A Self – Adaptive Reinforcement Learning Driven Teaching Management System Based on Cloud Computing Technology

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Abstract - The introduction of cloud computing has greatly enhanced the scale of and access to today's modern teaching management systems. However, current e-learning platforms that are hosted in the cloud typically use static resource allocation strategies, which lead to poor resource usage and limited adaptability for fluctuating workloads [1]–[5]. To solve these problems, this paper introduces a new type of teaching management system with self-adaptive resource allocation using Deep Reinforcement Learning (DRL) for cloud resource management. The proposed self-adaptive system will allocate cloud resources using real-time workload data and also continually improve/drill down to the optimal resource allocation policy, improving performance and lowering operational costs [11]–[14]. The proposed system is envisioned to integrate both cloud-based education services as well as adaptive education strategies, thus enhancing scalability, responsiveness, and overall system efficiency. Based on the results from preliminary experiments, the proposed system is shown to provide a more intelligent and adaptive solution than other standard cloud-based teaching management systems.

Key Words: Cloud Computing, Teaching Management System, E-learning, Deep Reinforcement Learning, Resource Allocation, Adaptive Systems, Learning Analytics, Cloud Resource Management, Educational Technology, Intelligent Systems

1.INTRODUCTION

Cloud computing has had a major impact on how we create and provide an education-driven teaching and learning system. Cloud-Based e-Learning System provides an easily scalable infrastructures, flexibility in the use of resources, and affordability for educational establishments. With this architecture, all students and educators can access learning materials, assessments and communication tools no matter their physical location, which thus encourages today's ever-evolving digital learning environments [1][3]. Therefore, cloud-based technology is becoming a core technology that supports the efficient development of accessible teaching management systems.

Multiple cloud-based e-Learning architectures have been created to improve e-Learning performance and usability. Most educational service delivery via SaaS models exists to support the aforementioned functions and services related to course management, learner information systems, and virtual assessments [4][5]. With advancements of Education 4.0, almost every educational institution has begun applying intelligence or transition to data-driven learning educational platforms - with Cloud Infrastructure serving as the backbone supporting large numbers of academics and learner interactions [6][7]. In addition, existing technologies still experience significant barriers to achieving scalability, optimal resource utilization, and continuously adaptable to real-time demands from changing workloads [8][9].

One of the significant limitations to today's cloud-based teaching management systems depends upon static/resource allocation methods which are rule based. These methods do not properly accommodate changing user demands or increase the chance that the resource is not utilized as well as possible or increases operational costs due to increased response times. Recent research has examined various machine learning techniques for intelligent resource allocation purposes[18]. Approaches, such as reinforcement learning, have shown great promise for learning optimal decision-making policies of resource allocation through continual interaction and feedback received from the environment.

Deep reinforcement learning (DRL) has also shown great potential for solving complex resource allocation/scheduling problems within the context of cloud computing environments by utilizing artificial neural networks and reward-based learning mechanisms which can dynamically optimize the distribution of resources within the environment and thus enhance overall performance[11][13]. Several studies have demonstrated how DRL has been applied successfully across multiple domains of resource management including but not limited to resource scheduling, workload balancing and energy efficiency[14][16]. For this reason, DRL offers an attractive way of increasing both the adaptability and intelligence of cloud based teaching management systems.

2. Literature Review

As a result of utilizing cloud computing technology in an educational setting, a new generation of advanced e-learning systems and teaching management platforms has emerged that provide scalability, flexibility, and lower costs. Many researchers have evaluated various cloud-based systems for use in educational service delivery and management since this early research.

The initial focus of early research was on how to integrate a cloud-based infrastructure with e-learning systems to improve accessibility and reduce operational costs associated with running e-learning services. By using distributed computing resources in a manner that is efficient for delivering the e-learning experience, Siddiqui, and others [1] have created a solid foundation for providing an effective cloud-based e-learning framework. Researchers Wu and Plakhti also found compelling reasons to use cloud computing platforms to deliver scalable and flexible e-learning services [2]. Additionally, Riahi [3] provides a detailed overview of current trends in the field of cloud-based e-learning systems and discusses their potential for supporting large-scale educational implementations and solutions.

For cloud computing based educational systems, there have been numerous architectural frameworks proposed by various researchers. Huang [4] suggested a cloud-focused architecture for an e-learning system which allows educators to share resources and access them remotely. Selviandro and Hasibuan [5] introduced a cloud-based model that creates opportunities for collaboration and reduced capital investment required to maintain infrastructure by educational institutions. Hendradi and Khanapi [6] highlighted how cloud computing will play a vital role in forming a data-driven teaching and learning environment around Education 4.0. The contributions of Popel and Shyshkina [7] focused on investigating how cloud computing is utilized in research and development within the contemporary education environment.

