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# A DEEP REINFORCEMENT LEARNING BASED FRAMEWORK FOR TASK SCHEDULING FOR ENHANCING EFFICIENCY IN CLOUD COMPUTING

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**Abstract**
With unprecedented popularity of cloud, there is drastic increase in cloud usage. In this context, it is indispensable to improve cloud computing towards achieving equilibrium by satisfying consumer needs and infrastructure efficiency. In this paper, it is achieved with an ideal task scheduling method. Many existing methods used for task scheduling are based on certain heuristics. However, with massive amounts of historical data available, in the wake of Artificial Intelligence (AI), learning based approach is found to have more benefits. Towards this end, we proposed a methodology based on reinforcement learning which is highly dynamic and makes decisions based learned knowledge and runtime situation. We proposed an algorithm known as Reinforcement Learning based Task Scheduling (RL-TS). This algorithm exploits benefits of deep reinforcement learning process which involves in taking runtime reward from each action and make well informed task scheduling decisions. It is an agent based mechanism suitable for large scale scheduling operations in cloud to enhance its performance. Our empirical study with workloads consisting of 1000 and 2000 jobs respectively revealed that the success rate of the proposed algorithm is higher besides improving optimal energy utilization when compared with the state of the art.

**Keywords**: Cloud Computing, Cloud Efficiency Enhancement, Reinforcement Learning, Task Scheduling

## I. Introduction

Cloud computing is being increasingly used across the globe. The rationale behind this is the affordability of cloud which enabled paper per use mechanism that avoids investment on computing resources. However, due to dynamic workloads and unexpected bursts in workloads, it is important to have optimizations in scheduling procedures in presence of Service Level Agreements (SLAs). It is indispensable for cloud service provider (CSP) to ensure that SLAs are not violated and there is equilibrium in resource optimization and consumer satisfaction [1], [2]. In the wake of AI, deep learning became very significant technology used to solve real world problems. Deep learning is widely used to schedule tasks in cloud using learning based approach [5], [6], [11], [15].[21] Zhaolong et la. [5] investigated on DRL for controlling traffic in 5G enabled IoT integrated vehicular network. Ji et al. [7] studied the dynamics of computation offloading and allocation of resources in cloud using DRL method. Jun et al. [11] considers UAV clusters where task scheduling is experimented based on RL. Mushu et al. [15] proposed DRL based methodology for collaborative approach in edge computing based vehicular networks.

RL methods are used in different environments like cloud computing, industrial IoT, edge computing and IoT with workflow applications. The methods focused not only task scheduling but also task offloading in the mobile cloud environments. Resource provisioning and energy efficiency are also studied in the existing works [10]. Here proposed a regional resource scheduler that exploits DRL for making well informed decisions. Zhaolong et al. [10] proposed an energy efficient RL approach towards intelligent decision making with offloading of tasks to cloud. From the literature, it is ascertained that there is need for improving DRL based approach in task scheduling towards improving success rate and leveraging cloud infrastructure optimization. Our contributions in this paper are as follows.

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1. We proposed a methodology based on reinforcement learning which is highly dynamic and makes decisions based learned knowledge and runtime situation.
2. We proposed an algorithm known as Reinforcement Learning based Task Scheduling (RL-TS). This algorithm exploits benefits of deep reinforcement learning process which involves in taking runtime reward from each action and make well informed task scheduling decisions. It is an agent based mechanism suitable for large scale scheduling operations in cloud to enhance its performance.
3. An application is built to evaluate our algorithm with empirical study having workloads of 1000 and 2000 jobs.

The remainder of the paper is structured as follows. Section 2 reviews existing works on learning based approaches for task scheduling. Section 3 presents the proposed method for dealing dynamic workloads and scheduling towards cloud performance. Section 4 presents results of experiments while section 5 concludes our work.

