Evaluation and technological solutions for a dynamic, unified cloud programming development environment

Ease of use and applicable system for uniformized practices and assessments

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Abstract—**With the acceleration of the Internet in Web 2.0, Cloud computing is a new paradigm to ofer dynamic, reliable and elastic computing services. Efcient scheduling of resources or optimal allocation of requests is one of the prominent issues in emerging Cloud computing. Considering the growing complexity of Cloud computing, future Cloud systems will require more efective resource management methods. In some complex scenarios with difculties in directly evaluating the performance of scheduling solutions, classic algorithms (such as heuristics and meta-heuristics) will fail to obtain an efective scheme. Deep reinforcement learning (DRL) is a novel method to solve scheduling problems. Due to the combination of deep learning and reinforcement learning (RL), DRL has achieved considerable performance in current studies. To focus on this direction and analyze the application prospect of DRL in Cloud scheduling, we provide a comprehensive review for DRL-based methods in resource scheduling of Cloud computing. Through the theoretical formulation of scheduling and analysis of RL frameworks, we discuss the advantages of DRL-based methods in Cloud scheduling. We also highlight diferent challenges and discuss the future directions existing in the DRL-based Cloud scheduling.**

The isolated environment offered by the virtual space guarantees private work sessions, and multi-project activities can also be handled more easily and uniformly. The analysis of the teaching program presented below provides insight into the practical and appropriate solutions offered by the containerization process. In addition to these, the topic will also cover the widely used and popular Docker application that supports the implementation of the process, as well as the NodeJS environment closely related to the project.

Keywords—teach program, virtual environment, containerization, Docker, NodeJS, cloud-based services

INTRODUCTION

In recent years, there has been steady growth in the development of cloud-based Integrated Development Environments (IDEs) to provide fast and reliable development services to software developers. The trend has been accelerated by the emergence of Docker Container-based online IDE solutions, which allow developers to access their development environments from anywhere with just an internet connection. This paper examines the effect of Docker Container-based online IDE [2] solutions on software developers from an economical and practical perspective. Furthermore, this paper will explore how Docker Containerbased online IDE solutions can revolutionize software development.

The development of modern computing systems and their applications have brought about various programming environments, each with advantages and disadvantages. For example, specific programming languages are more suited for web development, while other programming languages provide better support for machine learning algorithms. Additionally, specialized programming environments exist to solve distinct programming tasks, such as scripting and software automation, but they come with decreased readability compared to more general-purpose programming languages. Furthermore, programming environments can also be divided into language-specific and platform-specific ones. Unfortunately, platform-specific programming environments often require significant effort in their setup, which is often incompatible across different computers. Additionally, relying on platform-specific libraries and frameworks can introduce version compatibility and maintenance issues. These problems can be daunting to newcomers and experienced programmers and should be considered when selecting a programming environment.

Uniformized programming environments offer significant advantages to students. These environments provide a preconfigured and consistent work environment easily shared between users and machines. This uniformity provides a common platform for course material, enabling efficient collaboration and providing a consistent experience across classrooms and institutions. Furthermore, these environments allow efficient tracking of once identified issues and bugs and enable efficient sharing of software libraries and code among users. Finally, these environments can also offer connectivity to external tools, such as cloud resources, allowing students to access additional software, data, and resources [14]. Overall, uniformized programming environments provide students with consistent, accessible, and robust platforms to facilitate their learning of programming.

In our work, we create a unique, virtual-server-based system for programming students. This solution is helpful for both practice and examination purposes.

ALTERNATIV SOLUTIONS

There are many paid or free tools on the Internet. Unfortunately, most of them are too expensive for education purposes.

1. Cloud9: Cloud9 is a development platform that lets anyone write, run, and debug code in various languages, in any browser, or on any platform. It comes pre-installed with popular development tools and integrated libraries for many languages.
2. AWS Cloud9 IDE: Amazon Web Services Cloud9 IDE offers an integrated development environment based on the Eclipse platform. The IDE contains unique features that allow developers to create, debug, and deploy applications on AWS's servers.
3. Codeanywhere: Codeanywhere is a collaborative cloud-based IDE that allows teams of developers to work side-by-side on projects. It includes support for a variety of programming languages, as well as integration with popular version control systems.

