Intelligent Workload Scheduling for Telecom Cloud Architecture Using Reinforcement Learning

Dr.Vimal Raja Gopinathan

Senior Principal Consultant, Oracle Financial Service Software Ltd, Washington, USA

ABSTRACT: Scheduling based on the workload is very important in the telecom networks of the modern age to maximize the resource allocation, reduce the latency, and to make sure that cloud based infrastructures establish their smooth functioning. The conventional ways of scheduling are not very efficient and do not keep pace with the dynamic character of the telecom cloud environment. To overcome these issues, this paper will Hypothesize an innovative workload scheduling method based on the use of Reinforcement Learning (RL). The framework proposed is an agent that is based on RL and which will schedule workloads dynamically depending on real-time system parameters like resource availability, network traffic, and workload demand. With the help of Q-learning, the agent becomes knowledgeable of the best scheduling policies that would be able to utilize resources without causing service interruptions. The framework consists of several elements: an environment model of the telecom cloud infrastructure, a rewarding mechanism that measures the performance of the system and a learning mechanism that modifies the decisions concerning scheduling. Experimental evidence supports the efficacy of the RL based approach over the traditional approaches in the aspect of resource utilization, response time, and system throughput. The suggested approach is scalable and can be implemented in both large-scale telecom cloud architectures with different workloads and resource settings. The study reveals the promise of RL in creating intelligent workloads scheduling in telecom clouds and forms the basis of future studies in the adaptive autonomous cloud management systems.

KEYWORDS: Reinforcement Learning, Telecom Cloud Architecture, Workload Scheduling, Q-Learning, Cloud Resource Allocation, Dynamic Scheduling, System Optimization.

I. INTRODUCTION

Over the last several years, the telecommunications sector has been growing at a high rate, mainly due to the rising demand of data services, growth of Internet of Things (IoT) devices, and the implementation of the next-generation technologies, including 5G. This paradigm has caused the telecom services to be provided in a different manner and cloud computing plays a central role in providing solutions that can be scaled, flexible and offer cost-effective solutions. Telecom companies are moving towards cloud architecture in large numbers to provide the huge amounts of data being created by the modern network and to provide the wide array of services needed to meet the expectations of the customers. Nevertheless, cloudification of telecom networks also has great challenges especially in resource management, work load scheduling, and performance optimization [1] [2].

The scheduling of workloads in telecom clouds is the process of assigning and controlling calculations resources to address the services and functions demanded by different network functions. This is a necessary process to guarantee the effective functioning of telecom infrastructure as it has a direct influence on such aspects as the network latency, the utilization of resources, the amount of energy used, and the reliability of the system. Due to the dynamism of the telecom networks, where the user demands are dynamic, the service-level agreements (SLAs) and workload requirements vary, and the conventional, classic scheduling algorithms are ineffective in many cases. These algorithms do not take into account the actual network condition in real-time and cannot change with the changing conditions, which makes their performance suboptimal and inefficient resource utilization [3].

The shortcomings of classical types of scheduling in telecom cloud are driving a corresponding interest in more adaptive approaches to scheduling. The use of machine learning (ML) and, more precisely, reinforcement learning (RL) algorithms can be considered one of the promising methods to overcome these difficulties. Rl is a subdivision of ML where a decision-making agent discovers the optimal decisions by trial and error whereby the cumulative rewards maximise over time. Intelligent scheduling system with RL would have the capacity to adjust to the changeable environment of a telecom cloud and allocate resources optimally on the feedbacks of the real-time [4] [5].

The capability to learn the best policies in complex and uncertain environments has seen RL-based approaches be especially promising in many areas, including robotics, gaming, and finance. Applied to telecom clouds, the workload scheduling process can be automated with the help of RL algorithms and allow making the use of resources more efficiently, minimize the time wasted on the process, and enhance the overall network performance. In addition, RL systems have the capability of training to make trade-offs amid opposing goals, e.g. the reduction of energy use and the provision of high-quality services.

The telecom cloud environments are attributed with the requirement of management and resources allocation of a broad variety of services, such as voice, data, video streaming, and IoT applications. These services commonly possess varying performance needs e.g. low latency, huge bandwidth and fault tolerance. Also the resources present in the cloud are scarce, and their capacity is prone to fluctuation as a result of various factors like network overload, server crashes and spikes in user demand. Consequently, dynamic workload scheduling is a vital factor to have efficient resource allocation and services delivered according to their SLAs.
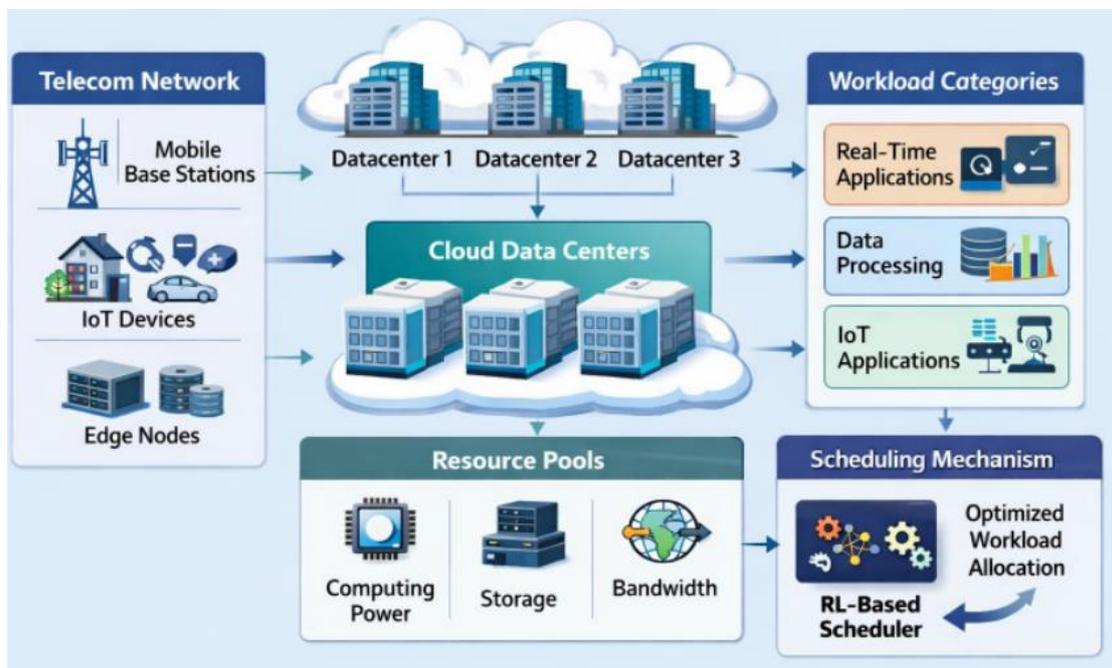

