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Reinforcement Learning-Driven Intelligent Resource Allocation in Enterprise Cloud Computing Environments

Dr. David Mguni

School of Electronic Engineering and Computer Science, Queen Mary University of London, London, United Kingdom

ABSTRACT
Enterprise cloud computing environments require efficient resource allocation to support dynamic workloads, maintain service quality, reduce operational costs, and improve infrastructure utilization. Traditional resource allocation approaches often depend on predefined rules, static thresholds, and reactive scheduling mechanisms, which may not adequately respond to rapidly changing application demands. This research proposes a reinforcement learning-driven intelligent resource allocation framework designed to optimize computing resources across enterprise cloud environments. The proposed framework utilizes reinforcement learning techniques to make adaptive allocation decisions based on workload characteristics, resource availability, application priorities, and infrastructure performance. The system considers essential resource parameters, including central processing unit utilization, memory consumption, storage requirements, network bandwidth, processing latency, and energy consumption. An intelligent decision-making mechanism continuously observes cloud infrastructure conditions, evaluates possible allocation strategies, and selects appropriate actions to maximize long-term operational efficiency. The framework also incorporates workload prediction, dynamic scaling, resource prioritization, and performance monitoring to improve resource management. Its effectiveness is examined through comparative evaluation against conventional resource allocation approaches using performance indicators such as resource utilization, response time, allocation efficiency, operational cost, and service-level agreement compliance. The proposed approach provides a flexible foundation for intelligent enterprise cloud management, supporting scalable infrastructure, improved application performance, and cost-effective utilization of distributed computing resources.

KEYWORDS: Reinforcement Learning, Enterprise Cloud Computing, Intelligent Resource Allocation, Cloud Resource Management, Dynamic Scheduling, Resource Optimization, Workload Management, Infrastructure Utilization, Cloud Performance, Adaptive Computing.

I. INTRODUCTION

Enterprise cloud computing has become an essential component of modern organizational information technology infrastructure because it provides scalable computing resources, flexible storage facilities, network connectivity, and application hosting capabilities. Organizations increasingly depend on cloud platforms to operate enterprise applications, manage business information, support distributed employees, and deliver digital services. The growing adoption of cloud-based technologies has significantly increased the complexity of infrastructure management, particularly in environments where workloads fluctuate according to business activities, user requests, application requirements, and seasonal demand. Efficient resource allocation is therefore necessary to maintain reliable application performance while controlling infrastructure expenditure. Cloud service providers offer virtual machines, containers, storage systems, processing capabilities, and networking resources that can be dynamically provisioned according to organizational

requirements. However, allocating these resources effectively requires continuous monitoring and intelligent decision-making. Conventional resource management mechanisms frequently depend on predefined allocation policies, threshold-based scaling, and static scheduling techniques. Although these mechanisms are relatively straightforward to implement, they may struggle to accommodate unpredictable workloads and changing application priorities. Overprovisioning can result in unnecessary infrastructure expenditure and underutilized computing capacity, whereas underprovisioning can produce application delays, service interruptions, and performance degradation. These challenges demonstrate the importance of developing adaptive resource allocation strategies that can continuously learn from operational conditions and improve allocation decisions over time.

Reinforcement learning offers a promising computational approach for addressing these resource management challenges because it enables intelligent systems to learn appropriate actions through interactions with their operating environments. Unlike traditional scheduling techniques that depend entirely on fixed rules, reinforcement learning algorithms evaluate the consequences of different decisions and progressively identify strategies that maximize cumulative rewards. In enterprise cloud computing, an intelligent agent can observe infrastructure conditions, including CPU utilization, memory availability, storage consumption, network traffic, workload intensity, and application response time. Based on these observations, the agent selects resource allocation actions such as increasing virtual machine capacity, redistributing workloads, adjusting container resources, or releasing unnecessary computing instances. Feedback obtained from subsequent infrastructure performance enables the agent to improve its decision-making policy. This learning-based mechanism supports dynamic adaptation to changing operational requirements and can improve resource utilization while maintaining service quality. Furthermore, reinforcement learning can be integrated with workload forecasting, cloud orchestration platforms, and automated monitoring systems to establish a comprehensive resource management architecture. The proposed research investigates a reinforcement learning-driven intelligent resource allocation framework for enterprise cloud computing environments, emphasizing adaptive scheduling, operational efficiency, scalability, and cost optimization. It aims to establish an integrated approach that addresses the limitations of conventional allocation mechanisms while supporting reliable and sustainable cloud infrastructure management.