## II RELATED WORK

This section reviews literature on different existing methods for cloud performance enhancement. Mingxi et al. [1] proposed a method for task scheduling and resource provisioning using deep learning approach. Hongjia et al. [2] explored DRL based methods and their utility in solving many real time problems and applications. Ding et al. [3] focused on Q-learning mechanism to define a dynamic approach in task scheduling towards realizing energy efficiency. Qu et al. [4] incorporated a meta-learning approach on top of DRL in edge resources. They also exploited offloading phenomenon towards cloud performance. Zhaolong et la. [5] investigated on DRL for controlling traffic in 5G enabled IoT integrated vehicular network. Jiechao et al. [6] focused on runtime prediction of workloads to be scheduling in cloud based on ML techniques. Their method could estimate workload dynamics. Ji et al. [7] studied the dynamics of computation offloading and allocation of resources in cloud using DRL method. Junfeng et al. [8] proposed a regional resource scheduler that exploits DRL for making well informed decisions. Ali et al. [9] focused on parallel environment in bringing performance enhancement in scheduling of workflows and balance load besides resource provisioning with agent based approach. Zhaolong et al. [10] proposed an energy efficient RL approach towards intelligent decision making with offloading of tasks to cloud.

Jun et al. [11] considers UAV clusters where task scheduling is experimented based on RL. Wenhan et al. [12] used edge computing resources for empirical study. Their offloading mechanism is based on scheduling of tasks and DRL. Zhiyuan et al. [13] proposed a methodology based on DRL for improving power efficiency. Ning et al. [14] considered a blockchain application operated through mobiles for security and also intelligent approach towards optimal resource allocation. Mushu et al. [15] proposed DRL based methodology for collaborative approach in edge computing based vehicular networks. Ying et al. [16] considered an industrial IoT scenario where DRL is exploited with efficient resource management. Other contributions include joint learning approach [17], intelligent computing approach [18], DRL with collaborating scheduling [19] and DRL based cost-aware approach [20]. From the literature, it is ascertained that there is need for improving DRL based approach in task scheduling towards improving success rate and leveraging cloud infrastructure optimization[8].

## III.PROPOSED FRAMEWORK

This section presents the proposed methodology for automatic task scheduling towards enhancement of cloud performance. The proposed framework is shown in Figure 1. It is cloud based architecture where different physical servers and VMs are involved in execution of jobs given by different users. Cloud servers with VMs are used to execute jobs. It demands Quality of Service (QoS) requirements and as per that jobs of users are executed. There are many cloud resource consumers or users who need the services of the proposed framework. Their jobs are dynamic in nature and there is need for dynamic task scheduling. Jobs are maintained in job queues and resources are also maintained in the framework. The monitoring module monitors both jobs and resources availability. Then it communicates RL based scheduler which is given knowledge of runtime jobs and also resources. Based on this the RL scheduler module has agent based approach as illustrated in Figure 2 to make scheduling decision for each job. VM selection is based on the action-feedback paradigm of DRL.