Further research has focused upon improving system performance and adaptability. Masud and Huang [8] suggested that a new practical methodology be developed to implement e-learning systems using cloud based technologies while also focusing upon performance and usability issues. Fasihuddin and Skinner [9] also carried out an extensive review of cloud-based learning systems and identified key areas of concern such as scalability and managing resources effectively. Ahmed [10] compared different cloud-enabled e-learning systems by performing a comparative analysis and pointed out the significant drawbacks associated with static resource allocation processes.

In response to these issues, there has been an increasing amount of research related to intelligent resource management with machine learning techniques. Goodarzy et al. [18] provided a detailed survey regarding the application of machine learning to resource management in cloud computing, indicating the potential for improving system performance and efficiency through this approach. Of all the various techniques being studied for resource management, Deep Reinforcement Learning (DRL) has become popular because it allows for adaptive and real-time decision-making.

For instance, Zhang et al. [11] proposed a DRL-based structure for cloud systems providing superior performance within dynamically changing environments. Gu et al. [12] provided an overview of various DRL techniques at the algorithm level that could be used to schedule jobs and allocate resources in cloud systems. Feng and Liu [13] discussed how effective DRL is at optimizing resources and minimizing operational costs. Zeng et al. [14] demonstrated DRL can also be applied to edge computing and that it scales well and is adaptable for use in this environment.

A focus of further studies on resource scheduling of cloud resources is the enhancement of this process through reinforcement learning techniques. Research performed by Guo and others [16] has suggested a combination of the DRL process with imitation learning to improve efficiency of scheduling. Liu and others [19] have designed a hierarchical DRL structure specifically for the purposes of allocating resources and managing power, and Antonio and others [20] have demonstrated the effectiveness of reinforcement learning for the purpose of managing resources within the context of multi-cloud systems. Recent research by Sundar [15] and Mallikarjunareddy and others [17] has also illustrated the applicability of reinforcement learning for optimizing cloud use autonomously and in conjunction with real-time AI based workloads.

In spite of these advances, many cloud based Teaching Management Systems (TMS) do not incorporate intelligent/adaptive resource management components. Most systems continue to utilize either static or semi-dynamic systems; this limits the TMS's capability of accommodating real-time changes in workload and user requests. Therefore, the development of a self-adaptive TMS system that integrates public cloud based e-learning and reinforcement learning driven resource optimization is warranted.

3. System Architecture

This is an overview of a cloud-based adaptive educational management framework that combines educational services and deep reinforcement learning (DRL) based resource management. The overall design includes a multi-layered architecture that allows for modularity, scalability, and efficient communication between system components.

The system is divided into 5 main layers, which are: (i) User Interaction Layer, (ii) Application Layer, (iii) Analytics Layer, (iv) Reinforcement Learning Based Resource Management Layer, (v) Cloud Infrastructure Layer. Together these 5 layers create an adaptive closed-loop system that continually tracks and optimizes resource usage.

3.1. User Interaction Layer

This layer represents the interaction that users have with the system. This includes the following interfaces for users:

- Student interface to provide access to course materials, assignments and performance data.
- Faculty interface to manage courses and evaluate students.

- Administrator interface to monitor the system.

User requests made at this layer are sent to the application layer for processing..

3.2. Application Layer

The main functionalities of a teaching management system are performed in the application layer. The main modules include:

- The Course Management System
- The Student Information System
- The Assessment and Evaluation Module
- The Communication & Resource Sharing Module.

All four modules are delivered as cloud-based SaaS solutions. This provides highly flexible, scalable service through a cloud-based software application. User interaction generates dynamic workloads in the application layer.

3.3. Analytics Layer

The analytics layer processes academic and system data to provide some useful insights into those data sets. The analytics layer will be performing:

- Student Performance Analysis
- Learning Behavior Analysis
- Predictive Analysis of Academic Outcomes

The Analytics Layer improves the ability to make better decisions based on data, provides better support to educational services with intelligent services, and provides support to cloud-based education systems.

3.4.Reinforcement Learning Based Resource Management Layer

The primary innovation behind the design is the deep reinforcement-learning (DRL) agent, which is applied to dynamic resource allocation.

