A Deep Reinforcement Learning Framework for Task Scheduling for Leveraging Energy Efficiency in Cloud Computing

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Abstract. Cloud computing and its popularity has resulted in increased usage of cloud in real world applications. Thus there is unprecedented growth in user base and their tasks. In this context, it is indispensable to improve cloud computing towards achieving equilibrium by satisfying consumer needs and infrastructure efficiency. In this paper, we proposed a framework for efficient task scheduling based on Reinforcement Learning (RL). Instead of heuristics based approach employed traditionally, our framework is based on learning runtime situation for making scheduling decisions. As there are number of historical instance available, our approach is based on RL. We proposed an algorithm known as Reinforcement Learning based Task Scheduling (RL-TS). This algorithm exploits RL for making scheduling decisions based on the action-reward cycle for decision convergence. In presence of large number of tasks arriving for scheduling our agent based phenomenon strives to improve efficiency of cloud infrastructure with appropriate scheduling decisions. Our empirical study with workloads consisting of 1000, 2000 and 5000 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

1 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

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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]. Zhaolong et al. [7] investigated on DRL for controlling traffic in 5G enabled IoT integrated vehicular network. Ji et al. [10] studied the dynamics of computation offloading and allocation of resources in cloud using DRL method. Jun et al. [17] considers UAV clusters where task scheduling is experimented based on RL.

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. [11] 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.

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, 2000 and 5000 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 Sect. 5 concludes our work.

2 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. [3] explored DRL based methods and their utility in solving many real time problems and applications. Ding et al. [2] 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. Kardani et al. [5] proposed a method for Cloud fir DRL based resource scaling. Wang et al. [6] focused on DRL for energy efficient VM scheduling for Future Generation. Zhaolong et al. [7] investigated on DRL for controlling traffic in 5G enabled IoT integrated vehicular network. Qi et al. [8] studied Task Scheduling for

Autonomous driving vehicle's using multi-Task DRL. Uma et al. [9] explored DRL for detection and classification of Rheumatoid Nodule. Ji et al. [10] DRL based resource allocation and computation Offloading. Zhaolong et al. [11] used DRL for IOT of vehicles for energy efficient and offloading schemes. Mekala et al. [12] proposed a method for cloud computing to map reduce frameworks. Zhao et al. [13] used cloud computing for a Novel ML scheduling schemes. Asghari et al. [14] worked on task scheduling and load balancing on scientific works using RL agents and genetic algorithm. Fatemeh et al. [15] A DL approach for computation offloading and auto-scaling the mobile fog. Mengting et al. [16] investigated on Blockchain-Enabled wireless using DLR based transcoder frameworks. Jun et al. [17] worked used RL in UAV cluster task scheduling. Wenhan et al. [18] used edge computing resources for empirical study. Their offloading mechanism is based on scheduling of tasks and DRL. Zhiyuan et al. [19] proposed a methodology based on DRL for improving power efficiency. Ning et al. [20] considered a blockchain application operated through mobiles for security and also intelligent approach towards optimal resource allocation.

3 Proposed Framework

This section presents the proposed methodology for automatic task scheduling towards enhancement of cloud performance. The proposed framework is shown in Fig. 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 Fig. 2 to make scheduling decision for each job. VM selection is based on the action-feedback paradigm of DRL. Cloud usage in the real world is increasing and there is need for efficient scheduling of user tasks in order to improve cloud infrastructure's capabilities in improving Quality of Service (QoS).

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 1000, 2000 and 5000 jobs 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.