4. Code Envy: Code Envy is a cloud-based development environment that supports popular programming languages, such as Java and JavaScript. It allows developers to edit, debug, and deploy their code in the cloud without any external installation.
5. Koding: Koding is a cloud-based IDE that provides a graphical interface for quickly creating and testing web applications. It supports various programming languages, including Python, Ruby, HTML, CSS, and more.

These are good solutions for companies or individuals, but some abilities are missing for education purposes.

Missing important features: full access to the virtualized operating system, teachers can create templates, and preinstalled software.

TECHNOLOGY FOUNDATIONS

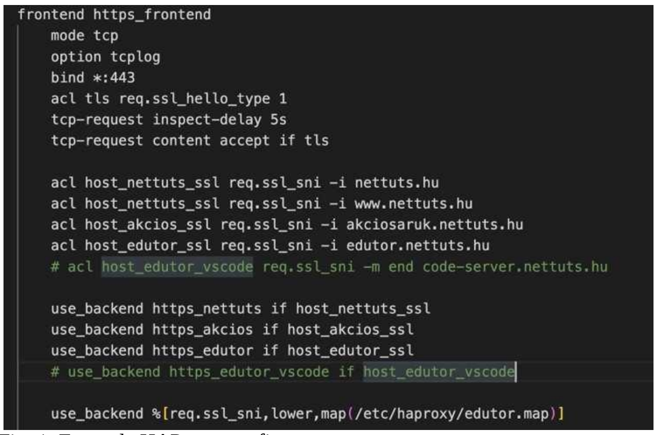
VPS

A Virtual Private Server (VPS) is a virtualized server, a software simulation of physical server hardware. It is a secure and cost-effective solution to host websites and applications, enabling multiple users to run multiple operating systems and software on a single server. A VPS typically also provides data storage and remote access via the Internet, creating a mix of physical and virtual infrastructure. VPS architecture allows us to create cost-effective applications.

We use an Ubuntu VPS. This OS is the host of Docker containers. The VPS runs a special software for proxying HTTP requests named HAProxy.

HAProxy is a high-performance load balancer and a reverse proxy that enables an optimized delivery of applications. It helps improve an application's availability and performance by distributing the workload across multiple servers. It can also be used for other types of network traffic, such as HTTP, MSBB, DNS, TCP, and UDP. [9] In addition, HAProxy can detect server failures in real-time and can be used as a proxy for HTTP, HTTPS, SMTP, POP3, and IMAP servers. It also supports WebSockets, content switching, and SSL/TLS offloading, among other features.

Furthermore, HAProxy can route requests to multiple web servers while ensuring that the traffic is distributed optimally. It also helps to ensure that IP whitelisting and rate-limiting rules are applied. HAProxy provides SSL certificate management, automatic SPOF prevention, and health checks to ensure that only healthy servers receive traffic.
HAProxy has config files that contain domain mappings.
The host machine runs Docker containers on specified ports and HAProxy redirects requests to these.



```
frontend https_frontend
    mode tcp
    option tcplog
    bind *:443
    acl tls req.ssl_hello_type 1
    tcp-request inspect-delay 5s
    tcp-request content accept if tls

    acl host_nettuts_ssl req.ssl_sni -i nettuts.hu
    acl host_nettuts_ssl req.ssl_sni -i www.nettuts.hu
    acl host_akcios_ssl req.ssl_sni -i akciosaruk.nettuts.hu
    acl host_edutor_ssl req.ssl_sni -i edutor.nettuts.hu
    # acl host_edutor_vscode req.ssl_sni -m end code-server.nettuts.hu

    use_backend https_nettuts if host_nettuts_ssl
    use_backend https_akcios if host_akcios_ssl
    use_backend https_edutor if host_edutor_ssl
    # use_backend https_edutor_vscode if host_edutor_vscode

    use_backend %[req.ssl_sni,lower,map(/etc/haproxy/edutor.map)]
```

