completion times. They can also result in resource imbalance where some VMs are overloaded and others underutilized. Moreover, traditional approaches are not predictive and do not anticipate future workloads, less effective in very dynamic clouds.

2.2. Metaheuristic Optimization Methods

Researchers have proposed a number of metaheuristic optimization algorithms to address the limitations of traditional scheduling methods including: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Firefly Algorithm. The algorithms simulate natural or biological processes to find near-optimal scheduling solutions. The Genetic Algorithm is based on the ideas of evolution like selection and mutation; the Path Finding Algorithm is inspired by the social behavior of bird flocks; and the Firefly Algorithm is based upon the attraction mechanism of fireflies. The techniques are popularly applied for optimizing multiple scheduling goals such as execution time, energy consumption and resource utilization.

2.2.1. Advantages of Metaheuristic Optimization Methods

Metaheuristic algorithms have some benefits over conventional scheduling methods. They are able to search a wide solution space and create almost optimal solutions for an optimization problem. The techniques can enable multi-objective optimization where cloud systems can optimize for various factors such as cost, makespan, load balancing and energy efficiency. They are flexible and can be used in various cloud environments and scheduling requirements, which makes them suitable for solving NP-hard scheduling problems.

2.2.2. Disadvantages of Metaheuristic Optimization Methods

Metaheuristic algorithms have been shown to enhance the performance of scheduling, but they also have some drawbacks. Many of these techniques require a large number of parameters to be tuned to get the best performance, making the implementation more complex. They tend to be very costly to compute and can have slow convergence, particularly in large-scale cloud systems. Moreover, there are some algorithms that may become stuck in local optimum, which would lead to a suboptimal scheduling solution and decrease the efficiency of the algorithm.

2.3. AI-Based Scheduling Techniques

The use of Artificial Intelligence (AI) has become a significant solution in intelligent resource scheduling in cloud computing. AI scheduling methods leverage machine learning and deep learning algorithms to analyse workload patterns and make data-driven scheduling decisions. Historical data can be used to classify and predict the requirements for the resources as is done in common machine learning techniques like Decision Trees, Support Vector Machines (SVM), Random Forest and

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Artificial Neural Networks (ANN). More sophisticated deep learning algorithms like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks can learn complex workload behaviors and time-dependent patterns. Such models can help cloud systems to adjust their predictions and optimise the allocation of the resources dynamically.

2.3.1. Reinforcement Learning in Cloud Scheduling

Cloud scheduling has attracted a lot of interest from the community since it allows for intelligent agents to learn the optimal cloud scheduling policies by interacting with the cloud environment. In RL, an agent sees the current state of the cloud system, chooses among all of its scheduling actions, and gets rewarded or punished depending on the results. The agent, through the trial and error of the trials, learns strategies to maximize the cumulative rewards, thus resulting in better utilization of the resources and a reduced execution time. In particular, RL is well suited to a dynamic cloud environment where workloads are constantly shifting and there are rules that cannot be defined beforehand that can be applied.

2.3.2. Benefits of AI-Based Scheduling Techniques

Cloud Computing Scheduling Methods offers many benefits based on AI. They enable adaptive learning, which means the scheduling system can be continually improved as more data is received. These techniques can be used for self-optimization, which includes automatic adjustment of scheduling policies to varying workloads and resource conditions. AI models can also be used to make real-time decisions, minimizing delays and enhancing Quality of Service (QoS). Moreover, predictive analytics enables cloud service providers to better allocate their resources in advance, thereby reducing the likelihood of SLA breaches and improving the performance of the system.

2.4. Research Gap

While the use of AI in scheduling shows promise, there are some issues that need to be addressed. Many studies have already been conducted but have limited support for heterogeneous multi-cloud configurations with varying resources in capacities and configuration. AI models can be complex and require significant computational power, which can make them inefficient for real-time applications.AI models can be complex and require a lot of computation, making them inefficient for real-time applications. Besides, there are a lot of scheduling frameworks which emphasize on performance measures and fail to provide a proper optimization of Service Level Agreements (SLAs). One of the other key challenges is the lack of integration between workload prediction and scheduling decisions, which leads to inefficient resource utilization when workloads are volatile. To solve these problems, this study suggests an integrated AI scheduling framework, which combines intelligent workload forecasting with adaptive resource scheduling to enhance the efficiency, scalability and SLA compliance in contemporary cloud computing systems.