As presented in Fig. 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

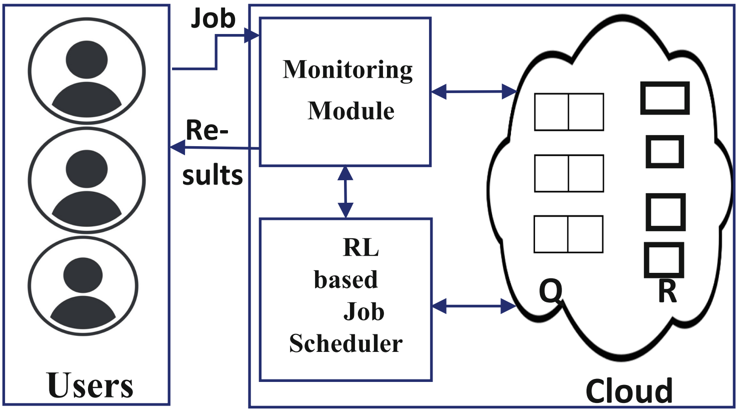

Fig. 1. Proposed framework for DRL based task scheduling for enhancing efficiency in cloud computing

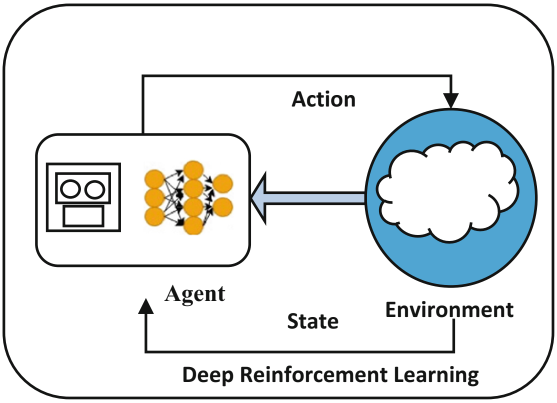

Fig. 2. Agent based approach with DRL for scheduling decision making

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. There is continuous interaction process between environment and agent with action space and reward space for faster convergence of decisions. 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 fas 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.

$$\begin{aligned}\mathrm{Q\_(t+1)(s\_(t,)a\_t)} &= \mathrm{Q\_t(s\_(t,)a\_t)} \\ &+ \alpha(r\_(t+1,)\ \gamma\_(a\_(t+1))^\wedge \max Q\_t(s\_(t+1,)a\_(t+1)) \\ &- Q\_t(s\_(t,)a\_t))\end{aligned} \tag{1}$$

where Q(s,a) is the value function that gets updated iteratively. The learning rate is denoted by α 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 schedul ing actions. The convergence rule in Eq. 1 plays an important role as there is interaction between environment and agent continuously in terms of state, reward space and action space. When the convergence rule is satisfied, scheduling decision is made. Our framework is evaluated in terms of finish time, success rate and energy efficiency. Finish time refers to the time required to complete execution of jobs.

Energy efficiency refers to the usage of energy. If less energy is used relatively when compared with other methods, it is known as energy efficiency. Success rate refers to the ratio between the number of jobs scheduled and the number of jobs completed successfully by fulfilling their QoS needs.

4 Results and Discussion

Experiments are made with workloads consisting of 1000, 2000 and 5000 jobs. The proposed method is evaluated in terms of different performance metrics and compared with state of the art methods. As presented in Figs. 3, 4 and 5, different methods are compared for their performance in terms of success rate, time and energy efficiency. The methods compared are Random, Round-Robin, Earliest and the proposed method. Experimental results are provided for 1000 jobs, 2000 jobs and 5000 jobs. The proposed method is evaluated and its performance is compared against state of the art. With 1000 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 2000 jobs, the proposed method achieved 79% success rate, 24.3% energy utilization and finish time with 75 ms. With 5000 jobs, the proposed method achieved 80% success rate, 27% energy utilization and finish time with 155 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 isincurred due to DRL method which could achieve high success rate and energy conservation in cloud infrastructure.