II. LITERATURE REVIEW

Cloud resource allocation has been extensively investigated as an important research area because enterprise applications require efficient management of distributed computing infrastructure. Early approaches primarily concentrated on static scheduling, resource reservation, priority-based allocation, and rule-driven provisioning. These mechanisms provided predictable resource distribution by assigning computing capacity according to predefined application requirements. However, their effectiveness becomes limited when application workloads change frequently or when multiple enterprise services compete for shared infrastructure resources. Threshold-based resource management introduced greater flexibility by monitoring utilization levels and initiating additional provisioning when predefined limits were exceeded. Nevertheless, such approaches frequently depend on reactive decisions and may experience delays when workloads increase unexpectedly. Similarly, traditional scheduling algorithms generally optimize individual allocation parameters without adequately considering the relationships between application performance, infrastructure expenditure, energy consumption, and resource availability. Researchers have therefore explored more adaptive techniques capable of coordinating multiple resource management objectives. Cloud virtualization and containerization have further expanded these opportunities by allowing applications to operate within independently managed computing

environments. These technologies support flexible resource distribution but also increase the complexity of scheduling decisions, particularly in large-scale enterprise deployments.

Artificial intelligence and machine learning have introduced new opportunities for improving cloud infrastructure management. Predictive models can analyze historical workload information to estimate future resource requirements, identify utilization patterns, and support proactive provisioning decisions. Supervised learning techniques have been investigated for workload classification, resource demand estimation, and performance prediction. Unsupervised learning methods can identify unusual utilization patterns and group applications according to their computational characteristics. However, predictive approaches generally provide recommendations rather than directly learning the consequences of resource allocation actions. Reinforcement learning addresses this limitation by establishing an interaction between an intelligent agent and a cloud resource management environment. The agent receives observations, performs allocation actions, and obtains rewards according to the resulting infrastructure performance. Different reinforcement learning approaches, including Q-learning, Deep Q-Networks, and policy-gradient methods, provide alternative mechanisms for learning allocation policies. Deep reinforcement learning is particularly relevant to enterprise cloud environments because neural networks can approximate complex decision functions involving multiple infrastructure variables. Research in this area has examined adaptive scheduling, virtual machine placement, energy-aware provisioning, workload distribution, and dynamic scaling. These investigations demonstrate the potential of learning-based resource management, although challenges remain concerning training efficiency, operational stability, and the transferability of learned policies across heterogeneous cloud infrastructures.

Recent research directions increasingly emphasize multi-objective optimization, autonomous cloud management, distributed decision-making, and intelligent orchestration. Enterprise environments require resource allocation strategies that simultaneously consider response time, infrastructure cost, application availability, energy consumption, and service-level agreement requirements. Optimizing only one parameter may negatively affect other operational objectives. For example, maximizing resource utilization without considering application performance may increase processing delays, while prioritizing low response times may result in excessive infrastructure expenditure. Multi-objective reinforcement learning provides a potential solution by incorporating several performance indicators into the reward function. Furthermore, distributed cloud architectures require coordination between different geographical locations, availability zones, virtualized environments, and container clusters. Hierarchical and multi-agent reinforcement learning approaches can support these complex management scenarios by distributing decision-making responsibilities among cooperating agents. Despite these developments, several research gaps remain, including insufficient consideration of changing enterprise priorities, limited explainability of allocation decisions, training overhead, and difficulties in maintaining consistent performance under unexpected workload fluctuations. The present research addresses these concerns by proposing an integrated reinforcement learning-driven framework that combines continuous infrastructure monitoring, adaptive resource allocation, performance feedback, and multi-objective optimization for enterprise cloud computing environments.

