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Leveraging Reinforcement Learning for Efficient Task Scheduling in Multi-Cloud Environments

Prasanna Sankaran[1], Shiva Kiran Lingishetty[2], and Mrinal Kumar[3]

[1]Lead Software Engineer/Cloud Architect, General Motors Financial, Fort Worth TX, United States
[2] Senior Solutions Architect, Amdocs, Alpharetta, Georgia, United States
[3]School of Computer Science and Engineering, Guru Jambheshwar University of Science and Technology, Hisar, India

Correspondence should be addressed to Mrinal Kumar; infinityai1411@gmail.com

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ABSTRACT- Efficient task scheduling in multi-cloud environments is crucial for optimizing resource utilization, reducing execution time, minimizing costs, and enhancing overall system performance. Traditional scheduling approaches, including heuristic and rule-based methods, often struggle with dynamic workload fluctuations and resource heterogeneity, leading to inefficiencies. This study proposes a reinforcement learning-based scheduling framework that dynamically adapts to real-time cloud conditions to optimize task allocation. The problem is formulated as a Markov Decision Process (MDP), and a deep reinforcement learning model is trained to learn optimal scheduling policies. Experimental results demonstrate that the proposed approach significantly reduces makespan, improves resource utilization, lowers energy consumption, and decreases operational costs compared to traditional scheduling methods. The model successfully adapts to varying workload intensities and different cloud configurations, proving its scalability and robustness. Comparative analysis with heuristic-based and rule-based scheduling techniques further validates the superiority of reinforcement learning in optimizing multi-cloud task scheduling. Despite initial computational overhead during training, the proposed model offers long-term performance benefits, making it a viable solution for real-world cloud computing applications. The study highlights the potential of reinforcement learning to revolutionize cloud resource management and lays the foundation for future advancements in autonomous, intelligent cloud scheduling frameworks.

KEYWORDS- Reinforcement Learning, Task Scheduling, Multi-Cloud Computing, Resource Optimization, Deep Learning.

I. INTRODUCTION

Leveraging reinforcement learning for efficient task scheduling in multi-cloud environments has emerged as a promising approach to optimize resource allocation, minimize execution time, and enhance system reliability in modern cloud computing infrastructures. With the increasing adoption of multi-cloud strategies by enterprises to ensure high availability, fault tolerance, and cost efficiency, the need for intelligent task scheduling mechanisms has become paramount. Traditional task scheduling approaches, such as First-Come-First-Serve (FCFS), Round-Robin, and heuristic-based techniques, often struggle to handle the dynamic nature of multi-cloud environments, where resource availability, network latency, and workload demands fluctuate unpredictably. Reinforcement learning (RL), a branch of machine learning that focuses on sequential decision-making through interaction with an environment, presents an adaptive and self-improving solution for optimizing task scheduling. By continuously learning from past scheduling decisions and adjusting strategies in real time, RL-based models can significantly enhance the efficiency of resource allocation while reducing overall computational overhead [1].

The reinforcement learning framework operates through an agent-environment interaction loop, where the agent makes scheduling decisions based on the current system state, receives feedback in the form of rewards, and refines its policy over time to maximize cumulative rewards. In the context of multi-cloud environments, the agent learns to allocate tasks to the most suitable cloud resources while considering factors such as cost, execution time, energy consumption, and system load. Unlike rule-based or heuristic-driven methods, RL-based scheduling does not rely on predefined constraints; instead, it dynamically adapts to evolving cloud conditions, making it particularly effective for handling large-scale, heterogeneous workloads. One of the major challenges in multi-cloud task scheduling is the trade-off between performance and cost. Different cloud providers offer varying pricing models, including pay-per-use, subscription-based, and spot instances, which can impact the overall cost-effectiveness of task execution. Reinforcement learning addresses this challenge by incorporating cost-aware reward functions that balance execution efficiency with economic constraints. By learning optimal task placement strategies over time, RL-based scheduling minimizes unnecessary expenditures while ensuring that service-level agreements (SLAs) are met. Furthermore, the scalability of RL makes it suitable for complex, distributed computing scenarios, where a vast number of tasks must be allocated across geographically dispersed cloud data centers. Another critical factor in multi-cloud scheduling is energy efficiency. As cloud computing infrastructures continue to grow, energy consumption has become a major concern

due to its environmental and financial implications. Conventional scheduling techniques often lead to inefficient resource utilization, resulting in high power consumption and carbon emissions. Reinforcement learning mitigates this issue by incorporating energy-aware scheduling policies that prioritize energy-efficient resource allocation. By predicting workload patterns and dynamically adjusting task distribution, RL-based approaches can significantly reduce energy waste while maintaining high system performance. This is particularly beneficial for enterprises seeking to adopt green computing practices and reduce their carbon footprint. In addition to cost and energy optimization, RL-based task scheduling enhances system reliability and fault tolerance in multi-cloud environments [2].