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3. METHODOLOGY

3.1. Workload Prediction Model

The workload prediction model is a crucial element in the proposed cloud scheduling framework assisted by an AI system. It is mainly designed to predict the future demand of resources based on the patterns of workloads in the past. With accurate workload prediction, cloud service providers can allocate resources efficiently, avoid delays, operate with reduced costs and refrain from overloading the system. The scheduler can predict or anticipate future requests, rather than being reactive after workloads are up.

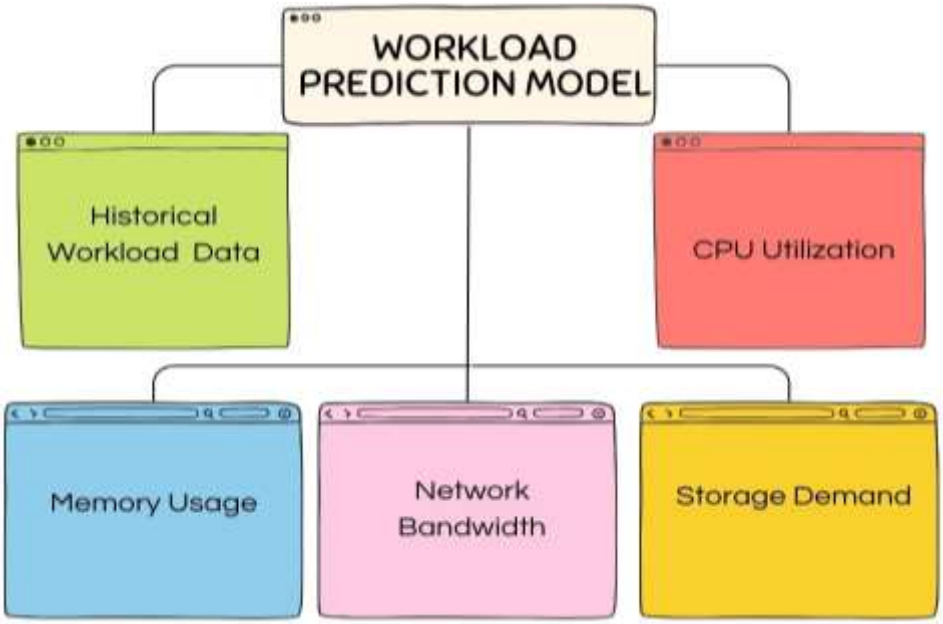

Fig 2 - Workload Prediction Model

3.1.1. Historical Workload Data

Historical workload data are data records gathered during the past executions of cloud applications and services. The data comprises of information gathered over a period of time regarding resource consumption, arrival rate of tasks, execution time, and user behavior. Machine learning models can be used to analyze historical workload patterns and detect trends or repeating workload characteristics to make more precise predictions of future resource needs.

3.1.2. CPU Utilization

CPU utilization is a percentage of the processor's usage for running processes and programs. One of the most important parameters for workload prediction is CPU utilization – when it exceeds the threshold, it can affect the performance and increase response times. CPU utilization can be tracked to determine future processing needs and allocate computing resources efficiently, aiding the prediction model.

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3.1.3. Memory Usage

Memory usage reflects the amount of RAM actively used by virtual machines, applications and cloud services. If not managed, high memory requirement can lead to resource contention and instability of the system. The workload prediction model can predict the memory usage of the past to help allocate resources appropriately.

3.1.4. Network Bandwidth

Network bandwidth is the amount of data that flows between cloud resources, users and data centers over a period of time. If a large amount of data is being moved, streamed or a distributed application is being used, there needs to be adequate network capacity to ensure that the application remains responsive. The scheduling system can then use this prediction of the bandwidth usage to minimize usage of the network and maximize the overall efficiency of communication.

3.1.5. Storage Demand

Storage demand is the amount of disk space needed to store application data, user files, databases and backup information. Cloud workloads typically have changing storage demands, resulting from differences in user activity and data growth. The workload prediction model predicts future storage requirements, allowing for better management of storage allocation, preventing overloading resources, and ensuring the reliability of cloud services.