III. RESEARCH METHODOLOGY

The proposed research adopts a quantitative and experimental methodology to investigate reinforcement learning-driven intelligent resource allocation in enterprise cloud computing

environments. The primary objective is to develop an adaptive resource management framework capable of dynamically distributing computing resources according to changing application requirements and infrastructure conditions. The research architecture consists of five interconnected components: cloud infrastructure monitoring, workload characterization, reinforcement learning-based decision-making, resource allocation execution, and performance evaluation. The cloud infrastructure environment is represented through virtual machines, containerized applications, storage services, processing nodes, and network resources. Each infrastructure component generates operational information that is collected through monitoring mechanisms. Important parameters include CPU utilization, memory consumption, storage availability, network bandwidth, processing time, application response time, and energy usage. Historical and real-time workload information is analyzed to characterize application demand patterns and identify resource-intensive operations. The reinforcement learning agent interacts with this environment by observing the current infrastructure state, selecting an allocation action, and receiving feedback based on the resulting performance. The methodology considers a simulated enterprise cloud environment to enable controlled experimentation across different workload conditions. Workloads may include transaction processing, web application requests, database operations, enterprise information systems, and computationally intensive business applications. Different workload intensities are considered to evaluate the framework under normal, peak, and unpredictable operating conditions. The experimental architecture is designed to provide a consistent environment for comparing the proposed intelligent approach with conventional allocation mechanisms.

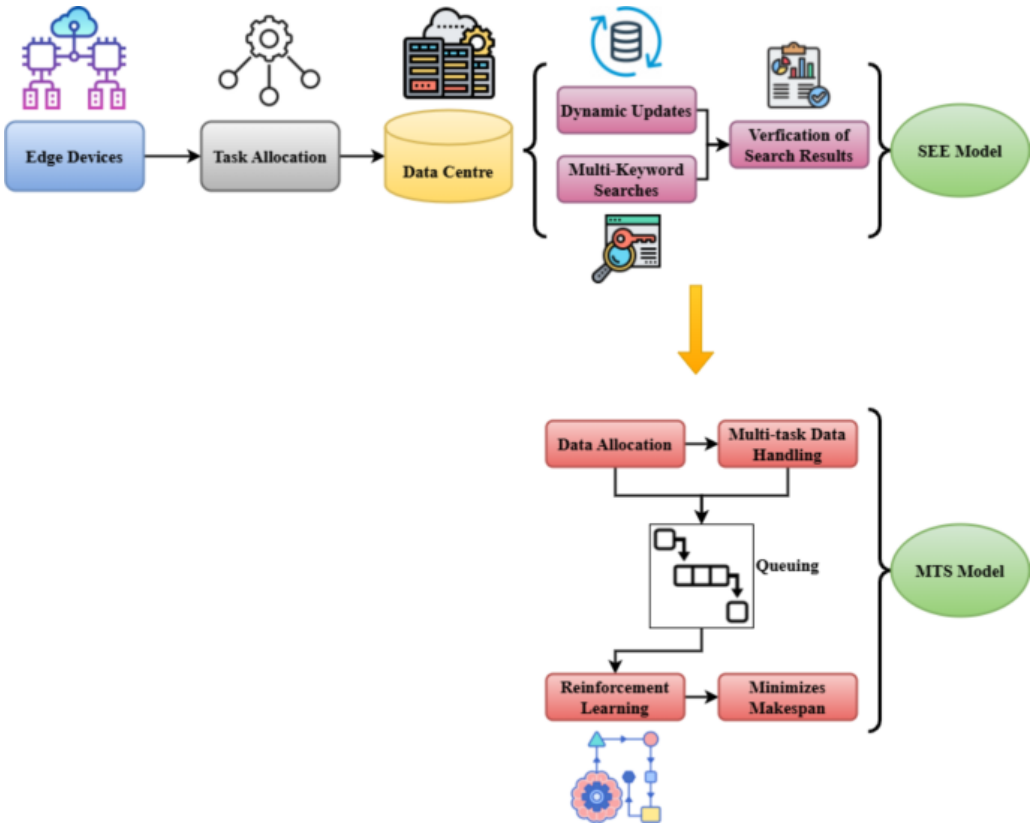

Fig.1. Reinforcement learning based Secure edge enabled multi task scheduling model for internet of everything applications