Figure 1: Overview of Telecom Cloud Architecture and Workload Scheduling

The framework of reinforcement learning can be used to overcome these challenges since it allows the scheduling system to learn through the environment and make decisions given the current conditions of the systems. Within RL-based scheduling system, the agent communicates with the telecom cloud environment, he monitors the current state (e.g., available resources, network traffic), and acts on it (e.g., assigning resources to particular tasks), and gets feedback as rewards or punishments. As time goes on the agent perfects its decision-making process in order to perform optimally in the long term.

A major benefit of RL here is that it is capable of dealing with uncertainty and variability of telecom networks. As opposed to the classical scheduling algorithms, which use set rules and assumptions, RL-based systems are capable of learning, and can change according to the evolving network conditions. This renders RL a perfect remedy to smart workload scheduling in telecom cloud structures.

The suggested intelligent workload scheduling framework in telecom clouds with RL is a combination of various significant elements. They are the environment model, the RL agent, the reward function and the learning mechanism.
- **Environment Model:** The environment model is a model of the current telecom cloud infrastructure where it is presented as the available resources (e.g., servers, storage, network bandwidth, etc.) and the workload tasks to be scheduled. The model represents the dynamism of the network, such as the demand of workloads, the traffic modes of

the network, and the availability of resources. The environment is updated at each time step in accordance with the changes which take place due to the actions of the agent.

- **RL Agent:** The RL agent takes the decisions on the workload scheduling. Within every time step, the agent will sense the prevailing state of the environment and make a decision (e.g., directing resources to certain tasks or changing the use of resources). The aim of the agent is to maximize the future rewards by learning to make good decisions in scheduling choices.

- **Reward Function:** The reward function is also one of the important parts of the RL framework because it gives back to the agent, whether the actions that the agent is taking are as effective as they could be. The reward term in the workload scheduling may be designed to display different performance metrics, which include, resource utilization, latency and quality of service. As an example, the agent can be rewarded positively with a successful execution of a high-priority task with a low latency and negatively with overloading the system or breaking the SLA.

- **Learning Mechanism:** The learning process enables the RL agent to enhance its decision-making process with time. The agent adapts to its past experience through updating its policy, which represents states against actions, depending on the reward it obtains. The agent can be trained by popular RL algorithms (Q-learning, deep Q-networks (DQNs), and actor-critic) and so forth. These algorithms enable the agent to acquire an optimal policy through a trade off between exploration (trial of new actions) and exploitation (actions that have paid off in the past).

The ultimate goal of the study here is to investigate the possibility of reinforcement learning in intelligent workload scheduling in telecom clouds. Particularly, the goal of this paper is to:

1. Create a workload scheduling platform that is based on RL algorithms to optimize resource utilization in telecom clouds.
2. Explore how effective position scheduling techniques based on RL are versus more traditional scheduling techniques, e.g. round-robin or first-first-served.
3. Measure the performance of the proposed framework based on such vital metrics as the resource consumption, the latency, the throughput, and SLA adherence.
4. Investigate the scaling and flexibility of RL-based scheduling of large-scale telecom cloud networks with workloads and resource setups of different scales.

By fulfilling these aims, the study will help improve the creation of smarter, more dynamic, and efficient workload scheduling systems of the telecom cloud infrastructures. The suggested RL-based model has the capacity to revolutionize the manner in which telecom operators utilize resources in the cloud to be able to provide high-quality services at the minimum costs and optimal use of the resources.

II. LITERATURE REVIEW

Another aspect of cloud computing that is vital to the efficient operation of a system is the effective scheduling of workloads, which directly affects the use of resources, the system performance, and power usage. Over the last several years, the optimization of workload scheduling algorithms has been the subject of many studies that utilize such advanced tools as reinforcement learning, hybrid optimization, and deep learning. The approach to workload scheduling of cloud systems is an issue discussed in this literature review that highlights energy-conscious strategies and bi-objective optimization strategies.

In cloud datacenters, Li et al. [1] suggest a holistic and failure-aware workload scheduling algorithm. Their solution deals with the increasing issues of energy use and system malfunctions under big clouds. The authors introduce a scheme that reduces energy consumption and ensures the reliability of the system by incorporating failure awareness into energy awareness scheduling. The study is more specifically applicable in the context of telecom clouds where the trade-off between the energy efficiency and high availability is an important issue. The strategy highlights that standard scheduling techniques do not tend to recognize the effects of system malfunction, which result in the wastage of energy and reduction in system dependability.