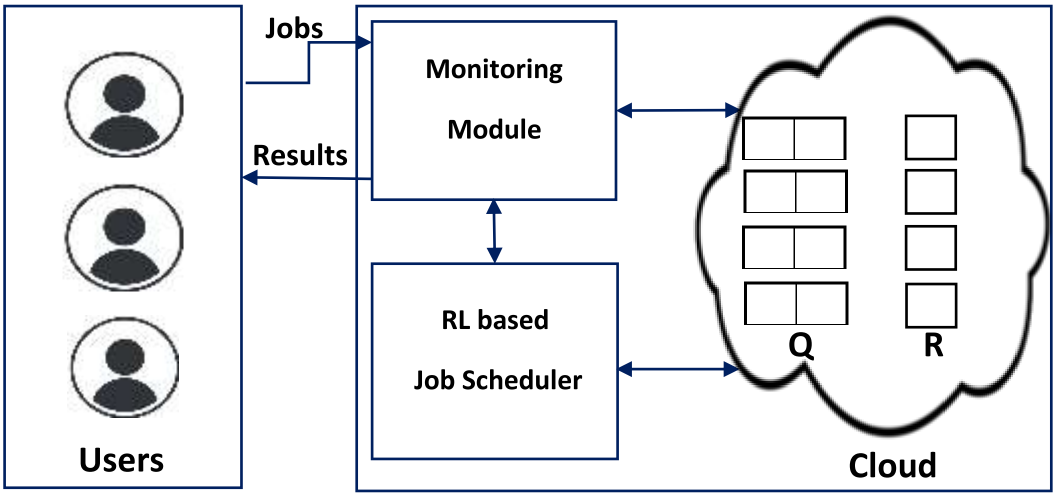


**Figure 1:** Proposed framework for DRL based task scheduling for enhancing efficiency in cloud computing

In the proposed framework, cloud maintains resources (R) and job queues Q. the model is designed in such a way that it works with dynamic workloads. Empirical study is made with 100 and 200 workloads. The cloud has different servers and each server can have associated VMs. Actual job execution is done by a VM. Jobs of different users are scheduled based on the proposed DRL approach. Each user job is characterized by its arrival time, the computational power needed and request time. The proposed framework is supposed to schedule the tasks to improve QoS of the overall cloud.

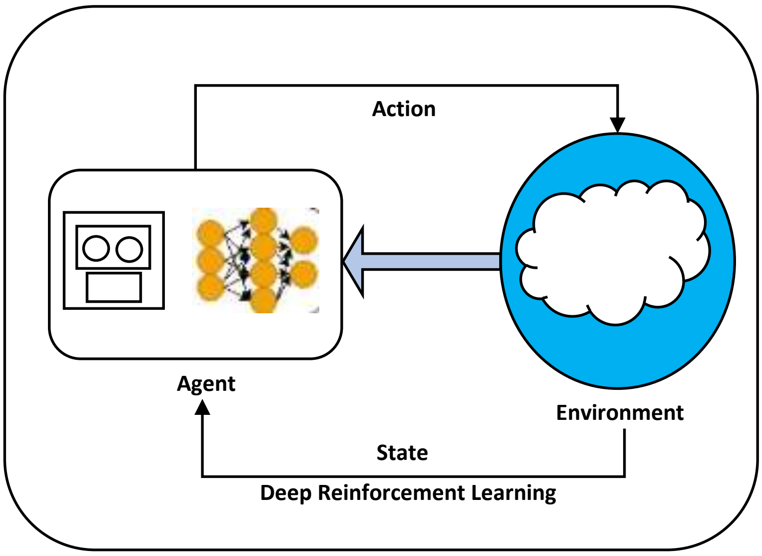


**Figure 2:** Agent based approach with DRL for scheduling decision making

As presented in Figure 2, our methodology is based on agent based approach that is based on DRL. DRL is an important technique in ML to have learning based approach for making intelligent decisions. The agent explores training data at runtime and makes scheduling decisions. However, there is feedback on every decision. The feedback is known as reward. When the reward is highest the learning based approach converges in scheduling decision for given job. In each time step t, agent learns runtime situation and observes the state and makes an action. Then the agent is given reward for the action. This iterative process converges with number of episodes when argmax condition is satisfied. We proposed an algorithm known as Reinforcement Learning based Task Scheduling (RL-TS). This algorithm exploits benefits of deep reinforcement learning process which involves in taking runtime reward from each action and make well informed task scheduling decisions. It is an agent based mechanism suitable for large scale scheduling operations in cloud to enhance its performance.

**Algorithm:** Reinforcement Learning based Task Scheduling (RL-TS)
**Inputs:** Number of jobs J, learning rate $f$
**Output:** Cloud efficient scheduling

```
1.  Begin
2.  Initialize action-feedback queue Q
3.  Initialize resources vector R
4.  For each job j in J
5.    For each episode e in E
6.      Reset initial state of environment
7.      Perform scheduling action aj
8.      Employ RL
9.      Receive reward rj
10.     Update Q
11.     IF rj satisfies argmax property with resource in R Then
12.       Schedule job to a resource in R
13.     End If
14.   End For
15. End For
16. End
```

**Algorithm 1:** Reinforcement Learning based Task Scheduling (RL-TS)

As presented in Algorithm 1, it takes Number of jobs J and learning rate $f$ as inputs and perform learning based approach in task scheduling. In Step 1 and Step 2 action-feedback Q of RL and resources vector R are initialized. Then there is an iterative process to have number of DRL episodes and each time, the algorithm checks scheduling action based on its learned knowledge and take feedback from RL module. The feedback helps in making well informed scheduling decision. The DRL module provides feedback or reward for every action. When the reward is highest, then the algorithm converges towards making final scheduling decision. The algorithm is based on the convergence rule provided in Eq. 1.