The reinforcement learning model is formulated using a Markov Decision Process consisting of states, actions, transition probabilities, and reward functions. The state representation includes the current resource utilization levels, available computing capacity, application workload intensity, queue length, network traffic, response time, and service priority. These parameters collectively

describe the operational condition of the enterprise cloud infrastructure. The action space represents the decisions available to the intelligent agent, including allocating additional CPU capacity, modifying memory assignments, increasing or decreasing virtual machine instances, redistributing application workloads, and releasing unnecessary resources. The agent selects actions according to its learned policy, which is updated using feedback obtained from the environment. The reward function is designed to encourage efficient infrastructure utilization while discouraging excessive operational costs, long response times, resource wastage, and service-level agreement violations. A conceptual reward formulation can be expressed as a weighted combination of resource utilization efficiency, application performance, cost reduction, and service reliability. Positive rewards are assigned when allocation decisions improve infrastructure performance and satisfy application requirements, whereas penalties are introduced when decisions cause resource shortages, unnecessary provisioning, or unacceptable service delays. The research considers Deep Q-Network-based learning as a primary decision-making approach because it can approximate complex state-action relationships through neural network representations. The learning process involves experience collection, replay-based training, target network updates, and policy refinement. An exploration strategy allows the agent to investigate alternative allocation decisions, while exploitation uses previously learned knowledge to select actions expected to produce favorable results. Learning parameters, including learning rate, discount factor, exploration probability, batch size, and training episodes, are configured experimentally to examine their influence on convergence and allocation performance.

The implementation methodology integrates the trained reinforcement learning model with a cloud resource management architecture. A monitoring component continuously collects infrastructure measurements and converts them into a structured state representation suitable for the intelligent agent. The state information is transmitted to the decision-making component, which evaluates available actions and determines an appropriate resource allocation strategy. The resulting decisions are communicated to the resource orchestration component, which executes the required infrastructure adjustments. These adjustments may involve modifying virtual machine configurations, changing container resource limits, migrating workloads between available nodes, or scaling computing instances according to application demand. A feedback mechanism subsequently evaluates the impact of each action by comparing the updated infrastructure condition with the previous state. The observed transition and corresponding reward are stored in the agent's experience memory for subsequent learning. To ensure reliable operation, the framework incorporates resource capacity limits, minimum application requirements, workload priorities, and service-level constraints. Safety-oriented allocation rules prevent the agent from assigning resources beyond infrastructure availability or reducing critical applications below their minimum operational requirements. The proposed architecture also considers the integration of workload forecasting information to support proactive allocation decisions. Historical utilization patterns can be analyzed to estimate potential workload increases and provide additional context for the reinforcement learning agent. The combination of forecasting and reinforcement learning is intended to improve decision quality by allowing the system to consider both current infrastructure conditions and anticipated application requirements. The framework is designed to support heterogeneous cloud environments in which different applications require different combinations of processing power, memory, storage, and network capacity.

The experimental evaluation is organized around comparative testing of the proposed framework against conventional resource allocation methods, including static allocation, threshold-based autoscaling, and traditional priority-based scheduling. Identical workload conditions, infrastructure configurations, and application requirements are maintained across the comparison methods to improve evaluation consistency. The experimental dataset consists of infrastructure monitoring measurements, application workload records, allocation decisions, and performance observations