3.2. AI-Assisted Resource Scheduling

The AI-assisted resource scheduling module is intended to schedule cloud resources sensibly, taking into account the existing condition of the cloud environment and chooses the most appropriate resource for every new job. The AI-based scheduler keeps track of the availability and performance of computing resources and can make dynamic decisions based on various factors, unlike traditional scheduling methods that rely on fixed rules. The scheduler takes into account all available virtual machines or cloud servers and matches the resources they provide to the resources needed for those tasks. This will help utilize resources more, delay less execution and deliver better quality service for users. The proposed scheduling framework is based on an objective function that takes into account several important performance parameters to make an effective scheduling decision. The objective function is given as:

$$\mathbf{F = \alpha C + \beta T + \gamma E + \delta SLA}$$

where C is cost of execution, T is task execution time, E is energy consumption, and SLA is the Service Level Agreement requirements. The parameters α, β, γ, and δ are weight factors which relates to the importance of each objective in the system requirements. If the main objective is to minimize operating costs, for instance, the cost factor can have a greater weightage. Likewise, if saving energy or compliance with SLA has more priority, the corresponding weights can be raised. The AI agent uses information about the availability of resources, the workload situation and past scheduling records, to determine the objective value of each possible resource. It then computes the ratio of these

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values and picks out the resource that has the least value of the objective function. Selecting the minimum value means that the task is done at a cheaper price, faster execution time, less energy usage, and more likely to meet the SLA constraints. Furthermore, the AI scheduler can evolve over time based on historical scheduling decisions and continuously optimize its performance. It can manage dynamic cloud environments and heterogeneous cloud sets better than traditional approaches, by adapting to varying workloads and cloud conditions. This intelligent scheduling process optimizes the use of resources and reduces delays in the processes, improving overall system efficiency and resource balance in cloud computing services.

3.3. Reinforcement Learning Scheduler

The proposed intelligent framework for cloud resource management is composed of an intelligent component, called Reinforcement Learning (RL) scheduler. Compared with the traditional scheduling algorithms which are based on fixed rules, the RL scheduling is learning its optimal scheduling strategy via continual interaction with the cloud environment. Gets information about the current state of the system, makes scheduling decisions and gets rewards or penalties based on the results. As time goes on, the scheduler gets better at what it does and learns from its experiences, picking actions that will maximize future performance. Reinforcement learning is therefore particularly well suited for dynamic cloud environments like there are frequent changes in workloads and resource availability. The RL scheduler consists primarily of three basic components: State, Action and Reward. State indicates the current state of the Cloud infrastructure. It provides details about the resources available for the computation, including CPU usage, memory usage, network bandwidth, storage space, virtual machine load and pending tasks. The RL agent will continually observe these parameters and have full knowledge of the current cloud environment prior to making a scheduling decision. The action refers to the scheduling decision taken by the RL agent. The scheduler selects the most suitable cloud resource or virtual machine for a workload based on the state of the resource or virtual machine. The action selected is designed to distribute the tasks over the resources available, and to minimize the execution time and the operational cost. The cloud environment comes and goes and the RL agent can adapt its scheduling policy and choose different resources to maximize its performance. The reward mechanism is the learning signal which directs the RL scheduler to make better decisions. Once a task is allocated, the agent will be rewarded if scheduling the task results in desirable outcomes like reduced execution time, reduced energy consumption, balanced resource utilization, reduced operational cost, and improved compliance to Service Level Agreement (SLA). However, if the chosen resource delays or overloads resources, consumes high energy or violates SLA, the agent is charged a negative reward or penalty. The RL scheduler, which aims at maximising the cumulative payoff across repeated interactions, slowly learns the optimal scheduling policy. The suggested reinforcement learning scheduler is constantly learning and changing its knowledge as the workload pattern evolves without human interaction. This self-learning mechanism improves the use of resources, decreases the makespan, increases the scalability and improves the quality of service of the cloud system. This makes the RL-based

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scheduling approach a more efficient and intelligent scheduling solution than traditional cloud scheduling methods.

3.4. Proposed Framework

The proposed framework is an intelligent and adaptive resource scheduling solution for multi-cloud environment. It works by merging the power of Artificial Intelligence (AI) with Reinforcement Learning (RL) to anticipate workload requirements, categorize available resources and manage them to execute tasks efficiently. The framework is systematic, starting from the user's request, and moving towards feedback learning continuously and enabling the system to evolve its scheduling decisions from time to time. All stages of the framework can help to improve resource utilization, execution time, operational costs and Service Level Agreement (SLA) compliance.