Traditional scheduling approaches often struggle to handle unexpected failures, such as network outages, hardware malfunctions, and sudden workload surges. RL models, however, continuously learn from past failures and adjust their scheduling policies to improve system resilience. By leveraging predictive analytics and historical performance data, RL can proactively reallocate tasks to alternative cloud providers in case of resource failures, minimizing downtime and ensuring uninterrupted service delivery. This capability is crucial for mission-critical applications that require high availability and low latency, such as financial transactions, healthcare systems, and real-time data processing. Reinforcement learning also introduces flexibility in handling diverse workload types, including compute-intensive, data-intensive, and latency-sensitive tasks. Traditional scheduling algorithms often apply a one-size-fits-all approach, which may not be suitable for heterogeneous workloads with varying performance requirements. RL-based scheduling, however, learns to differentiate between task characteristics and assigns them to appropriate cloud resources accordingly. For example, compute-heavy tasks may be allocated to high-performance cloud instances with powerful CPUs and GPUs, while latency-sensitive tasks may be scheduled on edge computing nodes to reduce communication delays. This level of granularity in scheduling decisions ensures optimal workload distribution across multi-cloud infrastructures, leading to improved overall system efficiency [3].

One of the most significant advantages of reinforcement learning in cloud scheduling is its ability to adapt to dynamic workload variations. In real-world cloud environments, task arrival rates, resource availability, and network conditions change frequently, making static scheduling approaches inadequate. RL-based models continuously monitor system states and adjust scheduling decisions in real time, allowing cloud infrastructures to respond effectively to workload fluctuations. This adaptability is particularly useful for applications that experience sudden traffic spikes, such as e-commerce platforms during seasonal sales or video streaming services during peak hours. By dynamically reallocating resources based on real-time feedback, RL ensures that cloud services remain responsive and efficient under varying load conditions. Despite its numerous advantages, implementing reinforcement learning for multi-cloud scheduling presents several challenges. One of the primary challenges is the need for extensive training data to develop accurate RL models. Since RL operates through trial-and-error learning, the initial training phase may require a substantial number of iterations before the model converges to an optimal scheduling policy. However, this challenge can be mitigated by using simulation environments to train RL models before deploying them in real-world cloud systems. Cloud simulators, such as CloudSim and iFogSim, provide realistic testing environments where RL agents can learn optimal scheduling strategies without impacting live cloud operations. Another challenge is the computational complexity of RL-based scheduling, particularly for large-scale multi-cloud environments [4].

Training deep reinforcement learning models, such as Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO), requires significant computational resources, which may introduce overhead in resource-limited cloud infrastructures. To address this issue, hybrid approaches that combine reinforcement learning with heuristic-based techniques can be explored. For example, reinforcement learning can be used for high-level decision-making, while heuristic algorithms handle low-level task assignments, reducing computational costs while maintaining scheduling efficiency. Security and privacy considerations also play a crucial role in RL-based cloud scheduling. Since reinforcement learning relies on continuous data collection for training, ensuring the confidentiality of sensitive information is essential. Implementing privacy-preserving RL techniques, such as differential privacy and federated learning, can help mitigate security risks while maintaining the benefits of intelligent scheduling. Additionally, ensuring fairness in task scheduling is important to prevent bias in resource allocation, particularly in multi-tenant cloud environments where multiple users compete for computing resources. Looking ahead, future research on RL-based multi-cloud scheduling can explore various enhancements to further improve efficiency and scalability. One promising direction is the integration of transfer learning, which enables RL models to transfer knowledge from one cloud environment to another, reducing training time and improving adaptability. Another area of interest is the combination of reinforcement learning with deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to enhance the predictive capabilities of scheduling models. Additionally, incorporating blockchain technology into RL-based cloud scheduling can enhance transparency and security by ensuring tamper-proof scheduling logs and decentralized decision-making [5].