collected from the simulated environment. The evaluation considers different workload scenarios, including stable demand, sudden workload increases, fluctuating application traffic, concurrent enterprise operations, and resource-intensive processing activities. Performance is assessed using several quantitative indicators. Resource utilization efficiency measures how effectively available computing capacity is employed, while average response time evaluates the time required to process application requests. Allocation efficiency examines the relationship between assigned resources and actual application requirements. Operational cost is estimated through resource consumption and provisioning duration, whereas SLA compliance measures the ability of the framework to satisfy predefined service requirements. Energy consumption is also considered to examine the sustainability of allocation decisions. Additional measurements include allocation decision frequency, workload distribution balance, resource wastage, and learning convergence. Repeated experimental runs are recommended to reduce the influence of random workload variation and training instability. Comparative analysis is conducted using descriptive statistics, performance trends, and graphical representations. The research also considers sensitivity analysis to examine how different reward weights and learning parameters influence allocation behavior. Since reinforcement learning performance depends on the quality of environmental feedback, the methodology evaluates the stability of learned policies under changing workload conditions. The resulting evaluation provides a structured basis for determining whether the proposed framework can improve enterprise cloud resource management compared with conventional allocation strategies.

IV. RESULTS AND DISCUSSION

The proposed reinforcement learning-driven resource allocation framework provides a systematic approach to addressing the limitations of conventional enterprise cloud resource management. The expected experimental evaluation focuses on the framework's ability to respond dynamically to changing workloads, distribute computing resources efficiently, and maintain application performance. Unlike static allocation approaches, which assign predetermined infrastructure capacity, the proposed system continuously evaluates operational conditions before selecting resource management actions. This adaptive mechanism is particularly relevant to enterprise environments where application demand varies throughout the day and different business services compete for shared infrastructure resources. During periods of low workload intensity, the agent can identify underutilized computing instances and recommend reducing unnecessary capacity. During increased demand, it can allocate additional resources or redistribute workloads to maintain application responsiveness. The resulting allocation strategy is expected to improve the relationship between available computing capacity and actual application requirements. CPU utilization, memory consumption, storage availability, and network bandwidth provide the primary information required for these decisions. By considering multiple parameters simultaneously, the framework can avoid allocation decisions based solely on individual resource thresholds. For example, an application experiencing high CPU utilization may not necessarily require additional processing capacity if the actual bottleneck originates from memory limitations or network congestion. The reinforcement learning model can consider these interconnected infrastructure conditions when evaluating possible actions. Such contextual decision-making is expected to improve resource allocation quality and reduce unnecessary provisioning. The framework also introduces continuous feedback into the allocation process, allowing the agent to learn from the operational consequences of previous decisions. This characteristic distinguishes the proposed approach from traditional mechanisms that repeatedly apply fixed provisioning rules without adapting their decision policies. The experimental analysis should therefore examine how effectively the learning agent identifies suitable allocation patterns under different enterprise workload conditions. Particular attention should be given to the consistency of allocation decisions during stable operating periods and the agent's responsiveness during sudden workload changes. These observations can help determine

whether reinforcement learning provides meaningful advantages over conventional scheduling approaches in complex cloud environments.

Resource utilization and application response time represent two important dimensions for evaluating the effectiveness of the proposed framework. In conventional cloud environments, excessive resource provisioning can increase infrastructure expenditure, while insufficient allocation can negatively affect application responsiveness. The proposed reinforcement learning approach attempts to balance these competing requirements by incorporating resource utilization and response time into its reward function. When application demand decreases, the agent can identify opportunities to reduce unnecessary resource assignments without violating minimum application requirements. Conversely, when workload intensity increases, it can recommend additional computing capacity or workload redistribution to prevent excessive processing delays. This adaptive behavior is expected to improve resource utilization while maintaining acceptable application performance. In enterprise environments, the benefits may be particularly important for applications supporting financial transactions, customer relationship management, enterprise resource planning, database processing, and business intelligence operations. These applications frequently exhibit different workload patterns and performance requirements. A resource allocation strategy that performs effectively for one application may not be appropriate for another. Therefore, the proposed framework considers application priorities and resource consumption characteristics as part of its decision-making process. The agent can learn to prioritize critical enterprise services while distributing remaining infrastructure capacity among less demanding applications. Furthermore, workload forecasting can provide additional information about anticipated resource requirements, enabling the system to initiate provisioning decisions before demand reaches critical levels. This combination of predictive information and reinforcement learning can reduce the dependence on purely reactive scaling mechanisms. However, the effectiveness of the approach depends on the quality of the workload information, the accuracy of the state representation, and the suitability of the reward function. Poorly selected reward weights may encourage excessive provisioning or resource conservation at the expense of application performance. Therefore, the experimental discussion should consider how alternative reward configurations influence resource utilization, response time, and allocation stability. A balanced reward mechanism is essential because enterprise cloud environments require consistent application performance rather than optimization of a single infrastructure metric. The proposed framework is consequently expected to provide a more flexible allocation strategy by considering the combined effects of resource availability, application priorities, and operational performance.