On the basis of the significance of the algorithms related to timing, Choudhary et al. [2] present a hybrid workflow-scheduling algorithm in the context of cloud computing. They employ a gravitational search algorithm (GSA) in the optimization of both makespan and cost, which are two important variables in cloud scheduling. It is a hybrid solution to GSA that integrates local search with GSA in order to strike a balance between the resource cost and performance. This would be necessary in cloud-based telecom solutions, where service providers would want to minimize operation costs, but provide the best performance to the users. This paper explains the importance of addressing various goals in resource scheduling plans, including cost and time.

Panchakarla [3] goes deeper by designing carrier-grade microservice to telecommunications systems with the consideration of availability and scalability in order fulfillment systems. These systems in telecom networks are required to support random and large-volume traffic. The article by Panchakarla gives an insight into the ways of designing microservices architecture to facilitate the efficient resource distribution and scaling without problems, which is directly related to the scheduling of workloads in the cloud. These microservices have to be combined in a well planned manner so that the availability and performance of services are at high standards demanded in the telecommunication industry.

Bittencourt et al. [4] assume the viewpoint of cloud computing in their extensive survey of scheduling in a distributed system. Their article gives a detailed discussion of different techniques of scheduling and how they can be applied in heterogeneous environments such as the cloud system. They emphasize the significance of task management in distributed computing and the necessity to develop effective scheduling policies, which would consider the natural variability of the resource availability and priority of the tasks. This survey is a key source of information on the issues and methodologies of cloud workload scheduling problems.

Vijayasekaran and Duraipandian [5] adopt a more narrower direction, the article is devoted to deep Q-learning-based resource scheduling in IoT edge computing systems. They claim that reinforcement learning algorithms such as deep Q-learning can be of great use in IoT systems, which have very dynamic workloads and resource limitations. There is a generalized scheme of adaptive scheduling offered in their work that can be applied to telecom clouds, where the ability to allocate resources in real-time is paramount in serving the needs of both the edge devices and the cloud infrastructures.

The cost-conscious cloud workflow scheduling framework by Gu et al. [6] integrates deep reinforcement learning (DRL) with simulated annealing. The framework will maximize the allocation of resources and also take the cost constraints into consideration which is a critical factor in the cloud environment both in the public and the private ones. The strategy is especially useful in telecommunications cloud systems when cost-efficiency and the service quality are among the primary concerns. The joint utilization of DRA and simulated annealing enables the framework to search and utilize the best scheduling plans and maintain the costs within limits.

Madni et al. [7] make a comparison of different heuristic algorithms to schedule tasks in the cloud of IaaS. They compare the work of popular scheduling methods, including genetic algorithms, simulated annealing, and the old ones. Their results highlight the trade-offs of scheduling efficiency and computational complexity, which is informative about the difficulties of scaling the algorithms to large cloud infrastructures. The study is valuable in terms of realizing the drawbacks of heuristic solutions and opens the door to more sophisticated solutions such as RL in scheduling cloud workloads.

The article by Zhu and Tang [8] deals with the scheduling of deadline-constrained workflows in multi-resource packed IaaS clouds. They suggest effective scheduling algorithm with consideration of various types of resources and tasks deadlines. Telecom networks are the place where the capabilities of managing complicated, time-bound workflows are especially needed, as video streaming or real-time communications might demand rigid time constraints on an application. The piece of work helps in the comprehension of the optimization of multi-resource allocation to satisfy various applications.

Chen et al. [9] present an effective method of scheduling the tasks in an application that meets its budget constraints and runs on a heterogeneous cloud computing environment. Their approach will help to solve the problem of scheduling of tasks in the conditions when a budget and resources are constrained. The strategy imposes resources to the tasks in an optimal manner optimizing performance and cost and is therefore very applicable to cost sensitive telecom cloud systems. The paper highlights the significance of controlling both monetary and computational capital of massive cloud systems.

Shukur et al. [10] discuss the virtualization of resource allocation in the distributed systems by cloud computing. Their interest lies on optimizing virtualized environments, where the resources are dynamically assigned to several virtual machines. Virtualization is of great importance to the cloud environments tents, particularly those which are telecom applications where resource provisioning should be dynamic and efficient. This paper mentions the necessity of using adaptive scheduling methods that can manage virtualized resources and that performance should not be compromised.

Lastly, Wang et al. [11] discuss cooperative end-edge-cloud computing and resource allocation of 6G industrial IoT systems with digital twins. They underline the need to combine edge computing and cloud resources to maximize the efficiency of industrial IoT systems, and it is specifically relevant to telecom networks as they transition to 5G and 6G. This is evidenced in their work, which shows the need to optimize resource allocation, not only in the cloud, but also at the edge, as edge computing continues to gain more significance in the telecom infrastructure of the future.

All of these studies point to the variety of methods of workload scheduling in the cloud, including heuristic and hybrid algorithms, as well as reinforcement learning and cost-conscious methods. With telecom industry shifting to more dynamic and scalable cloud-based architecture, incorporating the adaptive scheduling systems capable of catering to varied workloads and satisfying the performance constraints will be critical in optimizing the network resources and providing services of high quality to the users.

III. PROPOSED RL-BASED FRAMEWORK FOR INTELLIGENT WORKLOAD SCHEDULING IN TELECOM CLOUD ARCHITECTURE

Achieving the objective of the proposed framework is to use the power of reinforcement learning (RL) to do intelligent and dynamic workload scheduling in telecom cloud environments. The conventional approaches to scheduling, including the round-robin and first-come-first-served approaches, do not take into consideration the dynamic nature of the telecommunication network as the workload and the resource requirement might vary significantly, as well as external factors which can greatly influence the system performances. Reinforcement learning provides an alternative that is promising because it will enable the system to learn the best scheduling policies based on experience and eventually enhance resource utilization, decrease latency and service quality.