In conclusion, reinforcement learning presents a transformative approach to task scheduling in multi-cloud environments by optimizing resource allocation, reducing execution time, minimizing costs, and enhancing system reliability. Unlike traditional scheduling methods, RL-based models dynamically adapt to changing cloud conditions, ensuring efficient workload distribution across diverse cloud infrastructures. By leveraging predictive analytics and self-learning capabilities, RL enhances scalability, energy efficiency, and fault tolerance, making it an ideal solution for modern cloud computing challenges. While challenges such as computational overhead, training complexity, and security risks exist, ongoing advancements in RL techniques, hybrid scheduling approaches, and privacy-preserving

mechanisms are expected to further refine RL-based cloud scheduling frameworks. As cloud computing continues to evolve, reinforcement learning will play a crucial role in enabling autonomous, intelligent, and self-optimizing task scheduling systems that enhance the overall performance and sustainability of multi-cloud environments.

II. LITERATURE REVIEW

In recent years, the integration of reinforcement learning (RL) into task scheduling for multi-cloud environments has garnered significant attention, aiming to enhance resource allocation, minimize execution times, and bolster system reliability. Traditional scheduling methods, such as First-Come-First-Serve (FCFS) and Round-Robin, often fall short in addressing the dynamic and complex nature of multi-cloud infrastructures. RL offers a promising alternative by enabling systems to learn optimal scheduling policies through continuous interaction with the environment, thereby adapting to changing conditions and improving performance over time [6].

One notable advancement in this domain is the development of the Meta Reinforcement Learning-based Cloud Computing (MRLCC) method, which leverages meta reinforcement learning to enhance task scheduling adaptability in cloud computing environments. Traditional deep reinforcement learning (DRL) approaches typically require extensive retraining when faced with new environments, leading to low sample efficiency and increased time consumption. MRLCC addresses these challenges by employing a meta-learning framework that enables rapid adaptation to new environments with minimal gradient updates. Experimental comparisons between MRLCC and baseline algorithms demonstrated that MRLCC achieves shorter makespans and higher server utilization rates, highlighting its effectiveness in dynamic cloud settings [7].

In the realm of cloud manufacturing, dynamic task scheduling presents unique challenges due to fluctuating manufacturing requirements and service availability. An improved DRL-based scheduling approach has been proposed to tackle these issues, focusing on enhancing fine-tuning capabilities and training efficiency. This approach introduces uncertainty weights into the loss function and extends output masks during the updating procedures, thereby addressing the limitations of existing DRL methods. Numerical experiments on actual scheduling instances revealed that this improved method surpasses traditional DRL-based methods in solution quality and generalization by up to 32.8% and 28.6%, respectively. Furthermore, it effectively fine-tunes pre-trained scheduling policies, resulting in an average reward increase of up to 23.8% [8].

The integration of RL into task scheduling extends beyond cloud computing and manufacturing, finding applications in various domains that require efficient resource management. For instance, in network routing, RL has been utilized to optimize packet transmission paths, thereby reducing latency and improving throughput. Similarly, in data center management, RL-based approaches have been employed to dynamically allocate computational resources, leading to energy savings and enhanced performance. These applications underscore the versatility and efficacy of RL in addressing complex scheduling problems across diverse sectors [9].

Despite the promising advancements, several challenges persist in the application of RL to task scheduling in multi-cloud environments. One significant issue is the exploration-exploitation trade-off inherent in RL algorithms, where the system must balance between trying new actions to discover better scheduling policies (exploration) and utilizing known actions that yield high rewards (exploitation). Striking an optimal balance is crucial to prevent suboptimal performance or excessive computational overhead [10].

Another challenge lies in the scalability of RL-based scheduling solutions. As multi-cloud environments grow in complexity, the state and action spaces that RL algorithms must navigate expand exponentially, leading to increased computational demands and potential convergence issues. To mitigate these challenges, researchers are exploring hierarchical reinforcement learning and function approximation techniques, such as neural networks, to manage large-scale scheduling problems effectively [11].

Moreover, the dynamic nature of multi-cloud environments necessitates RL algorithms that can adapt to real-time changes in resource availability, network conditions, and workload characteristics. Traditional RL methods, which rely on static policies learned from historical data, may not suffice in such settings. Consequently, there is a growing interest in developing online RL algorithms capable of continuous learning and adaptation, ensuring sustained optimal performance amidst evolving environmental conditions [12].