Operational cost, energy consumption, scalability, and service reliability provide additional dimensions for examining the proposed framework. Cloud infrastructure expenditure is influenced by the number of active computing instances, resource consumption levels, storage requirements, and duration of infrastructure provisioning. Inefficient resource management can result in unnecessary spending, particularly when organizations maintain excess computing capacity to accommodate uncertain workload conditions. Reinforcement learning can help reduce such inefficiencies by learning when resources should be increased, maintained, redistributed, or released. The proposed reward mechanism incorporates operational cost considerations to discourage unnecessary provisioning while maintaining sufficient capacity for enterprise applications. Energy consumption is another important consideration because large-scale cloud infrastructure requires substantial electrical power for computing, cooling, and supporting associated facilities. By reducing unnecessary resource activation and improving infrastructure utilization, intelligent allocation strategies may contribute to more energy-efficient cloud operations. However, energy optimization must be balanced against service availability and performance requirements. An allocation policy that reduces computing capacity excessively may create performance bottlenecks or increase application failure risks. Therefore, service-level

agreement compliance is incorporated as an essential evaluation criterion. The proposed framework is expected to support improved SLA management through application prioritization, resource monitoring, and feedback-based decision-making. Its scalability is also important because enterprise cloud environments may contain thousands of virtual machines, containers, and interconnected services. Deep reinforcement learning provides a flexible mechanism for handling complex allocation decisions, although model training and inference introduce computational overhead. As infrastructure size increases, the system must process larger state spaces and evaluate a greater number of possible allocation actions. Distributed or hierarchical reinforcement learning may help address these challenges by dividing resource management responsibilities across infrastructure layers. Another important consideration is training stability. The agent must learn effective policies without generating excessive resource fluctuations or disruptive allocation changes. Experience replay, controlled exploration, and operational constraints can improve the reliability of the learning process. The evaluation should also investigate performance under unfamiliar workload conditions to determine whether the trained policy can generalize beyond its initial training scenarios. Since no empirical measurements or completed experimental dataset have been supplied, specific numerical improvements cannot be claimed as observed findings. Instead, the proposed results constitute an evaluation framework and anticipated performance outcomes that must be validated through implementation and repeated experiments. Overall, the discussion indicates that reinforcement learning offers a promising foundation for adaptive enterprise cloud resource management, provided that its learning efficiency, operational reliability, and multi-objective performance are systematically validated.

V. CONCLUSION

The research presents a reinforcement learning-driven intelligent resource allocation framework for improving resource management in enterprise cloud computing environments. The increasing dependence of organizations on cloud infrastructure has created significant challenges concerning dynamic workload management, resource utilization, application performance, operational expenditure, and service reliability. Conventional resource allocation mechanisms based on static provisioning, predefined rules, and threshold-based scheduling may not adequately respond to complex and continuously changing enterprise workloads. The proposed framework addresses these limitations through an adaptive learning mechanism that observes infrastructure conditions, evaluates possible resource allocation actions, and improves its decisions using feedback from the cloud environment. The framework considers important operational parameters, including CPU utilization, memory consumption, storage availability, network bandwidth, workload intensity, response time, and energy consumption. By representing cloud resource management as a reinforcement learning problem, the system can progressively develop allocation policies that balance competing infrastructure requirements. The integration of workload monitoring, intelligent decision-making, automated orchestration, and continuous performance evaluation establishes a comprehensive approach to enterprise cloud management. Deep Q-Network-based learning provides a suitable mechanism for identifying allocation strategies in environments characterized by multiple interconnected resource variables and changing application requirements. The proposed architecture also incorporates application prioritization, infrastructure constraints, and service-level requirements to support reliable resource distribution. Its multi-objective design emphasizes the importance of balancing infrastructure utilization, application responsiveness, operational cost, and energy efficiency. The research methodology establishes a comparative experimental framework for evaluating the proposed approach against conventional allocation techniques under different workload scenarios. Through this evaluation structure, the research provides a foundation for understanding the practical advantages and limitations of reinforcement learning-based cloud resource management.