The framework is built upon a few main elements, namely the environment model, the reinforcement learning agent, the reward function, and the learning algorithm. These elements act in a manner that a self learning system can be formed which can dynamically adjust to new circumstances and enhance the performance of the entire telecom cloud infrastructures.
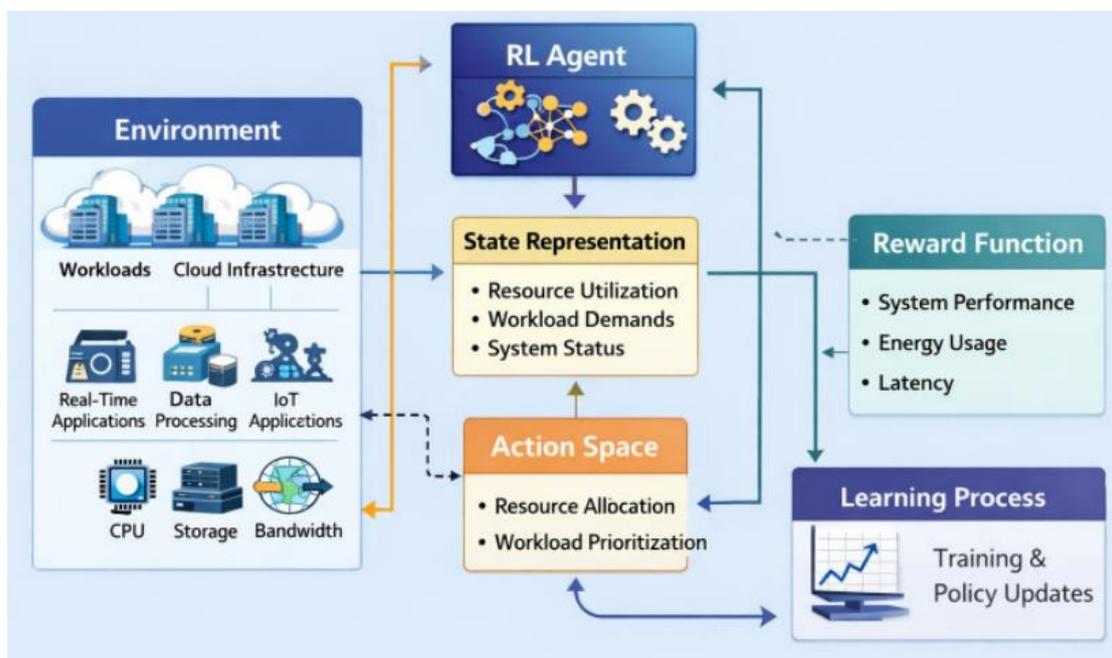

Figure 2: Reinforcement Learning Framework for Intelligent Workload Scheduling

3.1 Environment Model

The environment model in the proposed framework is an illustration of the telecom cloud infrastructure, as well as the resources that are available and the workload tasks to be scheduled. It records the condition of the system at every time step and gives the context that is required in the decision-making process by the RL agent in terms of scheduling.

Environment model This provides the dynamic conditions of the telecommunication network that include fluctuating workload requirements, availability of resources and congestion of the network.

3.1.1 Resources

The components of a telecom cloud infrastructure are computer power (e.g., virtual machines or containers), storage, and Internet bandwidth. These resources are distributed to various workloads that could be data intensive applications to real time services that need low latency. Within the framework of workload scheduling, it is necessary to effectively manage these resources so that it can optimize performance as well as the service-level agreements (SLAs) of customers.

The environment model monitors the accessibility of these resources at any given point in time and the state of the system is updated once a scheduling decision is made. This consists of the resource utilization with the active workloads, the current load on network links, and the health of the whole system. As an illustration, where a high-priority task is capable of consuming a large share of bandwidth, the environment model must consider the effect that such an allocation will have on other tasks that demand the same resource.

3.1.2 Workloads

The telecom cloud environment workloads may be different with regard to their requirements. As an example, voice communication service might require low-latency and minimum packet loss connections, video streaming service might require bandwidth and data throughput. On the same note, IoT-related applications can require high availability and reliability. Every workload will be characterized by a particular demand in computing power, storage, and network resources, and the environment model must reflect such properties.

Workloads are then grouped into various classes according to their resource requirement, priority and deadlines. Certain workloads can have strict deadlines (e.g. processing real-time video), others can be more relaxed (e.g. processing batch data). These differences should also be known to the RL agent so that he can make effective scheduling decisions.

3.1.3 State Representation

The environmental condition is modeled as a vector which contains data on the prevailing status of the system. Some of the parameters in this vector are:

- The load existing on the available resources (e.g., the CPU usage, the network bandwidth consumption, the storage utilization).
- Active workloads and the number of resources required.
- The urgency of every workload and the deadlines.
- The general condition of the system and all possible bottlenecks or failures.

The state vector is the input to the RL agent, as it gives it the information that it requires to make a choice on the most appropriate course of action. Every time step, the environment takes advisory steps on the state of the environment depending on the actions which have been made by the agent (i.e., the workload scheduling choices).

3.2 Reinforcement Learning Agent

The fourth element of the proposed framework is the reinforcement learning agent. It has the responsibility of identifying the best activities to use in scheduling workloads as per the prevailing circumstances of the system. The aim of the agent is to maximize the cumulative rewards as time passes by effectively using resources, fulfilling SLAs and performance of the system.