$$Q_{t+1}(s_{t,}a_t)=Q_t\left(s_{t,}a_t\right) + \alpha(r_{t+1,}\gamma^{max}_{a_{t+1}}\, Q_t\left(s_{t+1,}a_{t+1}\right) - Q_t(s_{t,}a_t)) \qquad (1)$$

Where Q(s,a) is the value function that gets updated iteratively. The learning rate is denoted by $\alpha$ whose value should belong to (0 , 1]. An action is denoted by a while a reward is denoted by r. A discount factor is used which can belong to (0 , 1]. Our algorithm is aimed at minimizing energy consumption in cloud data centres with optimal job scheduling. In presence of dynamic changes in workloads and runtime environment, DRL is found best method. Without any prior knowhow, DRL learns at runtime and performance scheduling actions.

## IV.RESULTS AND DISCUSSION

Experiments are made with workloads consisting of 100 and 200 jobs. The proposed method is evaluated in terms of different performance metrics and compared with state of the art methods.

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**Table 1:** Shows results of experiments with 100 jobs

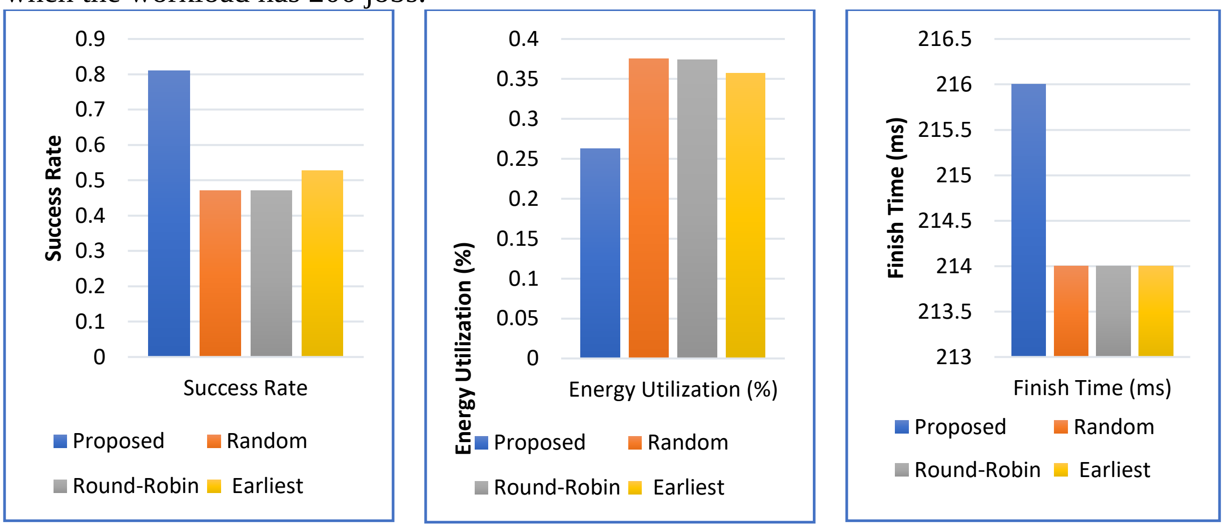
| 1000 JOBS WORKLOAD | | | |
|---|---|---|---|
| **Scheduling Method** | **Success Rate** | **Energy Utilization ()%** | **Finish Time** |
| Proposed | **0.81** | **0.263** | 216 |
| Random | 0.471 | 0.375 | 214 |
| Round-Robin | 0.471 | 0.374 | 214 |
| Earliest | 0.528 | 0.357 | 214 |

As presented in Table 1, the results of experiments with different scheduling methods are provided when the workload has 100 jobs.