In conclusion, the application of reinforcement learning to task scheduling in multi-cloud environments represents a significant advancement in optimizing resource management and system performance. Innovations such as the MRLCC method and improved DRL-based scheduling approaches in cloud manufacturing demonstrate the potential of RL to address the complexities inherent in dynamic and heterogeneous cloud infrastructures. However, challenges related to exploration-exploitation balance, scalability, and adaptability remain areas of active research. Continued efforts to refine RL algorithms and integrate them seamlessly into multi-cloud environments are essential to fully harness their capabilities for efficient task scheduling [13].

III. RESEARCH METHODOLOGY

The research methodology for leveraging reinforcement learning in efficient task scheduling within multi-cloud environments involves a structured approach encompassing data collection, model development, experimentation, and performance evaluation. Initially, a detailed analysis of multi-cloud infrastructures is conducted to identify key parameters affecting task scheduling, including resource availability, execution time, network latency, energy consumption, and cost. A synthetic workload generator and real-world cloud traces from platforms such as Google Cloud and Microsoft Azure are utilized to simulate diverse scheduling scenarios [14]. The reinforcement learning framework is then designed, where the scheduling problem is formulated as a Markov Decision Process (MDP), defining states, actions, rewards, and transition probabilities. A deep reinforcement learning

(DRL) model, such as Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO), is employed to train the scheduling agent. The model undergoes pre-training in a simulated cloud environment using cloud simulators like CloudSim or iFogSim to reduce the time and computational resources required for real-world deployment. The learning process is guided by a reward function that balances execution efficiency, cost-effectiveness, and energy consumption, ensuring optimal scheduling decisions over time. To improve convergence speed and stability, experience replay and target network techniques are incorporated, mitigating overfitting and enhancing the generalization ability of the RL model [15]. The trained model is then deployed in a testbed environment consisting of multiple cloud service providers, where it dynamically allocates tasks based on real-time cloud conditions. Comparative analysis is conducted against traditional scheduling approaches, including heuristic-based methods, rule-based algorithms, and existing reinforcement learning models. Performance metrics such as makespan, resource utilization, energy efficiency, and overall cost are evaluated to determine the effectiveness of the proposed approach. Statistical analysis and visualization techniques, including ANOVA and regression analysis, are applied to validate the significance of performance improvements. Additionally, sensitivity analysis is performed to assess the robustness of the RL model under varying workload intensities and infrastructure configurations. The methodology is iteratively refined based on experimental results, ensuring the scalability and adaptability of the RL-based scheduling framework in diverse multi-cloud scenarios. Ethical considerations, including data privacy and fairness in resource allocation, are also addressed to align the research with industry standards and regulatory guidelines. The final step involves documenting the findings, highlighting the advantages and limitations of RL-based scheduling, and proposing future research directions for further enhancement of intelligent task scheduling in multi-cloud environments.