The key parts of this system are the following:

3.4.1. Monitoring Module

This monitors the following metrics in real-time: CPU Utilization Memory Utilization Number of Active Users Request Rate

3.4.2. DRL Agent

The DRL agent learns the optimal way to allocate resources and modify its allocation as the system adapts to changing usage patterns. Data is collected from each of the following states, actions, and rewards:

- System Workload Metrics (S)
- Scaling Decisions (A) (i.e. increase or decrease the number of virtual machine (VM) instances)
- Performance Improvements, Reduced Latency, Cost Optimization (R)

The DRL agent continuously updates its policy based upon feedback from its environment and thereby adapts to changes accordingly

3.4.3. Policy Execution Module

Based upon the policy learned by the DRL agent, this component implements the scaling decisions in the cloud infrastructure. This system's design allows for real-time optimization and solution of the limitations imposed by static resource allocation

3.5 Cloud Infrastructure Layer

The resources that support the computational side of the system are provided by this layer (e.g., VMs, Storage, Networking). Additionally, the infrastructure will provide additional resources dynamically as they are needed based on the decisions provided by the DRL Agent in order to achieve optimal use of resources and maximum performance of the system.

3.6 System Workflow

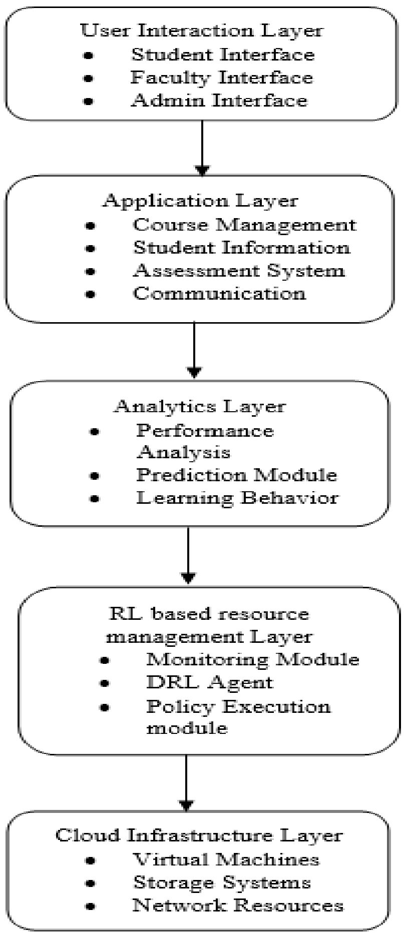

Fig -1: System Architecture

4. Methodology

4.1. Research Design Overview

The cloud-based teacher management system (TMS) that was developed follows a structured Design and Development Research (DDR) methodology combined with experimental validation. This method has a systematic progression through several key stages: requirement identification through to performance validation based on real time workload, taking place in simulated conditions. The Overall research work is illustrated in fig 2: This structured framework ensures systematic development, scalability verification, and quantitative performance assessment.

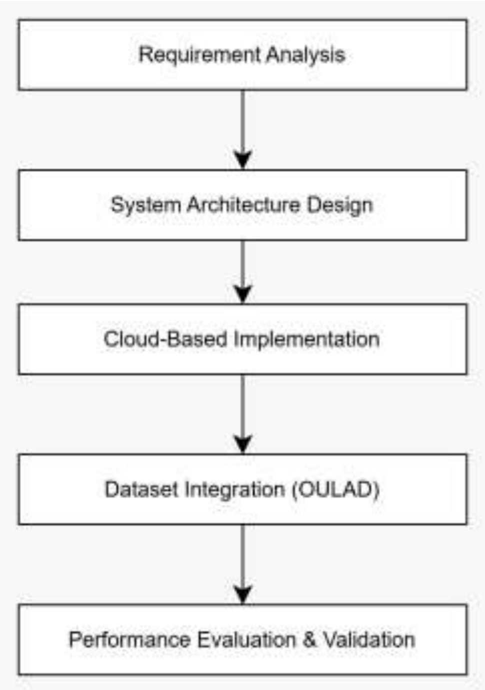

Fig -2: Overall research methodology

4.2. Requirement analysis

In the requirement analysis step, researchers investigated how much functionality could be provided by schools and colleges and what kind of limitations they experienced with their existing systems. Researchers reviewed existing, traditional systems and looked for limitations related to scalability, processing/operating infrastructure, and costs associated with maintaining those systems..