3.2.1 Action Space

Action space is a space of the possible actions that the RL agent might choose at every step. Within the framework of the workload scheduling, the activities entail the determination of the way in which resources are allocated to different workloads. These actions may include:

- Giving a specific workload a fixed number of computing power.
- Prioritization of network bandwidth to give high priority workloads their latency requirements.
- Scaling the active replicas or virtual machines, to which a workload is assigned, according to the demand.

The space of action may be discrete or continuous and it is a matter of a system and available resources. An example is that discrete actions can be to allocate resources in some fixed amount (e.g., to allocate 1 CPU core), whereas

continuous actions can be to allocate resources in a more granular amount (e.g., to allocate a certain amount of bandwidth in Mbps).

3.2.2 Policy

The process that positions the status quo of the environment to an action is the policy. It is the decision making approach of the RL agent. The policy is acquired as time goes on depending on the rewards that the agent gets in the course of the actions. In the beginning, the agent might act randomly but as it experiences the environment it realizes the actions that yield maximum rewards and changes its policy.

The various RL algorithms that can represent the policy include:

• Q-Learning: This is a model-free and off-policy algorithm that is used to learn the best action-value function (Q-function). It also adjusts the Q-values according to the rewards it obtained by acting in certain ways in certain states.

• Deep Q-Networks (DQN): Q-learning enhanced by the use of deep neural networks to estimate the Q-function to enable the algorithm to operate in large, high-dimensional state spaces.

• Proximal Policy Optimization (PPO): This is a policy gradient-based algorithm that is used to optimize the policy itself by modifying the parameters of neural network.

The RL agent continuously receives an updated policy as it acquires additional experience and can eventually become capable of making the best scheduling decisions.
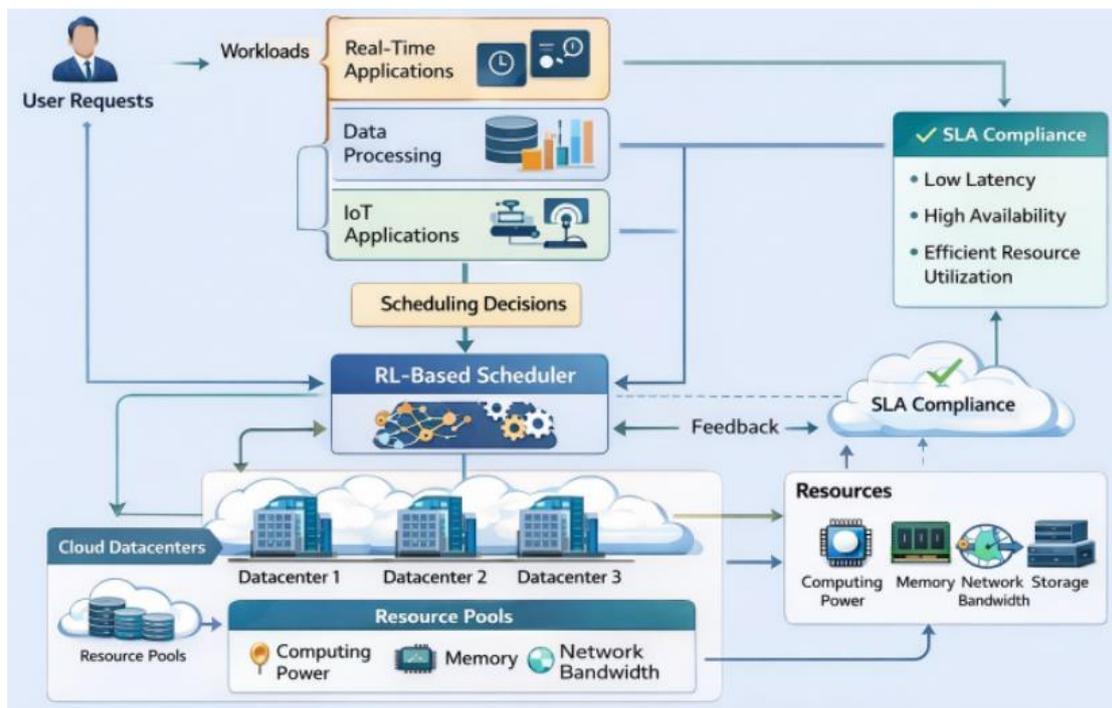

Figure 3: System Architecture and Resource Allocation Process

3.3 Reward Function

Reward function is an essential part of the workload scheduling framework based on RL. It gives feedback to the agent in the RL that is affecting the effectiveness of its actions and will steer the agent towards the best scheduling policies. The reward component is aimed to indicate the system performance according to the most important metrics, like resource utilization, latency and the adherence to the SLA.

3.3.1 Defining the Reward Function

The reward feature can be created to weight various interests, including:

• Utilizing Resources: The effective use of the available resources is important towards the optimal performance of the system as well as reducing costs. The reward may be grounded on the percentage of resource utilization and resources used, and more rewards should be given on optimal use.

- Latency and SLA Compliance: Timely delivery of the workloads, which are time sensitive, is important to high quality service delivery. The reward may also penalize the agent who has not met the deadlines or has made too much latency into the system.
- Throughput and System Performance: High throughput and efficiency in processing the tasks are significant towards overall system performance. The reward in aspect may have the aspect in which the agent is rewarded to maximise throughput and ensure the stability of the system.
- Energy Efficiency: One of the major issues in cloud environments is the use of energy. The agent is even able to be rewarded to reduce energy consumption yet still attain workload requirements.