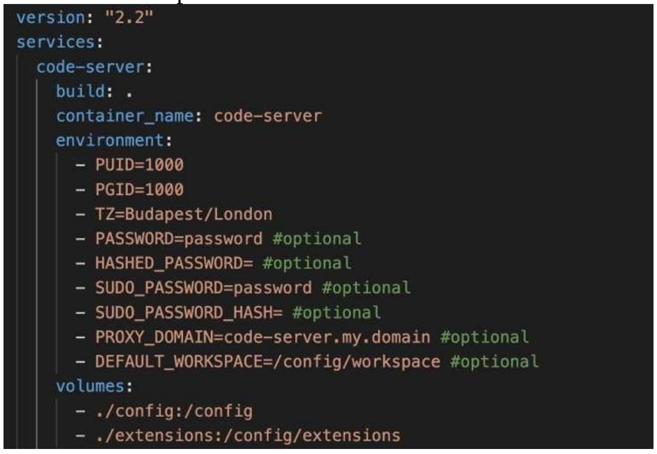
Fig. 1. Example HAProxy config

Docker

Docker [1] is an open-source software platform that enables developers to easily package, deploy, and manage applications in a virtual environment known as a container. Docker Compose is an open-source tool for defining, running and managing multi-container applications. It provides a way to define and configure all the services (containers) that make up an application in a YAML file. It also allows users to manage and scale their applications effectively.

To manage containers, we use dockerfile and dockercompose files. The dockerfile contains the configuration of the container instance, such as VSCode server installation steps, exposed ports, and secured directories.

The docker-compose file contains environment variables and a list of real ports.



```
version: "2.2"
services:
  code-server:
    build: .
    container_name: code-server
    environment:
      - PUID=1000
      - PGID=1000
      - TZ=Budapest/London
      - PASSWORD=password #optional
      - HASHED_PASSWORD= #optional
      - SUDO_PASSWORD=password #optional
      - SUDO_PASSWORD_HASH= #optional
      - PROXY_DOMAIN=code-server.my.domain #optional
      - DEFAULT_WORKSPACE=/config/workspace #optional
    volumes:
      - ./config:/config
      - ./extensions:/config/extensions
```

Fig. 2. Example docker-compose.yml

Web Server

NodeJS is a JavaScript-based run-time environment for building web applications. NodeJS allows us to write serverside JavaScript code for our web applications and run it directly in the server environment. [8] In addition, NodeJS is an open-source software, so anyone can use it to create great web applications quickly and easily.

We needed a secure and easy-to-use interface to manage containers. We chose NodeJS and a web interface. Each

Fig. 3. The login page

DIFFICULTIES

So, therefore this project was pretty complex, and there were many difficulties.

When students start in a new environment, the system often duplicates them. So we created a routine that checks the environment names and opens the existing ones if available.

The second was with the resources. [4] We ran Angular applications in the Docker container. Angular needs a lot of memory and CPU time for building applications because it is built with TypeScript. Browsers do not know TypeScript code; therefore, before running an application in the browser, it is necessary to create JAVASCRIPT codes from it. Converting TypeScript to JAVASCRIPT is the building task.

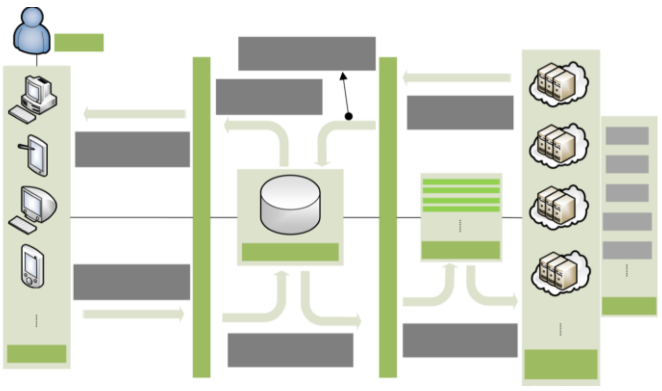
When the container ran with 1GB of memory, the VSCode server hung an out-of-memory error. So we had to find the proper memory amount for this task. It will be 1.3GB of memory. After all, we created a new and more memoryefficient builder for Angular written by GoLang instead of the original NodeJS implementation.

We found that each setup requires thorough pre-testing for good functionality. It requires testing memory, CPU, and file system.