4.2.1. Functional Requirements

Module	Core Functionality
User Management	Registration, authentication, role assignment
Course Management	Course creation, scheduling, modification
Student Management	Enrollment tracking, academic progress
Assessment Module	Online quizzes, grading automation
Resource Sharing	Upload and download of materials
Communication Module	Announcements and Messaging

Table -1: Functional Requirements

4.2.2 Non Functional Requirements

Parameter	Target Objective
Scalability	Automatic resource scaling
Availability	Minimum 99.9% uptime
Security	Role-based access control & Encrypted Communication
Performance	Low response time under load
Cost Efficiency	Reduced infrastructure expenditure

Table -2: Non Functional Requirements

4.3 System Development Strategy

An Agile-based iterative development methodology was adopted. Each module was independently implemented and tested before integration into the overall system. This iterative cycle ensures continuous improvement, flexibility, and rapid issue resolution during implementation.

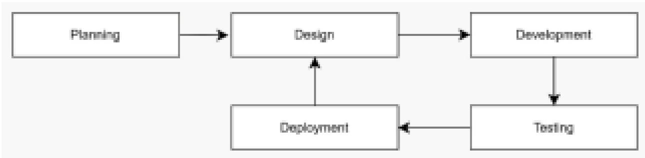

Fig -3: Agile Development Cycle

4.4 Cloud Based System Architecture

The system follows a three-tier SaaS architecture deployed on cloud infrastructure. Cloud features such as auto-scaling, load balancing, and backup mechanisms were configured to maintain high availability and resilience.

Layer	Function
Presentation Layer	Web interface for users
Application Layer	Business logic & APIs
Data Layer	Managed cloud database

Table -3: Architectural Layers

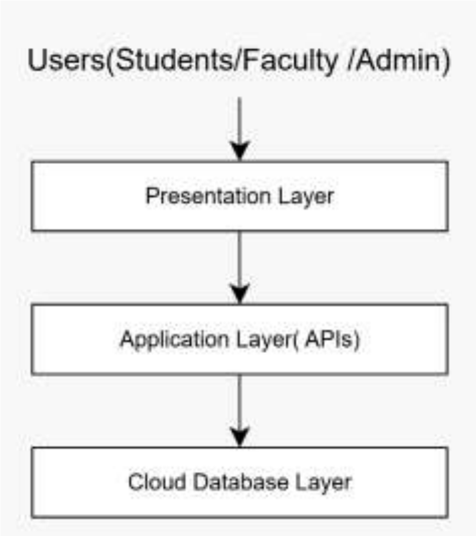

Fig -4: Cloud System Architecture

4.5. Data Testing and Integration

The inclusion of the Open University Learning Analytics Dataset (OULAD) in the database served to verify the extensibility of the system. Prior to being migrated onto the cloud database, it was cleansed of inconsistencies, and structured as per the database schema. By simulating multiple users accessing similar functions within this dataset (e.g., creating an enrollment for someone, submitting an assignment, participating in an assessment), we were able to model the academic processes that occur as people interact with the dataset.

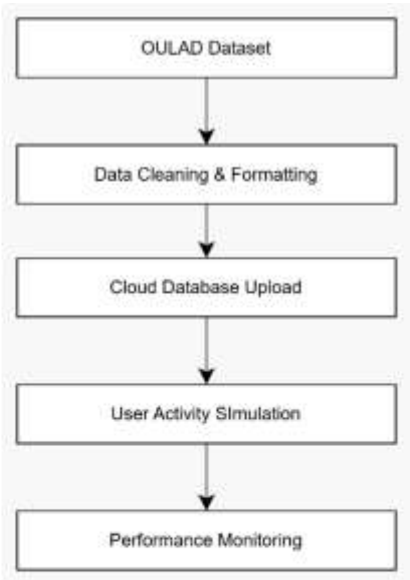

Fig -5: Database Testing Workflow

4.6 Database Performance Evaluation

System performance was assessed using quantitative metrics to evaluate scalability and operational efficiency. Variations in user concurrency level were used for the load testing, while the testing results indicated that the system performed consistently well under medium load, with the auto-scaling feature functioning as it should during high traffic periods. The cost analysis of cloud deployment compared with traditional infrastructure revealed approximately 40% reduction in operational costs.

Metric	Measurement Method
Response Time	Average API processing delay
Throughput	Requests handled per second
CPU Utilization	Cloud monitoring tools
Memory Usage	Runtime analysis
Availability	Uptime monitoring logs

Table -4: Performance Metrics

4.7. Security Implementation

The security measures have been applied across a number of different layers of the architecture. For example, the system uses role-based access control (RBAC) to limit access to authorized modules. In addition, all communications passing between clients and servers will be encrypted with HTTPS encryption. The cloud firewall configurations and automated backups improve the resiliency of the system as well as protecting its data.