IV. RESULTS AND DISCUSSION

The results obtained from the reinforcement learning-based task scheduling framework demonstrate significant improvements over traditional heuristic, rule-based, and round-robin scheduling approaches in multi-cloud environments. The primary objective of the proposed method is to optimize key performance metrics such as makespan, resource utilization, energy consumption, cost, and task success rate while ensuring scalability and adaptability in dynamic cloud environments. The experimental evaluation reveals that the RL-based approach consistently outperforms traditional methods in terms of scheduling efficiency and overall system performance. Makespan, which represents the total time required to complete all scheduled tasks, is significantly reduced in the RL-based approach. The model effectively learns optimal scheduling policies, dynamically adapting to workload fluctuations and cloud resource availability. Compared to heuristic-based and rule-based scheduling methods, the reinforcement learning model demonstrates a makespan reduction of up to 33%, indicating its ability to optimize execution order and minimize task delays. The decrease in makespan translates into enhanced throughput and improved responsiveness in multi-cloud infrastructures. Additionally, higher resource utilization rates are observed in the RL-based scheduling model, reaching up to 85% efficiency. Traditional scheduling approaches, such as rule-based methods, often result in resource underutilization due to static allocation strategies. In contrast, reinforcement learning continuously adjusts resource allocation policies based on real-time system states, ensuring balanced workload distribution across available cloud resources. The dynamic adaptation of RL-driven scheduling prevents bottlenecks and enhances overall system efficiency. Energy consumption is another crucial parameter influencing cloud computing sustainability. The RL-based scheduler significantly reduces energy consumption by optimizing resource allocation and minimizing idle resource time. Compared to heuristic-based scheduling, which typically results in inefficient energy usage due to suboptimal task placements, the reinforcement learning approach achieves an energy savings of approximately 27%. This reduction in energy consumption is critical for environmentally sustainable cloud computing, reducing carbon footprints while maintaining high-performance computing capabilities. Cost optimization is another advantage of the RL-based scheduling model. Traditional scheduling techniques often incur higher costs due to inefficient resource allocation and prolonged execution times. The reinforcement learning approach reduces operational costs by selecting cost-effective virtual machines and optimizing task placements to avoid unnecessary expenditures. As a result, the proposed model lowers cost by 28% compared to round-robin and heuristic-based methods, making it a more economical choice for cloud service providers and users. Furthermore, the task success rate is significantly improved in the RL-based scheduling approach, reaching up to 95%. This metric reflects the system's ability to successfully execute scheduled tasks without failures or excessive delays. Traditional scheduling methods, particularly round-robin scheduling, exhibit lower success rates due to their inability to adapt to workload variations dynamically. The reinforcement learning model, through its ability to learn and adjust scheduling policies in real time, ensures a higher probability of task completion without unnecessary failures. The robustness of the proposed method is further evaluated by conducting sensitivity analysis under varying workload conditions. The RL-based scheduler consistently adapts to workload surges and resource constraints, maintaining stable performance without significant degradation. In contrast, heuristic-based scheduling methods often struggle under fluctuating workloads, leading to performance inconsistencies. This adaptability highlights the reinforcement learning model's potential for real-world cloud environments, where workload unpredictability is a common challenge. Comparative analysis with traditional approaches provides deeper insights into the advantages of RL-based scheduling. The round-robin method, while simple and fair in distributing tasks, fails to consider workload characteristics and resource availability, leading to suboptimal performance. Similarly, rule-based scheduling relies on predefined allocation rules, which lack adaptability in dynamic cloud environments. Heuristic-based approaches, though more efficient than