SUMMARY

Cloud-based development environments provide quick, easily accessible opportunities for development, including collaboration [5] [14]. They also support education well by significantly reducing the time required to prepare and manage the technical implementation of educational processes. In the current educational system, the role of teachers must also constantly evolve and adapt to the direction of digitalization [6] [11] [15]. With central regulation, it is possible to quickly and efficiently provide the necessary technological background for teaching, and a failure of a particular machine does not affect the entire system [10] [12]. There are many cloud servers that offer their services to the market, but we must consider that their use can be financially burdensome for education and teachers may have limited options. Taking into account modern technological opportunities, this article presents a solution for creating a unique, virtual server-based system designed for the unified and efficient teaching of programming to university students. Using VPS Docker, we provide a container-based environment for students to work on a unified interface, yet independently and without interference. The containers run simultaneously on the server, and Docker provides a platform for managing the containers that allow for the setting of different environmental variables, installation, development, and testing of applications in an isolated environment [7] [13]. We provide an Ubuntu LTS server system for VPS. This Debian-based Linux operating system provides a high level of security and scalability for such systems, and it is completely free. The biggest challenge in our work was the proper use of resources, but an effective solution to this could be the further development or migration of the application to Kubernetes. The current development environment is only suitable for serving small groups, but with Kubernetes, it can easily be integrated into the system of large providers, and the management of resources is also optimized.

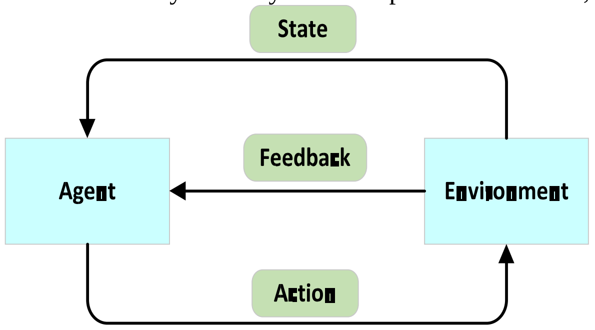
The benefits of using virtual environments are undeniable, and the educational programs running in them also bring the same advantageous characteristics, such as mobility, flexibility, and consideration of personal attitudes, as their counterparts used on other platforms. With the system we introduced, we wanted to present an alternative option for using technology for educational purposes, which we plan to develop further in order to publish many additional possibilities in the future.



Cloud computing provisions computing resources based on CPU, RAM, GPU, Disk Capacity, and Network Bandwidth. Additionally, "time" and "space" are crucial resources. Time refers to the service life cycle of the Cloud platform, while space indicates the physical location for devices. Electrical components in Cloud systems rely on energy and operate within these time and space constraints. Therefore, Cloud computing fundamentally utilizes electric energy conversion per unit of space and time. The limited resource capacity of Cloud computing increases costs and energy consumption. Moreover, issues like long response times and delays can reduce the quality of service (QoS). Efficient, energy-saving resource scheduling is critical for the future of Cloud computing.

Challenges arise due to the vast scale of devices, the complexity of scenarios, unpredictability of user requests, randomness of components, and variable operating temperatures. Common strategies to resolve resource management include multi-phase approaches, virtual machine migration, queuing models, service migration, workload and application migration, task migration, and scheduling algorithms. The scheduler, designed based on these algorithms, is central to efficient resource management. Users submit tasks to a Cloud center, which uses scheduling algorithms to allocate tasks to server nodes, providing services to users.

The scheduling problem in distributed systems is typically NP-complete or NP-hard. Solutions involve various methods, including Dynamic Programming, Probability algorithms, Heuristic methods, Meta-Heuristic algorithms, Hybrid algorithms, and Machine Learning (ML). While traditional methods struggle with the complexities of Cloud computing scheduling, the application of ML, especially Deep Reinforcement Learning (DRL), has shown promise.



5 A fundamental framework of RL

There are many surveys that provide detailed, comprehensive reviews of various fields in Cloud computing. Examples related to Cloud resource optimization management include:

- Reviews of workflow scheduling in Cloud and analyses of its techniques, classifying them based on objectives and execution mode.
- Focus on performance interference of virtual machines, revisiting interference-aware strategies and co-optimization-based approaches for scheduling optimization.
- Literature surveys on task scheduling strategies, including meta-heuristic algorithms and discussions on scheduling methodologies and limitations.
- Reviews of load balancing algorithms for virtual machine placement, covering heuristic, meta-heuristic, and hybrid algorithms.
- Comprehensive surveys of evolutionary approaches in Cloud resource scheduling, including genetic algorithms, ant colony optimization, and particle swarm optimization.
- Taxonomy of meta-heuristic scheduling techniques in Cloud and fog computing, from physics-based to biology-based algorithms.

Some surveys discuss the application of machine learning (ML) in Cloud scheduling. For example, ML methods for resource provisioning in edge-Cloud applications include deep neural networks (DNN), support vector machines (SVM), decision trees, Bayesian networks, and others. In mobile edge computing, ML models like fuzzy control, tree-based naive Bayes, and SVM have been applied for computation and communication control. Other reviews focus on prediction and classification approaches like SVM, k-nearest neighbors (KNN), and deep learning (DL) in Cloud resource management.