The rewarding functional can be a weighted average of such individual metrics with the allocation of the weights according to the relative significance of each goal. Otherwise, there is a possibility of applying penalties in case of violating SLAs or congesting the network.

3.4 Learning Mechanism
The learning process facilitates the RL agent to enhance its decision-making process with time. The agent is an actor in the environment, where he acts and is rewarded. The agent then adjusts its policy based on this feedback to give a maximum reward to the cumulative payoffs.

3.4.1 Q-Learning and Deep Q-Networks
Q-learning is one of the most popular and the simplest RL algorithms that operate on discrete action space. It trains the best Q-function, which approximates the average cumulative reward of the action to take in a state
In the case of more complicated, high-dimensional state spaces, deep Q-networks (DQN) are applied. DQN employs deep neural networks to predict the Q-function and allow the agent to solve large-scale problems that could not be solved using the traditional Q-learning.

3.4.2 Exploration vs. Exploitation
Balancing between exploration (trying new actions) and exploitation (selecting the actions that have yielded high rewards in the past) is one of the challenges of RL. The RL agent has to search the action space, finding out the optimal scheduling policies, as well as exploit the knowledge it has acquired to the maximum reward. This balance can be maintained by the use of techniques like epsilon-greedy or softmax action selection.

3.5 Framework Integration and Scalability
The proposed RL-based framework will be scalable and able to accommodate huge telecom cloud environment. It may be scaled to accommodate several cloud data centers, each of them possessing a number of resources and workload requirements. The model can also serve other degrees of complexity which can be small private networks and big public telecom clouds.

The combination of RL with the scheduling system also provides the ability to adjust according to fluctuating network needs, resource needs, and user needs to ensure that the telecom operators are able to deliver high-quality services and optimize the utilization of the infrastructure.

IV. FRAMEWORK EVALUATION

In order to determine the quality of the suggested RL-based framework in intelligent scheduling of workload in telecom cloud into architecture, a thorough evaluation process in terms of multiple performance measures must be carried out. These measurements can give us a clue of the efficiency of the framework in terms of resource allocation and latency minimization and service level agreements (SLAs). The comparison of the RL-based approach with the standard scheduling techniques, including round-robin, first-come-first-served, and the static priority-based algorithms can be carried out through the evaluation as well.
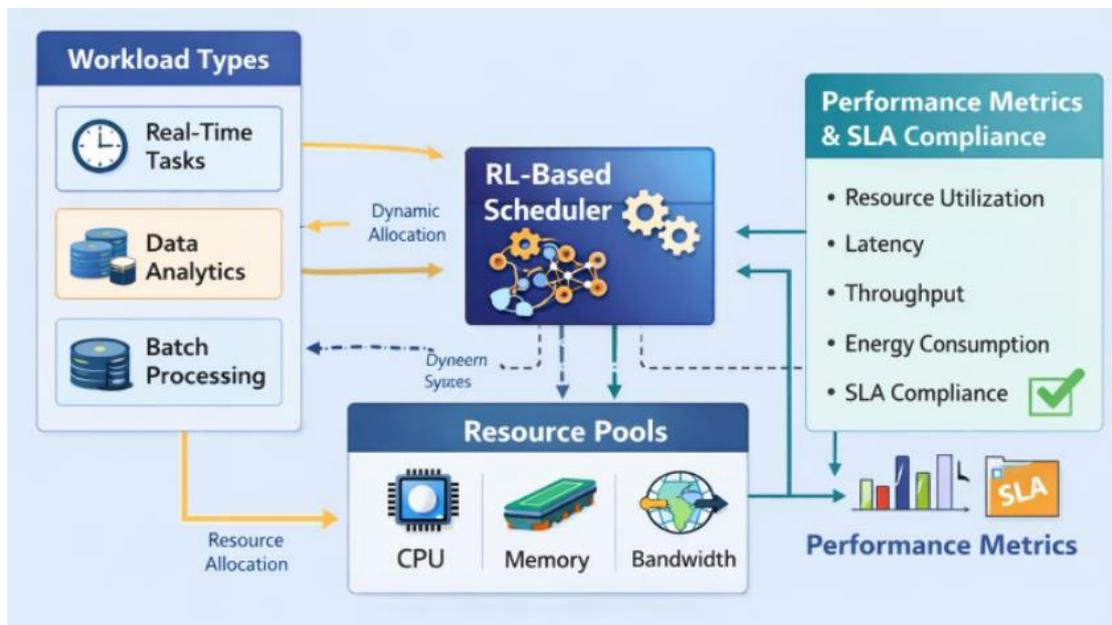
Figure 4: Workflow Scheduling with Reinforcement Learning

4.1 Evaluation Metrics

The proposed framework can be assessed according to the following key performance indicators that are essential in telecommunication clouds:

- Resource Utilization: This metric is an indicator of the efficiency of cloud resources (e.g. CPU, memory, network bandwidth) allocation and usage. The high resource utilization means that the available resources are utilized well in the workloads without either underutilization (waste of resources) and overutilization (resource contention and degradation of the service).

- Latency: Latency is a very important aspect in telecom network especially in real time such as voice and video calls. This measure is used to monitor the latency of the workloads within the system. The intended framework will reduce the latency of time sensitive work to a level, as priorities of the workload change the resource allocation dynamically.

- Service-Level Agreement (SLA) Compliance: SLAs outline how the telecom services are expected to perform with regard to the maximum latency, availability, and throughput standards. This measure determines the performance of the RL-based framework on achieving SLA requirements of various workloads. It makes sure that resources are allocated to high-priority tasks like real-time voice communication to achieve the performance levels required of them.