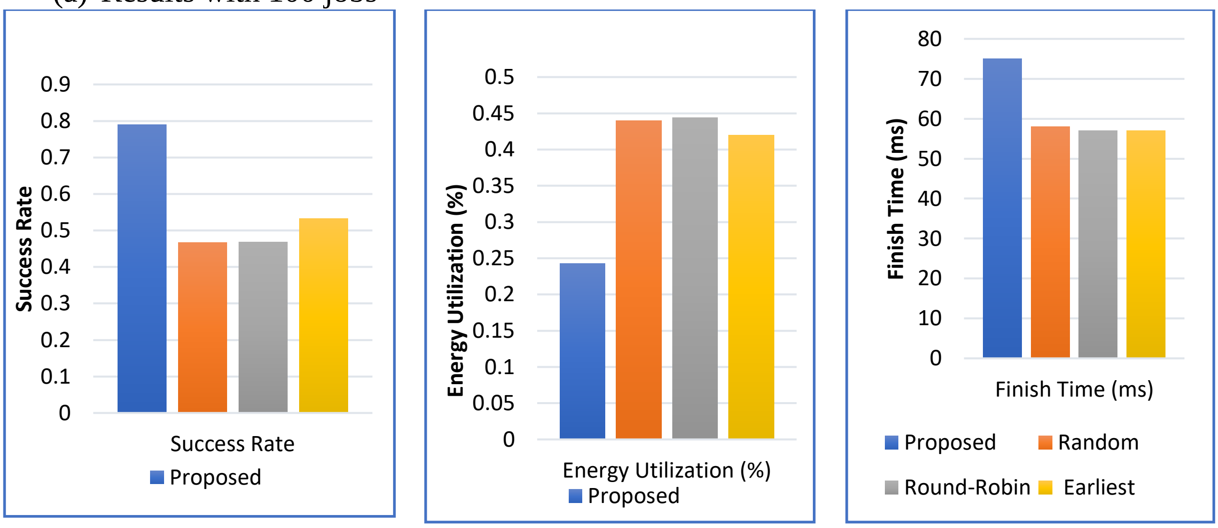
**Table 2:** Shows results of experiments with 200 jobs

| 2000 JOBS WORKLOAD | | | |
|---|---|---|---|
| **Scheduling Method** | **Success Rate** | **Energy Utilization ()%** | **Finish Time** |
| Proposed | **0.79** | **0.243** | 75 |
| Random | 0.467 | 0.44 | 58 |
| Round-Robin | 0.469 | 0.444 | 57 |
| Earliest | 0.532 | 0.42 | 57 |

As presented in Table 2, the results of experiments with different scheduling methods are provided when the workload has 200 jobs.




(a) Results with 100 jobs




(b) Results with 200 jobs

**Figure 3:** Results of experiments with 100 jobs and 200 jobs

As presented in Figure 3, experimental results are provided for 100 jobs and 200 jobs. The proposed method is evaluated and its performance is compared against state of the art. With 100 jobs, the proposed method achieved 81% success rate, 26.3% energy utilization and finish time with 216 ms. The proposed method showed highest performance in terms of energy efficiency and success rate. However, the finish time is a little bit more than other methods which is negligible considering high success rate and energy conservation in cloud infrastructure. With 200 jobs, the proposed method achieved 79% success rate, 24.3% energy utilization and finish time with 75 ms. The proposed method showed highest performance in terms of energy efficiency and success rate. However, the finish time is more than other methods which is incurred due to DRL method which could achieve high success rate and energy conservation in cloud infrastructure.

## V CONCLUSION AND FUTURE WORK

We proposed a methodology based on reinforcement learning which is highly dynamic and makes decisions based learned knowledge and runtime situation. We proposed an algorithm known as Reinforcement Learning based Task Scheduling (RL-TS). This algorithm exploits benefits of deep reinforcement learning process which involves in taking runtime reward from each action and make well informed task scheduling decisions. It is an agent based mechanism suitable for large scale scheduling operations in cloud to enhance its performance. Empirical study is made with workloads consisting of 1000 and 2000 jobs. With 100 jobs, the proposed method achieved 81% success rate, 26.3% energy utilization and finish time with 216 ms. The proposed method showed highest performance in terms of energy efficiency and success rate. However, the finish time is a little bit more than other methods which is negligible considering high success rate and energy conservation in cloud infrastructure. With 200 jobs, the proposed method achieved 79% success rate, 24.3% energy utilization and finish time with 75 ms. The proposed method showed highest performance in terms of energy efficiency and success rate. However, the finish time is more than other methods which is incurred due to DRL method which could achieve high success rate and energy conservation in cloud infrastructure. In future we intend to improve our method with hybrid evolutionary methods for leveraging performance further.

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