While there are many surveys covering ML applications in Cloud scheduling, there is no specific survey on deep reinforcement learning (DRL) in this area, which is a novel and evolving field. Researchers are actively exploring the use of reinforcement learning (RL), particularly DRL, in Cloud scheduling.

Recognizing the potential of DRL in Cloud scheduling, a comprehensive survey is needed for existing research using DRL-based methods. The key contributions of this paper include:

1. A comprehensive review of existing scheduling algorithms in Cloud computing.
2. An analysis of the frameworks of RL and DRL from a model structure perspective.
3. A structured review of existing research using DRL in Cloud scheduling.
4. Identified challenges and future directions for DRL-based methods in Cloud scheduling.

The rest of the paper is structured as follows:

- Section 2 reviews existing scheduling algorithms in Cloud computing.
- Section 3 presents an analysis of RL and DRL structures in Cloud scheduling.
- Section 4 discusses existing research using DRL methods in Cloud scheduling.
- Section 5 lists challenges and future directions for applying DRL in Cloud scheduling.
- Section 6 concludes the paper.

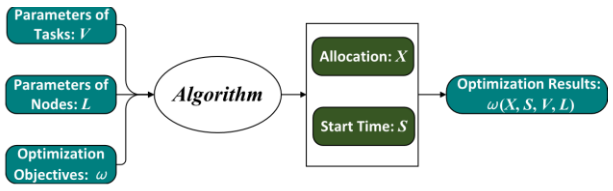


Fig. 2 A diagram of scheduling algorithm to generate the scheme $\langle X, S\rangle$

In reinforcement learning (RL), the agent learns a strategy through trial and error, requiring a balance between exploration and exploitation. Exploration involves trying new actions to discover their effects, while exploitation focuses on making the best decision based on known information. Methods like the greedy approach, random selection, and metaheuristic techniques simulate the decision-making process between exploration and exploitation. The Markov Decision Process (MDP) is commonly used to model the action choice process, while the Bellman Equation, a dynamic programming equation, is frequently used to update the action strategy. This RL framework, consisting of action selection and strategy updates, is illustrated in Fig. 6.

Although the RL framework depicted in Fig. 6 can solve some optimization problems, it lacks sufficient consideration for temporal changes in both system and agent states. As a result, it is inadequate for addressing time-related scheduling problems.

In more complex scenarios, the state of both the system and agent changes over time. Decisions must be made in real-time based on these evolving states, and feedback from the environment directly influences the strategy. Therefore, an agent-state-based RL framework, as shown in Fig. 7, is more suitable for such cases.

In most real-world situations, systems are not completely independent and often change due to external stimuli. The environment in Fig. 7 represents the internal system environment, which cannot account for interference from other external systems. As a result, the RL system in Fig. 7 should be considered an autonomous system because the agent and environment evolve according to fixed rules. Autonomous systems include examples like computer games, Go, and large-scale natural language processing tasks, where the system's regulation remains stable without external modification.

However, certain systems, such as vehicle movement or competitive sports, are affected by external factors. Similarly, a Cloud computing system is not autonomous. It is influenced by time-varying user demands, optimization objectives, and requests. The update function of the internal environment, as well as the agent-state and decision-making function, also varies over time. For instance, the revenue ratio of Cloud computing can fluctuate throughout different periods of the day. Thus, the decision-making process in Cloud computing must adapt to these dynamic changes.