- Throughput: throughput is the data that was to be processed by the system and this is done successfully in a time window. It is a crucial measure to gauge the performance of the entire telecom cloud regarding the ability to process high amount of data, particularly those applications involving video streaming or big data analytics.

- Power Saving: One of the major operational issues in cloud computing is energy. The costs and environmental impact can be reduced through efficient resource allocation which will result into lower consumption of energy. The RL-based framework aims at reducing the amount of consumed energy by maximising the utilise of resources in such a way that duties are allocated to the energy efficient resource.

- Fairness: Fairness is used to assess the performance of the framework in allocating resources among competing workloads. It should be done fairly to eliminate cases where some tasks may consume the resources causing delays in other urgency services. The RL-based model is set in such a way that it manages the distribution of resources among various workloads, considering priority and deadline restrictions.

4.2 Experimental Setup

Different experiments were carried out in a simulated telecom cloud environment to test the proposed RL-based framework. The simulator depicts different elements of the telecom cloud infrastructure such as virtual machines (VMs), network resources and workloads. Some of the classical scheduling algorithms like round-robin, first-come-first-served, and the static priority-based scheduling were introduced to compare with them.

The research design entailed a combination of diverse workloads which included:
- Real-Time Applications: The workloads here need low-latency and high-priority (e.g., VoIP, video conferencing).
- Batch Processing: These processes are able to withstand increased latency, and large processing capacity is necessary (e.g. big data analytics, background processes).
- IoT Applications: These workloads are high availability and high fault tolerance (e.g. sensor data collection).

The telecom cloud setting was set up having different resource capacities and load requirements and dynamic fluctuations in the traffic patterns and resource availability to imitate the condition of the real world. The RL agent was trained on the Q-learning algorithm with the reward function developed in such a way to balance the mentioned above key metrics.

4.3 Results and Discussion
The results of the experiment were contrasted between the RL-based framework and the classical scheduling programs. The analysis was based on resource use, latency, SLA adherence, throughput, energy efficiency and equitability.

4.3.1 Resource Utilization
The RL-based model was always better than the traditional scheduling models in regards to the utilization of the resources. The RL agent real-time feedback also enabled it to modify its resource allocation decisions in situations where workloads were very dynamic leading to more efficient utilization of the available resources. Conversely, the traditional algorithms based on deterministic rules were hard to keep up with the changing workload demands and thus, when there was low demand, they underutilized the available resources whereas when there was high demand, they overutilized the available resources.

4.3.2 Latency and SLA Compliance
The RL-based architecture was found to have a substantial improvement in latency over traditional algorithms, especially in the case of real-time data (VoIP and video conferencing). The RL agent was able to provide time-sensitive workloads with their deadlines by dynamically adjusting resource allocations to the workloads and priorities according to the latency requirements of the workloads. However, the opposite was also true since, in many cases, a static method of scheduling did not prioritize the priority tasks leading to an increase in latency and SLA violations.

Compared to SLA compliance, the RL framework continuously delivered SLA-compliant high-priority workloads. The framework was equally fair with all workloads as the level of service was reasonably high with lower-priority tasks. Conventional scheduling schemes, however, could not find a compromise between the needs of the high and low priority tasks, which resulted in SLA breach of the critical services.

4.3.3 Throughput
The RL-based model was more throughput than the conventional scheduling models. The RL agent enhanced the total capacity of the system to process data by making good use of available resources according to workload requirements and scheduling tasks to maximize their utilization. Conventional scheduling algorithms were not always able to optimum throughput particularly when two or more workloads were contending with one another through the same resource and thus bottlenecks were occurring.

4.3.4 Energy Efficiency
Another area that the RL-based framework performed highly was on energy efficiency. The RL agent minimized the energy used in the telecom cloud hardware by minimizing resource use and over-provisioning. This is especially relevant in the telecom networks, whereby, the power bill may constitute a substantial part of the operation cost. The traditional scheduling algorithms that did not take into account the factor of energy consumption caused increase in energy consumption because of the inefficient distribution of resources.

4.3.5 Fairness
The RL-based system was seen to have a fairer allocation of the resources between competing workloads. The flexibility of the RL agent to dynamics of the workload and priorities guaranteed the allocation of resources equally even when there was variable traffic situation. The scheduling algorithms used traditionally, especially, the first-come-first-served and the use of the static priority algorithms, tended to create an uneven allocation of the resources, where the highest priority task would end up consuming all resources, leaving the other tasks with low priority without the necessary resources.

4.4 Scalability and Adaptability

Scalability and flexibility can be considered one of the most valuable benefits of the RL-based framework. The RL-based system could support more workloads and resources without affecting the performance of the telecom cloud infrastructure in a considerable way as the telecom cloud infrastructure size increased. The RL agent could also learn and evolve according to the changing network situations, which preconditioned its applicability to large-scale cloud environments and dynamically changing requirements of resources.

Conversely, the conventional scheduling algorithms were very problematic as the system grew. The inherent difficulties with the use of static methods of scheduling were that it could not be sustained in larger and more complex environments to ensure performance and fairness, which resulted in inefficiency and the inappropriate use of resources.

4.5 Limitations and Future Work

Although the RL-based framework did fine in the aspect of resource utilization, latency, SLA compliance, throughput, energy efficiency, and fairness, it could be improved in a number of areas. As an example, the existing application is mostly centered on Q-learning that can be not the most effective in very complicated and large-scale settings. Future research is able to look into more sophisticated RL algorithms, including deep reinforcement learning (DRL) and actor-critic frameworks, in order to deal with more complex state and action space.