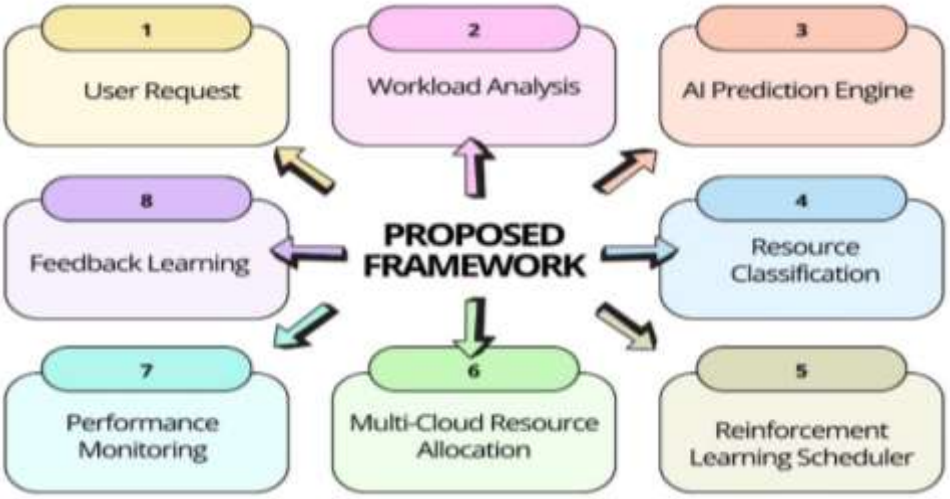

Fig 3 - Proposed Framework

3.4.1. User Request

Its framework starts when a user requests a task or application from the cloud system. The request can involve various kinds of workloads, especially data processing, storage operations or computation tasks. The scheduler gathers the task requirements and decides what strategy for allocating the resources to the task should be used, such as processing power, memory requirements, storage requirements, and deadlines for the task execution.

3.4.2. Workload Analysis

The user request is received by the workload analysis module and analyzed for the nature of the incoming workload. It calculates such measures as CPU usage, memory usage, network bandwidth, task size, expected execution time, etc. The goal of this analysis is to get a better understanding of the complexity and resource requirement of each workload, which further helps the system to make better scheduling decisions.

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3.4.3. AI Prediction Engine

The AI prediction engine uses historical workload data and the conditions of the system to forecast what resources are needed in the future. Machine learning models detect workload patterns and forecast the changes in workload demand. This predictive feature enables the cloud system to proactively allocate resources, avoiding delays and shortages during peak periods.

3.4.4. Resource Classification

The resource classification module categorizes the resources available in the cloud according to their features and utilization. Virtual machines and servers are clustered together by such characteristics as processing power, memory space, storage capacity, and conservation of energy resources. The classification is useful to the AI system in quickly matching tasks with the most appropriate resources, simplifying the scheduling process.

3.4.5. Reinforcement Learning Scheduler

The reinforcement learning scheduler becomes the intelligent decision making part of the framework. It monitors the current cloud context, chooses resources to fulfill tasks and learns from the result of its choices. The RL scheduler continually optimizes the scheduling policy using a reward-based learning mechanism to maximize performance, minimize costs, and increase the utilization of the resources.

3.4.6. Multi-Cloud Resource Allocation

After the optimum resource is chosen, the framework distributes the workload amongst various cloud platforms, as required. The multi-cloud resource allocation feature allows resources to be allocated from multiple cloud providers to enhance reliability, scalability, and fault tolerance. This will help to prevent resource bottlenecks and optimize the use of resources available.

3.4.7. Performance Monitoring

The performance monitoring module continuously monitors the execution of the allocated tasks and the status of cloud resources. It records various performance indicators including execution time, resource usage, energy usage, throughput and SLAs compliance. When using continuous monitoring, you can find performance problems and gain insights to make scheduling improvements in the future.

3.4.8. Feedback Learning

The last phase of the framework is feedback learning, which involves evaluative analysis of the outcomes of past scheduling decisions. Data on performance and reward values are used to update the knowledge and adapt future scheduling strategies for the AI and reinforcement learning models. This ongoing learning process allows the framework to evolve as workloads change, become more accurate at predicting and optimizes the overall performance of the cloud system over time.

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4. RESULT AND DISCUSSION

4.1. Comparative Analysis

The comparative analysis compares the performance of the proposed AI-based resource scheduling framework with the traditional resource scheduling methods. Comparisons are based on key cloud computing parameters like response efficiency, resource utilization, energy efficiency, cost optimization, load balancing, satisfaction of service level agreements, and throughput. The results show that AI-driven scheduling is consistently superior to the traditional methods by making intelligent allocation decisions and adapting to the changes in the resources.