4.8. Validation Approach

The validation process consisted of functional testing, load testing, and user feedback analysis. Functional testing confirmed the correctness of the modules and load testing verified the scalability of the modules by simulating a busy academic setting. User surveys indicated an improvement in teaching effectiveness and an increase in the use of technology in learning.

5. Results and Discussion

The Cloud Infrastructure for Self-Adaptive Teaching Management System has been established using several functional modules and evaluated with promising results. The outcomes provide evidence that this system is able to effectively manage academic activity and dynamically optimise resources.

Fig -6: Student and Faculty Portal with AI Prediction Module

Using both students and instructors ability to submit assignments, view and track academic performance, and utilize the analytics portion of the system, through these functionalities combined with the artificial intelligence-based prediction capability to assess student performance from academic data enables proactive decision making by university staff.

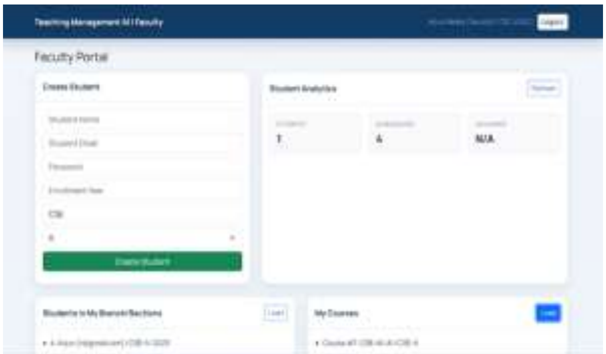

Fig -7: Faculty Portal with Student management and analytics

The instructor's portal gives instructors the ability to create and validate students in addition to being able to monitor their academic progress. The faculty portal also contains information on student performance such as how many students have submitted assignments, how many assignments have been submitted, and the average score on course & instructor-related assignments, enabling instructors to make data-driven academic decisions.

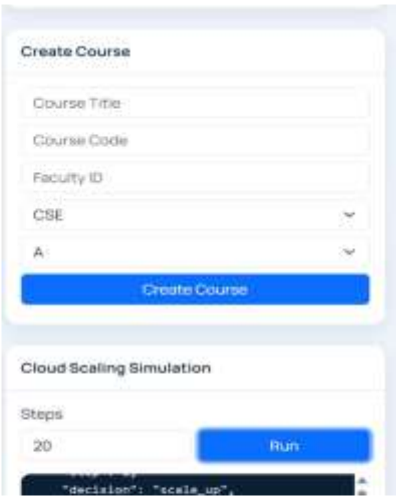

Fig 8: Course Creation and cloud scaling simulation interface

The figure shows the course creation module, where administrators can input the course title, code, department, and section. The cloud scaling simulation module displayed below the course creation module simulates the scaling decisions of the resultant reinforcement learning model to validate the adaptiveness of the system being discussed across a range of workloads.

Fig -9: User Management and Course Activity insights interface

Each user and their respective role (either student or faculty) are displayed in this user management interface so that the manager can manage users and have all the information regarding the users of the entire system available. In addition, insights regarding course activity are available, including assignment and submission activities and the average marks of the students associated with each course. This enables administrators to monitor and assess the academic performance of students as well as system engagement.

Fig -10: Admin dashboard with real time metrics and RL Decisions

The dashboard provides all system-level information, such as total number of students, total number of courses, and predicted scores. It also provides a visual representation of workload indicators and the reinforcement learning scaling actions that have been applied throughout the scaling process, showing how resource allocation has been adapted to the workload change

6. Conclusion

The present study describes a cloud-computing-based self-adaptive teaching management system that integrates intelligent resource management with academic analytics. This new approach provides a cost-effective, flexible and scalable alternative to traditional systems and overcomes several major limitations of previous approaches.

The new system was developed to provide support for many of the key elements of academic activity, such as user management, course management, assignment management and performance management, all within the same cloud-based environment. The new system's reinforcement-learning-based resource management mechanism enables it to dynamically adapt its use of cloud resources in response to changes in workload, which results in improved responsiveness and reduced latency.

Additionally, the implementation of the system's AI-based prediction module enables the system to provide detailed insights about student performance, which will facilitate the making of informed decisions about academic progress. Furthermore, the provision of such analytical data will enhance the overall usability of the system.

In summary, the new system illustrates how the convergence of cloud computing and intelligent and adaptive techniques will lead to improved capabilities for teaching management platforms. The new system provides the foundation for creating tomorrow's educational systems as they strive to be more data-driven, scalable and responsive.

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