The proposed framework has the potential to support enterprise organizations in developing more adaptive, scalable, and cost-effective cloud computing infrastructures. Its continuous learning capability can help cloud management systems respond to workload fluctuations and identify opportunities for improving infrastructure utilization. Intelligent resource allocation may also reduce unnecessary provisioning, improve workload distribution, and support consistent application performance when appropriately trained and integrated with existing cloud orchestration systems. Nevertheless, successful implementation requires careful consideration of training overhead, reward function design, workload variability, infrastructure heterogeneity, and operational safety. Reinforcement learning agents must be evaluated under realistic enterprise conditions before being deployed in production environments, particularly where application availability and transaction reliability are essential. The proposed framework should therefore be regarded as a research architecture requiring empirical validation rather than a system with already established numerical performance improvements. Future experimental implementation can provide additional evidence regarding its effectiveness, scalability, and adaptability across different enterprise cloud platforms. The integration of distributed learning, explainable decision-making, predictive workload analysis, and security-aware resource management can further improve its practical applicability. Ultimately, reinforcement learning-driven intelligent resource allocation represents a promising direction for transforming conventional cloud infrastructure management into a more autonomous and performance-oriented operational process. By combining adaptive learning with continuous infrastructure monitoring and multi-objective optimization, enterprise cloud environments can move toward more efficient computing resource distribution, improved service quality, and sustainable infrastructure utilization.

VI. FUTURE WORK

Future research can extend the proposed framework by investigating advanced reinforcement learning algorithms capable of managing increasingly complex enterprise cloud environments. Although Deep Q-Networks provide an appropriate foundation for discrete resource allocation decisions, other approaches, including Proximal Policy Optimization, Deep Deterministic Policy Gradient, and Soft Actor-Critic, may offer advantages when allocation decisions involve continuous resource adjustments. Multi-agent reinforcement learning can also be explored to distribute decision-making responsibilities across multiple cloud nodes, availability zones, and application clusters. Such an architecture could improve scalability by allowing individual agents to manage specific infrastructure components while coordinating with other agents to achieve overall resource management objectives. Future studies can additionally investigate hierarchical reinforcement learning, where high-level agents determine resource allocation priorities and lower-level agents execute individual provisioning and scheduling operations. Integration with workload prediction models may further improve proactive resource management by identifying anticipated demand changes before they affect application performance. Experimental investigations should include real-world enterprise workloads, heterogeneous cloud infrastructure, and extended operational periods to evaluate the generalization capabilities and stability of learned allocation policies.

Another important direction involves developing secure, explainable, and sustainable reinforcement learning-based cloud management systems. Enterprise organizations require transparency regarding automated infrastructure decisions, particularly when resource allocation affects business-critical applications and service availability. Future research can investigate explainable reinforcement learning techniques that provide understandable reasons for individual allocation decisions and identify the operational factors influencing agent behavior. Security-aware resource allocation can also be introduced to consider access control, workload isolation, infrastructure vulnerabilities, and unusual resource consumption patterns. Federated reinforcement learning may provide

opportunities for collaborative policy improvement across geographically distributed cloud environments while reducing the need to centralize sensitive operational information. Furthermore, future implementations can examine the integration of carbon-aware scheduling, renewable energy availability, and energy-efficient infrastructure provisioning to support sustainable cloud operations. The development of standardized evaluation datasets, reproducible experimental environments, and common benchmarking metrics would improve comparisons between different intelligent resource management approaches. These developments can help establish reliable guidelines for deploying reinforcement learning-driven resource allocation systems in large-scale enterprise cloud environments.

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