Also, the reward mechanism can be further enhanced to include other criteria, which are such as security and fault tolerance which are essential in telecom cloud settings. It might also be a good idea to consider multi-agent RL strategies, in which multiple agents coordinate resources in various regions or data centers of the clouds.

The performance of the evaluation shows that the workload scheduling framework which is based on RL is far much better than the traditional methods in the following aspects; resource utilization, latency, SLA compliance, throughput, energy efficiency and fairness. The flexibility and scalability of the RL methodology predisposes the approach as a potential solution to the optimization of telecom cloud architecture, the efficiency of resources distribution and delivering services of an appropriate quality. The second step is the refinement of the framework and the consideration of more sophisticated RL algorithms in order to work with even greater and more sophisticated telecom cloud settings.

V. CONCLUSION & FUTURE WORK

This study proposes a smart workload scheduling algorithm of the telecom cloud architecture with reinforcement learning (RL). The existing conventional methods of scheduling that are based on hard and fast rules and assumptions tend to fail to cope with the dynamism of telecom clouds. Conversely, the suggested RL-based system changes according to the real-time situation and optimizes resources allocation and performance in the key indicators related to resource usage, latency, SLA compliance, throughput, energy efficiency, and equity. The experimental findings prove that the RL-based framework is much more effective with traditional scheduling algorithms, which guarantee the efficient utilization of resources, the minimum latency of real-time-based applications, and the maximum throughput of the system.

Through the application of RL, the suggested framework allows a system to be self-learned to improve the scheduling policies with experience, and thus it is highly applicable in large-scale telecom cloud environments where the workload and demands vary. The framework also has the capacity to reassign the workloads according to their needs dynamically, such that the less urgent tasks do not affect the performance of other tasks with higher priorities, thus avoiding the breach of the SLAs. In addition, the energy efficiency and fairness of the framework help in lowering the cost of operation and enhancing the overall performance of the telecommunication networks.

Although the outcomes are promising, future studies and enhancement can be made in a number of areas. A major direction is incorporating more modern RL models, including deep reinforcement learning (DRL), and multi-agent RL to deal with large-scale telecom cloud systems that are both high-dimensional and high-dimensional. Deep Q-networks (DQN) and actor-critic based DRL methods have the potential to improve the capacity of the framework to process large volumes of data and optimize a schedule decision in a real-world environment.

The second possible direction of the future research will be the improvement of the reward function through the incorporation of other factors, including security, fault-tolerance, and cost-efficiency. These parameters are paramount in telecom network where data integrity and availability are of primary importance. Moreover, it would be worthwhile

looking into hybrid solutions along the lines of RL with other machine learning solutions, including supervised learning or optimization schemes, to enhance the effectiveness and flexibility of the scheduling model.

REFERENCES

1. **Li, X., Jiang, X., Garraghan, P., & Wu, Z.**
Holistic energy and failure aware workload scheduling in Cloud datacenters. Futur. Gener. Comput. Syst., 78, 887–900. https://doi.org/10.1016/j.future.2017.07.044 (2018).

2. **Choudhary, A., Gupta, I., Singh, V., & Jana, P. K.**
A GSA-based hybrid algorithm for bi-objective workflow scheduling in cloud computing. Futur. Gener. Comput. Syst., 83, 14–26. https://doi.org/10.1016/j.future.2018.01.005 (2018).

3. **Panchakarla, S. K.**
Designing carrier-grade microservices for telecom: Ensuring availability and scale in order fulfillment systems. International Journal of Engineering & Extended Technologies Research (IJEETR), 7(5), 10600–10604 (2025).

4. **Bittencourt, L. F., Goldman, A., Madeira, E. R. M., da Fonseca, N. L. S., & Sakellariou, R.**
Scheduling in distributed systems: A cloud computing perspective. Comput. Sci. Rev., 30, 31–54. https://doi.org/10.1016/j.cosrev.2018.08.002 (2018).

5. **Vijayasekaran, G., & Duraipandian, M.**
Deep Q-learning based Resource Scheduling in IoT Edge Computing. (2024). https://doi.org/10.1109/icict60155.2024.10544834.

6. **Gu, Y., et al.**
Cost-aware cloud workflow scheduling using DRL and simulated annealing. Digit. Commun. Netw. https://doi.org/10.1016/j.dcan.2023.12.009 (2024).

7. **Madni, S. H. H., et al.**
Performance comparison of heuristic algorithms for task scheduling in IaaS cloud computing environment. PLoS ONE, 12(5), e0176321. https://doi.org/10.1371/journal.pone.0176321 (2017).

8. **Zhu, Z., & Tang, X.**
Deadline-constrained workflow scheduling in IaaS clouds with multi-resource packing. Futur. Gener. Comput. Syst., 101, 880–893. https://doi.org/10.1016/j.future.2019.07.043 (2019).

9. **Chen, W., et al.**
Efficient task scheduling for budget-constrained parallel applications on heterogeneous cloud computing systems. Futur. Gener. Comput. Syst., 74, 1–11. https://doi.org/10.1016/j.future.2017.03.008 (2017).

10. **Shukur, H., et al.**
Cloud computing virtualization of resources allocation for distributed systems. J. Appl. Sci. Technol. Trends, 1(3), 98–105. https://doi.org/10.38094/jastt1331 (2020).

11. **Wang, Y., et al.**
Cooperative end-edge-cloud computing and resource allocation for digital twin enabled 6G industrial IoT. IEEE J. Sel. Top. Signal Process. https://doi.org/10.1109/jstsp.2023.3345154 (2023).