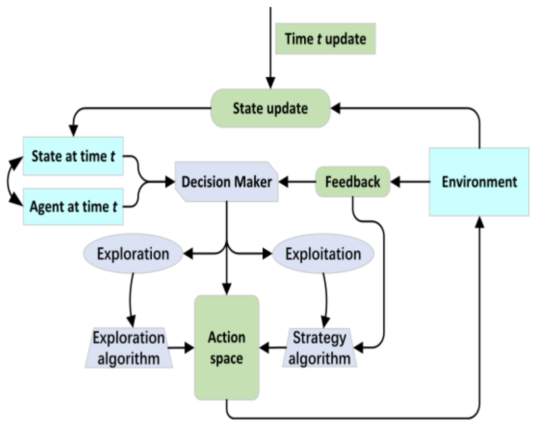


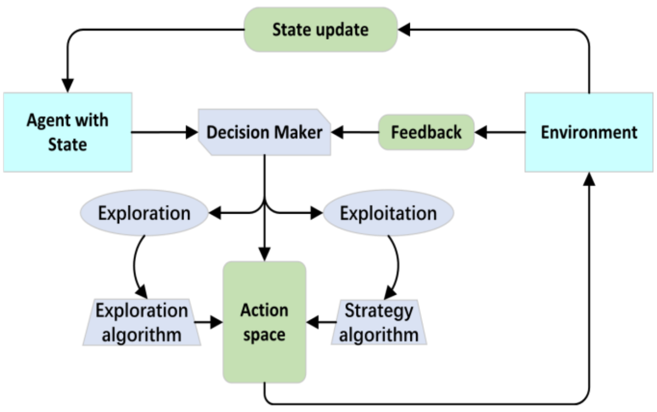
Fig. 7 A complex framework of RL based on varying agent-state

ADDITIONAL OPPORTUNITIES

We need to create an admin panel to change the program's settings. The required subpage is environment manager, user manager, and resource manager.

We plan to use Kubernetes for effective container management. [3]

Thus, a dynamic resource provisioning system is needed to provide cloud customers with a collection of various tools available in the field of computing that can be utilized to effectively manage job processes and organize data storage [1]. One of the motivations of this paper is to study the problem of resource provisioning using dynamic algorithms in a cloud-computing environment. When a consumer requests resources in the cloud, Effec tive allocation is essential for cloud users to guarantee that their performance requirements are constantly sat isfied [2]. There is an imbalance in the back-end burden caused by traditional server architectures' inability to adaptively assign computer resources for changing data requests. Processing problems and the possibility of data loss result from this imbalance. Therefore, a robust, scal able processing and storage infrastructure, that ensures a proactive and autonomous virtual resource allocation mechanism is needed. Resource provisioning, which is a crucial aspect of re source management, is essential in determining the necessary infrastructure resources (capacity) needed to support a set of applications. This plays a vital role in ensuring that there are



6 A framework of RL with action selection and strategy update

sufficient resources available to run the applications [3]. Two crucial processes make up the cloud provisioning process: First, VM Provisioning, which entails launching one or more virtual machines (VMs) on virtual servers in either a private or public cloud computing platform, several mapping requirements, such as memory and storage to the primary cloud, are consid ered when selecting a physical server for web hosting virtual machines in a cloud. The second is application service provisioning, which involves scheduling and map ping incoming requests to the services hosted in virtual machines (VMs) within a VM cluster.

Finally, there is a requirement for a template system for docker-compose files. In this place, teachers can create and reuse their templates.

Reinforcement learning is a branch of artificial intelli gence in which an agent keeps track of the condition of its surroundings and takes suitable optimal action through a trial and error method to determine the best solution to maximize the reward in a critical situation under dynamic circumstances. The agent finds the ideal system state at any given time based on historical data. Agents receive rewards based on their actions. The agent always wants to locate the biggest possible prize [45] [46]. 1) Markov decision process A discrete-time stochastic process called a finite Markov Decision Process termed MDP, which has a finite set of states (st), a finite number of rewards (rt), and a finite number of actions (at), can be used to formalize an RL problem . Only the finite MDP is taken into account in RL. Finding an optimal policy that can maximize the long term expected reward is the main objective of the MDP. There are numerous methods for solving MDP, including policy iteration, Q-learning, value iteration, linear pro gramming, etc. The issue that an agent is trying to resolve is the series of states (s1, s2, s3,..., sn). The agent acts and transfers it from one state to another. Each action must be performed at a specific time interval to maximize the reward