Table 1: Comparative Analysis

Performance Metric	Traditional Scheduling (%)	AI-Assisted Scheduling (%)
Resource Utilization	72	92
SLA Satisfaction	75	95
Throughput	70	91
Energy Efficiency	68	89
Cost Optimization	65	88
Load Balancing	73	93
Response Efficiency	71	90

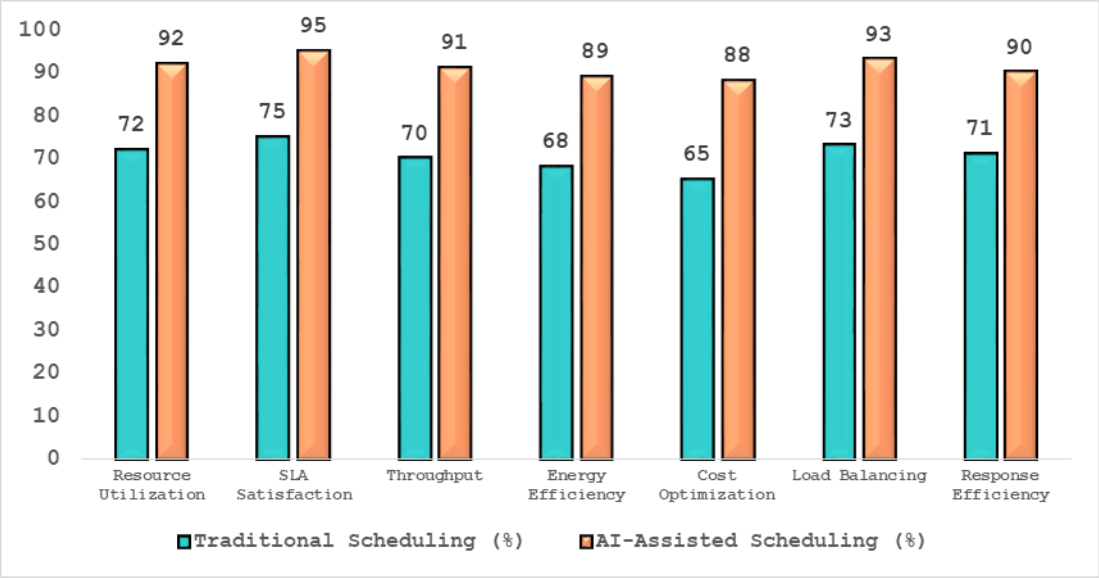

Fig 4 - Comparative Analysis

4.1.1. Resource Utilization

Resource utilization is a measure of the efficiency of the use of cloud resources. Traditional scheduling techniques do not allow for changes in workload in the future and only get about 72% utilization. The AI-assisted scheduling framework achieves 92% resource utilization by using AI to analyze workload patterns and dynamically allocate tasks to the most appropriate resources. This minimizes idle resources and optimizes the overall system efficiency.

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4.1.2. SLA Satisfaction

Service Level Agreement (SLA) satisfaction is a reflection of the capability of the cloud system to deliver the performance promise to the user. The traditional scheduling solutions achieve around 75% SLA fulfillment because of the delay and inefficient use of resources. The AI-driven scheduler improves SLA satisfaction to 95% by forecasting the workload requirements and allocating resources that are capable of delivering the workload on time and avoiding SLA violations.

4.1.3. Throughput

Throughput is the number of tasks which are completed successfully over a given time period. Traditional scheduling methods only have a throughput of approximately 70%, since it may lead to resource bottlenecks during peak loads. The proposed AI-assisted framework enhances throughput up to 91% by optimising the task distribution and workload balance among the available cloud resources for efficient processing of more tasks.

4.1.4. Energy Efficiency

Cloud computing is energy intensive due to large data centres and therefore energy efficiency plays an important role with cloud computing. Traditional scheduling approaches only use about 68% of the energy because they do not optimally use resources and consume energy. The AI-driven scheduling model also optimizes the use of resources and eliminates the use of underutilized servers, resulting in lower power consumption with 89% energy efficiency.