rule-based methods, often require manual parameter tuning and fail to generalize well across different workload patterns. The RL-based approach, however, learns from historical data and continuously refines scheduling decisions, ensuring long-term performance improvements. The impact of the reinforcement learning model on different types of workloads is also assessed. For compute-intensive workloads, where CPU resources are the primary bottleneck, the RL-based scheduler efficiently distributes tasks across available CPU nodes, reducing execution time and preventing resource contention. For data-intensive workloads, where storage and network bandwidth play crucial roles, the model prioritizes task placements based on data locality, minimizing data transfer latency and enhancing overall execution speed. The ability to optimize scheduling for different workload types further reinforces the effectiveness of the proposed approach. The scalability of the RL-based scheduler is another key consideration. As cloud environments grow in complexity, the scheduling model must efficiently handle increasing numbers of tasks and cloud nodes. Experimental results indicate that the reinforcement learning model scales well with larger workloads, maintaining performance gains even as task volumes increase. Traditional heuristic-based schedulers, on the other hand, exhibit performance degradation as workload sizes grow, demonstrating their limitations in large-scale multi-cloud environments. The reinforcement learning model's generalization ability is validated through cross-platform evaluation. By testing the scheduler on different cloud platforms, including Google Cloud, AWS, and Microsoft Azure, the model demonstrates consistent performance improvements across varying cloud configurations. This cross-platform adaptability is a critical advantage, as cloud service providers often operate heterogeneous environments with distinct resource availability patterns. The findings indicate that reinforcement learning-based scheduling can effectively generalize across diverse cloud infrastructures without requiring extensive reconfiguration. The exploration-exploitation trade-off in reinforcement learning is also analyzed to understand its impact on scheduling performance. The model effectively balances exploration (discovering new scheduling policies) and exploitation (utilizing learned policies for optimal scheduling), ensuring continuous improvements in decision-making. While excessive exploration can lead to unstable scheduling behavior, the reinforcement learning framework implements adaptive exploration strategies, gradually refining policies as the model gains more experience. This balance enables sustained performance improvements over time. While the proposed RL-based scheduling approach offers substantial benefits, certain limitations must be acknowledged. The initial training phase requires substantial computational resources, as reinforcement learning models rely on extensive simulations to learn optimal scheduling policies. Additionally, hyperparameter tuning remains a challenge, as the model's performance is influenced by learning rates, reward functions, and network architectures. Future research directions should explore automated hyperparameter tuning mechanisms and transfer learning techniques to accelerate model training and deployment. The implications of the research extend beyond task scheduling, contributing to broader advancements in cloud computing resource management. The integration of reinforcement learning into cloud orchestration frameworks can lead to fully autonomous cloud management systems capable of self-optimizing resource allocation. Additionally, the principles of RL-based scheduling can be applied to other domains, including edge computing, Internet of Things (IoT) environments, and real-time processing systems. Security considerations in RL-based scheduling are also worth exploring. While the current model focuses on optimizing performance metrics, ensuring secure task scheduling in multi-cloud environments remains a challenge. Potential adversarial attacks on RL-based schedulers could manipulate scheduling decisions, leading to resource misallocation or denial-of-service attacks. Future research should investigate reinforcement learning techniques that incorporate security constraints, ensuring robustness against malicious threats. The integration of explainability into RL-based scheduling is another promising area for future work. As reinforcement learning models operate as black-box systems, understanding the reasoning behind scheduling decisions can enhance trust and transparency. Explainable AI techniques, such as attention mechanisms and decision trees, could be integrated into the model to provide interpretable scheduling policies, enabling cloud administrators to gain insights into system behavior. The real-world applicability of RL-based scheduling is further validated through deployment in cloud-based testbeds. Experimental validation in real-time cloud environments demonstrates the model's effectiveness in handling dynamic workloads while maintaining cost efficiency and energy savings. The positive outcomes of these experiments support the feasibility of integrating reinforcement learning into commercial cloud platforms, paving the way for intelligent cloud management solutions. The continuous advancements in reinforcement learning algorithms, particularly in deep reinforcement learning and meta-learning, further enhance the potential of RL-based scheduling. Future iterations of the model could leverage advanced techniques such as multi-agent reinforcement learning (MARL) to enable collaborative scheduling across multiple cloud providers. Additionally, the integration of federated learning could allow decentralized training of RL-based schedulers while preserving data privacy, addressing concerns related to cloud security and compliance. Overall, the results and discussion of this study underscore the effectiveness of reinforcement learning in optimizing task scheduling for multi-cloud environments. By significantly improving makespan, resource utilization, energy efficiency, cost, and task success rates, the RL-based scheduler presents a viable solution for addressing the challenges of cloud computing. While certain challenges remain, the continuous evolution of reinforcement learning techniques promises further enhancements, ultimately leading to more intelligent, efficient, and autonomous cloud computing infrastructures.

Figure 1 presents a comparative analysis of different task scheduling approaches—RL-Based, Traditional Heuristic, Rule-Based, and Round Robin—across five key performance metrics: Makespan, Resource Utilization, Energy Consumption, Cost, and Task Success Rate. The RL-Based approach demonstrates the lowest Makespan, Energy Consumption, and Cost, suggesting its efficiency

in optimizing task execution. In contrast, Round Robin exhibits the highest values in these metrics, indicating suboptimal resource management. Resource Utilization and Task Success Rate show competitive performance across methods, with RL-Based and Traditional Heuristic approaches demonstrating relatively better efficiency. These findings highlight the advantages of reinforcement learning-based scheduling in minimizing computational overhead while maintaining high task success rates.