A. RESOURCEPROVISIONING BASED ONAUTONOMIC COMPUTING According to IBM, autonomic computing systems are autonomous and capable of producing optimized system performance with limited work for system administrators. The MAPE-K (IBM) paradigm has been suggested by Huebscher et al. to manage autonomic computing with a variety of self-management, self-configuration, self optimization, self-healing, and self-protecting properties [8] [5]. The performance of the resource management system, which is based on services, can be enhanced by predicting future resource needs in a way that satisfies the QoS standards specified in the SLA [9]. Using a service-level agreement, the dynamic resource provisioning and monitoring system (DRPM), as sug gested in [7] [10], maintains the resources and meets the QoS requirements of the customers. The three stages of the DRPM system are execution, analysis, and mon itoring. It does not, however, incorporate intelligence during the phases of planning and analysis. A hybrid resource provisioning approach is proposed by Ghobaei et al. [11], mainly for SaaS applications, that lowers costs, time factors, and SLA breaches. To reduce latency and virtualization overhead, Wang et al. [12] propose an autonomous virtual application provisioning system for big data centres. In [13], an auto-scaling method for cloud workload prediction combines the auto-regressive moving average (ARMA) and linear regression models to anticipate resource workloads at a reasonable cost. A framework for e-healthcare apps was created by Tushar et al. [14], which improved resource usage, decreased response times, and minimized rejected requests. For parallel scientific programmes, an extension in [15] of fered an elastic controller with fuzzy logic that resulted in better resource usage and quicker completion times. Horovitz et al. [16] provides a thorough comparison of these models that covers measurements, approaches, and policy types. Shakarami et al. [17] presented a survey for data replication scheme among different existing cloud computing solutions in the form of a classification approach. Our study uses real-world workload logs from ClarkNet and Google Traces from the literature to find the models that could estimate cloud resource usage. The effec tiveness of machine learning algorithms has also been evaluated.

ooperative Q-learning approach is presented in this work to encourage collaboration between multiple agents to improve efficiency in a specified environment.Ali et al. [19] proposed a dynamic resource allocation strat egy using an adaptive multi-objective teaching-learning based optimization (AMO-TLBO) algorithm that helps to minimize cost and maximize utilization using well balanced load across virtual machine. Shahidinejad et al. [20] proposed an efficient and highly secure blockchain assisted authentication scheme using a combined off chain and on-chain approach. Q-learning has also been used by Xu et al. [21] to design systems for vertical scaling. To reduce resource wastage and computation expenses, an ideal scaling alternative has been created under the assumption of an SLA guarantee. To manage the directed acyclic graph (DAG) structures' graph-based job scheduling issue and shorten the overall DAG execution time, Orhean et al. [10] employed state-action-reward-state-action (SARSA), which is a model-free reinforcement learning algorithm that shares similarities with Q-learning. Our proposal in this paper focuses on implementing the MAPE-K loop using Q-learning for optimal decision-making. Literature also finds the use of deep reinforcement learn ing (DRL) for resource provisioning in cloud applications [5]. In the DRL framework developed by Bao et al. [22] for batch processing, an artificial neural network (ANN) model has been trained using the actor-critic RL technique. The proposed method considerably reduces the amount of time the jobs take to execute on the Kubernetes cluster compared to conventional heuristic scheduling methods like bin packing and results in maximized migration decisions by decreasing the time overhead, energy consumption, and computational costs. Ghobaei et al. [23], utilizing the MAPE-K loop, provide a hybrid resource provisioning approach with a focus on the planner phase for forecasting future requests. The results demonstrate that the suggested technique lowers cost, time elements, and SLA violations. This approach, however, is limited by the assumption that the requests are for SaaS cloud apps [24], while our proposed model focuses on the interaction between SaaS, PaaS, and IaaS layers. Tushar et al. [25] develop an elastic resource provisioning framework for autonomic computing phases in e-health applications. The monitor and analyzer stages focus on using a queuing load prediction model. Results demonstrate improved resource use with quick response and completion times. When forecasting the resources used in the future, fuzzy logic aids decision-making, thus resulting in optimal resource use and rapid completion [10] [24]. The incorporation of Markov Decision Process (MDP), Q learning, and edge-cloud technologies in the framework of microservice coordination is further extended by Wang et al. [26] where the sequential decision system that underlies the process of microservice coordination is