4.1.5. Cost Optimization

Cost Optimization is the process of reducing operational costs of allocating cloud resources. Using traditional scheduling techniques will optimize costs by about 65% as they can choose to schedule more expensive resources when lower cost options are available. The AI-powered scheduler optimizes costs to 88% by making intelligent resource selection for the best performance and operational cost.

4.1.6. Load Balancing

Load balancing allocates workloads evenly across the cloud resources, avoiding overloading or underutilization. But conventional scheduling techniques only offer around 73% load balancing since they are not very flexible when system conditions change. The AI-driven framework is 93% load balancing by constantly checking the status of resources and allocating tasks dynamically among them in the cloud.

4.1.7. Response Efficiency

Response efficiency is the speed of cloud system reaction to the users' requests and the completion of task allocation. Traditional scheduling methods only get approximately 71% response efficiency since they are based on static scheduling rules. The AI-driven scheduling method boosts response efficiency to 90% by leveraging intelligent prediction and reinforcement learning algorithms

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to make quicker and more precise scheduling decisions, thus decreasing wait times and enhancing user satisfaction.

4.2. Discussion

The experimental results show that the overall performance of the cloud computing system can be improved significantly using the proposed resource scheduling framework as compared to conventional scheduling approaches. An important contribution of the proposed model is the significant improvement in the utilization of resources. This framework enhanced the utilization of resources by almost 20%, so it was able to utilize the cloud resources like CPU, memory, storage, network bandwidth, etc. to the maximum extent. Conventional scheduling algorithms have a fixed scheduling rule and they sometimes make some resource idle and some resource crowded. The proposed AI-based framework, on the other hand, constantly monitors the availability of resources and allocates tasks more efficiently, leading to optimal use and minimising resource wastage. One of the key features of the framework is the implementation of AI-based workload forecasting using a prediction engine. The prediction model can more accurately predict future demands by analyzing historical workload data and the state of the resources. This capability decreases the uncertainty of workloads and allows the scheduler to schedule the resources in advance rather than in response to system congestion. This makes the cloud environment more robust and stable, and can support dynamic and unpredictable workloads with minimal performance impact. Finally, the proposed framework is enhanced by integration of a reinforcement learning scheduler. The RL agent continuously interacts with the cloud environment, learns from past scheduling decisions and updates the scheduling policy by means of reward mechanisms. Rewards are achieved for tasks that are completed efficiently at lower costs and energy usage, and penalties are given for delays or failures to meet SLAs. The continuous learning process enables the scheduler to get better at making decisions over time and to be able to automatically adjust the workload conditions. The results also show considerable improvements in cost optimization and Service Level Agreement (SLA) compliance. Intelligent workload allocation automatically assigns the right workload to the right resources, eliminating wasted operating costs and over-provisioning of resources. At the same time, efficient scheduling helps complete tasks within their required deadlines, minimizing SLA violations and increasing user satisfaction. The proposed framework is different from the traditional scheduling policies and takes decisions based on the current state of the system and future predictions, resulting in efficient and reliable operations of the cloud. Overall, the discussion validates the effectiveness of integrating AI prediction with reinforcement learning to develop a smart and adaptive scheduling solution that boosts the efficiency, cost-effectiveness, and quality of cloud computing services.

The proposed model has many advantages. The proposed model brings many benefits. The proposed model has various important features that are not included in the traditional cloud scheduling model. The framework combines the power of Artificial Intelligence and Reinforcement Learning, offering a smart and adaptive resource management strategy that can adapt effectively to varying workloads. The proposed model is different from the traditional scheduling approach, which