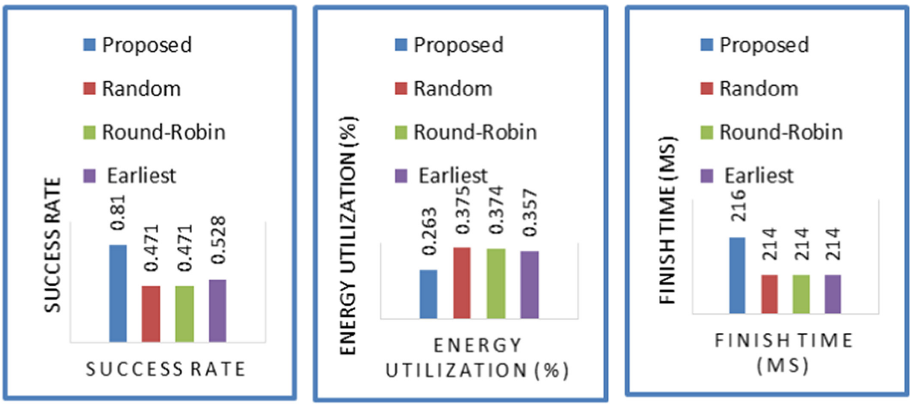

Fig. 3. Results of experiments with 1000 jobs

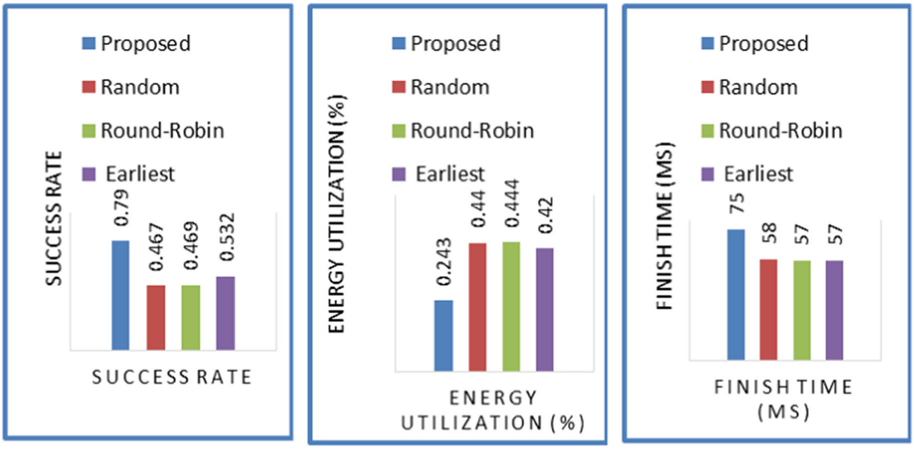

Fig. 4. Results of experiments with 2000 jobs

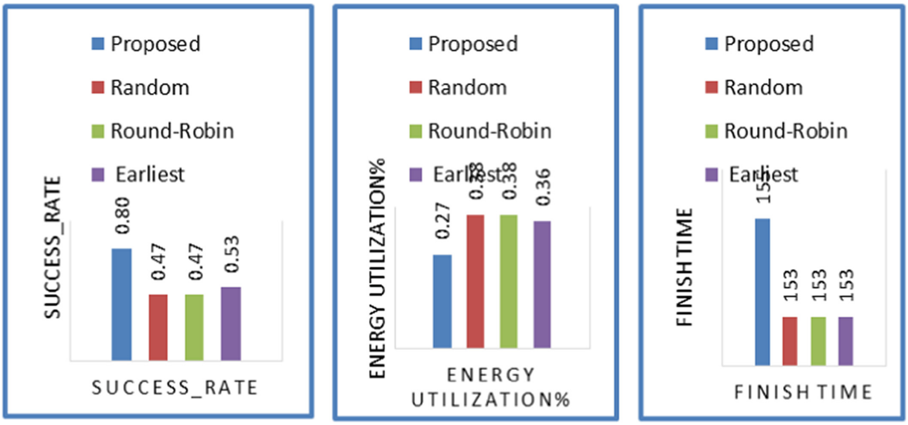

Fig. 5. Results of experiments with 5000 jobs

5 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, 2000 and 5000 jobs. With 1000 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 2000 jobs, the proposed method achieved 79% success rate, 24.3% energy utilization and finish time with 75 ms. With 5000 jobs, the proposed method achieved 80% success rate, 27% energy utilization and finish time with 155 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. Ahmad, S.S., Khan, A., Kawadkar, P., Khan, I., Kumar, M.U., Shravani, D. (2022). Proposed A Machine Learning Framework for Automatic Detection of Malware hence this paper proposed work can be extended to their work for technology transfer and better results as well [21].

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