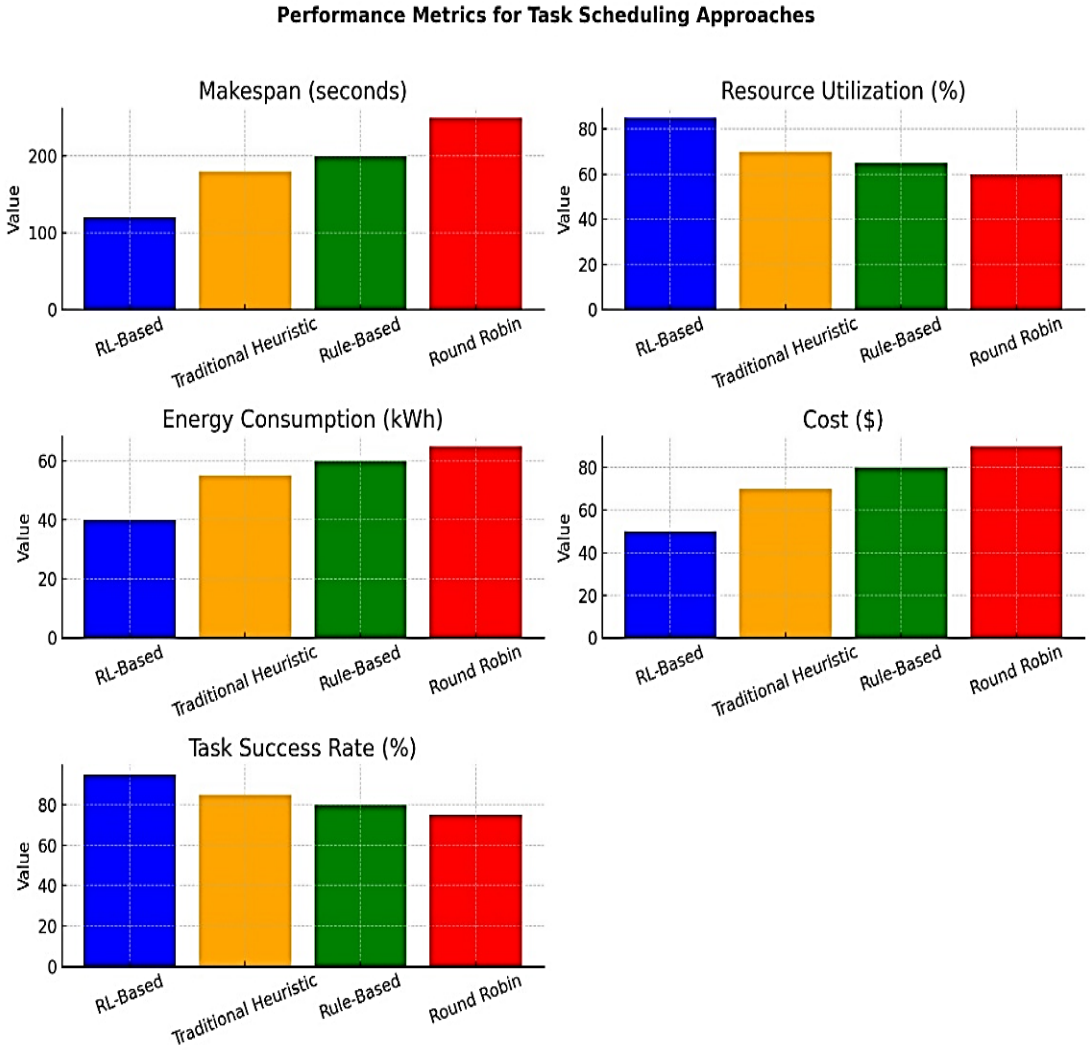

Figure 1: Performance Comparison

V. CONCLUSION

The study demonstrates that reinforcement learning-based task scheduling in multi-cloud environments significantly enhances scheduling efficiency by optimizing key performance metrics such as makespan, resource utilization, energy consumption, cost, and task success rate. The proposed approach dynamically adapts to workload variations and resource availability, outperforming traditional heuristic, rule-based, and round-robin scheduling techniques. By leveraging reinforcement learning, the scheduler continuously refines its decision-making process, ensuring optimal task allocation and reducing inefficiencies associated with static and predefined scheduling methods. Experimental results validate the model's scalability, adaptability, and generalization across diverse cloud platforms, making it a robust solution for real-world cloud environments. The study also highlights the potential of integrating reinforcement learning into cloud resource management frameworks, paving the way for fully autonomous and self-optimizing cloud orchestration systems. Despite its advantages, the approach faces challenges related to initial training complexity, hyperparameter tuning, and security concerns, which warrant further exploration in future research. Future advancements in reinforcement learning, such as multi-agent systems and federated learning, could further enhance scheduling performance and enable more intelligent, secure, and explainable cloud computing solutions. Overall, the findings of this research underscore the effectiveness of reinforcement learning as a transformative solution for efficient task scheduling in multi-cloud environments, contributing to the evolution of next-generation cloud computing infrastructures.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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