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is based on a set of rules, because it continuously learns from past experiences and adapts its scheduling strategy, thereby enhancing its performance and resource utilization One of the key benefits of the proposed model is the adaptive scheduling. The AI scheduler uses artificial intelligence to understand the cloud environment and allocate resources as needed for workloads. This flexibility enables the system to deal with abrupt fluctuations in user demands without substantial decrease in performance. Consequently, the scheduler can make smart decisions to maximize cloud resource utilization. A significant advantage is greater scalability. The number of users and applications in a modern cloud environment may grow quickly. The proposed framework can be deployed to handle big and scattered cloud environments, distributing the workload between a number of resources in an efficient way. The system's ability to scale means that it can handle increased workloads without compromising performance. The model also helps in reduced operational cost by intelligently selecting resources based on intelligent decision making process. The scheduler selects the best and cheapest resources to use for task execution, rather than wasting precious resources. This reduces resource waste and enables cloud service providers to reduce their infrastructure and maintenance costs. One of the great benefits of the framework is its use of the resources. The system can predict workload, and continuously monitor the available computing resources, including CPU, memory, storage, and network bandwidth, to ensure they are used effectively. Resource balance helps minimize idle time and prevents resource overload, which boosts overall cloud productivity. The proposed model also delivers enhanced level of Service Level Agreement (SLA) compliance. Intelligent scheduling helps tasks get completed in time, minimizing the risk of SLA breaches and enhancing customer satisfaction. The framework is able to estimate the future workloads and allocate the resources in advance so that services are delivered reliably and the quality of the cloud services remains constant. Last but not least, the model enables efficient cloud management. Balancing workloads and optimizing resource usage minimizes unnecessary energy usage by reducing energy waste from underutilized or overloaded servers. Reducing energy consumption not only reduces costs, but it also promotes cloud computing that is environmentally friendly. The proposed AI-driven scheduling framework is a comprehensive solution that greatly improves the performance, scalability, cost effectiveness, reliability, and sustainability of contemporary cloud computing systems.

5. CONCLUSION

Distributed infrastructures and cloud computing are rapidly increasing the complexity of resources scheduling and management. High performance and service reliability are requirements of the modern cloud environment when processing many user requests, a variety of applications, and variable workloads. The simple scheduling algorithms like First Come First Serve (FCFS), Round Robin (RR), Priority Scheduling, and Shortest Job First (SJF) are easy to implement and simple but cannot adapt to the dynamic nature of a multi-clouds environment. The use of these traditional approaches can lead to sub-optimal use of resources, slow execution, significant operational expenses, and regular breakage of Service Level Agreements (SLAs). Thus, a need for intelligent scheduling techniques that can make intelligent decisions in real-time arises. The present research

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proposed an AI-based resource scheduling framework in multi-cloud environment. The proposed model combines workload prediction, machine learning, and reinforcement learning to enhance the process of resource allocation. Historical workload data and real-time cloud information is analysed to forecast future resource needs, providing for pro-active scheduling decisions. The reinforcement learning scheduler interacts continuously with the cloud environment, and learns from the past scheduling results based on a reward-based approach. This adaptive learning process enables the system to determine over time the optimum strategy for the allocation of resources, and to react appropriately to varying workload requirements. The proposed methodology aims to pursue several scheduling goals at once: minimize execution time, maximize the utilization of resources, ensure greater compliance of the SLA, minimize the operational cost and enhance energy efficiency. The results demonstrated that the AI scheduling framework significantly outperforms the traditional scheduling methods in various performance measures in the comparative analysis. Predictive workload analysis prevents the waste of resources by planning resources ahead of the congestion; reinforcement learning further enhances the scheduling quality based on feedback learning.

The proposed framework is more flexible and scalable for modern cloud computing systems, as it provides the necessary capabilities. The other critical benefit of the framework is its capacity to aid smart load balancing and fault-tolerance. The system is designed to spread workloads across various cloud platforms, thus avoiding resource bottlenecks and increasing service availability. The multi-cloud approach to architecture also improves reliability as tasks can be moved from a cloud resource to another if they fail or if they're not performing as well as they should. It's a nice to have for large scale enterprise applications where downtime and poor performance are not acceptable. Moreover, the combination of Artificial Intelligence with cloud resources management, decreases the infrastructure costs and improves the overall operational efficiency. The optimized allocation of available computing resources and minimization of wasteful energy usage is done through intelligent scheduling. This helps to realize the economic value of cloud services providers and environmental friendly cloud services. Expansion of this framework is possible in the future, with the incorporation of new technologies like federated learning, edge computing, quantum-inspired optimization methods, and blockchain-based cloud security systems. Such advanced technologies can potentially bring full-fledged cloud management systems to life that can make intelligent decisions with little human involvement. These systems can effectively enable next-generation distributed applications, Internet of Things (IoT) environments and large-scale artificial intelligence services as well. Overall, the results from this research suggest that AI-driven resource scheduling is a viable alternative to the challenges presented by humans scheduling resources using cloud-based approaches. The proposed framework offers performance enhancement, increased scalability, increased resource utilization, improved SLA compliance, decreased energy use, and lower operational costs. This study paves the way for intelligent cloud resource management and lays a solid groundwork for future AI-supported multi-cloud scheduling and optimization.

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