assumed and formulated as an MDP design. To analyze the function invocation patterns and decide on the best function container scaling in advance, Agarwal et al. [27] provide a Q-learning agent that models system states using metrics such as available function containers, CPU utilization per container, and success/failure rates [23]. The work concludes that the model-free RL algorithms do not require prior knowledge of the input function because of their nature. However, these solutions only consider specific workloads, and hence performance cannot be assured under varying workloads, while our work focuses on prior knowledge for effective decision-making of vir tual machine utilization using Q-learning in the planner phase of the MAPE-K loop. The actor-critic approach is used by Qiu et al. [28] to scale the essential microservices identified by Support Vector Machine (SVM). This horizontal scaling approach alleviates SLA violations by analyzing three essential as pects: the SLO maintenance ratio, workload variations, and request composition. Dutreilh et al. [23] chose the Q learning method where the learning agent repeatedly ob serves the current state of a controlled system (workload, VM count, and performance SLA), performs a task, and then changes to a new state. To avoid a prolonged period of exploitation and exploration, the authors introduce a convergence speedup phase to accelerate learning at regular intervals. Dezhabad et al. [29] propose the GAR LAS approach, which combines genetic algorithm, rein forcement learning, and queuing theory to determine the ideal number of active firewalls based on incoming traffic intensity at any given time. The integration of RL and genetic algorithms enables the system to learn and adapt to changes in workload and network conditions, making it a robust and scalable solution for firewall management in dynamic and unpredictable environments; however, the system focuses on parameter response time alone, while our model focuses on different parameters like average response time and average load at IaaS level. Horovitz et al. [30] present a Q-learning technique for horizontal scaling that includes initialization steps, smoothing, and action monotonicity. For continuous actions in specified states, the method uses an action space methodology. The Q-threshold algorithm performs exceptionally well in Q learning-based auto-scaling, especially when it comes to response time. In their study, Wei et al. [31] propose a resource allocation method for SaaS providers operating in a dynamic and stochastic cloud environment. The method is based on the Q-learning adjustment algorithm (QAA) and aims to assist providers in making optimal resource allocation decisions [32]. This work aims to cut down rental costs as much as possible while offering enough processing capacity to meet client requests [31]. The model-free method-based works ([29]; [30]) not only need the space to reserve the action R(s, a), it also needs the effort and information to update it.

References

[1] David, Jaramillo., Duy, V., Nguyen., Robert, S., Smart. (2016). Leveraging microservices architecture by using Docker technology. 15.

[2] Gail, C., Murphy. (2019). Beyond integrated development environments: adding context to software development. 73-76. doi: 10.1109/ICSE-NIER.2019.00027

[3] Eric, Brewer. (2015). Kubernetes and the path to cloud native. 167167. doi: 10.1145/2806777.2809955

[4] Chen, Jianhai., Hou, Wenlong., He, Qinming., Zhang, Miao., Huang, Butian. (2018). Remote memory volume management method and system of Docker container.

[5] Pierluigi, Riti. (2018). Pro DevOps with Google Cloud Platform: With Docker, Jenkins, and Kubernetes. doi: 10.1007/978-1-4842-3897-4

[6] Éva, Karl., Molnár, György. (2022). IKT-vel támogatott STEM készségek fejlesztésének lehetőségei a tanulók körében. 144-155

[7] Kinary, Jangla. (2018). Accelerating Development Velocity Using Docker: Docker Across Microservices. doi: 10.1007/978-1-4842-3936-0

[8] Mithun, Satheesh., Bruno, Joseph, D'mello., Jason, Krol. (2015). Web Development with MongoDB and NodeJS.

[9] Willy, Tarreau. (2015). HAProxy Configuration Manual v1.5.14

[10] Stephen, R. Smoot., Nam, K. Tan. (2012). Private Cloud Computing: Consolidation, Virtualization and Service-Oriented Infrastructure.

[11] Beáta, Orosz (2021). Learner Experiences Related to Digital Education Schedules in Light of Empirical Data ACTA POLYTECHNICA HUNGARICA 18 : 1 pp. 141-157. , 17 p.

[12] Elod Gogh, Reka Racsko, Attila Kovari (2021). Experience of SelfEfficacy Learning among Vocational Secondary School Students, ACTA POLYTECHNICA HUNGARICA 18 : 1 pp. 101-119.

[13] József , Katona (2021). Clean and Dirty Code Comprehension by Eyetracking Based Evaluation using GP3 Eye Tracker, ACTA POLYTECHNICA HUNGARICA 18 : 1 pp. 79-99

[14] Zoltán Balogh, Kristián Fodor, Martin Magdin, Jan Francisti, Štefan Koprda, Attila Kővári (2022). Development of Available IoT Data Collection Devices to Evaluate Basic Emotions, ACTA POLYTECHNICA HUNGARICA 19 : 11 pp. 165-184

[15] Mónika Rajcsányi Molnár. Anetta Bacsa Bán. (2021). Towards Digitalisation Student Experiences in Online Education at a Higher Education Institution, JOURNAL OF APPLIED TECHNICAL AND EDUCATIONAL SCIENCES, Vol. 11, No. 1, pp. 88-110